Three Essays in Microeconometrics

Metin Nebiler

Thesis submitted for assessment with a view to obtaining the degree of Doctor of Economics of the European University Institute

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Three Essays in Microeconometrics

Abstract

This PhD dissertation discusses three important topics in labor economics. It consists of three chapters that inquire into the integration of migrants and their socioeconomic outcomes in the host country market by relying on an empirical framework combined with economic theory. The first chapter explores whether naturalization leads to faster occupational assimilation for immigrants in the labor market in Germany. In particular, the empirical analysis in this paper investigates whether immigrants become occupationally more mobile after naturalization and if this leads to better jobs in the labor market. Instrumental variable estimation is exploited to control for the time-invariant and -variant unobserved individual characteristics. In order to do so, changes in German immigration law in the 1990s is used as an instrument for naturalization. The results show that naturalization is not associated with an immediate increase in occupational mobility. Instead, the years following naturalization are associated with higher occupational mobility, which implies that immigrants use naturalization in the German labor market to pursue better occupation match and faster occupational assimilation. The second chapter exploits the September 11 as an exogenous event to explore whether September 11 decreased the exit rate from unemployment of immigrants from Muslim countries in the UK labor market. The empirical analysis exploits discrete time duration models. The results show that the exit rate from unemployment to paid employment decreases after the September 11 terrorist attacks for immigrants from Muslim countries compared to UK-born white population with similar socioeconomic characteristics. Moreover, a significant increase in the unemployment spell is found for the first generation immigrants from Muslim countries while no impact is found on second generation immigrants. The last chapter addresses issues related to religious identity which have been questioned more intensively in recent years. The first part of the empirical analysis answers the question about the extent to which religious identity is transmitted from one generation to the next by using longitudinal data from Germany. In addition, the empirical analysis investigates how socio-economic characteristics influence the transmission of

religious traits across generations. Furthermore, the paper explores whether migration background plays a role in the transmission process. The results show that parents play an important role in the development of the religious identity of their children in Germany. The transmission or religious traits across generations varies according to the socio-economic characteristics of transmitter and religious groups. Finally, the empirical research shows that migration background is an important factor in the transmission process. The results reveal that vertical transmission is higher among immigrant families by using data from Indonesia and Turkey.

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Contents

Chapter 1

Occupational Mobility and Impact of German Citizenship on Occupational Assimilation

Metin Nebiler

Abstract

Naturalization has been used as an important tool by immigrants to integrate into host countries. This article examines whether naturalization leads to faster occupational assimilation of immigrants in the labor market in Germany. In particular, the empirical analysis in this paper investigates whether immigrants become occupationally more mobile after naturalization and if this leads to better jobs in the labor market. The empirical analysis identifies the impact of naturalization on occupational mobility by eliminating other factors such as self selection, time-invariant, and -variant unobserved characteristics. Instrumental variable estimation is exploited to control for the time-invariant and -variant unobserved individual characteristics. In order to do so, we introduce the changes in the immigration law in Germany in 1990s as an instrument for naturalization. The law change provides an exogenous variation in the naturalization process. The results show that naturalization is not associated with an immediate increase in occupational mobility. Instead, the years following naturalization are associated with higher occupational mobility, which implies that immigrants use naturalization in the German labor market to pursue better occupation match and faster occupational assimilation.

1.1 Introduction

Naturalization has been used as an important tool by immigrants to integrate into host countries. Acquisition of citizenship provides several benefits for immigrants while it is considered to be a strong commitment for the future. This article examines whether naturalization leads to faster occupational assimilation for immigrants in the labor market in Germany. In particular, empirical analysis in this paper investigates whether immigrants become occupationally more mobile after naturalization and if this leads to better jobs in the labor market.

At a scholarly level discussions among economists has focused mainly on determinants of naturalization and its effect on wage assimilation or employment. Several studies show that labor market outcomes are increasing with the acquisition of citizenship (Fougre and Safi (2009), Bratsberg et al. 2002). Naturalized immigrants earn higher wages than non-naturalized counterparts with similar characteristics (Chiswick (1978); DeVoretz and Pivnenko 2006). Employment rate and probability of being employed in a white collar job increase with the acquisition of citizenship (Bratsberg et al. 2002, Steinhardt 2008). In their seminal paper, Bratsberg et al. (2002) suggest that the higher wages of naturalized immigrants is a result of being employed at higher paid jobs by using both cross-sectional and longitudinal data. Similarly, Steinhardt (2008) finds an immediate increase in wages after naturalization but also an accelerated increase in wages in the following years after naturalization in Germany[1]. Most recently, Gathmann and Keller (2014) find low benefit of citizenship for men and substantial benefit for women by using discontinuities in the eligibility rules introduced by changes in immigration law in Germany in the 1990s.

Acquisition of host country citizenship can provide several benefits including more job opportunities for naturalized immigrants. First, some jobs require German citizenship i.e. public jobs, self employed personal services, etc. (Steinhardt 2008). Second, employers may want to hire German citizens because of their preferences, fewer administrative costs, or free movement in the EU countries. On the other hand, value of German citizenship is different for individuals. In addition to greater employment opportunities, it provides further benefits such as right to vote, permanent residence and work permit, right to travel without visa in the EU, etc. There are also costs of

[1] See also Scott 2008, Hayfron 2008.

entailed in applying for the German citizenship i.e. time spent on the application process, loss of previous citizenship, exposure to ethnic criticism, etc. Furthermore, the country of origin of individuals is very important for the naturalization decision. Immigrants from the EU states or states which have bilateral agreement with Germany on dual citizenship have the right to keep their previous citizenship, while this is not possible for other non-EU countries. Hence, obtaining the German citizenship is more costly for immigrants from non-EU countries but also provides higher benefits. Therefore, immigrants who are utility maximizing agents have greater incentives to apply for German citizenship if they have a positive expected benefit.

Bratsberg et al. (2002) shows that after naturalization immigrants have a superior job distribution compared to non-naturalized immigrants. A neglected question in the literature is the mechanism behind the link between naturalization and better jobs. Do immigrants switch to better jobs immediately after the citizenship acquisition or spend some time before finding a satisfactory job? This article studies whether naturalization increases the occupational mobility of immigrants. Immigrants might move to better jobs immediately after naturalization. Alternatively, better job distribution of naturalized immigrants might be associated with higher occupational mobility of those immigrants. In particular, occupational mobility after naturalization can increase since immigrants can try to find better firm/sector match with the increasing job opportunities in the labor market.

It is well reported that when entering the host country labor market, immigrants are employed at lower level jobs compared to natives with similar individual characteristics. With the time spent in the host country labor market, some immigrants climb the ladder in the labor market while some remain trapped in certain sectors (self employed, ethnic labor market, etc.). For instance, an immigrant from Turkey who is an economist can start working in a kebap shop, then become a waiter in a hotel, continue as a salesperson in a store and finally work as an economist in a bank. Obtaining the German citizenship can encourage immigrants to adjust their career path so that those immigrants are more likely to change occupations compared to non-naturalized immigrants. In other words, immigrants can use naturalization as a tool to find a better sector/firm match, which can lead to higher occupational mobility until a satisfying job is found.

Alternatively, higher occupational mobility after naturalization can be the result of self-selection, in the sense that immigrants who were occupationally mobile before the citizenship acquisition are more likely to naturalize. Naturalization and occupational mobility can be correlated because of unobserved individual characteristics such as commitment or motivation. Naturalized immigrants can be more motivated or committed to perform better in the labor market, hence, change jobs more frequently compared to non-naturalized immigrants even before the German citizenship. This type of time-invariant unmeasured individual characteristics can cause biased estimates if not accounted for.

Similarly, naturalization can be associated with time-variant unobserved individual heterogeneity. For instance, a common reason for applying for naturalization is that employers may ask their immigrant workers to obtain the German citizenship even if the latter have no intention to naturalize. The reason behind this can be administrative costs of hiring a non-German citizen or individual preferences of employers. Even though this is neglected in previous studies, occupational mobility can be correlated with the unobserved time-variant individual characteristics, which can bias the results.

This research paper focuses on the impact of German citizenship on occupational mobility of immigrants in the German labor market. Individuals are described as occupationally mobile if they report a different occupation than the last employment. The empirical analysis presents several estimation methods to eliminate the factors such as self selection, time-invariant, and -variant unobserved characteristics. First, probit estimates from the pooled sample by using the German Socio-Economic Panel are reported. According to estimates, acquisition of German citizenship increases the job mobility of immigrants compared to non-naturalized immigrants with similar socioeconomic characteristics. Although results from the pooled sample depict a general picture, the well documented self-selection problem is not accounted for. Thus, the higher occupational mobility can be a result of unobserved characteristics of individuals who are naturalized. An alternative solution is to use the longitudinal feature of the data and estimate a fixed effect logit regression which controls for unobserved time-invariant heterogeneity among individuals. Results from fixed effects model indicate a small and insignificant correlation between naturalization and oc-

cupational mobility, and a negative correlation between years since naturalization and occupational mobility. However, the fixed effects model does not control for potential time-variant unmeasured characteristics. More importantly, it restricts the sample and estimates a smaller sample where sample selection can be a major problem.

Next, the empirical analysis continues with instrumental variable estimation to control for the time-invariant and -variant unobserved individual characteristics. Similar to Gathmann et al (2014), changes in the immigration law in Germany in 1990s are introduced as an instrument for naturalization. The law change provides an exogenous variation in naturalization process. Since the requirements depend on age and years spent in Germany, immigrants with similar characteristics but with different age and years spent in Germany have different eligibility years for German citizenship. Hence, I use the eligibility criteria as an instrument for the naturalization. The results show that naturalization is not associated with immediate increase in occupational mobility. Instead, the years following naturalization are associated with higher occupational mobility which implies that immigrants use naturalization in the German labor market to find a better occupation match. Finally, the last section investigates whether naturalization leads to faster occupational assimilation in the German labor market. Results reveal that naturalized immigrants are more likely to experience upward occupational mobility compared to to non-naturalized immigrants.

The contribution of this paper to literature is that it is the first attempt to investigate the link between citizenship acquisition and occupational mobility in the labor market. This question has never been addressed before since papers mostly focus on the benefits of naturalization on wages and employment. However, naturalization can also influence the behavior of immigrants such that they can change occupation more frequently. Thus, this can lead to better jobs and explain part of the benefits of naturalization in the labor market. Furthermore, changes in the German immigration law is used to eliminate the well reported self selection problem in naturalization literature.

This paper is organized as follows. Section 1.2 describes the citizenship law in Germany. Section 1.3 explains the empirical model used in the article while section 1.4 presents the data. Results are presented in section 1.5 and finally, section 1.6

discusses the results and concludes.

1.2 Citizenship Law in Germany

Immigration to Germany started in 1960s with the arrival of labor workers after the World War II. Those immigrants, referred as "guest workers", were expected to return to their home countries. Not only did they choose to stay in Germany but also family members arrived in Germany soon after through family reunification processes, which increased the number of immigrants substantially. For an immigrant country, Germany had a very strict immigration law until 1990s. Although it was possible to have access to German citizenship, there were no explicit requirements for the naturalization process; only German descendants[2] were able to obtain the citizenship by birth. One way of acquiring the citizenship for immigrants was to marry a German citizen. However, the final decision was taken by local authorities, who had the right to reject the application.

In early 1990s, the legal situation changed substantially. In particular, the new immigration law, which came into force on 1 January 1991, included explicit criteria for the naturalization process. Fulfilling the requirements was enough to get the German nationality. The new law included several requirements for immigrants who wanted to obtain the German citizenship. These requirements were to have legal residence in Germany, to be associated with social assistance, to give up the previous nationality[3], and to have no criminal background. The residency requirement differed among individuals depending on age. An individual who was 23 years old or older required at least 15 years of legal residence while it was at least 8 years for an immigrant who was between the age of 16 and 22.

Changes in the immigration law continued in 1999. According to the new law that entered into force on 1 January 2000, legal residency requirement was reduced to eight years for every individual independent of their age. In addition, agreements for dual citizenship were signed with more countries. On the other hand, knowledge

[2] Individuals whose parents have German citizenship.

[3] Immigrants from the EU states or states which have bilateral agreement with Germany on dual citizenship have the right to keep their previous nationality while immigrants from other countries have to give up their previous nationality to obtain the German citizenship.

of German language was added as another criterion. An important change was to allow the second (or further) generation immigrants to have the German citizenship by birth[4]. These individuals were able to keep two citizenships (German and parents' country) until the age of 23, when they had to decide between one of the two citizenships. Finally in 2008, Germany introduced a naturalization test that individuals have to pass in order to naturalize. The citizenship law changes in Germany in 1991 and 2000 are used to construct the eligibility for German citizenship as an instrument for naturalization.

1.3 Empirical Model

The link between citizenship and the labor market outcomes has been widely studied by economists and sociologists. Studies mainly focus on wage and employment of naturalized immigrants compared to non-naturalized counterparts. This research paper is the first empirical attempt to analyze the link between occupational mobility and host country citizenship. The empirical analysis models the relationship between naturalization and occupational mobility as follows,

$$OCC_{it} = \mathbb{1}\{\alpha_0 + \alpha_1 N_{it} + \alpha_2 N_{it}(E_{it} - E_{iN}) + \alpha_3 E_{it} + \alpha_4 X_{it} + \alpha_5 YSM_{it} + \alpha_6 N_{it} YSN_{it} + \phi_i + \epsilon_{it}\} \tag{1.1}$$

where OCC_{it} refers to occupational change which takes value 1 if the individual i changes occupation and 0 otherwise. $\mathbb{1}\{.\}$ is an indicator function, N_{it} is an indicator variable which takes value 1 if the individual i is naturalized at time t, E_{it} is experience in the labor market at time t, E_{iN} is the experience after naturalization, X_{it} is the set of control variables, YSM_{it} is the years since migration, YSN_{it} is the years since naturalization, ϕ_i is the individual fixed effect, and ϵ_{it} is a transitory shock. The set of independent variables are aimed to control for observable characteristics of individuals. Age, gender, education, and country of origin are included since they are expected to have an important impact on occupational mobility.

The empirical analysis here first reports the results from probit estimation using the pooled sample from 1991-2011. This model considers that the naturalization is exogenous to occupational mobility and is the best specification if the unobserved

[4] Any individual born in Germany, either German descendant or not, had the right to obtain the citizenship.

individual heterogeneity is ignored. The individual fixed effect, ϕ_i, is excluded from the regression in this model. The above specification allows us to estimate the impact of naturalization on occupational mobility through two channels. First, α_1 captures the immediate impact of naturalization on occupational mobility. Second, instead of a sudden impact, occupational mobility can increase in the years following the naturalization which is captured by α_6. The estimation results from the pooled sample provide a general picture of the impact of naturalization and several explanatory variables on occupational mobility.

Empirical models that study citizenship have to take into consideration the self-selection problem at the naturalization process. For instance, those who obtain host country citizenship have better educational attainment, higher occupational status and wages relative to non-naturalized immigrants (Yang 1994, Steinhardt 2008, Bratsberg et al. 2002). Regression analysis includes observable characteristics as independent variables to explain observable differences among individuals. Furthermore, citizenship acquisition can be correlated with unobservable characteristics. Immigrants who naturalize may have higher motivation or commitment to achieve better in the German labor market. Alternatively, the higher occupational mobility of naturalized immigrants might be attributed to the fact that immigrants who are occupationally more mobile are also the ones more likely to apply for German citizenship. Those who are occupationally more mobile can use naturalization as an opportunity to reach better jobs. This can be directly associated with higher occupational mobility independent of obtaining the German citizenship for those immigrants. A recent study in Germany among immigrants who are at the naturalization process confirms this kind of behavior. Table 1.1 shows the outcomes of a survey in Germany, according to which more than 80 percent of immigrants who are at the naturalization process report that having more job opportunities is one of the main reasons that they applied for German citizenship (Blicke et al. 2011)[5].

The pooled probit estimation will provide biased estimates if individual unobserved heterogeneity is not accounted for. An alternative solution is to use fixed-effects model to control for time-invariant unobservable characteristics. The individual fixed effect, ϕ_i, in equation 1.1 captures the individual time-invariant characteris-

[5]The survey is conducted among the immigrants who are at the naturalization process.

tics which can have an impact on the occupational mobility such as motivation, commitment, etc. Thus, logit fixed effect estimation strategy is exploited in the empirical analysis. The fixed-effect model contains a particular disadvantage in terms of the estimated sample. This model excludes from the estimation those individuals whose occupation does not change during the time participated in the survey. For instance, individuals who never change sectors or change sectors in every period are dropped out in equation 1.1. Thus, the sample that is used to estimate the fixed effects is different than the sample estimated with the pooled sample. The estimation of fixed effect results can differ from the results reported by using the probit estimation from the pooled data because the samples that are used in the analysis are different.

Finally, naturalized immigrants can have time-variant unobserved heterogeneity which has been often overlooked in the literature. A common reason to apply for German citizenship can be because there is a prior demand by employers. The reason behind this can be administrative costs of hiring a non-German citizen or individual preferences of employers. This type of individual heterogeneity is described as time-variant since immigrants may not have any intention to naturalize. Fixed-effects estimation can control for time-invariant unobserved heterogeneity but cannot control for time-variant unobserved individual heterogeneity. Any model that does not control for this type of unobserved heterogeneity can have biased estimation results.

According to the previous discussion, estimation of probit equation by using pooled sample and the fixed effects analysis might not reveal the correct relationship between naturalization and occupational mobility. Thus, this research paper suggests another possible solution to this kind of problem by using the recent changes in citizenship law in Germany as an instrument for naturalization.

1.3.1 Eligibility as a Proxy for Naturalization

The main concern with equation 1.1 is the unobserved individual heterogeneity. The probit model does not control for unobserved heterogeneity. Fixed effects models control for time-invariant unobserved heterogeneity but restrict the sample and do not control for time-variant unobserved heterogeneity, which is correlated with naturalization and affects occupational mobility through ϵ_{it}. This section introduces an instrumental variable approach that exploits in its empirical analysis changes in im-

migration law to identify the impact of naturalization on occupational mobility. Law changes provide an exogenous variation which allows us to use it as an instrumental variable.

Two Stage Least Squares Approach

I use a two-stage least square approach to address the endogeneity. The first stage estimates the regression equation using OLS where naturalization is the dependent variable. In the second stage, the predicted values from the first stage are replaced with the endogenous variable in the main equation. In particular, we estimate two stage least squares (2SLS) and two stage predictor substitution (2SPS). A two stage regression method consists of the following system of equations,

$$OCC_{it} = \beta_0 + \beta_1 \hat{N}_{it} + \beta_2 \hat{N}_{it}(E_{it} - E_{iN}) + \beta_3 E_{it} + \beta_4 X_{it} + \beta_5 YSM_{it} + \beta_6 \hat{N}_{it} YSN_{it} + u_{it} \tag{1.2}$$

$$N_{it} = \gamma_1 EL_{it} + \gamma_2 Z_{it} + \omega_{it} \tag{1.3}$$

where OCC_{it} refers to occupational change which takes value 0 if the individual i changes occupation and 0 otherwise, $\hat{N}_{it}$ is the predicted value from equation 1.3, N_{it} is an indicator variable which takes value 1 if the individual i is naturalized at time t, $\mathbb{1}\{.\}$ is an indicator function, E_{it} is experience in the labor market at time t, E_{iN} is the experience after naturalization, X_{it} is the set of control variables,YSN_{it} is the years since naturalization, EL_{it} is the indicator variable which takes value 1 if individual i is eligible for German citizenship and 0 otherwise, Z_{it} is the set of all exogenous variables in equation 1.2, and u_{it} and ω_{it} are transitory shocks.

The two stage least squares estimation strategy takes care of time-invariant and -variant unobserved individual characteristics. In equation 1.3, eligibility is used as an instrument for naturalization. To define eligibility for citizenship after the 1990 and 1999 law changes, we use information on the immigrant's year of birth and arrival to Germany. The validity of the empirical strategy depends on two important assumptions: (i) eligibility for German citizenship is not correlated with occupational mobility, (ii) eligibility is correlated with naturalization behavior. Eligibility for citi-

zenship is expected to satisfy the assumption that it is correlated with the naturalization behavior of immigrants since immigrants have to qualify to apply for the German citizenship. One concern might be naturalization through other possible procedures such as marriage, refugee status, etc. If the number of those individuals is large enough, eligibility may not be correlated with the naturalization.

Although eligibility is more likely to be exogenous, exclusion restrictions have to be satisfied. It requires that eligibility is not correlated with occupational mobility directly or through ϵ. First, it is less likely that eligibility directly affects occupational mobility. Eligibility to apply for German citizenship does not provide any benefits for immigrants, instead benefits are received after naturalization. One possible channel is that immigrants who just become eligible can change their behavior in the labor market by becoming more mobile since they expect to obtain the German citizenship. Second and more importantly, eligibility can be correlated with occupational mobility through language. Immigrants who are residents for more than 8 or 15 years are more likely to be proficient in German compared to non-eligible immigrants. It can be an important source of violation of the eligibility instrument if better language skills are associated with higher occupational mobility in the labor market.

Equation 1.3 is estimated in the first stage to obtain the predicted values to include in the estimation of equation 1.2, second stage regression. As Angrist and Kruger (2001) showed, the functional form of the first equation should be linear since the consistency in the second stage depends on the correct specification of the first stage functional form. Thus, 2SLS provides consistent estimates while there is no evidence on the consistency of the 2SPS (Wooldridge, 2009). Thus, several functional forms are used in the empirical analysis. First, predicted values from linear probability model specification are used in the second stage IV regression. Later, I use the predicted probabilities from the probit model by using the maximum likelihood estimation. Then, equation 1.2 is estimated using the predicted values with linear probability and probit models.

Bivariate Probit Approach

Bivariate probit estimation strategy is another approach to tackle endogeneity in a system of regressions with two binary dependent variables. This estimation is differ-

ent from two stage IV estimation, since it is a recursive method in which error terms are assumed to be correlated. Consider the following system of equations,

$$OCC_{it} = \mathbb{1}\{\theta_0 + \theta_1 \hat{N}_{it} + \theta_2 \hat{N}_{it}(E_{it} - E_{iN}) + \theta_3 E_{it} + \theta_4 X_{it} + \theta_5 YSM_{it} + \theta_6 \hat{N}_{it} YSN_{it} + \upsilon_{it}\} \tag{1.4}$$

$$N_{it} = \mathbb{1}\{\delta_1 EL_{it} + \delta_2 Z_{it} + e_{it}\} \tag{1.5}$$

where variables above are as defined previously. The error terms are assumed to have the following form

$$\begin{aligned} \upsilon &= \eta_i + \xi \\ e &= \eta_i + \nu \end{aligned} \tag{1.6}$$

where η_i is the common error term, ξ and ν are independent error terms. Typically, υ and e have zero mean and a finite variance. The consistency of estimation results depends on the assumption that eligibility is correlated with naturalization but uncorrelated with occupational mobility. As discussed previously, eligibility satisfies this requirement which leads to consistent estimation results from the system of equations.

1.4 Data

The data that are used in the empirical analysis is the German Socio-Economic panel (GSOEP). It is a longitudinal survey that is conducted every year by the German Institute for Economic Research (DIW) in Berlin. The survey started in 1984 in West Germany with around 4,500 household while the East Germany sample is included in the survey in 1990. The survey collects socio-economic information at the household and individual level. The data allow us to identify the occupational mobility and the naturalization year of the individuals taking part in the survey. Another advantage of the data is the oversampling of immigrants. The empirical analysis uses 21 waves in the period of 1991-2011.

The GSOEP is an unbalanced panel data with information on labor market outcomes and citizenship status of interviewed respondents. The data provides information about the occupational history of immigrants before and after the naturalization event in addition to change of citizenship in the immigrants panel. I exclude individuals who are German citizens without migration background. Also individuals with migration background but naturalized before they participated in the survey are removed from the sample. Finally, respondents who obtained the German citizenship before 1991 are excluded from the sample to exploit the law changes after 1991. Our final sample includes only individuals with migration background which includes both first and second generation immigrants. The sample used in this survey consists of 15,676 observations and 2,443 individuals interviewed between 1991 and 2011.

1.4.1 Occupational Mobility in the GSOEP

The dependent variable in the empirical analysis is occupational mobility of immigrants. This research paper identifies the occupation of respondents by using the International Standard Classification of Occupations (ISCO-88) code developed by the International Labor Office (ILO). The ILO provides four different types of ISCO-88 codes according to detail levels. First, the most general coding system is one-digit ISCO-88 code which includes 9 groups, while two-digit code consists of 28 job groups which are subgroup of one-digit code. Further, occupational code in three digits specify 116 occupations. Finally, the most detailed four-digit ISCO-88 code provides 390 occupations.

In the literature, the four-digit occupational code is used more frequently. Individuals are identified as occupationally mobile in a year if they report a different occupation than previous year. If the individual is unemployed in the current year, he/she is excluded from the sample in that year. If the respondent is unemployed in the previous year, the last employment is taken into consideration. Thus, the occupational mobility is an indicator variable which takes value 1 if the individual is occupationally mobile and 0 otherwise.

Measurement Error

A significant number of studies show that surveys suffer from the measurement error while assigning respondents into specific occupations[6]. Typically, there are two sources of measurement error. First, it can arise as a result of survey design. The question on occupation is not included in each wave of the GSOEP, instead individuals are asked to report their occupation in some years. In other years, respondents are asked to report their occupation if there is a change in their employment status. For example, if an individual changes job in 1992 but didn't report it (job change can be after the interview) in 1992, he/she will be assigned with the previous job in the survey while the job change is included in the survey next year. Second, the measurement error can originate from misreporting or coding mistakes. It is possible that respondents report wrong occupations in the interview as well as the coder can make mistakes while assigning the respondents into the ISCO-88 code.

To reduce the measurement error, we use a similar approach followed by Isaoglu (2009). The GSOEP provides information on the employment history of each individual in detail. This variable keeps track of exact employment changes in every wave. First, the exact year of job change is decided. It is possible that an individual is interviewed in year t and changed job after the interview in the same year. Thus, the individual reports a different occupation in year $t+1$. We correct the this type of error by following the variable in interest. Second, a different occupation can be reported in year t, although the individual did not change job in year t-1 and t. In the case of no job change, the occupation reported in year t is replaced by the occupation in year t-1 while this individual is not reported as occupationally mobile.

Figure 1.1 illustrates occupational mobility before and after the correction. As mentioned by Isaoglu (2009), it is more likely that the spikes exist as a result of survey design. The coding error does not explain the spikes illustrated in the graph since one would expect similar errors across years. Figure 1.2 shows the occupational mobility in the GSOEP after the correction of measurement error. The occupational mobility in the German labor market is consistent with the one of Isaoglu (2009) which varies between 3 and 10 percent.

Figure 1.3 compares occupational mobility between immigrants and natives. Al-

[6] Isaoglu 2009, Kambourov and Manovskii (2002a, 2002b), McCall (1990), Neal (1999) and Parent (2000)

though occupational mobility of immigrants and natives are similar, immigrants are occupationally more mobile than natives in general. The occupational mobility of immigrants in the 90s is lower than that of natives: immigrants change occupations more frequently between 2000 and 2011. The implication of these results might be that immigrants are more mobile compared to natives because they are employed in lower level jobs.

Figure 1.4 depicts occupational mobility among eventually naturalized immigrants and non-naturalized immigrants. Although it is unconditional occupational mobility, Figure 1.4 shows that immigrants with German citizenship are more mobile. This can be explained by the fact that naturalization opens the door to more job opportunities which can facilitate the access to preferred jobs, hence, increase the occupational mobility. Furthermore, this can also be a result of self-selection since naturalized immigrants are already more mobile even before naturalization.

1.4.2 Naturalization in Germany

There is no explicit variable indicating the time of naturalization in the GSOEP. However, individuals who acquired the German nationality report a change of nationality. Hence, this study assumes that the reported change of the nationality is the exact date of naturalization. Moreover, the 2002 wave includes a question asking migrants to report the year of their naturalization. This information is exploited to reduce the measurement error. Figure 1.5 shows the naturalization rates in Germany. The naturalization rate in Germany before the immigration law change in 1990 is very low (less than 1 percent). The change in the immigration law increases the number of naturalized immigrants starting from 1991 and has the peak rate in 1995 (around 4 percent). Following the peak in 1995, the naturalization rate shows a decreasing trend. The initial increase after the law change can be attributed to the fact that German descendants coming from ex-Soviet countries obtained the citizenship during the same period. Furthermore, immigrants who are more committed, motivated, or expected positive utility applied for the citizenship right after the law change.

Eligibility for German Citizenship

This paper uses eligibility for German citizenship as an instrument for the naturalization because of potential time-variant and -invariant unobserved individual heterogeneity. A regression approach that uses the naturalization can overstate the occupational mobility because of the potential positive self selection problem. The citizenship law changes in Germany in 1991 and 2000 allows us to use the eligibility for German citizenship as an instrument for naturalization.

Eligibility for German citizenship was first introduced in 1991. New citizenship law introduced requirements of residency and age. For instance, two immigrants coming to Germany at the same time could have a different eligibility year if one was younger than the other. Similarly, two immigrants of same age coming to Germany in different years could have a different eligibility year for citizenship. With the second change in the eligibility criteria in 2000, the residency requirement was reduced from 16 years to 8 years. Thus, some immigrants immediately became eligible in 2000 while others had to satisfy 8 years of residency instead of 16 years. In particular, a similar strategy to Gathmann et al (2014) for identifying variations in the IV estimation is used. First, immigrants become eligible immediately with the 1991 reform. Second, immigrants get eligibility status with the 1991 reform in the 1991-1999 reform. Third, immigrants become eligible with the 2000 reform immediately. Finally, immigrants get the eligibility status with the 2000 reform in the 2000-2011. Therefore, the variation in the eligibility criteria is expected to capture the variation in naturalization behavior of immigrants. Regression results from the first stage IV estimation provides such evidence in the next section.

1.4.3 Control Variables

This paper also takes into account the other observable characteristics. The set of explanatory variables included in the analysis aims to control for the differences in occupational mobility among individuals. Table 1.2 reports the descriptive statistics.

The mean age of natives in the sample is 42.0 and for all immigrants 41.3. Eventually naturalized immigrants are on average younger (39.3) than non-naturalized immigrants (41.93). Gender takes the value of 1 if the individual is a male and 0 otherwise. The sample mainly consists of male individuals which constitute around 70

percent of the sample.

Work experience of respondents is provided by the GSOEP. An important note is that naturalized immigrants obtain the German citizenship early in their career. Similar to age, one expects more experienced immigrants to be less mobile since the job specific training/knowledge is higher for those immigrants. Unfortunately, the GSOEP does not provide information on job specific experience of individuals which would allow to check whether occupation-specific experience influences occupational mobility.

The GSOEP provides different levels of educational attainment. The average years of education is higher among naturalized immigrants (11.66) than non-naturalized immigrants (10.14). The empirical analysis uses five levels; no degree, elementary, high school, vocational training, and university.

Marital status is constructed with the information provided by the survey. The variable takes the value 1 if the individual is married and 0 otherwise. Divorced and widows are included in the single category. One would expect that being married affects occupational mobility negatively.

Sectors are included in the empirical analysis. Here, the sectors are divided according to the 9 different one-digit ISCO-88 code. The categories are Managers, Professionals, Technicians, Clerks, Service workers, Agriculture workers, Craft, Operators, Elementary, and other sectors. Figure 1.6 illustrates the job distribution of natives, eventually naturalized immigrants and non-naturalized immigrants. It is clear from the figure that naturalized immigrants have more favorable job distribution than non naturalized immigrants.

Years since migration is calculated by using the year of arrival to Germany. This variable is also used to calculate the duration of legal residence in Germany. The average age of arrival for naturalized immigrants is lower than that of non-naturalized immigrants, which implies that the younger the age of arrival the higher the likelihood to apply for citizenship.

Finally, the country of origin of individuals is included in the survey to check whether the difference in acquisition of citizenship exists according to different benefits for individuals from different countries. The variable takes the value 1 if the immigrant is from a non-EU country and 0 otherwise. It is expected that individuals

from non-EU countries are more likely to naturalize and use citizenship as a tool to be more mobile in the labor market.

1.5 Estimation Results

The empirical analysis starts with the pooled probit estimation. Table 1.3 reports the estimation results from the pooled probit model with different specifications where the coefficient of interest is α_1 in equation 1.1. This model is the most appropriate choice if potential unobserved time-invariant and -variant individual heterogeneity is ignored. Looking at the table, immigrants who are naturalized German citizens are more likely to change occupations. In particular, estimation results in the first specification reveals that naturalized immigrants are 2.5% more likely to change occupations compared to non-naturalized immigrants with similar socioeconomic characteristics. This reveals that acquisition of German citizenship is associated with an immediate increase in occupational mobility.

Years since naturalization is included in the further specifications which is positively associated with occupational mobility but the coefficient is insignificant. It estimates the average impact of every additional year that passes following the German citizenship. Naturalized immigrants are expected to change occupations more frequently in the first years following naturalization instead of a permenant increase in occupational mobility. After including years-since-naturalization in the equation, the coefficient of naturalization drops from 2.5% to 1.9% (column 2) but is still significant.

The fourth and the fifth columns include the dummy variables indicating the years after and before naturalization. This set up allows to identify the timing of higher occupational mobility. Each indicator variable estimates the marginal effect of i^{th} year after/before naturalization on occupational mobility. Looking at the last column, coefficient of variables after naturalization are positive and significant in the sense that after first three years occupational mobility can increase upto 10%. The last column includes two dummy variables to estimate the occupational mobility after naturalization. The results report that naturalized immigrants are on average 4.5% more likely to be occupationally more mobile in the first five years. Furthermore,

dummy variables are included to allow for higher occupational mobility before naturalization. The estimated coefficients are very small and insignificant which implies that immigrants do not start changing occupations before obtaining German citizenship. Moreover, naturalization coefficient loses its significance on occupational mobility. The results suggest that naturalization does not increase occupational mobility immediately, instead, immigrants change their behavior in years following the naturalization and become more mobile in the German labor market.

Further specifications include years since naturalization (column 2) and country of origin (column 3) to control for individual differences. Ten year of experience decreases occupational mobility by 4.3 percent (column 4) which confirms the previous discussion that increasing occupation-specific human capital lowers the probability of changing occupations. Another important determinant of occupational mobility is the experience since naturalization. Results reveal that one year of experience following naturalization is associated with 4% to 9% decrease in occupational mobility. Immigrants who accumulate occupation-specific human capital after naturalization are less likely to change occupations. Interestingly, years since migration and education are not significantly associated with occupational mobility.

Results reported above can overstate the benefit of naturalization because potential unobserved individual heterogeneity is neglected. It is well documented that naturalized immigrants are more likely to be positively selected in terms of observable and unobservable characteristics. An alternative approach is to estimate fixed-effects models to control for time-invariant unobservable characteristics. The next table reports the results from fixed effects logit estimate. After controlling for individual fixed effects, Table 1.4 shows that the coefficient of naturalization is positive and not significant. The years following naturalization are negatively associated with occupational mobility which is contradictory to the pooled probit results previously presented. There are two potential channels for different results between two estimation methods. First, the positive relationship reported by pooled probit model is driven by the unobserved characteristics of individuals. After controlling for the individual fixed effects, the relationship between naturalization and occupational mobility is negative and not significant.

Alternatively, the sample that is estimated with the fixed effects is different than

the sample estimated with the pooled data. The fixed effects model estimates the observations where the dependent variable changes at least once during the observation period. For instance, individuals who do not change sectors or change sectors in every period are dropped out from equation 1.1. The number of observations reported at the bottom of each table confirms the different samples used in two estimations such that number of observations decreased from 15,676 to 5,738. To better understand the reason of the negative relationship between naturalization and occupational mobility, we use the same sample and estimate the probit estimation. Table 1.5 confirms that the relationship years since naturalization and occupational mobility is negative. Similar to fixed effects estimation coefficient of naturalization is positive and not significant. This confirms that the contradictory results between fixed effects and pooled probit estimations is not because of the individual unobserved characteristics but instead the sample selection for the fixed effects estimation.

According to the previous discussion, although the fixed effects model controls for individual fixed effects, the estimates are biased because of the sample selection. Moreover, there can also be time-variant unobservable characteristics associated with occupational mobility and naturalization. Therefore, this research paper exploits the instrumental variable approach to identify the relationship between naturalization and occupational mobility.

1.5.1 Evidence from Instrumental Variable Estimation

In this section, the empirical analysis reports the results from two stage IV estimation. As discussed previously, eligibility for German citizenship can be used as an instrument for naturalization if immigrants are more likely to naturalize when they are eligible to apply for German citizenship. Table 1.6 reports the results from the first stage linear probability and the probit estimations of equation 1.3. Looking at the table, the eligibility criteria are significant and positive in both specifications. An individual who is eligible for naturalization is between four and eight percent more likely to obtain the German citizenship compared to non-eligible individuals with same characteristics. The results confirm the first assumption of two stage IV estimation which requires that instrument to be correlated with naturalization.

Several explanatory variables are also reported in the first stage IV estimation

which give important insights about the naturalization behavior of immigrants. Educational attainment is positively associated with the German citizenship. In particular, immigrants with university degree are more likely to apply for the host country citizenship. Men are more likely to obtain the German citizenship than women. Negative relationship between age and naturalization suggests that immigrants are more likely to apply citizenship at a younger age.

Table 1.7 reports the results from the 2SPS and 2SLS in equation 1.2 where the predicted values from equation 1.3 is used instead of naturalization at the second stage IV estimation. This estimation strategy takes care of the time-invariant and -variant unobserved heterogeneity by using the exogenous variation stem from the citizenship law change in Germany. The results reveal that naturalization is positively associated with occupational mobility. In particular, higher occupational mobility is not a result of immediate impact of naturalization, instead immigrants change occupations more frequently after naturalization. Each specification includes the dummy variables indicating the years after and before naturalization to assess the timing of the impact of naturalization on the occupational mobility of immigrants. The coefficient of years after naturalization is significant and positive in the fourth and fifth year after naturalization: three years after naturalization occupational mobility can increase between 6% to 8%. Immigrants with German citizenship do not start changing occupations prior to naturalization since the year dummies before naturalization are negative and insignificant, indicating that higher occupational mobility succeeds German citizenship. Similar to previous estimation, experience since naturalization still has a negative impact on occupation change such that one year of experience following naturalization decreases the occupational mobility by 1.5 percent.

Finally, the empirical analysis reports results from the bivariate probit model. The model differs from the two stage IV model because it is a recursive method where the error terms are correlated. The results from the bivariate probit estimation are showed in Table 1.8. First of all, the correlation between the error terms, ρ, reported at the bottom of the table is insignificant in both specifications. This indicates that the two error terms are not stronly related. Results depict a similar picture with the two stage IV estimation. Naturalization is not associated with an immediate increase in occupational mobility. Immigrants with German citizenship change their behavior

in the years following the naturalization and become more mobile in the German labor market.

1.5.2 Naturalization and Occupational Assimilation

Previous results reveal that immigrants change occupations more frequently after obtaining the German citizenship. Now, empirical analysis investigates whether naturalization leads to faster occupational assimilation in the labor market. To estimate the occupational assimilation, upward occupational mobility is defined which indicates whether the occupational change results with a better job. To decide the ranking between the occupations we use the prestige codes giving by ISEI code. ISEI code is a measure that is created after taking education and income into account to scale occupations.

Table 1.9 illustrates the averages of three occupational scores on four interested groups for our analysis. There are three available occupational scores mentioned in the GSOEP: ISEI, KLAS, and SIOPS. Immigrants are more likely to be employed in jobs with lower occupational scores compared to natives. It is also documented in the table that the naturalized immigrants, on average, work in more prestigious jobs relative to non-naturalized immigrants. Furthermore, Figure 1.6 shows the distribution of different groups in the German labor market according to ISCO-88 code. The ranking followed by ISCO-88 code is a general description of sectors which require more job specific training. For instance, 1 refers to Managers while 9 is Elementary jobs. It is important to note that the distribution of naturalized immigrants is more favorable than non-naturalized immigrants. Naturalized immigrants are more likely to be employed in jobs with higher occupational code compared to non-naturalized immigrants without controlling of individual characteristics.

The better job distribution of naturalized immigrants can be because of the impact of naturalization to create more job opportunities and easier access to better jobs. Alternatively, better jobs of naturalized immigrants can be associated with unobserved individual characteristics independent of naturalization. To estimate the impact of naturalization on occupational assimilation, upward occupational assimilation is defined which equals to 1 if occupational change results with a better job and 0 otherwise. Later, the instrumental variable estimation strategy is employed

where the dependent variable is upward occupational mobility. Table 1.10 reports the results for the 2SPS, 2SLS and bivariate probit estimation. The results reveal that naturalization is not associated with an immediate upward occupational assimilation relative to non-naturalized immigrants. The coefficients are insignificant and different in sign for two estimation methods. Instead, faster assimilation in terms of occupations and sectors only starts in the years following naturalization. Naturalized immigrants are on average 3 to 6 percent more likely to move to better jobs compared to non-naturalized counterparts five years after the naturalization.

1.6 Conclusion

Germany has been an immigrant country with the arrival of guest-workers from different destinations from Europe. Although it has been an immigrant country, Germany was very ignorant with their immigrant communities until 1990. Then, further steps had taken to improve the integration of those communities with the new immigration law. Under the new law, immigrants had easier access to German citizenship, which brings additional benefits to immigrants. This article examines whether immigrants change their behavior in the labor market after naturalization in Germany. In particular, we investigate whether immigrants become occupationally more mobile after naturalization and if the latter leads to better jobs in the labor market.

The empirical analysis from probit estimations reports that naturalization is associated with higher occupational mobility. However, this model does not take into consideration self-selection problems. In order to do so, we use the changes in the immigration law in Germany in 1990s. The law change provides an exogenous variation in the naturalization process. Hence, we use the eligibility criteria as an instrument for the naturalization. This controls for the unobserved heterogeneity both time-variant and time invariant. The results show that naturalization is not associated with immediate impact on occupational mobility. Instead, years following the naturalization event are associated with higher occupational mobility.

The law change in Germany provides easier access to citizenship which results in better labor market outcomes for the individuals. This is very important for the policymakers either in the destination or home country. The destination country

can lower the requirements for citizenship to help the immigrants integrate into the labor market while the home country can sign dual citizenship agreements with the destination country to accelerate the labor market integration of their expatriates.

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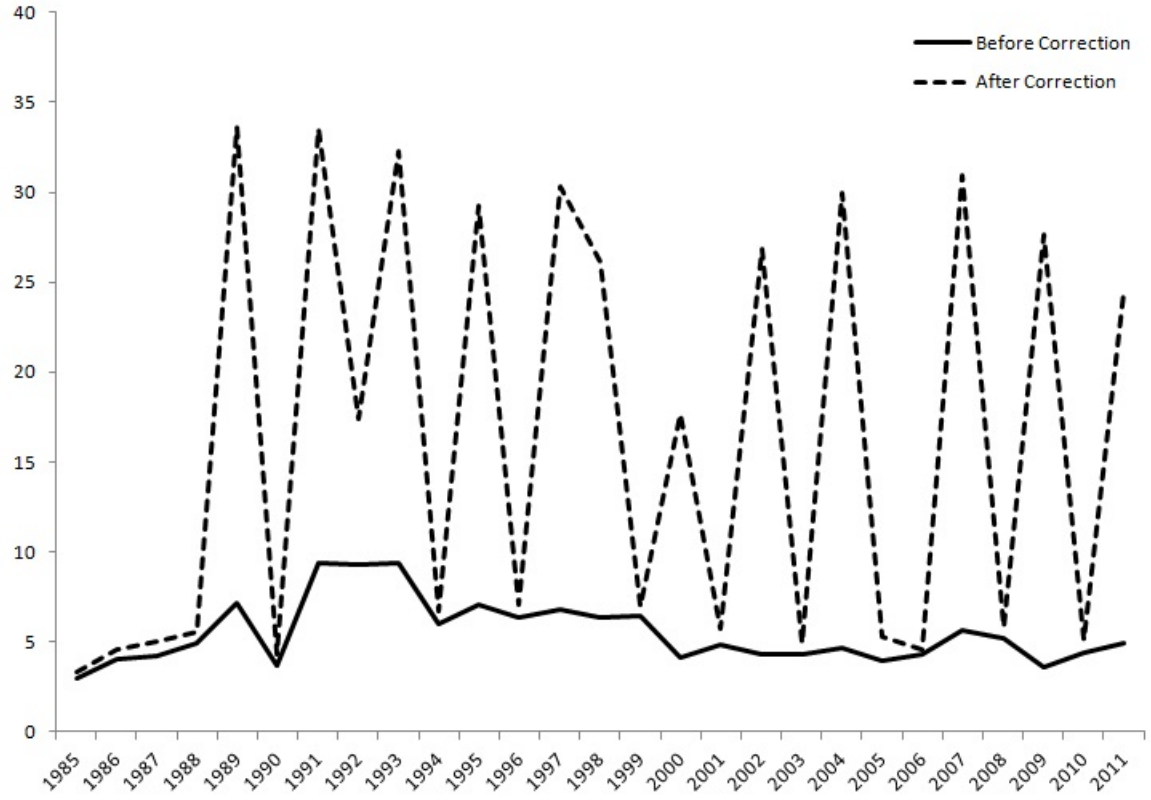
Figure 1.1: Occupational Mobility in the GSOEP before and after Correction, 1985 - 2011



Source: own calculations GSOEP.

Table 1.1: Reasons to Naturalize

	Important	Not Important	No statement given
Because I want to retain all the rights of a German Citizen	*86.4*	*12.9*	*0.7*
Because I want/wanted to retain the advantages of being an EU citizen	*85.3*	*13.0*	*1.7*
Because I have always lived here	*83.4*	*16.6*	*0.0*
Because my job opportunities will be better with German nationality	*82.3*	*16.6*	*1.1*
Because I was born in Germany	*76.4*	*23.0*	*0.6*
Because it is easier to deal with official bodies as a German citizen	*72.6*	*26.2*	*1.2*
Because I feel myself to be rooted in Germany	*69.1*	*30.7*	*0.2*
Because without German nationality I will have to apply for a residence permit in order to remain in Germany	*53.4*	*43.9*	*2.7*
Because I feel myself to be a German	*53.3*	*45.9*	*0.8*
Because it is/was what my family wanted/wants	*22.9*	*76.8*	*0.3*

Note. Source: The table is taken from The naturalisation behaviour of foreigners in Germany, and findings concerning Optionspflichtige (persons required to choose between two nationalities) (Blicke et al. 2011)

Table 1.2: Descriptive Statistics

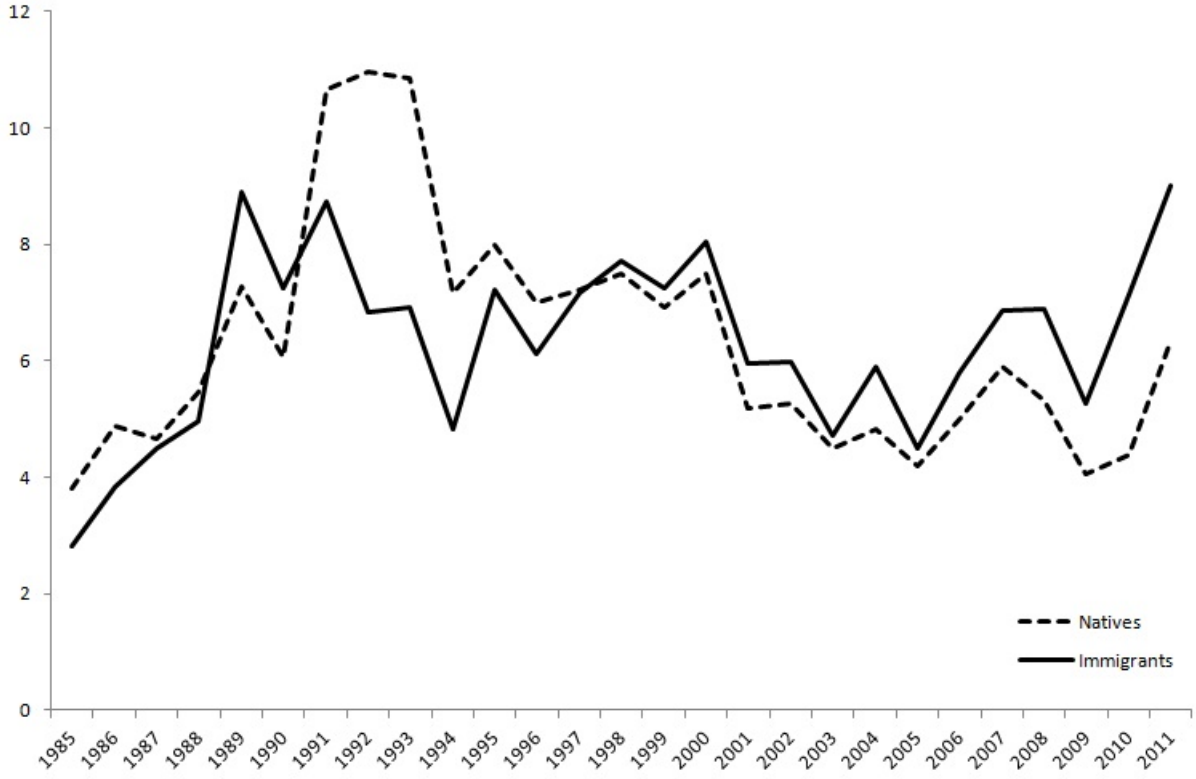
	Natives	Immigrants	Eventually Naturalized Immigrants	Non-Naturalized Immigrants
Age	42.03	41.34	37.75	41.93
	(10.554)	*(10.522)*	*(9.697)*	*(10.535)*
Gender	.69	.72	.70	.73
	(.462)	*(.447)*	*(.460)*	*(.445)*
Years of Education	12.79	10.36	11.66	10.14
	(2.675)	*(2.331)*	*(2.556)*	*(2.219)*
Experience	18.86	18.92	14.85	19.60
	(10.871)	*(10.845)*	*(9.721)*	*(10.875)*
Married	.71	.88	.82	.89
	(.454)	*(.328)*	*(.387)*	*(.316)*
Years Since Migration		19.32	17.19	19.669
		(10.006)	*(11.758)*	*(9.639)*
Age at Migration		21.10	17.84	21.58
		(9.231)	*(9.695)*	*(9.065)*
Observations	121,521	21,031	2,996	18,035

Own Calculations, GSOEP. The reported numbers in the first row are the means of corresponding variables and standard errors are in the second row in paranthesis.

Figure 1.2: Occupational Mobility after Correction in Germany, 1985 - 2011

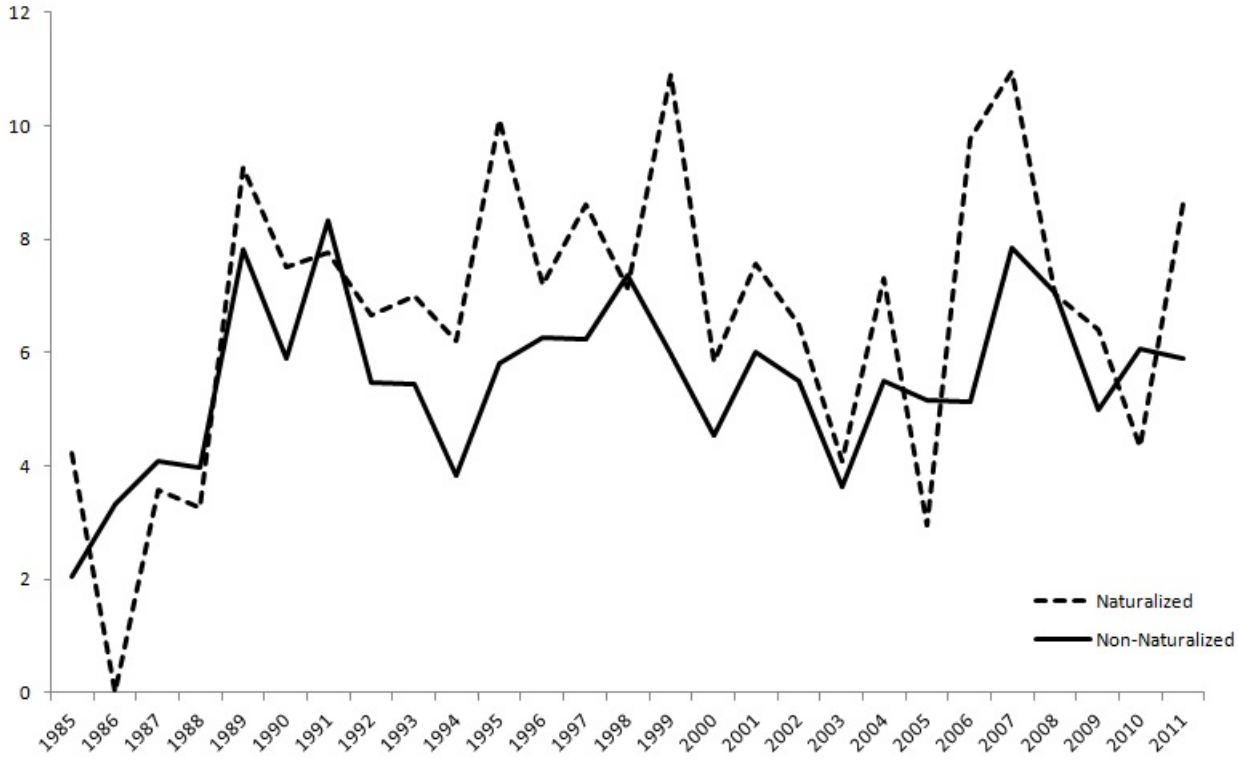
Source: own calculations GSOEP.

Figure 1.3: Occupational Mobility for Natives and Immigrants in Germany, 1985 - 2011



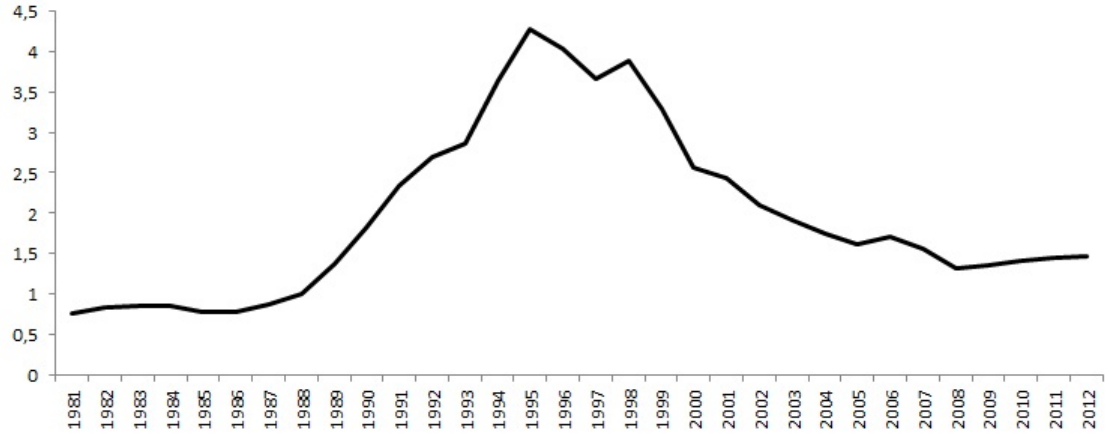
Source: own calculations GSOEP.

Figure 1.4: Occupational Mobility for Naturalized and Non-Naturalized Immigrants, 1985 - 2011



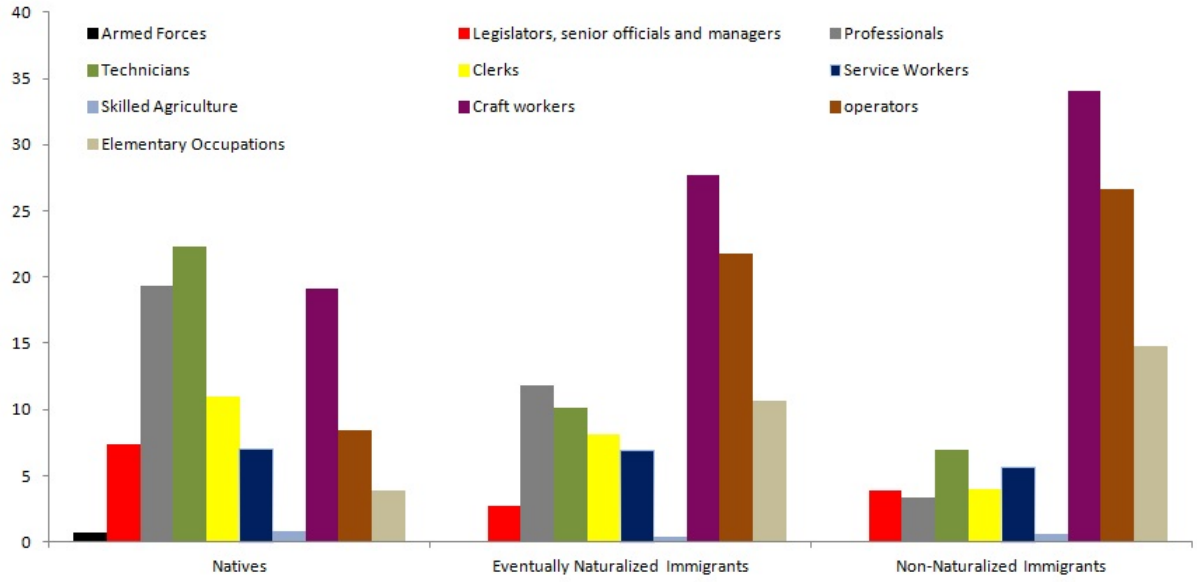
Source: own calculations GSOEP. Naturalized immigrants refers to eventually naturalized immigrants.

Figure 1.5: Naturalization Rate in Germany 1981 - 2012



Source: own calculations with data of the Federal Statistical Office of Germany.

Figure 1.6: Occupational Distribution in the GSOEP, 1985-2011



Source: own calculations GSOEP.

Table 1.3: Probit Estimates for the Pooled Sample, Naturalization on Occupational Mobility

	(1)	(2)	(3)	(4)	(5)
Naturalized	0.0251566 **	0.0191842 *	0.0204129 *	-0.0010635	-0.0012491
	0.01033	0.01015	0.01046	0.01427	0.01427
ESN	-0.0040113 **	-0.006618 **	-0.0070902 **	-0.0086888 ***	-0.0064878 **
	0.0018	0.00299	0.00317	0.00331	0.00285
YSN		0.0029251	0.0035344		
		0.00236	0.00255		
Nat_{t+1}				0.0127018	
				0.02432	
Nat_{t+2}				0.0512625	
				0.03337	
Nat_{t+3}				0.044103	
				0.03539	
Nat_{t+4}				0.1045898 **	
				0.05025	
Nat_{t+5}				0.1034518 *	
				0.05815	
$Nat_{t+1-t+5}$					0.0450121 *
					0.02599
$Nat_{t>5}$				0.0842581	0.0607917
				0.05239	0.04302
Nat_{t-1}				0.0275341	0.0273871
				0.01862	0.01863
Nat_{t-2}				-0.0076447	-0.0076966
				0.01458	0.01461
Nat_{t-3}				0.001844	0.0017989
				0.01631	0.01633
Age	0.0005674	0.0005502	0.0005391	0.000538	0.0005394
	0.00039	0.00039	0.00039	0.00039	0.00039
Gender	-0.0146072 ***	-0.0145729 ***	-0.0150712 ***	-0.0151892 ***	-0.0152122 ***
	0.00491	0.00491	0.00496	0.00494	0.00495

Table 1.3 Continued

	(1)	(2)	(3)	(4)	(5)
Experience	-0.0042728 ***	-0.0042321 ***	-0.0042767 ***	-0.0042546 ***	-0.0042816 ***
	0.0004	0.0004	0.0004	0.0004	0.0004
Elementary	-0.0069582	-0.0067074	-0.0072842	-0.0070511	-0.0074723
	0.00886	0.00886	0.00885	0.00884	0.00884
High School	-0.0216492 ***	-0.0213395 ***	-0.0221663 ***	-0.0219957 ***	-0.0223705 ***
	0.00774	0.00778	0.00765	0.00767	0.00763
Vocational	-0.007673	-0.0074942	-0.0076522	-0.0075107	-0.0079121
	0.00985	0.00988	0.00988	0.00988	0.00982
University	-0.0127829	-0.0130131	-0.015444 *	-0.0152879 *	-0.0155477 *
	0.00895	0.00896	0.00866	0.00868	0.00862
YSM	0.0000498	0.0000373	0.0000567	0.0000591	0.0000711
	0.00023	0.00024	0.00024	0.00024	0.00024
Controlled for					
Period dummy	✓	✓	✓	✓	✓
Country of Origin	**X**	**X**	✓	✓	✓
Number of Observations	15,676	15,676	15,676	15,676	15,676
Psuedo R2	0.0636	0.0639	0.0650	0.0667	0.0657

Note. * *significant at* 10%; ** *significant at* 5%; *** *significant at* 1%. *The reported numbers are the marginal coefficients. Standard errors are in parentheses.*

Note. The dependent variable is the occupational mobility. $Naturlized_{t+/-i}$ *is a dummy variable referring to i years before/after naturalization year, thus, is equal to 1 if survey year is equal to* $Naturlized_{t+/-i}$ *and 0 otherwise.*

Table 1.4: Fixed Effects Logit Estimates, Naturalization on Occupational Mobility

	(1)	(2)	(3)
Gender*Age	.0669343 ***	.067565 ***	.0702149 ***
	(.0172259)	(.0173558)	(.0174407)
No degree*Experience	-.4346559 ***	-.4342062 ***	-.4405752 ***
	(.0828653)	(.0828872)	(.0838127)
Elementary*Experience	-.3065978 ***	-.3058349 ***	-.3105609 ***
	(.0339758)	(.0340888)	(.0343182)
High School*Experience	-.2761162 ***	-.2750236 ***	-.2824762 ***
	(.0402133)	(.0403862)	(.0406719)
High School+Voc*Experience	-.2945583 ***	-.2923855 ***	-.294476 ***
	(.0478025)	(.0483092)	(.0487851)
University*Experience	-.2407138 ***	-.238484 ***	-.2461724 ***
	(.041974)	(.0426008)	(.0431261)
YSM	.1002312 ***	.099484 ***	.0988701 ***
	(.0240769)	(.0242197)	(.0244035)
Naturalized	.1140096	.1428098	.140429
	(.2132268)	(.2308138)	(.2321622)
Years Since Naturalization		-.0115054	-.0149538
		(.035961)	(.0362474)
Controlled for			
Sector	**X**	**X**	✓
Number of Observations	5,738	5,738	5,738
Log-likelihood	-1578.3166	-1578.2652	-1568.5005

Note. * *significant at* 10%; ** *significant at* 5%; *** *significant at* 1%.

Note. The dependent variable is the occupational mobility. The reported numbers are the coefficients, not the marginal effects. Standard errors are in parentheses.

Table 1.5: Pooled Probit Estimates with Fixed Effects Sample, Naturalization on Occupational Mobility

	(1)	(2)	(3)
Gender*Age	.0001041	.000117	.000033
	(.00024)	(.00024)	(.00025)
No degree*Experience	-.0035826 ***	-.0035713 ***	-.0032161 ***
	(.00109)	(.00109)	(.00105)
Elementary*Experience	-.0062265 ***	-.0061562 ***	-.0059198 ***
	(.00063)	(.00063)	(.00065)
High School*Experience	-.0082856 ***	-.0082608 ***	-.0081024 ***
	(.00107)	(.00107)	(.00106)
High School+Voc*Experience	-.0068895 ***	-.0067157 ***	-.0067045 ***
	(.001)	(.00099)	(.00102)
University*Experience	-.0053474 ***	-.0051235 ***	-.0050622 ***
	(.00104)	(.00103)	(.00108)
YSM	-.0002687	-.0002576	-.0003087
	(.00049)	(.0005)	(.0005)
Naturalized	-.0301132 **	.00537	.0056125
	(.01222)	(.021)	(.02114)
Years Since Naturalization		-.0074119 **	-.007437 *
		(.00323)	(.00321)
Controlled for			
Sector	**X**	**X**	✓
Number of Observations	5,738	5,738	5,738
Psuedo R2	0.0287	0.0297	0.0319

Note. * *significant at* 10%; ** *significant at* 5%; *** *significant at* 1%.

Note. The dependent variable is the occupational mobility. The reported numbers are the marginal coefficients. Standard errors are in parentheses.

Table 1.6: First Stage IV Estimation, First Stage IV

	Linear Probability	Probit
Eligible	0.0762738 ***	0.0362452 ***
	0.0134381	0.00602
Age	-0.0017529 *	-0.001272
	0.0010405	0.00083
Gender	0.008432 **	0.0057543
	0.0153606	0.00946
Experience	0.0007832 ***	0.0004476
	0.0009965	0.00079
Elementary	0.013386 **	0.026147
	0.0125159	0.01752
High School	0.0425193 **	0.0600665 *
	0.0212569	0.03423
Vocational	0.0472914 *	0.0682446
	0.0280618	0.0422
University	0.0935384 ***	0.1095046 **
	0.0303297	0.04856
YSM	0.0000359	0.0000576
	0.0009693	0.00051
Controlled for		
Time Period Dummies	✓	✓
Country of Origin	✓	✓
Number of Observation	15,676	15,676
R2	0.1590	0.2379
F-statistic	F(19, 2442) = 16.01	Wald chi2(19) = 407.43

Note. * *significant at* 10%; ** *significant at* 5%; *** *significant at* 1%.

Note. The dependent variable is naturalization. First stage IV in equation 1.3 is estimated. The reported numbers in the probit estimation in the first column are marginal effects. Standard errors are in parentheses.

Table 1.7: Probit Estimates for the Pooled Sample, Second Stage IV

	2SLS		2SPS	
	(1)	(2)	(3)	(4)
Naturalized	0.1349025	0.1364651	-0.0156666	-0.0149486
	0.1262265	0.1262975	0.0379	0.03789
Experience Since Naturalization	-0.023869 ***	-0.0196094 **	-0.0131499 *	-0.0099552
	0.0088506	0.0082516	0.00706	0.00654
Nat_{t+1}	0.0080612		0.0065047	
	0.0262519		0.02253	
Nat_{t+2}	0.0426209		0.0355653	
	0.0283617		0.02864	
Nat_{t+3}	0.0295984		0.0241519	
	0.0285374		0.02833	
Nat_{t+4}	0.0756944 **		0.0706566 *	
	0.0339203		0.03979	
Nat_{t+5}	0.0643722 *		0.0653732	
	0.0358654		0.04368	
$Nat_{t+1-t+5}$		0.0381764 *		0.0321946
		0.0216414		0.02258
$Nat_{t>5}$	0.0480857	0.0402285	0.0366847	0.0287494
	0.0297801	0.0287704	0.03126	0.02878
Nat_{t-1}	0.0354262	0.0354232	0.0294705	0.0294879
	0.0271157	0.0271098	0.02605	0.02607
Nat_{t-2}	-0.0088559	-0.0088066	-0.0065773	-0.0065208
	0.0251089	0.0251063	0.01902	0.01907
Nat_{t-3}	0.005411	0.0054121	0.0032103	0.0032449
	0.0256141	0.0256096	0.0209	0.02093
Age	0.0008458	0.0008421	0.0005274	0.0005275
	0.0005443	0.0005443	0.00039	0.00039
Gender	-0.01924 ***	-0.0192437 ***	-0.0150268 ***	-0.0150651***
	0.0058862	0.00589	0.00498	0.00499
Experience	-0.0043647 ***	-0.0043626 ***	-0.0043206 ***	-0.0043292***
	0.0004946	0.0004946	0.0004	0.0004

Table 1.7 Continued

	2SLS		2SPS	
	(1)	(2)	(3)	(4)
Elementary	-0.0120973	-0.0122751	-0.0074327	-0.0076698
	0.0088455	0.0088373	0.00886	0.00886
High School	-0.0360668 ***	-0.0364465 ***	-0.0217386 ***	-0.0220426***
	0.0116767	0.0116716	0.00781	0.00778
Vocational	-0.0170073	-0.0173687	-0.0074508	-0.0076982
	0.0146866	0.0146879	0.01006	0.01003
University	-0.0333624 *	-0.0338875 **	-0.0142098	-0.0144791
	0.0170924	0.0170797	0.00918	0.00914
YSM	-0.0001106	-0.0001082	0.0000825	0.0000891
	0.0003147	0.0003151	0.00024	0.00024
Controlled for				
Time Period Dummies	✓	✓	✓	✓
Country of Origin	✓	✓	✓	✓
Number of Observation	15,676	15,676	15,676	15,676
R2	0.0295	0.0290	0.0658	0.0651

Note. * *significant at* 10%; ** *significant at* 5%; *** *significant at* 1%. *Second stage IV in equation 1.2 is estimated. Reported numbers are the marginal effects. Standard errors are in parentheses.*

Note. The dependent variable is the occupational mobility. $Naturlized_{t+/-i}$ *is a dummy variable referring to i years before/after naturalization year, thus, is equal to 1 if survey year is equal to* $Naturlized_{t+/-i}$ *and 0 otherwise.*

Table 1.8: Bivariate Probit Estimates on Occupational Mobility

	(1)		(2)	
	First Stage Biprobit	Second Stage Biprobit	First Stage Biprobit	Second Stage Biprobit
Eligible	0.0362473 ***		0.0362454 ***	
	0.00602		0.00602	
Naturalized		-0.0198472		-0.0145255
		0.02656		0.03008
Experience Since Naturalization		-0.0086743 ***		-0.006447 **
		0.00331		0.00286
Nat_{t+1}		0.0134275		
		0.02446		
Nat_{t+2}		0.053016		
		0.03353		
Nat_{t+3}		0.0460436		
		0.03561		
Nat_{t+4}		0.108248 **		
		0.05041		
Nat_{t+5}		0.1072792 *		
		0.05862		
$Nat_{t>5}$		0.0893127 **		0.0635412
		0.05265		0.04308
$Nat_{t+1-t+5}$				0.0461627 *
				0.02596
Nat_{t-1}		0.0277424		0.0275175
		0.01864		0.01865
Nat_{t-2}		-0.0077265		-0.0077491
		0.01459		0.01461
Nat_{t-3}		0.0017289		0.0017172
		0.01631		0.01633
Age	-0.001311	0.0004986	-0.0012988	0.0005131
	0.00086	0.00039	0.00086	0.00039
Gender	0.0057093	-0.0149382 ***	0.0057248	-0.0150381 ***
	0.00945	0.00499	0.00946	0.00499

Table 1.8 Continued

	(1)		(2)	
	First Stage Biprobit	Second Stage Biprobit	First Stage Biprobit	Second Stage Biprobit
Experience	0.0004816	-0.0042452 ***	0.0004713	-0.0042737 ***
	0.00081	0.0004	0.00081	0.0004
Elementary	0.0259911	-0.0065868	0.026068	-0.0071737
	0.01752	0.0089	0.01752	0.00889
High School	0.0599673 *	-0.021132 ***	0.0600545 *	-0.0217988 ***
	0.03419	0.00795	0.03422	0.00786
Vocational	0.0677876	-0.0064334	0.0679943	-0.0072052
	0.04212	0.0103	0.04217	0.01015
University	0.1093861 **	-0.013615	0.1094999 **	-0.0144393
	0.04854	0.00939	0.04857	0.00925
YSM	0.0000644	0.0000725	0.0000621	0.0000801
	0.00051	0.00024	0.00051	0.00024
Controlled for				
Time Dummies	✓	✓	✓	✓
Country of Origin	✓	✓	✓	✓
Number of Observations	15,676		15,676	
Rho(ρ)	.1048833		.0708451	
Loglikelihood	-7463.9737		-7468.1013	

Note. * *significant at* 10%; ** *significant at* 5%; *** *significant at* 1%. *The system of equations in equation 1.4 and 1.5 are estimated. Reported numbers are the marginal effects. Standard errors are in parentheses.*
Note. The dependent variable is given at the top of each column. $Naturlized_{t+/-i}$ *is a dummy variable referring to i years before/after naturalization year, thus, is equal to 1 if survey year is equal to* $Naturlized_{t+/-i}$ *and 0 otherwise.*

Table 1.9: Average Occupational Scores

	Natives	Immigrants	Non-Naturalized Immigrants	Naturalized Immigrants
ISEI	44.092	33.76	33.25	36.89
	(10.767)	*(1.0285)*	*(12.937)*	*(11.712)*
KLAS	59.605	42.672	41.76	48.32
	(24.884)	*(15.877)*	*(14.611)*	*(21.304)*
SIOPS	42.77	35.30	34.91	37.72
	(12.108)	*(10.365)*	*(10.123)*	*(11.461)*

The number in the first row is the mean, the number in the second row in parenthesis is the standard deviation.
Source: GSOEP, own calculations.

Table 1.10: Pooled Sample Probit Estimates on Occupational Mobility, Two Stage IV and Bivariate Probit Estimation

	2SPS	2SLS	Bivariate Probit Estimation
Naturalized	0.0027902	-0.0071264	-0.0037156
	0.01911	0.0799849	0.01322
Experience Since Naturalization	-0.0133952 ***	-0.0187266 ***	-0.0063271 ***
	0.00382	0.0047958	0.00152
$Nat_{t+1-t+5}$	0.0156681	0.0206917	0.0282227
	0.01432	0.0149954	0.01868
$Nat_{t>5}$	0.0280417	0.0327957 *	0.0596771 *
	0.02149	0.018605	0.03509
Nat_{t-1}	-0.0014151	-0.0020512	0.0016656
	0.01029	0.0171646	0.00876
Nat_{t-2}	0.0004863	0.0006861	0.0037506
	0.01136	0.0180515	0.00969
Nat_{t-3}	0.0027488	0.0046754	0.0061005
	0.01267	0.0191854	0.0105
Age	0.0001961	0.0001952	0.0001741
	0.0002	0.00032	0.0002
Gender	-0.0070413 ***	-0.0090875 ***	-0.0069156 ***
	0.00247	0.0032163	0.00245
Experience	-0.0015981 ***	-0.0016803 ***	-0.0015491 ***
	0.0002	0.0002815	0.0002
Elementary	-0.0071473	-0.0084881 *	-0.0066374
	0.00444	0.0049487	0.0044
High School	-0.0105053 ***	-0.0160117 **	-0.0101469 ***
	0.00324	0.0067593	0.00327
Vocational	-0.0014802	0.0008894	-0.0007924
	0.00484	0.0088234	0.00497
University	-0.0064472	-0.0069474	-0.0058352
	0.00394	0.010169	0.00399
YSM	0.0000164	0.0000207	0.000016
	0.00011	0.0001637	0.00011
Controlled for			
Time Period Dummies	✓	✓	✓
Country of Origin	✓	✓	✓
Number of Observations=15,676			

Note. * *significant at* 10%; ** *significant at* 5%; *** *significant at* 1%.

Note. First column reports the results from equation 1.2 and the second column reports the results from the estimation of equation 1.4. Reported numbers are the marginal effects. Standard errors are in parentheses.

Note. The dependent variable is the upward occupational mobility. $Naturlized_{t+/-i}$ *is a dummy variable referring to i years before/after naturalization year, thus, is equal to 1 if survey year is equal to* $Naturlized_{t+/-i}$ *and 0 otherwise.*

Chapter 2

Being Muslim After September 11: An Evidence From the UK Labor Market

Metin Nebiler

Abstract

Ethnic discrimination in the workplace is an important obstacle to the integration of migrant communities in the host countries. This research paper exploits September 11 as an exogenous event to investigate discrimination against immigrants from Muslim countries in the UK labor market. In particular, the article explores whether September 11 decreased the exit rate from unemployment among immigrants from Muslim countries in the UK labor market. Empirical analysis exploits discrete time duration models where results from semi-parametric and parametric duration models are reported. Moreover, channels of discriminatory behavior in the UK labor market are also investigated in this research paper. Results show that the exit rate from unemployment decreases after September 11 terrorist attacks for immigrants from Muslim countries compared to UK-born white population with similar socioeconomic characteristics. There is no evidence for discrimination against immigrants who work in more visible sectors. Although a significant increase in the unemployment spell is found for the first generation immigrants from Muslim countries, no impact is found with regard to second generation immigrants.

2.1 Introduction

The integration of immigrants from Muslim countries in the UK has been debated for several decades. It is widely discussed that those immigrants experience disadvantage in the labor market compared to other communities (Shields and Price, 2003). The relevant discourse reached its peak after the terrorist attacks of September 11 and the London bombings, following which Western governments grew sceptical towards immigrants from Muslim countries. Since then, a number of reports have shown that there is an increasing violence and discrimination towards those immigrant groups in social life. When it comes to discussing discrimination in the labor market however, the results appear vague. This research paper exploits September 11 as an exogenous event to investigate the discrimination in the UK labor market against immigrants from Muslim countries. In particular, I study whether negative attitudes after September 11 decreased the exit rate from unemployment to paid employment of those immigrants in the UK labor market.

Several studies report increasing discrimination and violence against immigrants from Muslim countries after the September 11 terrorist attacks. Negative attitudes against Muslim immigrants were higher in the United States (Saroglu and Galand, 2004). Those individuals experienced 1,700 percent more hate crimes from 2000 to 2001 (Anderson, 2002). Almost one third of American Muslims have pointed out negative attitudes as a primary problem while 20 percent refer to discrimination and prejudice (US Department of Justice, 2011). Similar cases of discrimination and violence were observed in the UK after the terrorist attacks (Sheridan and Gillett, 2005). Sheridan (2006) describes a significant increase (76.3%) in discriminatory behavior against Muslims. It has also been reported that hate crimes did not only take place in the UK but also in other parts of Europe (Allen and Nielsen 2002). The main target group of hate crimes were individuals associated with Muslim stereotypes such as women wearing veil, men with beards and turbans, etc. even if they were not Muslims (Lambert and Githens-Mazer 2010). Although many reports document discrimination in social life,this does not necessarily reflect discrimination in the labor market. Considering terrorist attacks as a negative signal on immigrants from Muslim countries, discrimination exists if employers change their preferences towards those immigrants. It is also possible that preferences of employers are not influenced by

the terrorist attacks, in which case no link would exist among labor market outcomes of those migrant groups and terrorist attacks.

Empirical studies depict an unclear picture between September 11 and labor market outcomes of individuals from Muslim countries. Kaushal et al. (2007) show that wages of Arab and Muslim men decreased between nine and eleven percent in the US after the September 11 attacks although no impact was found on the employment rate of those immigrants. Rabby and Rodgers (2009) argue that labor market outcomes of young Muslims decreased shortly after the terrorist attacks in the US. Braakman (2007) finds however no evidence of decrease int the wages of Muslim workers in the UK. Similarly, Aslund and Rooth (2005) document that September 11 attacks are not associated with any negative impact on the labor market outcomes of Muslim minorities in Sweden.

The present research paper investigates the impact of the September 11 terrorist attacks on the unemployment spells of immigrants from Muslim countries. Previous studies generally focus on the impact of those terrorist attacks on employment or wages. However, it can be difficult to observe the impact of the terrorist attacks on wages or unemployment rates since employers cannot fire their employees or lower their wages on such a ground. In addition, employers (or co-workers) are often already well acquainted with their current employees (or colleagues) from Muslim countries. Instead, employers might be hesitant to hire new workers from Muslim countries. The exit rate from unemployment can therefore be lower and the time spent on job search longer than before. Evidence from several countries shows that this kind of discrimination exists in the national labor market towards different communities. For instance, Bertrand et al. (2003) analyze the impact of discrimination in the labor market on the basis of an experiment carried out in Boston and Chicago. The authors sent two identical resumes with traditional African American and Caucasian names. They found that the return rate for African Americans were 53 percent less than the other group. A similar experiment was conducted in France in 2010 where individuals with traditional Muslim names had 2.5 times less positive returns compared to individuals with traditional French names (Adida et al. 2010). Although such studies are not necessarily related to the September 11 terrorist attacks, their outcomes confirm that discriminatory behavior based on ethnic background does

exist in the labor market.

The September 11 terrorist attacks allow us to identify their impact on the labor market outcomes since terrorist attacks are exogenous, sudden and do not correlate with any individual characteristics of nationals from Muslim countries. A difference-in-difference method (DD) is used in order to identify the impact of September 11. The target group comprises individuals from two Muslim countries in the UK; Pakistan and Bangladesh. Religion is not used as a category variable. It is assumed that if there is discrimination in the labor market, it should be against individuals who are associated with Muslim stereotypes. Discrete time duration models are employed in the empirical analysis by using a household survey from the UK, a country with a big community of Muslim immigrants. The data include information on unemployment spells and the ethnic background of individuals, which allow us to investigate the impact of September 11.

Furthermore, channels of discriminatory behavior in the UK labor market are also investigated in the present research paper. It is widely assumed that the main target of discriminatory behavior are individuals who are associated with Muslim stereotypes, even if those individuals are not followers of Islam. If this is true, immigrants who are more "visible" should be running a higher risk of being subjected to discrimination compared to others. This is a further question that the empirical analysis investigates by identifying two channels of discrimination. First, first generation immigrants are more traditional, tend to keep their original names, are more likely to have accent and dress in line with their dogma; they are thus "more visible" to employers. This is the first channel of discrimination investigated in the empirical analysis, namely whether first generation immigrants are more likely be subjected to discriminatory behavior. Second, individuals who work in sectors which are more visible to customers are assumed to be more "visible" Muslims. This is the second channel of discriminatory behavior that the empirical part explores, namely whether discriminatory behavior is higher in those sectors against immigrants from Muslim countries.

To outline our results briefly, exit rate from unemployment to paid employment decreases after September 11 terrorist attacks for immigrants from Muslim countries compared to UK-born white population with similar socioeconomic characteristics.

However, a smaller effect is observed compared to non-UK born immigrants. Furthermore, a significant increase on the unemployment spell is found for the first generation immigrants from Muslim countries while no impact is found on the second generation immigrants. Finally, no evidence is found for enhanced discrimination against immigrants who work in more visible sectors. Overall, I conclude that the September 11 terrorist attacks significantly decrease the exit from unemployment of first generation immigrants from Muslim countries compared to UK-born white population even after controlling for individual characteristics.

The current study contributes to the existing literature in several ways. First, exit from unemployment into employment is studied in this research paper, since it can be difficult to observe the impact of terrorist attacks on wages or employment rates. Instead, we expect to observe a significant effect, if there is any, in the exit rate from unemployment. Second, I explore whether the terrorist attacks have had an impact on labor market outcomes of immigrants from Muslim countries in the UK. There are several works similar to ours that study the effect of terrorist attacks in the US. This paper is among the few attempts to study the effects in the UK. Finally, two channels of discrimination are analyzed in the empirical part putting thus into test a hypothesis that has never been investigated before, namely that visible immigrants from Muslim countries are more exposed to discrimination in the labor market than others.

The paper is organized as follows. Section 2.2 will represent the theoretical framework. The next section will discuss the empirical methodology while section 2.4 will describe the data. Section 2.5 will present the results.The robustness of the results will be reviewed in Section 2.6. The last section then discusses the results and concludes.

2.2 Theoretical Framework

The theoretical framework in this article relies on the exit rate defined in the job search model by Mortensen (1986). Consider the exit rate from unemployment

$$\theta = \lambda(s)(1 - F(w^*)) \tag{2.1}$$

where θ is the exit rate from unemployment, $\lambda(s)$ is the arrival of job offers which is a

function of search intensity (s), and $(1-F(w^*))$ is the probability that a wage offer w is higher than the reservation wage w^* (Aslund and Rooth 2005).

The September 11 terrorist attacks can be considered as a negative signal on immigrants from Islamic countries in the UK. This can be introduced into the model in several ways. First, September 11 might change preferences of employers that can make them more hesitant to hire immigrants from Muslim countries. Similarly, the terrorist attacks might also change preferences of customers. Even if preferences of employers do not change, they can still be hesitant to offer jobs to those immigrants because of customers' changing preferences. Second, instead of a direct effect on employers' preferences,the negative signal after September 11 can increase the statistical discrimination. In that case, observed average productivity of Muslims can be lower than other groups which in its turn leads to lower exit rates from unemployment (Fryer, 2011). Finally, discrimination can increase the search costs for immigrants from Muslim countries, which can decrease their exit from unemployment under plausible assumptions (Aslund and Rooth, 2005). Following Aslund and Rooth (2005), if discrimination exists in the UK labor market after the September 11 terrorist attacks, it is assumed that it is most likely to be based on changing preferences of employers. If immigrants from Muslim countries are less likely to receive job offers due to discrimination, exit from unemployment will be lower ($\frac{d\theta}{d\lambda} > 0$).

The job arrival function of other ethnic communities is assumed to be unchanged after the September 11 terrorist attacks[1]. Discrimination theory predicts that the difference of arrival functions among ethnic groups is assumed to arise from the association with Muslim stereotypes. Therefore, if discrimination exists in the UK labor market, it is against individuals who are associated with Muslim stereotypes instead of only the followers of Islam. Thus, it is assumed that immigrants from Pakistan and Bangladesh are the treated group. Immigrants of other ethnic origin who are not associated with Muslim stereotypes are assumed not to be affected by the negative impact of terrorist attacks and are used as control groups. The empirical analysis in the paper exploits two control groups in the UK labor market, which are the UK- born white population and the non-UK born white immigrants.

[1]It is possible that other groups job arrival function is affected from the terrorist attacks. Since there is a job to be offered to someone, other minority groups can be positively affected by the terrorist attacks. In that case, other minority groups do not form a proper control group, since the effect can be doubled.

The impact of the terrorist attacks can also vary within ethnic groups that are associated with the Muslim stereotypes. As reported widely, the main target of discrimination were individuals who were more visible in the public sphere. Thus, if discrimination in the labor market is similar to discrimination in the public sphere, it is expected that discriminatory behavior is higher against more visible immigrants. A primary channel of discrimination can be based on sectors that are more visible to customers. In that case, one would expect to observe a stronger negative impact on exit rates in visible sectors as opposed to other less visible ones, such as manufacturing, etc. Second, first generation immigrants can be more visible compared to second generation immigrants since they are more traditional, tend to keep the homeland names, dresses or appearances, are less fluent in the host country language, etc. Hence, one might expect that the first generation immigrants are more likely to experience discrimination compared to second generation.

2.3 Empirical Model

The empirical analysis investigates the impact of the September 11 terrorist attacks on the exit rate from unemployment of immigrants from Muslim countries by using discrete time duration models. In particular, semi-parametric and parametric models are estimated to identify the impact of terrorist attacks. In line with the previous theoretical discussion, if increased discrimination exists in the UK labor market after the terrorist attacks, a lower rate of exit from unemployment is expected for individuals from Islamic countries compared to other groups with similar characteristics.

In the literature, unemployment duration is usually assumed to be a continuous variable. Nonetheless, it is generally reported in discrete time intervals in most surveys. Assuming that the unemployment duration is continuous while reported in discrete time intervals can be problematic. Since the unemployment duration in the data used for this article is reported in large intervals, discrete time duration models are exploited for the empirical analysis. Several different econometric frameworks can be relied upon to estimate discrete time unemployment exit. This research paper uses complementary log-log model to investigate the existence of discrimination in the labor market.

Consider a random variable T which represents unemployment duration. Continuous time duration models assume that T is continuous (T=(1,T)) and there is only one exit from unemployment at a time; discrete time models assume that T is a positive integer (T=1,2,...,T). Individuals enter the sample when they are unemployed which is the beginning of their unemployment spell, $t = 1$. Individuals stay in the sample until they find a job or exit the survey so that no further information is available. In the case of leaving the survey or labor force before exiting unemployment, these individuals are censored, which is assumed to be uncorrelated with the dependent variable.

Discrete time duration models define the exit from unemployment to employment for the individual i at time t as follows,

$$P_{it}(T,x) = Pr(T_i = t | T_i \geq t, x) \tag{2.2}$$

where P_{it} is the probability that individual i exits unemployment at time t, conditional on staying unemployed until time t. Several different approaches assume a functional form for this relationship[2]. The complementary log-log model assumes that hazard rate is given by

$$P_{it} = 1 - exp[-exp(h_0(t) + \beta X_{it})] \tag{2.3}$$

where $h_0(t)$ is the baseline hazard function and X_{it} is the set of explanatory variables. The complementary log-log model is the discrete time representation of continuous time proportional hazard models (Allison 1982). In this model, the baseline hazard function is the same for every individual where the relative hazard shifts the baseline hazard according to individual characteristics.

The baseline hazard function can be assumed to have different parametric and non-parametric forms. Piecewise constant baseline function is a semi-parametric functional form that is most commonly used in the literature since no assumptions about the shape are made. This model assumes that hazard rate is constant within each reported interval while it can vary between intervals[3].

[2]Linear regression assumes the relationship as $P_{it} = h_0(t) + \beta X_{it}$ while a logit model assumes a nonlinear relationship as follows $P_{it} = [1 + exp(-h_0(t) - \beta X_{it})]^{-1}$

[3]In our setting, unemployment spell is grouped into months: 0-3, 4-6, 7-12, 13-24, 25-36, 37-48, 49-60, and over 61, thus, dummy variables are created accordingly.

The dependent binary variable, exit from unemployment to employment, takes value 1 if the individual finds a job and 0 otherwise. In order to estimate the above model,the sample is reorganized in a way that every survival is treated as a single observation for all individuals[4]. Later, observations are pooled to estimate the coefficients by maximum likelihood. The likelihood function is given by

$$L = \prod_{i=1}^{N} \prod_{j=t_i}^{t_i+s_i} [P_{it}(j, x_i)]^{\delta_i} [1 - P_{it}(j, x_i)]^{1-\delta_i} \tag{2.4}$$

where s_i is the number of time periods individual i is represented in the sample, δ_i is the censoring variable which is equal to 1 if the individual exits from unemployment and zero otherwise, and P_{it} is the complementary log-log hazard rate.

A parametric log-time model is also estimated in the empirical part. The log-time model assumes that hazard rate monotonically changes with time. The hazard rate is assumed to have the following form

$$P_{it} = 1 - exp[-exp((q-1)ln(t) + \beta X_{it})] \tag{2.5}$$

where $q-1$ is the log-time parameter and P_{it} is the log-time hazard rate. This model assumes a parametric functional form for duration dependence.

A difference-in-difference estimation method is employed to investigate the impact of the September 11 terrorist attacks. Consider the following model,

$$h(t; X) = X_{it}\beta + h_0(t) + Sept11_t\alpha_1 + Muslim_i\alpha_2 + Sept11_t^* Muslim_i\delta \tag{2.6}$$

where $h(t, X) = log[-log(1 - P_{it})]$ is the complementary log log hazard rate, X_{it} is set of characteristics of individual i at time t including age, gender, age left education, employed sector, region, and dependents at the household. $Muslim_i$ is an indicator variable takes the value 1 if the individual i is from Muslim countries or 0 otherwise, $Sept11_t$ is a dummy variable takes the value of 1 if it is after third quarter in 2001 or 0 otherwise. The dependent variable is exit from unemployment which is a binary outcome. The interaction term, δ, measures the impact of September 11 on the exit rate from unemployment of immigrants from Muslim countries.

[4]For instance, if an individual finds a job in the third period, $t = 3$, three observations are created for the individual where the dependent variable is zero for the first two periods and one for the third observation.

This specification allows us to estimate the change in the exit rate from unemployment after September 11. If any deterioration exists after the terrorist attacks, one expects the exit rate to be lower ($\delta < 0$) and the unemployment duration to be longer for those immigrants. The set of explanatory variables is included to explain the differences among individuals. Independent variables included in equation 2.6 are time-invariant by the construction of the sample[5].

The treated group comprises individuals from Muslim countries. The focus of the empirical part is on two countries, Bangladesh and Pakistan, since over ninety percent of population in those countries are Muslims. At the same time, immigrants from those countries are also perceived to be Muslims in the UK. For instance, although Indian immigrants are very similar to those immigrants in terms of visual characteristics, Indian Muslims constitute a small portion of the population in India. It is therefore more likely that Indian immigrants are not associated with the September 11 terrorist attacks, thus, they are not included in the treated group. The indicator variable $Muslim$ refers to individuals from two Islamic countries (in this case, Pakistan or Bangladesh). Although some individuals from those countries may not be followers of Islam, it is assumed that it is not only followers of Islam but also individuals who are associated with Muslim stereotypes that are affected by the terrorist attacks. Thus, all individuals from those countries are assumed to be treated by the terrorist attacks. The choice of the comparison group is important in order to estimate the correct impact of the terrorist attacks. Treated and comparison groups should have similar characteristics except the treatment variable. It is assumed that UK-born white population and non-UK born white immigrants are considered to be untreated and taken as control groups.

2.4 Data

The data used in the empirical analysis stem from the UK Quarterly Labor Force Survey (QLFS). Starting from 1992, this survey has been conducted on a quarterly basis according to a rotation system where each household participates for five consecutive quarters and twenty percent of the sample is replaced every quarter. The UK sam-

[5]As mentioned by Allison, this procedure leads to maximum likelihood estimator for the corresponding model where it is asymptotically efficient and consistent.

ple consists of around 57,000 households in each wave, out of which the UK sample includes around 55,000 households and the Northern Ireland sample around 2,000 households. The data provide information on the duration of unemployment of the respondents in each wave. The information on ethnic background allows us to identify different ethnic groups which are classified into 14 different categories. Among those, we construct five groups which are in our interest; UK born white population, Pakistani, Bangladeshi, Indian, and non-UK born white immigrants. Since there is no information on the country of birth of parents, second or further generation immigrants cannot be identified separately. For simplicity, all UK-born immigrants are referred to as second generation from now on.

The empirical part uses waves from 1995 to 2007. The data is reconstructed for the purpose of the article in a panel format. Individuals are followed for five quarters until when they either exit from unemployment or from the survey. To measure the complimentary log-log model, the data are reorganized in a way that every survival or exit is represented as a separate observation in the sample. For instance, if the individual exits from unemployment at t_i (where i=1,2,3,...), i observations are then created for this individual where the dependent variable is assigned 1 for the i^{th} period and 0 for the previous $i-1$ periods. If the individual leaves the survey without exiting from unemployment, i observations are created where the dependent variable is assigned 0 for all i observations. Finally, the observations are pooled to create the final sample. The size of the groups in the sample is reported in Table 2.1. Around 88 percent is composed of UK-born white population while Muslims constitute around 3 percent of the sample.

2.4.1 Duration of Unemployment

The dependent variable is the exit rate from unemployment which takes value 1 if the individual exits from unemployment and zero otherwise. The question about the unemployment spell of individuals is asked in every wave in the QLFS. The variable values are presented in Table 2.2. An important feature of the unemployment duration variable is that it is estimated in large time intervals. Generally, duration of unemployment is estimated in days, weeks, or months. Therefore, the time span reported in the survey allows us to employ a discrete time duration model instead of

a continuous time duration model.

Complete unemployment spell of some individuals cannot be assessed since they are observed for only five quarters in the survey. It is possible that those individuals found a job when they left the survey but it is also possible that they have remained unemployed for longer time periods. Thus, if the individual leaves the survey before reporting that the unemployment spell ended, it is referred to as right censored observation. The unemployment spell observed in the data takes the form $t = min(t;8)$ where t is the reported unemployment spell.

2.4.2 UK Labor Market 1995-2010

Before starting the empirical analysis, labor market indicators in the UK are presented. If the labor market conditions worsen during the same period as the September 11 terrorist attacks, the longer unemployment spell of individuals from Muslim countries can be driven by this fact instead of the terrorist attacks. Table 2.3 documents the several economic indicators during the period of 1995-2010 (OECD database). Looking at the table, labor market in the UK had a positive trend starting from 1995 to 2007. In particular, employment grew around 20 percent from 1995 to 2008 while the labor force increased 10 percent during the same period. Similarly, unemployment dropped around 40 percent, from 8.6 percent in 1995 to 4.9 percent in 2005. The severe impact of the worldwide financial crisis can be seen after 2007.

The above analysis documents that the labor market had a positive trend during the years of the empirical analysis. Thus, it is less likely that the longer unemployment spell can be explained by labor market conditions. The sample is restricted during the period 1995-2007, in order to avoid the effects of the financial crisis.

2.5 Empirical Results

2.5.1 Survivor Functions

The theoretical framework predicts that the unemployment spell of immigrants from Muslim countries is longer if increased discrimination exists in the UK labor market after the terrorist attacks. The empirical part first presents descriptive evidence from

the UK labor market. Survivor functions of the ethnic groups in the sample are illustrated in Figure 2.1 and 2.2. The survival function presents the probability that individuals stay unemployed at least until time t. It is calculated as follows;

$$S_i = \prod_{j=1}^{i} \frac{n_j - d_j}{n_j} \tag{2.7}$$

where n_j is the number who are at the risk at the beginning of interval t, d_j is the number of failures at interval t. Figure 2.1 contrasts the survivor function for UK-born white population, immigrants from Muslim countries, Indian immigrants and non-UK born white immigrants in the period of 1995-2007. Clearly, immigrants from Muslim countries are more likely to stay unemployed for longer periods compared to other groups. It is quicker for UK-born white population to exit from unemployment compared to those immigrants. It is interesting that Indian immigrants and non-UK born white immigrants display a similar trend as UK-born white population, with slightly more time spent as unemployed. Difference between ethnic groups can stem from the low demand of employers against those immigrants in the UK labor market (Shields and Price, 2003). Or alternatively, the figure reports unconditional probabilities which can be the reason behind the difference among ethnic groups.

A similar pattern is shown in Figure 2.2 which illustrates the survivor functions before and after September 11. The figure includes UK-born white population as a reference group in addition to the survival function of immigrants from Muslim countries. The empirical analysis focuses on relative change instead of absolute change at the exit rates. Looking at the graph, the difference before and after September 11 is very small for immigrants from Muslim countries while there is an improvement for the UK-born white population, i.e. less time spent on looking for jobs. A decrease in the survival rate of the UK-born white population is observed after September 11 2001, meaning higher exit rates from unemployment.

Table 2.4 reports a more detailed picture of those groups for each unemployment spell. The estimates of survival function for two groups before and after the September 11 terrorist attacks, the number of individuals at the beginning of each period, the number of exits from unemployment to employment and the number of censored observations are presented in the table.The high number of observations before September 11 is based on the high number of individuals at the first waves and

high unemployment rates during this period. Table 2.4 also reports a 95% confidence interval for the survivor function which shows a significant decrease for the UK-born white population after September 11 at every level of unemployment spell. This confirms the favorable economic conditions in the UK labor market. The same trend is not observed for immigrants from Muslim countries; instead, the survival function for the first period is higher and similar to other periods after September 11 for those groups.

The descriptive analysis provides evidence on the worsening labor market conditions for immigrants from Muslim countries compared to UK-born white population. The data report no absolute change in the exit rate from unemployment for immigrants from Muslim countries. However, it shows that favorable economic conditions did not benefit those immigrants and a decrease in the exit rate compared to UK born white population is observed. Although survival functions represented in the table are unconditional probabilities, it provides preliminary evidence. One implication can be that the positive trend in the exit rates (more exits from unemployment) in the UK labor market never occurred for immigrants from Muslim countries because of increased discrimination after September 11. It is also possible that the worsening labor market outcomes of immigrants from Muslim countries might be associated with socio-economic characteristics. A more detailed regression analysis is presented in the next section.

2.5.2 Results from Discrete Time Proportional Hazard Models

This section presents regression analysis from the QLFS to assess the impact of the September 11 terrorist attacks on unemployment exit rates in the UK labor market. Semi-parametric and parametric discrete time complementary log-log models with different baseline hazard functions are employed. The first model reports the results relying on a piecewise constant baseline hazard and the second one using a log-time baseline hazard.The results from each specification are reported in Tables 2.5, and 2.6. In each table, the first three columns present results from the estimation of equation 2.6 with different specifications where the comparison group is the UK-born white population while the last column uses non-UK born white immigrants as the control group. Note that the reported results are coefficients and one needs to

exponentiate the reported coefficients to obtain the hazard rates[6]. Several explanatory variables are included in the regression to control for individual heterogeneity. In addition to individual characteristics, year and quarter dummies are included to control for the business cycle effects. The coefficient of interest is the interaction term (δ in equation 2.6), $Muslim^{*}September11$, which measures the impact of the September 11 terrorist attacks on unemployment exit rates of individuals from Muslim countries.

Table 2.5 presents the results from the estimation with a piecewise constant baseline hazard. This specification assumes that exit from unemployment is constant within the intervals but can change between the intervals. The results in the first column suggest that there is a significant deterioration for immigrants from Muslim countries after the the September 11 terrorist attacks in the UK labor market. The coefficient -0.20 implies that those immigrants are 18% less likely to leave the unemployment compared to UK-born white population with similar socioeconomic characteristics in the UK. The results are robust even after including several explanatory variables in the second and third column such as the method of applying for jobs and the region of residence. The results suggest that September 11 has a negative impact on the labor market outcomes of immigrants from Muslim countries. Lower levels of exit from unemployment also translates into longer unemployment duration for those immigrants.

Several explanatory variables are included in the estimation to control for individual heterogeneity. Adding more observables enables to capture more of the unobserved heterogeneity since discrete time duration models assume that $X_{it}\beta$ explains the hazard rate perfectly. Comparing the model fit in the first three columns suggests that the log likelihood statistic improves significantly after including the method of applying for jobs and the region of residence in the regression[7]. Men are less likely to exit from unemployment, which suggests that it is easier for women to find em-

[6] To obtain the hazard rate , one has to calculate $exp(\beta) - 1$.

[7] Table 2.5 presents the log likelihood ratio statistic for each specification. One can compare the fit of the model by employing a simple log likelihood ratio test. The null hypothesis that models are the same can be tested by comparing the difference between log likelihood statistics which has a chi square distribution. For instance, difference between first and second specification is 53.3 which is above the critical value of the 0.01 level of significance with 17 degrees of freedom.

ployment compared to men. As regards age, older workers spend more time as unemployed compared to their younger counterparts (Bover et al. 2002). This can be explained by the fact that young employees change jobs more frequently to find better a job/firm match compared to older workers. Similarly, years since migration have a similar impact on the exit rate such that when entered the host country, immigrants are more likely to find a job.

Results also show that education is positively associated with the exit rate from unemployment. The data contain information with regard to the highest level of educational qualification, however, this variable is problematic. Since the educational system in the UK and the one in the immigrants' home countries vary significantly, the educational level is usually reported as 'other qualifications' for immigrants in the data. Thus, the age at which the migrant left education is used as a proxy for educational attainment, which allows us to estimate the impact of education on the exit rate.

Several other variables which are associated with exit rates are included in the estimation. In particular, having dependent children at home increases the exit rate from unemployment. As expected annual unemployment rate is negatively associated with the exit rate. Furthermore,the period after September 11 is associated with quicker exit from unemployment.

Model 4 uses non-UK born white immigrants in the UK labor market as a comparison group instead of UK-born white population. The choice of the comparison group is important in order to estimate the impact of the terrorist attacks more accurately, since a misspecification of the comparison group can give wrong results. One possible reason of the significance shown in Table 2.5 can be driven from differences between two groups that are not controlled in the regression. Thus, we report the results in the last column to check whether the impact is robust for other comparison groups. Immigrants from Muslim countries experience disadvantage in the labor market compared to non-UK born white immigrants. However, the coefficient is smaller and insignificant. This can suggest that the favorable economic conditions reported in Table 2.3 can lead to higher exit rates for natives compared to all immigrants in the UK labor market. Immigrants from Muslim countries experienced a decrease in the exit rate compared to both UK-born white and non UK-born white

populations.

Estimation results from a model with a log-time baseline hazard function is presented in Table 2.6. This specification assumes that duration is time-dependent in a way that unemployment exit rate changes monotonically in time. The model with the log-time baseline hazard function gives very similar results. In particular, the coefficient on the interaction term is similar to the piecewise constant specification. For each estimation in Tables 2.5 and 2.6, test statistics are reported at the bottom of the table. They show that the semi-parametric piecewise constant baseline hazard model has a slightly lower log likelihood. The empirical analysis uses thus this specification for further estimations.

The evidence from the regression analysis above confirms that discrimination against immigrants from Muslim countries exists in the UK labor market after the September 11 terrorist attacks compared to UK-born white population in the sense that employers are more hesitant to hire those immigrants. The coefficients are robust even after controlling for socio-economic characteristics and economic indicators in the UK labor market.

2.5.3 Channels of Discrimination

On this basis, we can further discuss one possible channel of discrimination; visibility. Scholars argue that immigrants from Muslim countries who are more visible in the public sphere are exposed to discrimination more than others in social life (Lambert and Githens-Mazer 2010). Thus, it is investigated in this section whether this is also the case in the labor market. Visibility is defined as a concept of more recognizable individuals. First, it is possible that immigrants who work in certain sectors are more visible to the public, for instance hotels, restaurants, wholesale, or retail sectors. Typically, those immigrants are more visible to customers, which can make employers more hesitant to hire them. Second, we assume that first generation immigrants are more visible compared to second generation immigrants since they are more likely to be traditional, speak English less fluently, keep their homeland names and dresses etc.

Discrimination in Visible Sectors

This section investigates whether the degree of discrimination varies across sectors. Table 2.7 reports the distribution of sectors for each ethnic group in the UK labor market. Immigrants from Muslim countries are mainly employed in manufacturing, wholesale, hotels, and restaurants while the distribution of UK-born white population across sectors is more balanced. An important concern of the data is the percentage of missing sectors which constitutes around one third of the sample. For practical reasons, sectors are further grouped into four larger groups which are primary, secondary, tertiary, and missing sectors[8]. Sectoral differences between ethnic groups can bias the results if some sectors are affected more by the the September 11 terrorist attacks. If immigrants from Muslim countries work in those sectors, previous results can be due to worsening in those sectors instead of increased discrimination in the labor market.

Table 2.8 reports the results from the estimation of equation 2.6. The first column includes interaction terms to estimate the exit rates of immigrants from Muslim countries in different sectors. The results indicate that the exit rate of immigrants from Muslim countries does not differ across the different sectors. The coefficients of the interaction terms between sectors and the indicator variable $Muslim$ are positive and insignificant. The second column includes further interaction terms to capture the impact of September 11 on different sectors. Individuals working in the secondary and tertiary sector have lower exit rates after the September 11 terrorist attacks compared to their counterparts in the primary sector. One implication of these results can be that the impact of September 11 on immigrants from Muslim countries is ascribed to the employment of those immigrants in sectors where the exit rates are in general lower after September 11. If this statement were true, the effect of discrimination in the labor market can be overstated. To check this, three interaction terms are included in the third column to identify the impact of September 11 on Muslims in different sectors. Looking at the table, although coefficients are not significant, the

[8]The sectors are regrouped according to their degree of visibility. The primary group includes sectors of Agriculture, Fishing, Mining, Manufacturing and Electricity, Construction; the second group consists of Wholesale and Hotels; the tertiary group comprises Transport, Financial Intermediation, Real Estate, Public Administration, Education, Health, Other Community, Private Households, Extra-territorial.

exit rate of immigrants from Muslim countries in the secondary and tertiary sectors increased after September 11. Thus, we can conclude that the observed discrimination in the UK labor market is not due to sectoral difference.

Furthermore, the last column in Table 2.8 restricts the sample to only secondary and tertiary sectors. It is possible that immigrants who are working in more visible sectors are more likely to be exposed to discriminatory behavior. This type of discrimination can be based on customer discrimination which assumes that customers do not want to have contact with immigrants from Muslim countries or that employers in customer-related sectors are more hesitant to hire those immigrants even in the absence of customer discrimination. Thus, sectoral visibility is defined here with reference to customer interaction, in the sense that sectors with a higher interaction are considered as more 'visible'. If discrimination is stronger in visible sectors, a significantly higher coefficient is expected in those sectors. Results in the last column give evidence of discrimination based on visibility in the labor market. The coefficient of the interaction term in the restricted sample is similar to the unrestricted sample in Table 2.5. This suggests that discrimination does not differ according to sectoral visibility.

Discrimination against First Generation

Another channel of discrimination based on visibility relates to the migration background of the immigrants. It is assumed that first generation immigrants are more visible compared to second generation immigrants because they tend to be more traditional, keep the homeland names, dresses or appearances, are less fluent in the host country language, etc. Table 2.9 presents the distribution of immigrants across ethnic groups compared to their migration background. First generation immigrants constitute around 70 percent of the Indian and Muslim ethnic population in the UK labor market. According to discrimination theory, if visibility is a channel of discrimination, we expect to see a significant impact of the terrorist attacks on first generation immigrants.

Table 2.10 reports that the impact is strong and significant on the first generation of immigrants while the coefficient for the second generation immigrants from Muslim countries is small and not significant. This implies that discrimination in the

labor market takes place primarily against first generation immigrants from Muslim countries. The exit from unemployment for first generation immigrants from Muslim countries can be lower because they are more visible and more likely to be associated with Muslim stereotypes by employers. The last column reports the results from the model where the comparison group is the non-UK born white immigrants. The coefficient is still negative but smaller and not significant.

2.6 Robustness Checks

This section provides several issues to check the robustness of the reported results. Previous results report that exit rates of immigrants from Muslim countries is lower after the September 11 terrorist attacks compared to the UK-born white population. Moreover, it is showed that discrimination is not based on sectoral visibility. Those immigrants who are working in visible sectors are not exposed to discrimination more than individuals working in other sectors. Instead, it is showed that first-generation immigrants experience discrimination while no impact of September 11 is observed in the unemployment exit rate of second generation immigrants from Muslim countries. There are several issues that the empirical analysis has to take into consideration to check the robustness of the results.

2.6.1 Indian Immigrants

It is important to distinguish whether discrimination in the labor market is based on appearance or country of origin. To check, equation 2.6 is estimated by including immigrants from India who are very similar to Pakistani and Bangladeshi immigrants in terms of appearance. Although they have similar visual characteristics, Indian immigrants are mostly followers of Hindu religion, are more educated, and do not have traditional Islamic names, dresses, veil, or beard which are associated with Muslim stereotypes. If discrimination is based on appearance, one could expect a similar impact on exit rates after September 11 on Indian immigrants. On the other hand, if employers are rational enough to differentiate between those two communities, no impact on exit rates should be observed.

Table 2.11 reports the results from the estimation of equation 2.6 with a sample

of UK-born white immigrants, immigrants from Muslim countries, and immigrants from India. Looking at the table, we see that there is no significant impact as regards Indian immigrants while the impact is still significant in the case of Muslim immigrants. Similarly, Table 2.12 reports the results for the first and second generation immigrants from Muslim countries and India. Similar to the previous discussion, the impact on first generation immigrants from Muslim countries still exists while there is no impact on the first and second generation Indian immigrants compared to the UK-born white population. This implies that employers are rational enough to differentiate between those two communities. There are thus no changing preferences as regards immigrants from India that can lead to lower exit rates after September 11.

2.6.2 Different Intervention Dates

Another important issue is the robustness of the results for different intervention dates. It is possible that the DD estimation strategy employed by the empirical analysis captures an ongoing trend where the relative exit rate from unemployment is negative for immigrants from Muslim countries. To check whether the results are due to the September 11 terrorist attacks instead of a negative trend, DD estimates with different intervention dates are reported in Table 2.13. Looking at the table, intervention dates that are closer to September 11 report significantly lower exit rates. This suggests that closer intervention dates could still capture the impact of increased discrimination while more remote intervention dates report insignificant coefficients. The further the intervention dates from September 11, 2001, the higher the isolation from the impact of increased discrimination. This confirms that the reported results are a result of the September 11 terrorist attacks instead of a negative trend in the UK labor market.

2.6.3 Different Comparison Groups

The DD analysis presented here is sensitive to the choice of the comparison group. An important assumption in DD analysis is that the comparison group is not affected by the treatment. In addition, the change in the exit rate (conditional on individual characteristics) would over time be similar for both the comparison group and the treated group, even in the absence of treatment. This means that any difference in

the exit rate between the comparison and the treated groups can be attributed to the impact of the treatment. Until now, the empirical analysis has focused on two comparison groups, UK-born white population and non UK-born white immigrants as they are assumed to satisfy the conditions (similar change in the exit rates over time in the absence of treatment and no influence by the the September 11 terrorist attacks). Another important advantage of employing the UK-born white population as a comparison group is the size of the population, which produces more precise estimates.

Table 2.14 reports the results for different comparison groups. The first two columns document the estimated coefficients from the previous analysis while the latter columns present regression results by using different comparison groups. Individuals with black ethnic background, first generation immigrants from Eastern European countries[9], and immigrants with Asian ethnic background are the comparison groups that can be identified in the data. Immigrants from Eastern European countries are the most appropriate comparison group compared to other two immigrant groups. First, immigrants from Eastern European countries are less likely to be affected by increased discrimination after the terrorist attacks, since it is less likely that they are associated with Muslim stereotypes. Second, they work in low level jobs like immigrants from Bangladesh and Pakistan. It is also important to note that immigrants with black and asian ethnic background are much more established in the UK. Equation 2.6 is estimated by using the original sample in the first row and following the previous discussion, the sample is restricted to the first generation immigrants in the second row. Looking at the first row in the table, all coefficients have a negative sign except for the Asian comparison group. Although the estimated coefficients are not significant, the negative sign in all specifications confirms the previous discussion, namely that immigrants from Muslim countries have lower exits after the the September 11 terrorist attacks. When restricting the sample only to the first generation immigrants (second row in Table 2.14), the estimated effect is stronger, revealing that the discrimination has been even stronger for the first generation immigrants.

[9]Immigrants included in the Eastern European comparison group are from the following countries; Cyprus, Albania, Bulgaria, Czech Republic, Hungary, Poland, Romania, Greece, former- Yugoslavian countries, Russia, former-USSR, Belarus, Estonia, Lithuania, Latvia, Moldova, Slovakia, Slovenia, Ukraine

2.6.4 Unobserved Heterogeneity

An important disadvantage of discrete time models is the unobserved heterogeneity. Consider the complementary log-log model in equation 2.6,

$$h(t;X) = X_{it}\beta + h_0(t) \tag{2.8}$$

where $h(t;X) = log[-log(1-P_{it})]$, which does not include an error term, thus does not control for individual heterogeneity. Discrete time duration models without controlling for unobserved heterogeneity assume that $X_{it}\beta$ explains the hazard rate perfectly which is a very strong assumption. Thus, a regression analysis that does not control for unobserved heterogeneity can report biased and inconsistent estimates. One possible method is to include an error term in the above equation which has zero mean and finite variance. The most common distributional form that is used in the literature is the gamma distribution which is also the assumption used in this paper to control for unobserved heterogeneity.

Table 2.15 reports the results from the complementary log-log model with unobserved heterogeneity. First, the test statistics at the bottom of the table indicate significant unobserved heterogeneity. Looking at the table, the results are very similar to previous results estimated without unobserved heterogeneity. The coefficients on the interaction terms confirm the previous findings concerning discrimination in the UK labor market.

2.7 Conclusion

The debate on the integration of Muslim immigrants in the European labor market has preoccupied scholars for several decades. In this paper, I study the effects of the September 11 terrorist attacks on the labor market outcomes of Muslim immigrants in the UK. Interestingly, the impact of such terrorist attacks is a neglected field in economics. Unlike other papers which studied the situation in the US on wages, this paper analyzes the effect in European countries with a significant Muslim population. I contribute to extant literature by analyzing the impact of the September 11 terrorist attacks on the exit rate from unemployment on grounds that it offers a better basis to investigate discriminatory behavior in the labor market.

By using discrete time duration models, I conclude that the unemployment spell of immigrants from Muslim countries is longer after September 11. Moreover, the channel of discrimination is investigated by defining two concepts of visibility. It is well reported in the literature that visible immigrants are exposed to discriminatory behavior more frequently. The paper argues that there is no evidence confirming the sectoral discrimination in the UK labor market. Instead, first generation immigrants are exposed to discrimination after September 11 while the same effect is not observed for second generation immigrants from Muslim countries. This suggests that first generation immigrants are more exposed to discrimination since they are more visible.

This paper is among the first attempts to investigate the effects of terrorist attacks on unemployment spells in Western European countries. Discrimination has been observed not only in social life but also in the workplace in the aftermath of terrorist attacks. It is therefore of increased significance to investigate the labor market effects of terrorist attacks in terms of anti-discrimination policymaking.

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Table 2.1: Sample Size of Selected Groups

Ethnicity	Observations	Perc.	No. of Indv.	Perc.
UK-born White	198,395	90.16	75,791	89.98
Imm. from Muslim Countries	6,108	2.78	2,125	2.52
Indian Immigrants	4,890	2.22	1,859	2.21
non-UK born White	10,649	4.84	4,452	5.29
Total	220,042	100.00	84,227	100.00

Source: UKLFS, sample size of selected groups.

Table 2.2: Variable Definition. Duration of Unemployment

Value	Definition
1	Less Than 3 months
2	More Than 3 Months but Less Than 6 months
3	More Than 6 Months but Less Than 1 Year
4	Less Than 1 Year
5	More Than 1 Year But Less Than 2 Years
6	More Than 2 Years But Less Than 3 Years
7	More Than 3 Years But Less Than 4 Years
8	More Than 4 Years But Less Than 5 Years

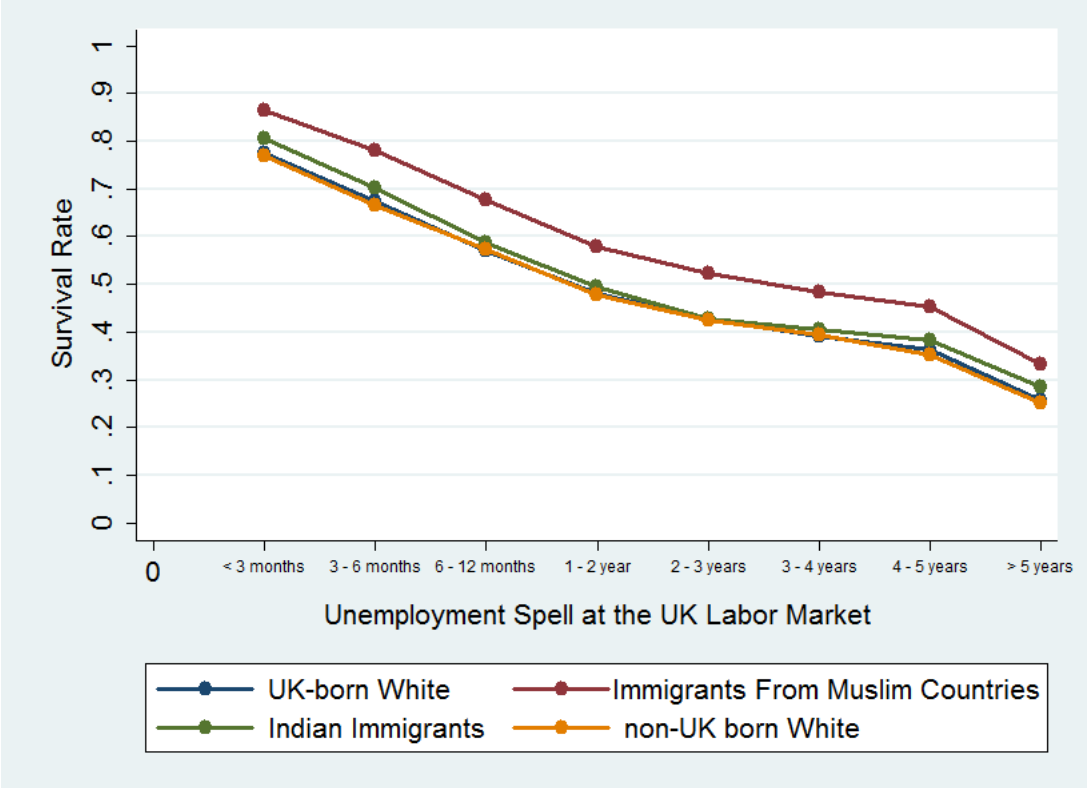
Source: UKLFS, description of unemployment spell.

Table 2.3: UK Labor Market 1995-2010

Year	GDP Growth	Unemployment Rate	Total Employment	Labor Force
1995	3.1	8.6	25,818	28,254
1996	2.9	8.1	26,059	28,356
1997	3.4	7.0	26,525	28,513
1998	3.8	6.3	26,795	28,583
1999	3.7	6.0	27,168	28,895
2000	4.5	5.5	27,483	29,070
2001	3.2	5.1	27,710	29,199
2002	2.7	5.2	27,919	29,448
2003	3.5	5.0	28,182	29,672
2004	3.0	4.8	28,480	29,906
2005	2.1	4.9	28,769	30,206
2006	2.6	5.5	29,025	30,698
2007	3.5	5.4	29,228	30,881
2008	-1.1	5.7	29,440	31,222
2009	-4.4	7.6	28,960	31,355
2010	2.1	7.9	29,034	31,513

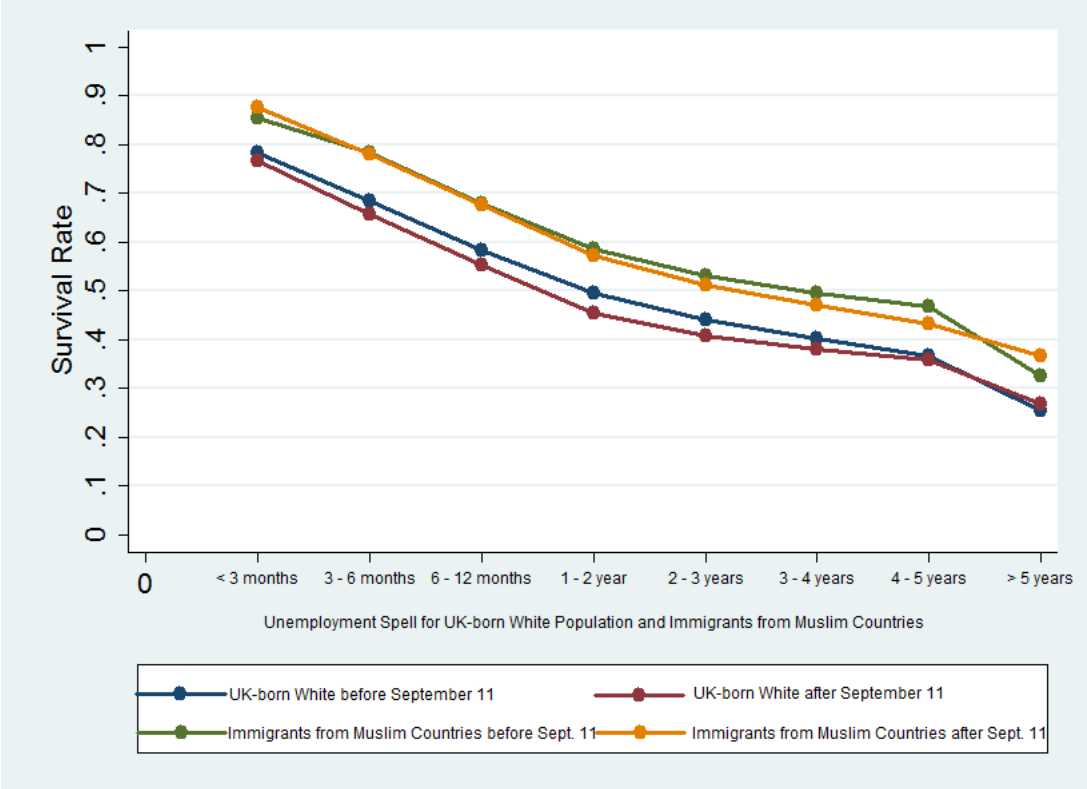
Source: OECD

Figure 2.1: The Survivor Functions for all Ethnicities



Source: UKLFS, sample size of selected groups.

Figure 2.2: The Survivor Functions Before and After September 11



Notes. Own calculations form the QLFS.

Table 2.4: Descriptive Evidence for Survival Rates Between Ethnic Groups Before and After September 11

	Interval	Beg. Total	Deaths	Lost	Survival	Std. Error	[95% Conf. Int.]
Uk-born White							
Population	0 - 3 months	45883	9966	7610	0.7828	0.0019	0.7790 - 0.7865
Before September 11	3 - 6 months	28307	3602	3904	0.6832	0.0023	0.6787 - 0.6876
	6 - 12 months	20801	3024	4088	0.5839	0.0026	0.5788 - 0.5889
	1 - 2 years	13689	2086	3498	0.4949	0.0028	0.4894 - 0.5004
	2 - 3 years	8105	890	1715	0.4406	0.0030	0.4346 - 0.4465
	3 - 4 years	5500	493	1048	0.4011	0.0032	0.3947 - 0.4074
	4 - 5 years	3959	333	726	0.3673	0.0035	0.3605 - 0.3741
	> 5 years	2900	885	2015	0.2552	0.0040	0.2475 - 0.2630
Uk-born White							
Population	0 - 3 months	28651	6667	6777	0.7673	0.0025	0.7624 - 0.7722
After September 11	3 - 6 months	15207	2168	3039	0.6579	0.0031	0.6519 - 0.6639
	6 - 12 months	10000	1577	2694	0.5542	0.0035	0.5472 - 0.5610
	1 - 2 years	5729	1031	2026	0.4544	0.0040	0.4465 - 0.4623
	2 - 3 years	2672	281	688	0.4066	0.0045	0.3978 - 0.4155
	3 - 4 years	1703	112	318	0.3799	0.0049	0.3704 - 0.3894
	4 - 5 years	1273	69	192	0.3593	0.0052	0.3491 - 0.3695
	> 5 years	1012	259	753	0.2673	0.0063	0.2551 - 0.2797
Immigrants from							
Muslim Countries	0 - 3 months	1126	163	185	0.8552	0.0105	0.8333 - 0.8745
Before September 11	3 - 6 months	778	65	129	0.7838	0.0128	0.7574 - 0.8077
	6 - 12 months	584	79	118	0.6778	0.0157	0.6459 - 0.7074
	1 - 2 years	387	52	113	0.5867	0.0180	0.5506 - 0.6209
	2 - 3 years	222	21	53	0.5312	0.0199	0.4914 - 0.5694
	3 - 4 years	148	10	26	0.4953	0.0216	0.4523 - 0.5368
	4 - 5 years	112	6	18	0.4688	0.0230	0.4231 - 0.5130
	> 5 years	88	27	61	0.3249	0.0280	0.2708 - 0.3801
Immigrants from							
Muslim Countries	0 - 3 months	965	119	206	0.8767	0.0106	0.8542 - 0.8959
After September 11	3 - 6 months	640	70	141	0.7808	0.0143	0.7511 - 0.8074
	6 - 12 months	429	57	114	0.6771	0.0178	0.6407 - 0.7106
	1 - 2 years	258	40	97	0.5721	0.0215	0.5289 - 0.6129
	2 - 3 years	121	13	44	0.5106	0.0250	0.4605 - 0.5584
	3 - 4 years	64	5	10	0.4707	0.0287	0.4135 - 0.5258
	4 - 5 years	49	4	12	0.4323	0.0322	0.3686 - 0.4942
	> 5 years	33	5	28	0.3668	0.0384	0.2921 - 0.4416

Own calculations from the UKLFS

Table 2.5: The effect of Terrorist Attacks on Exit from Unemployment in the UK. Piecewise Constant Baseline Hazard

	(1)	(2)	(3)	(4)
Age	-0.0046116 ***	-0.0048959 ***	-0.0056679 ***	-0.0182979 ***
	(0.0004533)	(0.0004547)	(0.0004557)	(0.0022982)
Sex	-0.5184377 ***	-0.5265733 ***	-0.5112038 ***	-0.5138993 ***
	(0.0118945)	(0.0119406)	(0.0119627)	(0.0443448)
Age Left Education	0.0645049 ***	0.0626545 ***	0.0605822 ***	0.0318055 ***
	(0.002465)	(0.0024727)	(0.0024979)	(0.0063062)
Number of dependent children	0.0553119 ***	0.0540565 ***	0.0517441 ***	0.0095216
	(0.0048751)	(0.0048816)	(0.0048969)	(0.0167544)
Years Since Migration	-0.0092237 ***	-0.0092797 ***	-0.008477 ***	-0.0011408
	(0.0025074)	(0.0025067)	(0.0024932)	(0.0017906)
Annual Unemployment Rate	0.1134685 ***	0.1113819 ***	0.1071496 ***	0.1172122 *
	(0.0186406)	(0.0186438)	(0.0186562)	(0.063062)
September 11	0.2498424 ***	0.2476405 ***	0.2270148 ***	0.3521281 *
	(0.0521782)	(0.0521812)	(0.0522225)	(0.1807357)
Muslim	-0.1179568	-0.1136539	-0.0902969	-0.2082347 ***
	(0.0690209)	(0.0690262)	(0.0692807)	(0.0661167)
Muslim*September 11	-0.208822 ***	-0.2127443 ***	-0.1764444 **	-0.0516797
	(0.0776148)	(0.0776202)	(0.0776861)	(0.0900646)
Controlled For				
Year	✓	✓	✓	✓
Quarter	✓	✓	✓	✓
Sector Employed	✓	✓	✓	✓
Method of Applying jobs	x	✓	✓	✓
Residence Region	x	x	✓	✓
Number of Observations	201,395	201,395	201,395	16,472
Number of Individuals	76,625	76,625	76,625	6,454
Log likelihood	-86555.322	-86502.025	-86137.022	-6669.5412

Note. * *significant at* 10%; ** *significant at* 5%; *** *significant at* 1%.

Note. Discrete time complementary log-log model is estimated where the dependent variable is the dummy variable indicating whether exit from unemployment occurred. Number in the first row is the estimation coefficient. To obtain the hazard rate, one has to calculate $[exp(\beta) - 1]$.

Note. Models 1, 2, and 3 use UK-born white population as comparison group and non UK born white immigrants is used in the last column. YSM takes value of zero for natives.

Table 2.6: The effect of Terrorist Attacks on Exit from Unemployment in the UK. Log Time Baseline Hazard

	(1)	(2)	(3)	(4)
Age	-0.0040428 ***	-0.0043362 ***	-0.0050918 ***	-0.0157327 ***
	(0.0004507)	(0.0004521)	(0.0004531)	(0.001964)
Sex	-0.5107114 ***	-0.5190077 ***	-0.5040747 ***	-0.4955584 ***
	(0.0118737)	(0.0119198)	(0.0119423)	(0.0441003)
Age Left Education	0.0640417 ***	0.0621537 ***	0.0600902 ***	0.0304376 ***
	(0.0024599)	(0.0024677)	(0.0024926)	(0.0061299)
Number of dependent children	0.0547812 ***	0.053505 ***	0.0511338 ***	0.0123379
	(0.0048784)	(0.0048849)	(0.0048997)	(0.0168433)
Years Since Migration	-0.0085953 ***	-0.0086552 ***	-0.0078032 ***	-0.0036981
	(0.0025066)	(0.0025059)	(0.0024919)	(0.0027029)
Annual Unemployment Rate	0.114508 ***	0.1123678 ***	0.108193 ***	0.1250662 **
	(0.0186327)	(0.0186359)	(0.0186471)	(0.0637596)
September 11	0.2546458 ***	0.2524375 ***	0.233174 ***	0.3819625 **
	(0.0521546)	(0.0521571)	(0.052195)	(0.1807522)
Muslim	-0.1359264 **	-0.1316754 *	-0.108193	-0.1324176
	(0.068843)	(0.0688462)	(0.0186471)	(0.0851871)
Muslim*September 11	-0.2079435 ***	-0.211728 ***	-0.1749366 **	-0.0939859
	(0.0774783)	(0.0774814)	(0.077541)	(0.0914479)
Controlled For				
Year	✓	✓	✓	✓
Quarter	✓	✓	✓	✓
Sector Employed	✓	✓	✓	✓
Method of Applying jobs	x	✓	✓	✓
Residence Region	x	x	✓	✓
Number of Observations	201,395	201,395	201,395	16,472
Number of Individuals	76,625	76,625	76,625	6,454
Log likelihood	-87618.268	-87562.757	-87206.100	-6746.089

Note. * *significant at* 10%; ** *significant at* 5%; *** *significant at* 1%.

Note. Discrete time complementary log-log model is estimated where the dependent variable is the dummy variable indicating whether exit from unemployment occurred. Number in the first row is the estimation coefficient. To obtain the hazard rate, one has to calculate $[exp(\beta) - 1]$.

Note. Models 1, 2, and 3 use UK-born white population as comparison group and non UK born white immigrants is used in the last column. YSM takes value of zero for natives.

Table 2.7: The Distribution of Individuals into Sectors in the UK 1995-2007

Sectors	UK-born White Population	Immigrants from Muslim Countries	Indian Immigrants	non-UK born White Population
Agriculture, Hunting, and Forestry	1.17	0.16	0.45	0.77
Fishing	0.11	0.00	0.00	0.00
Mining and Quarrying	0.54	0.15	0.02	0.27
Manufacturing	16.68	19.91	21.25	12.78
Electricity, gas, and water supply	0.53	0.21	0.22	0.23
Construction	9.48	0.77	2.9	7.91
Wholesale, Retail, and Motor Trade	12.37	12.84	16.26	9.96
Hotels and Restaurants	5.54	12.44	3.23	8.82
Transport, Storage, and Comm.	5.38	5.08	5.79	4.98
Financial Intermediation	1.83	1.16	3.23	2.06
Real Estate, Renting, and Busn. Act.	7.43	4.42	7.06	9.79
Public administration, and defence	2.66	1.11	2.78	2.85
Education	3.33	2.31	2.92	4.77
Health and Social Work	5.24	2.41	4.21	5.35
Other Community, Social, and Pers.l	4.79	1.78	2.52	5.08
Private Hholds with Employed Pers.	0.46	0.03	0.06	0.81
Extra-territorial Organisations,Bod.	0.05	0.31	0.18	1.02
Missing	22.42	34.91	26.91	22.56
Total	100.00	100.00	100.00	100.00

Source: UKLFS, own calculations.

Table 2.8: The effect of Terrorist Attacks on Exit from Unemployment in the UK. Sectoral Differences

	(1)	(2)	(3)	(4)
Age	-0.0053455 ***	-0.0054014 ***	-0.0054023 ***	-0.0026295***
	0.0004521	0.0004525	0.0004525	0.0005894
Sex	-0.5110166 ***	-0.5109364 ***	-0.5109989 ***	-0.4938311***
	0.0115761	0.011577	0.0115774	0.0146519
Age Left Education	0.0620064 ***	0.061867 ***	0.0618718 ***	0.0541253***
	(0.0024487)	(0.0024496)	(0.0024498)	(0.0029801)
Number of Dependent Children	0.0516355 ***	0.0518002 ***	0.0517501 ***	0.0522612***
	(0.0048922)	(0.0048934)	(0.0048939)	(0.0065448)
Years Since Migration	-0.0079518 ***	-0.0078865 ***	-0.0079981 ***	-0.0110151***
	(0.0025159)	(0.0025146)	(0.0025199)	(0.0035571)
Annual Unemployment Rate	0.107793 ***	0.1079734 ***	0.1080081 ***	0.12941***
	(0.0186541)	(0.0186556)	(0.018656)	(0.0240259)
September 11	0.2264144 ***	0.2916856 ***	0.2939172 ***	0.2774509***
	(0.0522139)	(0.0558747)	(0.0559251)	(0.0674665)
Muslim	-0.1917932 *	-0.1999613 *	-0.156185	-0.0439404
	(0.1049592)	(0.1052817)	(0.1176662)	(0.0975329)
Muslim*September11	-0.1791773 **	-0.1639351 **	-0.2894396	-0.2194464**
	(0.0779812)	(0.0781017)	(0.1831513)	(0.1059725)
Secondary Sector	0.01917	0.0449576 **	0.045382 **	
	(0.0165875)	(0.0201903)	(0.0202712)	
Tertiary Sector	0.0726406 ***	0.0936623 ***	0.093982 ***	
	(0.0145689)	(0.0176492)	(0.0176973)	
Missing Sector	-0.5856273 ***	-0.5372271 ***	-0.5341341 ***	
	(0.0187824)	(0.0229644)	(0.0230718)	
Muslim*Secondary Sect	0.0424277	0.0436744	0.011091	
	(0.1130798)	(0.1129912)	(0.1427888)	
Muslim*Tertiary Sect	0.1329478	0.1326688	0.115204	
	(0.1121533)	(0.112053)	(0.1430243)	
Muslim*Missing Sect	0.1937582 *	0.1960051 *	0.0920416	
	(0.1117997)	(0.1116937)	(0.1402451)	
Secondary Sect*September 11		-0.0799706 **	-0.0814212 **	
		(0.0334748)	(0.0338415)	
Tertiary Sect*September 11		-0.0661071 **	-0.0673074 **	
		(0.0289948)	(0.0292265)	
Missing Sect*September 11		-0.138747 ***	-0.1473477 ***	
		(0.0374169)	(0.038014)	
Muslim*Secondary Sect*September 11			0.1050046	
			(0.2351299)	
Muslim*Tertiary Sect*September 11			0.0746891	
			(0.2316263)	
Muslim*Missing Sect*September 11			0.2763604	
			(0.2324984)	
Controlled For				
Year	✓	✓	✓	✓
Quarter	✓	✓	✓	✓
Sector Employed	✓	✓	✓	✓
Method of Applying jobs	✓	✓	✓	✓
Residence Region	✓	✓	✓	✓
Number of Observations	201,395	201,395	98,597	
Number of Individuals	76,625	76,625	42,776	
Log likelihood	-86189.888	-86182.118	-47822.825	

Note. * *significant at* 10%; ** *significant at* 5%; *** *significant at* 1%.

Note. Discrete time complementary log-log model is estimated where the dependent variable is the dummy variable indicating whether exit from unemployment occurred. Number in the first row is the estimation coefficient. To obtain the hazard rate, one has to calculate $[exp(\beta) - 1]$.

Note. Models 1, 2, and 3 use UK-born white population as comparison group and non UK born white immigrants is used in the last column. YSM takes value of zero for natives.

Table 2.9: First and Second generation composition across ethnic groups

	UK-born White	Immg. from Muslim Countr.	Indian Immg.	non-UK born White
Native	198,395	0	0	0
First Generation	0	4,375	3,398	10,649
Second Generation	0	1,733	1,492	0
Total	198,395	6,108	4,890	10,649

Source: UKLFS, own calculations.

Table 2.10: The effect of Terrorist Attacks on Duration of Unemployment in Britain. First and Second Generation Immigrants from Muslim Countries

	(1)	(2)	(3)	(4)
Age	-0.0046066 ***	-0.0048906 ***	-0.0056625 ***	-0.0182317 ***
	(0.0004533)	(0.0004546)	(0.0004556)	(0.0023007)
Sex	-0.5185379 ***	-0.5266664 ***	-0.5113501 ***	-0.5134115 ***
	(0.011896)	(0.0119419)	(0.011964)	(0.0443599)
Age Left Education	0.0644081 ***	0.0625551 ***	0.0604652 ***	0.0320204 ***
	(0.0024664)	(0.0024742)	(0.002499)	(0.0063531)
Number of dependent children at home	0.0552287 ***	0.0539733 ***	0.0516111 ***	0.010094
	(0.0048766)	(0.004883)	(0.0048986)	(0.016857)
Years Since Migration	-0.0126697 ***	-0.012785 ***	-0.0131402 ***	0.013674
	(0.0041454)	(0.0041457)	(0.004123)	(0.0019489)
Annual Unemployment Rate	0.1136362 ***	0.1115629 ***	0.1073857 ***	0.1178045 *
	(0.0186415)	(0.0186448)	(0.0186571)	(0.0637519)
September 11	0.2503682 ***	0.2481974 ***	0.2277386 ***	0.354126 **
	(0.0521798)	(0.0521827)	(0.0522239)	(0.1807377)
First Generation Muslim	0.0198934	0.0263439	0.0856711	-0.1948694***
	(0.1284945)	(0.1285506)	(0.1282449)	(0.0749949)
Second Generation Muslim	-0.2152804 **	-0.2119118 **	-0.195782 **	-0.2389963 **
	(0.091615)	(0.0916183)	(0.0919689)	(0.1072876)
First Generation Muslim*September 11	-0.3154972 ***	-0.3204396 ***	-0.2846196 ***	-0.1233832
	(0.1003981)	(0.1004271)	(0.100445)	(0.1075546)
Second Generation Muslim*September 11	-0.0576947	-0.0605673	-0.033643	0.0657297
	(0.1260262)	(0.1260302)	(0.1260613)	(0.1356288)
Controlled For				
Year	✓	✓	✓	✓
Quarter	✓	✓	✓	✓
Sector Employed	✓	✓	✓	✓
Method of Applying jobs	x	✓	✓	✓
Residence Region	x	x	✓	✓
Number of Observations	201,395	201,395	201,395	16,472
Number of Individuals	76,625	76,625	76,625	6,454
Log likelihood	-86553.797	-86500.47	-86135.216	-6668.6927

Note. * *significant at* 10%; ** *significant at* 5%; *** *significant at* 1%.

Note. Discrete time complementary log-log model is estimated where the dependent variable is the dummy variable indicating whether exit from unemployment occurred. Number in the first row is the estimation coefficient. To obtain the hazard rate, one has to calculate $[exp(\beta) - 1]$.

Note. Models 1, 2, and 3 use UK-born white population as comparison group and non UK born white immigrants is used in the last column. YSM takes value of zero for natives.

Table 2.11: The effect of Terrorist Attacks on Duration of Unemployment in Britain. Immigrants from Indian and Muslim Countries

	(1)	(2)	(3)	(4)
Age	-0.0048011 ***	-0.0050807 ***	-0.0058447 ***	-0.0173618 ***
	(0.0004508)	(0.0004522)	(0.0004532)	(0.0018247)
Sex	-0.5151537 ***	-0.523214 ***	-0.5078451 ***	-0.4676462 ***
	(0.0117453)	(0.0117895)	(0.0118119)	(0.0382096)
Age Left Education	0.0631604 ***	0.0613515 ***	0.0593754 ***	0.0321803 ***
	(0.0024094)	(0.0024166)	(0.0024412)	(0.005406)
Number of dependent children at home	0.0542043 ***	0.0530482 ***	0.0509136 ***	0.0126677
	(0.0048215)	(0.0048275)	(0.0048428)	(0.0149744)
Years Since Migration	-0.0062868 ***	-0.0063313 ***	-0.0060116 ***	0.0010677
	(0.0016937)	(0.0016925)	(0.001688)	(0.0019342)
Annual Unemployment Rate	0.1114228 ***	0.1094183 ***	0.1053975 ***	0.1054014 *
	(0.0184372)	(0.0184405)	(0.0184538)	(0.0570258)
September 11	0.2495226 ***	0.2472118 ***	0.226878 ***	0.3335838 **
	(0.0516712)	(0.0516744)	(0.0517168)	(0.1635885)
Muslim	-0.174616 ***	-0.1702577 ***	-0.1391275 **	-0.2075432 ***
	(0.0599439)	(0.0599466)	(0.0602644)	(0.076023)
Indian	-0.0930553	-0.0860957	-0.073508	-0.0868732
	(0.060339)	(0.0603339)	(0.0607911)	(0.0736837)
Muslim*September 11	-0.1880307 **	-0.1920869 **	-0.1584258 **	-0.0580821
	(0.0765558)	(0.0765608)	(0.0766061)	(0.0904649)
Indian*September 11	-0.052155	-0.0535021	-0.038433	0.0899598
	(0.0749761)	(0.0749745)	(0.0750382)	(0.0891469)
Controlled For				
Year	✓	✓	✓	✓
Quarter	✓	✓	✓	✓
Sector Employed	✓	✓	✓	✓
Method of Applying jobs	x	✓	✓	✓
Residence Region	x	x	✓	✓
Number of Observations	206,209	206,209	206,209	21,286
Number of Individuals	78,456	78,456	78,456	8,285
Log likelihood	-88598.443	-88544.535	-88173.395	-8694.0963

Note. * *significant at* 10%; ** *significant at* 5%; *** *significant at* 1%.

Note. Discrete time complementary log-log model is estimated where the dependent variable is the dummy variable indicating whether exit from unemployment occurred. Number in the first row is the estimation coefficient. To obtain the hazard rate, one has to calculate $[exp(\beta) - 1]$.

Note. Models 1, 2, and 3 use UK-born white population as comparison group and non UK born white immigrants is used in the last column. YSM takes value of zero for natives.

Table 2.12: The effect of Terrorist Attacks on Duration of Unemployment in Britain. First and Second Generation Immigrants from Indian and Muslim Countries

	(1)	(2)	(3)	(4)
Age	-0.0048009 ***	-0.0050817 ***	-0.0058462 ***	-0.0173744 ***
	(0.0004509)	(0.0004523)	(0.0004533)	(0.0018269)
Sex	-0.5149496 ***	-0.5230093 ***	-0.5077132 ***	-0.4649684 ***
	(0.0117491)	(0.0117931)	(0.0118156)	(0.0383234)
Age Left Education	0.0631073 ***	0.0612772 ***	0.0592755 ***	0.031252 ***
	(0.0024141)	(0.0024216)	(0.0024456)	(0.0054426)
Number of dependent children at home	0.0542877 ***	0.0531176 ***	0.0509146 ***	0.0118617
	(0.0048245)	(0.0048304)	(0.0048461)	(0.015073)
Years Since Migration	-0.0060618 ***	-0.0063099 ***	-0.0064989 ***	-0.0031685
	(0.0027493)	(0.002748)	(0.0027378)	(0.0029582)
Annual Unemployment Rate	0.1115286 ***	0.1095705 ***	0.1055521 ***	0.1102917 *
	(0.0184408)	(0.0184443)	(0.0184575)	(0.0571699)
September 11	0.2498898 ***	0.2477294 ***	0.2273463 ***	0.3483448 **
	(0.0516798)	(0.051683)	(0.0517253)	(0.163962)
First Generation Muslim	-0.1635894 *	-0.1530721	-0.1006697	-0.1221916
	(0.0975298)	(0.0975098)	(0.0975941)	(0.1090494)
Second Generation Muslim	-0.2169321 **	-0.2133642 **	-0.1980392 **	-0.274016 ***
	(0.0916088)	(0.0916122)	(0.0919526)	(0.1032117)
First Generation Indian	-0.1108874	-0.0975547	-0.07241	-0.0268077
	(0.1032272)	(0.1031781)	(0.1032286)	(0.112152)
Second Generation Indian	-0.0695561	-0.0626953 **	-0.0431282	-0.0769736
	(0.0847632)	(0.0847618)	(0.0851139)	(0.0960152)
First Generation Muslim*September 11	-0.2663907 ***	-0.2723919 ***	-0.234483 ***	-0.1483733
	(0.0975202)	(0.0975344)	(0.097561)	(0.1090577)
Second Generation Muslim*September 11	-0.0564978	-0.0596307	-0.032701	0.0718905
	(0.1260233)	(0.1260272)	(0.1260574)	(0.1353523)
First Generation Indian*September 11	0.0008391	0.0028815	0.0114806	0.1373659
	(0.0956821)	(0.0956039)	(0.0957395)	(0.1073524)
Second Generation Indian*September 11	-0.1393299	-0.1492737	-0.1350155	-0.0232338
	(0.1233641)	(0.1233641)	(0.1233945)	(0.1333125)
Controlled For				
Year	✓	✓	✓	✓
Quarter	✓	✓	✓	✓
Sector Employed	✓	✓	✓	✓
Method of Applying jobs	x	✓	✓	✓
Residence Region	x	x	✓	✓
Number of Observations	206,209	206,209	206,209	21,286
Number of Individuals	78,456	78,456	78,456	8,285
Log likelihood	-88596.931	-88542.892	-88172.024	-8691.8494

Note. * *significant at* 10%; ** *significant at* 5%; *** *significant at* 1%.

Note. Discrete time complementary log-log model is estimated where the dependent variable is the dummy variable indicating whether exit from unemployment occurred. Number in the first row is the estimation coefficient. To obtain the hazard rate, one has to calculate $[exp(\beta)-1]$.

Note. Models 1, 2, and 3 use UK-born white population as comparison group and non UK born white immigrants is used in the last column. YSM takes value of zero for natives.

Table 2.13: The effect of Terrorist Attacks on Duration of Unemployment in Britain.Different Intervention Dates

	Muslim*September 11	First Muslim*September 11	Second Muslim*September 11
September 11, 2001	-.2030081 ***	-.3139925 ***	-.0484576
	(.0775382)	(.1003498)	(.1259921)
October - December, 2000	-.2026617***	-.3048271***	-.057828
	(.0759776)	(.0968533)	(.126162)
October - December, 1999	-.1425269*	-.2120473**	-.0462278
	(.0765982)	(.0961367)	(.1306056)
October - December, 1998	-.2448735***	-.3107147***	-.1430022
	(.0783297)	(.0963748)	(.1372451)
October - December, 1997	-.1067229	-.1172978	-.1042398
	(.0856758)	(.1030563)	(.1544326)

Note. * *significant at* 10%; ** *significant at* 5%; *** *significant at* 1%.
Note. Discrete time complementary log-log model is estimated where the dependent variable is the dummy variable indicating whether exit from unemployment occurred. Number in the first row is the estimation coefficient. To obtain the hazard rate, one has to calculate $[exp(\beta)-1]$.
Note. Each regression uses UK-born white population as comparison group.

Table 2.14: The effect of Terrorist Attacks on Duration of Unemployment in Britain. Different Comparison Groups

	UK-born White	Non UK-born White	Black	East Europe	Asian
September 11*Muslim	-.1764444**	-.0516797	-.006018	-.0755059	.1758489
	(.0776861)	(.0900646)	(.1002048)	(.1002048)	(.1329907)
(Original Sample)					
September 11*Muslim	-.2622632***	-.1180014	-.057006	-.1155211	.0494352
	(.0775382)	(.1076783)	(.1304091)	(.1557092)	(.1547747)
(First Generation Only)					

Note. * *significant at* 10%; ** *significant at* 5%; *** *significant at* 1%.
Note. Discrete time complementary log-log model is estimated where the dependent variable is the dummy variable indicating whether exit from unemployment occurred. Number in the first row is the estimation coefficient. To obtain the hazard rate, one has to calculate $[exp(\beta)-1]$.

Table 2.15: The effect of Terrorist Attacks on Duration of Unemployment in Britain. Unobserved Heterogeneity with Gamma Frailty. New Sample

	(1)	(2)
Age	-0.0026823 ***	-0.007191 ***
	(0.0005026	(0.0005255
Sex	-0.5839725 ***	-0.5952352 ***
	(0.0166954	(0.0161662
Age Left Education	0.082311 ***	0.0677471 ***
	(0.0033299)	(0.0030347)
Number of dependent children at home	0.055047 ***	0.0566731 ***
	(0.005733)	(0.005725)
Years Since Migration	-0.0089696 ***	-0.0156746 ***
	(0.0027913)	(0.004606)
Annual Unemployment Rate	0.1438934 ***	0.1265306 ***
	(0.0217217)	(0.0212877)
September 11	0.284992 ***	0.2755368 ***
	(0.0612577)	(0.0601171)
Muslim	-0.2703119	
	(0.0770582)	
Muslim*September 11	-0.1951618 **	
	(0.0863407)	
First Generation Muslim		0.1350635
		(0.1437328)
Second Generation Muslim		-0.2388676 **
		(0.1037732)
First Generation Muslim*September 11		-0.3226356 ***
		(0.1126749)
Second Generation Muslim*September 11		0.0033765
		(0.1426035)
Controlled For		
Year	✓	✓
Quarter	✓	✓
Sector Employed	✓	✓
Method of Applying jobs	✓	✓
Residence Region	✓	✓
Number of Observations	201,395	201,395
Number of Individuals	76,625	76,625
Log likelihood	-85481.308	-90631.357
LR test of Gamma var=0	χ^2=55.8224***	χ^2=109.935***

Note. * *significant at* 10%; ** *significant at* 5%; *** *significant at* 1%.

Note. Discrete time complementary log-log model is estimated where the dependent variable is the dummy variable indicating whether exit from unemployment occurred. Number in the first row is the estimation coefficient. To obtain the hazard rate, one has to calculate $[exp(\beta) - 1]$.

Note. Models 1, 2, and 3 use UK-born white population as comparison group and non UK born white immigrants is used in the last column. YSM takes value of zero for natives.

Table 2.16: Descriptive Statistics for Different Groups

Variable	UK-born White Pop.	Immg. from Muslim Count.	Indian Immg.	Other Immg.
%Gender	.57	.67	.53	.51
	(.495)	*(.469)*	*(.499)*	*(.500)*
Age	35.08	31.58	35.46	36.11
	(13.051)	*(11.396)*	*(11.835)*	*(11.785)*
Age Left Education	16.71	17.63	18.86	18.53
	(2.110)	*(2.994)*	*(3.324)*	*(3.609)*
Ysm	-	16.34	17.14	17.77
	(-)	*(15.183)*	*(16.786)*	*(15.142)*
No. of Dependents	.74	1.46	.86	.63
	(1.079)	*(1.505)*	*(1.110)*	*(.992)*
Duration of Unemp.	1.62	1.71	1.59	1.51
	(1.322)	*1.369)*	*(1.250)*	*(1.196)*

The number in the first row is the mean of corresponding variable and the number in the second row in parenthesis is the standard deviation.

Note: Age refers to the average age that the respondents are present in the survey.

Note: Age left Education refers to the age left education that is reported by the individuals.

Note: Duration of Unemployment refers to the duration of an individual spend unemployed, measured in years.

Note. Females are denoted by 0 and males are denoted by 1.

Note. YSM refers to years since migration and takes value of zero for natives.

Note: No. of Dependants refers to the number of children under the age of 16 in the household.

Chapter 3

Intergenerational Religious Mobility: Evidence from Germany

Metin Nebiler

Abstract

This paper addresses issues related to religious identity which have been the subject of extensive debate in recent years. Theoretical literature in economics focuses on parents who are utility maximizing agents with access to socialization of their children and have specific preferences over ethnic and religious traits they wish to transmit to their children. In the context of this wider theoretical literature, the first part of the empirical analysis answers the question about the extent in which religious identity is transmitted from one generation to the next by using longitudinal data from Germany. In addition, the empirical analysis investigates how socio-economic characteristics influence the transmission of religious traits across generations. Furthermore, the paper explores whether the migration background plays a role in the transmission process. Results show that parents play an important role in the development of the religious identity of their children in Germany. The transmission or religious traits across generations varies according to the socio-economic characteristics of both parents and children. Finally, the empirical research shows that the migration background is an important factor in the transmission process. Results reveal that vertical transmission is higher among immigrant families by using data from Indonesia and Turkey.

3.1 Introduction

Identity is a term that is used by social scientists to understand individual- and group-behavior. Human-beings can be categorized according to many identities such as, race, religion, class, job, nationality, ethnicity.The transmission of characteristic identities of groups is important for the survival of those groups. Some identities are emphasized more than others in particular times. What we have experienced in recent years is that the religious identity has gained more importance in political and cultural debates (Sen, 2006). This research paper studies the transmission of religious identity from one generation to the next. In particular,the persistence of religious traits across generations is investigated in comparison with other traits. In addition, the empirical analysis investigates how socio-economic characteristics influence the transmission of religious traits across generations. Furthermore, the paper explores whether the migration background plays a role in the transmission process.

Religious identity is receiving an increasing interest among economists. An economic framework on intergenerational transmission was first introduced by Cavalli-Sforza and Feldman (1981) and Boyd and Richerson (1985). Later, Bisin and Verdier (2000) presented an economic framework where parents have access to the socialization of their children. Their major finding was that the transmission rate among generations can differ according to the preferences of parents to exert pressure on their children. Several empirical studies in the economics literature investigated the transmission of different traits across generations (ethnic capital by Borjas (1995), national identity by Dustmann and Casey (2010), risk and discounting preferences by Arrondel (2009), generalized trust by Uslaner (2008), gender-role attitudes by Farre and Vella (2007) as well as Fernandez, Fogli and Olivetti (2004), individual responsibility by Baron, Cobb-Clark, and Erkal (2008)). Religion has been less studied compared to other ethnic and cultural traits. Among others, Sherkat and Wilson (1995) document that vertical transmission from parents to children during childhood positively influences the religious behavior of children later in their life. Cavalli-Sforza et al. (1982) show a strong association between two generations for several traits including religion among Stanford students.

Although secularization theorists predicted a religions decline as a result of the modernization of societies, distinct religious groups still exist in the world. The suc-

cessful transmission of religious traits across generations is necessary for the survival of religious identity. Two different transmission mechanisms are described in the literature; vertical transmission, from parents to children, and horizontal transmission, from peers to individuals. The transmission mechanisms can differ according to the trait to be passed on to the next generation. According to scholars, identity traits are developed at early stages of life. The focus of the paper is the first transmission mechanism; vertical transmission, from parents to children.

Since culture and religion are transmitted from one generation to the next as Boyd and Richerson (1985) argue, transmission from parents to children is the main part of this process. Scholars argue that parents are altruistic and consider that children will be better off by inheriting the family traits. They therefore want to pass on their traits to the next generation (Guiso et al., 2006). On the other hand, Ter Bogt et al. (2009) discuss that children do not receive everything from older generations but decide themselves how much to inherit.

Following up on the theoretical literature, this paper investigates the mechanism behind transmission of religious traits empirically. The first part of the empirical analysis answers the question about the extent to which religion and religiosity are transmitted from one generation to the next by using longitudinal data from Germany. By using several religious groups in the sample, I check whether the differences in transmission rates are religion specific. The second part explores the role of socio-economic characteristics in the transmission of religious traits within religion. The persistence of religious traits can differ significantly in terms of the socio-economic characteristics of transmitters. Although several socio-economic factors are associated with higher religious practice, their role in religious transmission is still unknown. Thus, the second part investigates whether education, the child's gender, neighborhood characteristics and homogeneous marriages influence the persistence of religious traits across generations. The last part focuses on the role of migration background in the transmission of religious values across generations. Theoretical literature focuses on the impact of migration background suggesting that immigrants transmit religious traits more persistently compared to natives. In order to identify the effect of being an immigrant, one needs to observe the transmission pattern of one ethnic group in host and home countries. The goal is to show how ethnic groups

transmit religious traits at home, as natives, and in the host country, as immigrants. It is important to note that this type of analysis can identify the overall impact of migration background instead of decomposing all factors in the process such as role of ethnic enclaves, etc.

Results from the empirical analysis show that parents play an important role in the development of religious identity of their children in Germany. I find very strong and significant persistence of religious identity. It is also documented that not only the religious identity but also the religiosity is strongly transmitted by parents to their offspring. It is showed that the transmission is strongest among Muslim families. This suggests that although Muslim identity is associated with discrimination and disadvantage in the integration process (Sachs 1998, Rooth 2010, Adida et al. 2010, Ahmed et al. 2008), Muslims still preserve their religious identity and Muslim parents play a very important role in this.

The high transmission of religious traits raises questions about the factors behind it. Empirical results reveal that socio-economic characteristics of families influence the persistence of religious traits across generations. In addition, the role of each parent in the socialization of the child changes according to socio-economic characteristics. The highest variation is observed among Muslim families. Moreover, in line with the theoretical framework, it is checked whether immigrants exert more pressure on their children to preserve their identity. To answer this important question, we exploit household data from two Muslim countries, Turkey and Indonesia, to observe transmission in a Muslim country. We show that the transmission of religious identity is really high in Turkey and Indonesia, however, the religiosity is transmitted less persistently compared to Muslim immigrants in Europe. This suggests that immigrant Muslims exert more pressure on their children to inherit their traits since parents want to protect their identity across generations. I also check whether it is true for other religious groups and it is showed that immigrants transmit their religious traits more strongly compared to native counterparts.

This paper contributes to existing research in several ways. First, it is among the few attempts to provide empirical evidence to confirm the predictions of the theoretical literature in economics. The empirical results reveal that the persistence of religious traits is very strong. Moreover, it is showed that immigrants are insisting

more on passing on their religious traits compared to natives. Second, by exploiting the longitudinal data from Germany which contain repeated information on individuals' characteristics, permanent lifetime outcomes are measured which reduce the measurement error and report more accurate results. Finally, the transmission of several traits allow us to reveal the strength of persistence of religious traits.

This paper is organized as follows. In section 3.2, I discuss the theoretical framework in economics while section 3.3 describes the empirical strategy. Section 3.4 presents the data and the religious measures. The results on the intergenerational transmission of religious identity are reported in section 3.5. Finally, I discuss my results and conclude.

3.2 Theoretical Framework

Several scholars have studied the transmission of ethnic and religious traits across generations. As mentioned previously, religious preferences are developed at early stages in life during which the family plays a significant role. Most studies focus therefore on the impact of parents on the transmission process (Bisin and Verdier 2000, Boyd-Richerson 1985, Sforza and Feldman 1981). This paper follows the theoretical model of Bisin and Verdier (2000) to provide empirical evidence on the transmission of religious traits. An important assumption in the economics literature is that parents have access to the socialization of their children and can therefore influence the preference development of their children. This can take the form of choosing the neighborhood, school or even friends, of spending time with the children, arranging marriages or attending cultural events (Bisin and Verdier 2000). Parents have all the information about the different types of traits. It is generally assumed that parents are altruistic and consider that children will get more utility by inheriting the trait of their parents. Bisin and Veridier (2001) define this assumption as the "imperfect empathy" where parents are myopic or altruistic while Dustmann (2010) assumes that children will get disutility by deviating from the trait of the ethnic group. Typically, it is assumed that the transmission rate is a function of the socialization efforts exerted by parents. If not socialized to a specific trait by parents, children adopt the trait of a randomly matched individual from society. Standard models in economics explain

the optimal socialization efforts along two factors. First, the socialization efforts of parents to transmit a specific trait vary according to the value attached to that trait. Assuming everything else constant, if "trait i" is valued more than "trait j", pressure exerted by parents on their children for "trait i" will be higher than "trait j", hence the transmission rate is expected to increase. For instance, a family can exert more pressure on their children to inherit their own religious traits than other religious traits. The difference between the transmission of religious traits in that specific case can be explained by the higher value attached to the own religious traits compared to alternatives.

Alternatively, the persistence of cultural traits can be different for two groups depending on the migration background (in other words,the relative size of the group in the society). Several scholars argue that in addition to direct socialization in the family, children can develop their cultural traits through society if the traits are substitutes for each other. It is assumed that the probability of obtaining a trait from society is a function of the size of the sub-group which possesses that specific trait in society. Hence a family which possesses the majority trait in society exerts less pressure on their children since vertical and horizontal transmission are substitutes. For instance, consider a society where people have either "trait i" or "trait j". If the size of the group possessing "trait i" is higher $S_i > S_j$, the probability that an individual meeting peers with "trait i" is higher, thus it is more likely to obtain "trait i". Accordingly, parents from majority group ("trait i") will be less likely to exert pressure on their children since children can learn from society. On the other hand, parents from minority group (with "trait j") exert more pressure on their children since it is less likely that their children obtain "trait j" from society.

Bisin and Verdier (2000) incorporated marriage into this model where socialization efforts are more efficient for homogeneous families. Typically, this affects the marriage decision of individuals. According to their findings, in equilibrium, immigrant groups are more likely to engage in homogeneous marriages, which increases then the transmission of cultural traits to the next generation. Several other scholars incorporated additional factors into the model i.e. geographical distance from home country (Cavalli Sforza et al., 1986) and fertility (Becker and Lewis, 1973).

3.3 Empirical Strategy

The association between parents' and children's outcomes has been widely studied by economists and sociologists. Studies on intergenerational mobility have mostly focused on examining the economic outcomes such as income, education, occupational class, social class etc. All studies use the intergenerational elasticity of the interested outcome. Consider the following empirical model of intergenerational mobility

$$Y_i^c = \alpha + \beta Y_i^p + \epsilon_i^c \tag{3.1}$$

where Y_i^c is the child's permanent status, Y_i^p is the permanent status of the parents, and ϵ_i^c is a white noise error term. Thus, β indicates how child's outcome is associated with his/her parents' outcome while intergenerational mobility, $1-\beta$, measures how child's outcome is independent of his/her parents'. Thus, trait development of children in equation 3.1 depends on parental outcome of that specific trait.

An important difficulty is to observe the permanent status of individuals. Measurement error on child's long-run status will be captured by the error term ϵ^c. Hence, as suggested by Zimmermann (1992), the main problem arises from the measurement of parents' long-run status. Typically, instead of measuring the permanent status, an econometrician observes the current status:

$$Y_{it}^p = Y_i^p + \theta X_{it} + w_{it} \tag{3.2}$$

where Y_{it}^p is the current status of parents i at time t, Y_i^p is the permanent status of parents, X_{it} is set of characteristics that causes current status to differ from the permanent status at time t, and w_{it} is a transitory shock. Using short-term status as a proxy for the permanent status in equation 3.1 causes the intergenerational coefficient β to be biased downward (Zimmermann (1992), Solon (1992)). Assuming that $E(w_{it}) = 0$ and $V(w_{it}) = \sigma_w^2$ and w is uncorrelated with Y_i^p and ϵ_i^c, one gets the classical attenuation bias where the probability limit is given by

$$plim\beta_{OLS} = \beta\left(\frac{\sigma_{Y^p}^2}{\sigma_{Y^p}^2 + \sigma_w^2}\right) \tag{3.3}$$

where $\sigma_{Y^p}^2$ is the variance of Y^p and σ_w^2 is the variance of error term. If not accounted for, measurement error can result with misleading estimates, since $(\sigma_{Y^p}^2/\sigma_{Y^p}^2 + \sigma_w^2)$

is between zero and one, the intergenerational coefficient β in equation 3.1 is biased downward. The advantage of GSOEP is to observe individuals for a long time period. This study follows thus the method described by Zimmermann (1992) in his seminal work, using averaged individual outcomes, which reduces the measurement error and diminishes the bias of the ordinary least squares estimate β. Averaging religiosity over T periods such that

$$\overline{Y_T} = \sum \frac{Y_{it}}{T} \tag{3.4}$$

and assuming the errors to be serially uncorrelated would reduce the bias such that the probability limit of β is given as follows:

$$plim\beta_{avg} = \beta \frac{\sigma_Y^2}{\sigma_Y^2 + \frac{\sigma_\epsilon^2}{T}} \tag{3.5}$$

Averaging the father's status reduces the bias as a function of the averaging periods T[1].

In the context of this paper, equation 3.1 is useful to understand the transmission of religious identity from one generation to the next. Since the intergenerational elasticity coefficient β only reports the association between generations, it is difficult to determine the strength of this association. Hence the same method is used for some other traits such as trust, years of education, height and weight. I use the coefficients for other traits to compare the persistence of different traits among generations.

The impact of migration background on intergenerational transmission is identified by comparing two groups from the same community in their host and home countries. Difference between two intergenerational transmission coefficients, (β_I - β_N)[2], captures the impact of migration on intergenerational mobility. This is true under the assumption that the migrated group in the host country has similar characteristics with the group in the home country before migration. The results can therefore also be associated with the socio-economic characteristics of those two groups.

[1] However, this derivation assumes that the ϵ_{it} is white noise.

[2] Two different samples with the same ethnic trait are used to compare the persistence of that trait in the home country, as natives and in the host country, as immigrants. β_I is the intergenerational coefficient in equation 3.1 measured with the immigrant sample while β_N refers to intergenerational coefficient in the same equation measured with the native sample

Although such an analysis cannot identify the specific impact of factors influencing intergenerational transmission, the results will report the general impact of migration background on intergenerational mobility.

This study uses the parents' outcomes as the independent variable instead of mothers' or fathers' outcomes individually. In particular, the outcomes of parents are created by averaging the specific outcome of both mother and father to have one value for the parents' outcome. We assume that the religious traits and also other traits examined in this analysis are a combination of both parents and not only one parent. Averaging the parents' outcomes can also reduce the measurement error on the estimated outcome and provide better estimates. Later, it is also checked whether mothers and fathers have different impacts on the transmission of religious traits separately.

Similar to the above discussion,the measurement error can be an important source of bias for other traits. It is more likely that height, weight, and years of education are measured accurately while trust is not. In this case,the measurement error would cause the intergenerational elasticity coefficient β for trust to be biased downward. However, Fehr et al. (2003) showed that answers to trust questions in surveys are good predictors of strategies in a trust game[3]. This is important in order to confirm that the measurement error on trust behavior of respondents is small.

3.4 Data

The main data requirements for studying intergenerational dynamics is to observe a long-run permanent measure for both children and parents. Panel data surveys can be used for this kind of studies. The advantage of panel data is that they have repeated observations, which allow to measure the long-run socio-economic status. The empirical analysis exploits the German Socio-Economic panel (GSOEP), the World Values Survey (WVS) and the Indonesian Family Life Survey (IFLS), all three of which are household based panel surveys.

GSOEP is carried out by the German Institute for Economic Research (DIW) so as to collect data on socio-economic characteristics in Germany. It is an annual longi-

[3]Fehr et al. (2003) conduct a field experiment with 429 respondents where he uses the survey questions asked in the GSOEP. Those respondents then play a trust game to measure the trust behavior of individuals.

tudinal survey at the household and individual level. The first wave in 1984 included individuals in private households in West Germany. The target population was extended to individuals in East Germany in 1990. The West Germany sample comprised around 4,500 households in 1984 while the East Germany sample surveyed 2,200 households in 1990. Both samples are combined to construct a representative sample for Germany. This study uses 28 waves from GSOEP in the period of 1984 - 2011.

IFLS is a longitudinal survey carried out to collect data on the socio-economic characteristics of individuals in Indonesia. The survey is at the household and individual level and includes 30,000 individuals. IFLS is not an annual survey. There are four waves available which were conducted in 1993, 1997, 2000, 2007 by the Research and Development Corporation (RAND) in collaboration with several organizations. Out of the four waves, the latest one is used since questions regarding religiosity are present only in this wave.

Religious Measures

Questions about the respondents' religion are asked in the survey. Most surveys group religions into four or five sub-groups and merge under an 'Other Religions' category the remaining religions. In the GSOEP however, religious groups are categorized separately[4].

Individuals are classified into different religious groups according to their response to the question about their religion. In the case of more than one reported religion, individuals are assigned into a specific religious group if they reported that they are more affiliated with that specific religion than the other ones. If they reported equal times for two different religious groups I assign them to the religion that they reported last. The same is also valid for the parents' religion. I classify as "parents' religion" both parents' religion in the case of a homogeneous marriage; the father's religion if the religion of the two parents is different; the mother's religion is no information is available about the father.

It is rare to find longitudinal data that include information about the respondents'

[4] In the GSOEP, six religious groups are Catholics, Protestants, Other Christians, Muslims, Other Religions, and No Religion.

and their parents' religion, attendance to religious services, basic characteristic variables and identification of parents and children. In the GSOEP, two questions are asked in order to identify the religious attributes of the respondents'. The first one is the "Importance of religion in one's life"[5]. The second question regarding the religiosity is "Attendance to church or other religious services"[6]. For the religious attributes of the respondents I use the question "Attendance to religious services" as a measure of religiosity. Most studies depend on verbal answers concerning religiosity. This is a problem in cases where the respondents are interviewed together with other household members. This study uses a behavioral measure that can be observed, thus, it is more difficult for household members to influence the answers of the other household members, which reduces the measurement error.

A numerical value is assigned to each answer to the question of attendance to religious services so as to make it numerically measurable. Individuals who report that they attend religious services even though they are not affiliated with a religion are kept in the analysis. The numerical values that are assigned to religiosity are as follows; 52 for weekly attendance, 12 for monthly attendance, 1 for yearly attendance, and 0 for never attendance. Attendance to religious services is thus a variable between 0 to 52 and defined as yearly attendance to religious services. Thus, as it is the case in intergenerational income mobility, religiosity can be used to measure the intergenerational association between children and their parents. Later, lifetime measure of religiosity is constructed by averaging the values of attendance to religious services for the entire time period that the respondents participate in the survey. The parents' religiosity is constructed by averaging the mother's and father's religiosity.

Moreover, the averaging is done for every variable that is used in the empirical analysis. The trust behavior of individuals is reported in the GSOEP[7]. The lifetime trust is a variable that varies between one and four where one indicates high trust and four is low trust. The parents' lifetime trust is constructed by averaging the lifetime trust behavior of mother and father. The same procedure is also exploited for weight.

A different procedure is followed for years of education and height where lifetime

[5] Respondent may answer the question by choosing one of the following options; Very Unimportant, Less Important, Important, and Very Unimportant.

[6] Respondents can answer the question by; Once a Week or More, Once a Month, Once a Year, and Never.

[7] The GSOEP reports four possible answers; Totally Agree, Slightly Agree, Disagree Slightly, and Totally Disagree.

educational attainment and height are created by extracting the highest reported value. Similar to other traits, parents' height and educational attainment are defined as the average of father and mother. Finally, the panel form of the data is eliminated in order to create a cross-section data where all variables are lifetime measures of the corresponding child-parent pair.

An important feature of the data is conducting in-person interviews to minimize measurement error.The respondents are visited in their address to run oral interviews[8]. Interviews are conducted separately to avoid influence by other household members while answering the survey questions. This is important since the correlation among parents and children can be biased upward otherwise.

Sample Selection

Before starting the analysis, it is checked whether the sample that is used is a representative sample of GSOEP. In order to do that, the characteristics of the individuals are checked to identify if there is a systematic difference between the selected and the excluded sample, which can bias the results. The reason to check this is that the selected sample must represent the population. Otherwise, what the findings can be correct for that particular sample but may not for the German society.

First, the sample selection rule is described for the purpose of the empirical analysis. Since intergenerational transmission dynamics are studied, for each observation one needs to observe both children's and their parents' outcomes. The datasets that are used were not originally conducted for intergenerational studies. However, since the number of respondents is large and parents can be identified, they can be used for that purpose. The data are organised into parent-child pairs. The sample is restricted to the parent-child pairs whose characteristics can be identified. In that sense, although I start with a high number of observations, after the selection 8,309 child-parent observations are left for Germany. The most important and restrictive criterion is the information on the identifiers for the parents. Observations are excluded if the identification for parents, religion, attendance, parents' attendance, and parents' religion is not possible.

Table 3.1 reports the characteristics of the selected sample and the excluded sam-

[8]One quarter of interviews are conducted through computer.

ple. Almost all characteristics are similar except age. The difference in age is natural since older respondents are less likely to have a father/mother who participated in the surveys. Apart from age, other characteristics are similar which suggests that the sample is sufficiently representative for the GSOEP.

Table 3.2 shows the distribution of religious groups that are used in the empirical analysis in both countries. In both datasets four religious groups are selected for the empirical analysis; Catholics, Protestants, Muslims, and No Religion[9].

3.4.1 Descriptive Stats

Table 3.3 reports the sample descriptive characteristics for children in Germany where religions are distinguished. The table shows that Catholics are more religious than Protestants. Looking at the table, individuals who are affiliated with Islam religion attend religious services (9.57) more than other religious groups. This suggests that when not controlled for other factors, Muslims attend religious services 35 percent and 177 percent more than Catholics and Protestants in Germany.

Sample characteristics show that all individuals who are affiliated with Islam have a migration background. Muslim existence in Europe is a recent phenomenon which started with the immigration of guest-workers from Muslim countries (mainly from Turkey and ex-Yugoslavian countries). The percentage of Catholics with migration background is around 23 percent(mainly from Italy and Poland) while it is only around 8 percent for Protestants in Germany. The immigration background can be important since several studies show that immigrants are more religious and attend religious services more than natives (Crockett and Voas 2006).

The average years of education for Muslims (10.5 years) is the lowest in Germany. The educational attainment is much higher for Catholics (12 years) and Protestants (12.4 years). This confirms the well-documented fact that immigrant groups from Muslim countries are on average less educated than their counterparts in Western European societies (Dustmann et al. 2010).

The average age among religious groups is very similar in Germany (around 23). Furthermore, trust behavior does not differ across religious groups. This may suggest

[9]The other available religious groups are the Other Christians and Other Religions in the GSOEP. These are excluded from the sample since the identification of individuals' religion can be identified clearly.

that trust behavior is not religion- specific.

Table 3.3 also presents information on height and weight in Germany. Muslims are on average shorter than other religious groups, while weight is very similar among all groups. These traits differ from others in terms of transmission dynamics. Genetic factors play a more influential role compared to cultural aspects. Thus the influence of parents on the physical attributes of their children is very limited. In that respect, weight is less dependent on genetic aspects compared to height.

3.5 Estimation Results

This section reports the results for the intergenerational transmission of religious identity and religiosity. Transition matricies and intergenerational transmission coefficients are presented for several traits across religious groups.

3.5.1 The Transmission of Religious Identity

The empirical analysis starts by studying the transition matrix, which is an alternative measure of intergenerational mobility. It is an nXn matrix where "n" represents the religion of parents and children. The element P_{ij} refers to the probability of a child to be affiliated with religion j given that his/her father is affiliated with religion i. The degree of persistence of "religion i" is shown by the diagonal elements P_{ii}. An identity matrix would imply that every child is affiliated with the parents' religion, while complete mobility would imply that all elements are equal to $1/n$. The advantage of transition matrices is that it shows the mobility direction of children moving between religions.

Tables 3.4 reports the transition probabilities of religious identity across generations in Germany. The diagonal elements are high in Germany for all religious groups. The most persistent religion is Islam; given that parent's religion is Islam, 91 percent of their children are affiliated with Islam in Germany. Similarly, 84 percent of children of Catholic parents have the same religious affiliation with their parents. Likewise, inter-religious transmission for Muslims is very low while it is higher for Catholics and the highest among Protestant families. Those who choose a different religion from their parents' religion, are more likely to choose no religious affiliation. An im-

portant outcome of the table is that it reports strong persistence of religious identity among all religious groups in Germany.

As a next step, the intergenerational transmission of religious identity is investigated by using a regression approach. The advantage of equation 3.1 is that it summarizes the extent of mobility in a single number, through an average coefficient. Indicator variables are created for each religion to estimate equation 3.1. The results are reported in Table 3.5. Overall, the estimates show some differences; similar to transition probabilities, the coefficient β is the highest among Muslim families. Persistence of religious identity is significantly stronger in Catholic families than Protestant families. The high transmission of religious identity suggests that the family background is very important when children decide their religious affiliation. On the other hand, these results can also be explained by the fact that children describe themselves being affiliated with their parents' religion so to please their parents and not because they actually believe or practice it.

3.5.2 The Transmission of Religiosity

Religiosity can be interpreted as the intensity of religious identity. In this section, attendance at religious services is used as a proxy for religiosity. It is assumed that individuals are more religious if they attend religious services more. Here, the sample is restricted to those who successively inherited their religion from their parents. Since intergenerational coefficient β is an average coefficient, it is difficult to interpret the strength of transmission across generations. Other traits are included in the analysis to determine the relative persistence of religious transmission. It is important to note that some of these traits can be influenced by family, similar to religiosity (education and trust) while the impact of parents can be very limited for others (height and weight).

Table 3.6 presents the estimation results from equation 3.1. Looking at the table, all coefficients are significant and positive. The coefficient of religiosity in Germany is as strong as height and stronger than other traits such as trust, weight, and education. Considering that religiosity persistence is as strong as transmission of height in which genetic factors play an important role, this finding is very interesting. It confirms the discussion that it is not only the religion pf the parents that children

affiliate themselves with, but that religiosity is also transmitted persistently across generations. There are several ways that families can affect the traits acquired by their children. For example, parents can influence the religious attributes of their own children through attendance at religious services, childhood religious teachings, school and neighborhood choice etc. (Bisin and Verdier 2000).

The influence of the family background on the educational attainment of children is very strong in Germany. The main reason for this can be the institutional aspects of the schooling system. Early track system adopted in Germany requires decisions of educational investment to be taken when the child is 10 years old, while this decision is taken at the age of 17-18 in other countries. As a result, it is more likely that parental influence is much higher in Germany, which leads to lower intergenerational mobility in educational outcomes.

The transmission of trust is low compared to other traits. It is possible that parents do not exert pressure on the development of trust behavior of their children. Low persistence observed in the data can also imply that it is not the vertical transmission that determines the trust behavior but the horizontal transmission through individual relations/experiences with peers. Alternatively, the low association between the parents and children can be a result of measurement error as discussed in the previous section. Moreover, the coefficient of height and weight is positive and significant. Unlike the other traits, genetic factors play a more influential role in the intergenerational association of height and weight compared to cultural aspects. The coefficient on weight is lower than height, which confirms that next to genes other factors may also influence weight i.e. diets, sports activities, etc.

Table 3.7 reports the estimation results of intergenerational elasticity for different religious groups. The intergenerational mobility equation includes gender, birth cohort, age, immigrant, foreign-born, educational attainment of parents, region of residence and country of origin as covariates. Since the aim of this paper is not to determine the effect of covariates in religious behavior, they are not reported. Looking at the table, coefficient on religiosity for all religious groups is significant and large compared to other traits. This indicates that family influence on the development of religious traits is very large across all religious groups. This confirms the findings of Iannoccone (1984) that childhood religious instructions and parents' mass atten-

dance has a positive impact on children's attendance of religious services for all religious groups. Considering the high transmission of religious identity among Muslim families (Table 3.5) and the high coefficient on religiosity in Germany indicates that family influence is stronger compared to other religious groups. Scholars argue that Muslim families exert more pressure on their children to protect their identity compared to other religious groups (Bisin et al 2008). High persistence of religious traits among Muslim families can be religion-specific. Muslims are more likely to protect their religious traditions compared to other religious groups. It is also important to note that Muslims in Germany are also immigrants. Many theoretical and empirical studies argue that immigrants transmit religious traits more persistently than natives (Crockett and Voas 2006, Van Tubergen 2006, Bisin and Verdier 2000). For instance, results can be associated with being an immigrant Muslim instead of being Muslim only. The empirical part tries to disentangle the impact of migration background on intergenerational transmission in the next section.

The transmission of trust is similar across all religious groups. This further confirms the previous discussion, namely that horizontal transmission (peer- to-peer transmission) can be the main component of the trust behavior of individuals. Furthermore, comparing the transmission of religious traits to that of trust behavior within each religious group suggests that the families prioritize religious traits more than generalized trust.

The influence of parents on children's educational attainment shows is similar across religious groups in Germany. One exception to this observation is the high educational mobility of Muslim families across generations. The mechanism behind high mobility can be the result of the low education of first-generation Muslim immigrants. By attending schools in Germany, their children are already performing much better than their parents, which lowers the coefficient β.

The similar persistence of height for all religious groups confirms the previous discussion, namely that the transmission process does not differ among religious groups, since, contrary to cultural traits, it is mainly affected by genetic characteristics. The coefficient on weight is lower for Muslims compared to other religions. This can be explained by the changing diets of immigrant groups; the association thus between parents and children is not as strong.

3.5.3 Role of Socio-economic Characteristics in Intergenerational Mobility

This section investigates whether socio-economic characteristics influence the transmission of religious traits across generations. Although several socio-economic factors are associated with higher religious practice, their role in religious transmission is still unknown. It is possible that child and family characteristics can change the preferences of parents to exert pressure and of children to adopt the parents' traits. The impact of those characteristics might also be different across religious groups. Thus, several regression equations are estimated to explore the influence of socio-economic characteristics on the persistence of religious traits within religion.

Roles in Family

Until now, the empirical analysis has used the parents' outcome to estimate the persistence of religious traits across generations. This section investigates separately the role of mothers and fathers in the development of the religious identify of children for different religious groups. Table 3.8 reports the intergenerational transmission coefficient of religion and religiosity. The results are positive and significant suggesting that both fathers and mothers are important determinants in the development of the religious identify of children. Mothers are more important when passing on the religion to their children for Catholic, Protestant, and No religion. Muslim families depicts a different picture where fathers are more important for the persistence of religion. In other words, when choosing the religious affiliation Muslim children follow their fathers as a role model, while it is the mother in other groups.

The second box reports the results for transmission of religiosity. Similar to religion, both parents have positive and significant impact on the religious practice of children. Parents who are more religious, are more likely to have religious children in the family. Unlike religion, the impact of parents do not differ, i.e. both parents have similar impact at the transmission process. An important note is that while all coefficients are similar across other religious groups, the religious practice of children with no religious affiliation has a lower coefficient. In line with the previous discussion, combined influence of parents' religiosity is stronger among Muslim families compared to other religious groups.

Gender

The transmission of religious traits can be different for daughters and sons. It is possible that mothers are more influential in the religious trait development of their daughters, while fathers are better role models for their sons. The first box in table 3.9 shows that mothers are the main channel of transmission of religion regardless of gender of the child in Catholic, Protestant, and No religion families. The intergenerational coefficient β does not show significant differences across gender in those families as well. In Muslim families, it is the case for sons that they develop religious traits similar to mothers while daughters' religiosity is mainly affected by fathers.

Intergenerational coefficient for religiosity is reported in the second box of Table 3.9. Unlike transmission of religion, the influence of mothers and fathers can be different for sons and daughters. Results reveal that daughters' religiosity is influenced by mothers and influence of fathers on sons' religiosity is higher although the differences are not significant in most cases. While the coefficients of parents' religiosity are similar in Catholic and Protestant families, the effect of mothers and fathers on their children is more clear in Muslim families.

Homogeneous Marriages

This section investigates whether homogeneous marriages are more successful in transmitting the religious traits across generations. Homogeneous marriage in this case refers to parents with same religion. The theoretical framework developed by Bisin and Verdier (2000) assumes that socialization efforts are more efficient in families where the parents share similar traits. Assuming that both parents are altruistic, persistence of religious traits can be higher among families with homogeneous marriages, since both parents want to pass on the same religious trait. In heterogamous marriages, it can be less persistent since both parents teach different religious traits to their children. Table 3.10 reports the intergenerational coefficient of religiosity for homogeneous and heterogamous marriages. Homogeneous marriages are more efficient when combining the effects of both parents, which confirms the assumption in the theoretical literature i.e.that transmission of religious traits is more successful across generations in homogeneous families. While the influence of both parents is equally high in Catholic homogeneous families, it differs in other religions. Similar to

previous results, mothers are more important in the religiosity development of their children in heterogamous families, while the father's influence is very small and not significant in Protestant families. This can be explained by the fact that if one of the parents is not interested in transmitting his/her religious trait to children, the other parent can be more influential in the religious trait development of the child in heterogamous marriages.

Education

This section investigates the relationship between the education level of children and transmission of religious traits. Although education is shown to be negatively associated with religious practices, the impact on transmission is still unknown. The education level of the child can negatively influence the transmission of religious traits since more educated children are more likely to develop their own religious traits and the influence of parents' can be lower. Children are grouped into two categories according to their education level. For each religious group, individuals below the median person is assumed to be low-educated, while individuals with a higher education level than the median are assumed to be highly- educated individuals[10]. Table 3.11 reports the results for the influence of education on religious transmission. Looking at the first box, religious identity is independent of the education level of children in Catholic, Protestant, and no religious affiliation i.e. the influence of both parents do not vary according to the education level of the child. Similar to previous results, Muslim children show a different pattern. In their case, mothers play a more important role in low- educated families, while in highly educated families it is the father.

The second box in Table 3.11 reports the results for religiosity transmission. Education has a more clear effect on religiosity transmission. The combined effect of parents is higher in Protestant families with low-educated children, while the effect diminishes significantly for highly educated children. This confirms that educated children are influenced less by their parents. On the other hand, the combined effect is similar in Catholic and Muslim families. Parental influence changes however according to the education level of the child. Fathers are more influential in the trans-

[10]While identifying the low and highly educated people years of education is used. The median person is assumed to be highly educated

mission of religious practices in Catholic families with a low-educated child, while mothers are more influential towards highly- educated children. In Muslim families, it is the other way around.

Characteristics of Residence

The characteristics of the neighborhood can be another important factor in the development of religious traits. Families can find it for instance easier to socialize children in the countryside.The countryside is also more likely to have a more homogeneous population in terms of religious traits. In big cities different traits are more likely to be observed and be accessible. It is also possible that individuals living in cities are more likely to access media, education, etc that are negatively associated with religiosity. Table 3.12 reports the results for the characteristics of the neighborhood in which the child was raised until the age of 16. Similar to previous results, mothers are in general more important in the transmission of religion to children. The transmission of religion does not vary according to the characteristics of neighborhood. The coefficients are similar with a slightly higher combined influence of parents in the countryside. The sole exception are the case of Muslims. While Muslim parents have a similar effect on children's religious affiliation in cities, in the countryside however, it is the Muslim father who has a very influential impact on the transmission of religion.

The second box reports the results for religiosity transmission according to the neighborhood characteristics. The results show that neighborhood characteristics have an influential effect on the transmission of religiosity, as the effect of each parent varies according to the characteristics of neighborhood. For instance, in Protestant families fathers are more important role models in cities, while mothers are more influential in the countryside. The outcome is different for Muslim and Catholic families, which show a more balanced influence by each parent.

3.5.4 Role of Migration Background in Intergenerational Mobility

The empirical analysis until now suggests that Muslim families in Germany transmit not only religious identity but also the religiosity trait more persistently compared to other religious groups. As discussed previously, the high persistence of religious

traits can be driven by several factors i.e.the value attached to religious traits, ethnic enclaves, migration background, homogeneous marriages etc. This section focuses on the impact of being an immigrant on intergenerational transmission of religious traits. Several studies show that immigrant groups still preserve their identity in host countries instead of being assimilated into the mainstream culture (Bisin and Verdier 2000, Dustmann 2010). For instance, affiliation to religious groups can make the integration process easier in the destination countries (Bruce 1996). Moreover, immigrant families in destination countries can exert more pressure on their children, if they want to preserve their identity. This can take the form of attendance at religious services, childhood religious teachings, school and neighborhood choice etc. (Bisin and Verdier 2000). If the results are driven by being an immigrant, then this would contradict the findings of Knafo and Schwartz (2009) who claim that immigrant families are less successful in passing on their characteristics to the next generation compared to natives. On the other hand, it would be in line with the findings of Borjas (1995) who shows strong a persistence of ethnic traits among second and even third generations.

To estimate the impact of migration background, one can compare the intergenerational religious transmission of two groups with the same ethnic background in a host country and their home country. Assuming that the migrated group in the host country has similar characteristics with the group in the home country before migration, the difference between the two intergenerational coefficients, $(\beta_I - \beta_N)$, captures the impact of migration on intergenerational mobility. However, the difference does not only capture the impact of migration but also other factors, which are associated with intergenerational transmission. Migration can influence the socialization preferences of parents. Migrated groups are for instance more likely to engage in homogeneous marriages, live in ethnic neighborhoods and send their children to specific schools in order to influence their identity development. Hence, one has to interpret this difference as a general impact of migration background on intergenerational mobility. It is not the scope of this paper to decompose these factors in the model.

In order to assess whether migrants transmit religious traits more persistently than natives, we exploit data from Turkey and Indonesia. The goal is to show how

Muslim communities transmit religious traits at home, as natives, and in the host country, as immigrants. An ideal approach is to compare Muslims in Germany and Turkish Muslims in Turkey since 63.2% of Muslims in Germany are of Turkish origin (Spiegel, 2010). The empirical analysis uses the World Values Survey from Turkey and the Indonesian Family Life Survey from Indonesia to estimate the persistence of religious traits in Muslim countries.

Evidence from IFLS

A similar analysis of intergenerational transmission in the previous section requires household data where parent and child pairs can be identified. The IFLS is a household data which allows us to estimate the persistence of cultural traits by using equation 3.1. Although there are four waves available which are conducted in 1993, 1997, 2000, 2007, only the last wave in 2007 contains information about the religious denomination of individuals and includes several questions regarding religious attitudes. Religiosity is measured by the question "How many times do you pray each day?". It is a numerical variable between 1 and 81[11]. To focus on the intergenerational transmission among Muslims in a native country, individuals with migration background and not affiliated with Islam are excluded from the survey. An important concern about the IFLS is the cross sectional feature of the data. It does not allow us to employ the averaging method which reduces the measurement error. Estimated results from equation 3.1 can be downward biased if permanent religiosity of individuals deviates from the current status that is measured in the data.

Table 3.13 reports the descriptive characteristics of Muslim communities in Germany and Indonesia. The socio-economic characteristics of the two groups should be sufficiently similar to compare the persistence of religious traits across generations. Children are similar in age and males are slightly more representative, constituting 54% of both samples. The Muslim community in Germany is more educated compared to their Indonesian counterpart. The data also report better educational attainment across generations. Because years of education are not reported in the

[11] In addition, two other questions are included in the analysis: i) How religious are you? - Possible answers to this question vary from 1 to 4 where 1 refers to "very religious" and 4 refers to "not religious". ii) How many times do you pray each day (categorical) - Respondents can choose from three different answers which are 1 "given times", 2 "not everyday" 3 "do not practice".

IFLS, I calculate the years according to the highest level of education attained. Thus, the large difference in education can arise because of the measurement error. An important difference between these two samples is religiosity[12]. Religiosity persists in the next generation in Indonesia, while children in Germany attend religious services less compared to their parents.

Table 3.14 shows the results of intergenerational transmission among Indonesian families. Looking at the table, the transmission of religious identity is very strong. The coefficient is stronger compared to religious identity transmission among Muslim immigrants in Germany. This suggest that children respond not only to parents' preferences over religious traits, but also to society's preferences at the same time. On the other hand, the transmission of religiosity reported in columns 2- 4 is small compared to the one estimated in Table 3.7 for Muslim immigrants in Germany. An important implication of this result can be that native parents are less protective of their children as regards their religious trait development, since children can also learn from the society. The correlation thus between parents and children is low. On the contrary, immigrant parents are more concerned with carrying on their traits to the next generation, since they cannot learn these from society. This increases the intergenerational correlation. These results imply that migration changes the preferences of individuals. Immigrant parents are more protective about the persistence of their traits compared to natives since they may not want to see their children lose their identity.

Evidence from WVS

As discussed above,the high persistence of religious traits among Muslim immigrants in Germany compared to native Muslims in Indonesia can be misleading if the two groups are systematically different from each other. The persistence of religious traits in Indonesian families can be in general lower than Turkish ones. This section further compares Muslims in Germany and Turkish Muslims in Turkey to understand the transmission mechanism between immigrants and natives. A similar approach to Borjas (1992) is employed to estimate the persistence of religious traits between

[12]As noted earlier, religiosity is measured as the yearly attendance at religious services in Germany. IFLS includes a more detailed information which reports the

natives and immigrants. Consider the equation 3.1,

$$Y_i^c = \alpha + \beta Y_i^p + \epsilon_i$$

which can be organized as the mean religiosity of individuals from the same birth cohort as follows,

$$1/n \sum Y_i^c = 1/n \sum \alpha + 1/n \sum \beta Y_i^p + 1/n \sum \epsilon_i$$

$$\overline{Y_i^c} = \alpha + \beta \overline{Y_i^p} + \overline{\epsilon_i} \tag{3.6}$$

where $\overline{Y}_i^c$ is the average religiosity of children's generation while $\overline{Y}_i^p$ is the average religiosity of the parents' generation. Instead of measuring the persistence of religious traits between parents and children, equation 3.6 measures the transmission of average religiosity between birth cohorts.

The empirical analysis in this section uses the World Values Survey from Turkey. First, all three waves in the WVS survey are pooled to construct five-year-interval birth cohorts as showed in Table 3.15. For each birth cohort the average religiosity is estimated. Birth cohorts are then matched accordingly to create parent-child pairs, by exploiting the fact that an average adult in Turkey becomes father/mother at the age of twenty[13]. For instance, birth cohort 1930-1935 is assumed to form a pair with birth cohort 1950-1955. The empirical analysis assumes that individuals who belong to the 1950-1955 birth cohort are more likely to be the descendants of parents from the 1930-1935 cohort. In addition to the WVS from Turkey, the results from the GSOEP are also reported by using the same estimation strategy. Should equation 3.6 provide accurate estimates for the persistence of religious traits across generations, then the coefficients that are estimated with these two strategies for the German sample would have to be similar.

Table 3.16 reports the estimated coefficients for Turkey and Germany. The first row repeats the results for equation 3.1 in Table 3.6. The second row reports the persistence of religious traits for equation 3.6 by using the GSOEP for all religious groups. Finally,the last row reports the results for equation 3.6 by using the WVS in

[13] Turkish Statistical Office

Turkey. The similarity of the results in the first two rows suggests that equation 3.6 is a good approximation for intergenerational transmission coefficient estimated in equation 3.1. Applying the same method for Turkey reports much smaller transmission coefficient for native Muslims in Turkey. These results support the hypothesis that migration background plays an important role in the transmission of religious traits from parents to children.

Evidence from GSOEP

A final approach is to divide the GSOEP data into two different samples according to the migration background; immigrants and natives. The high number of observations in the GSOEP allows us to do this. In Table 3.17, I report the intergenerational coefficients of religiosity, education and height among different religious groups. Table 3.17 reports the results for Protestants and Catholics. The results show that religion and religiosity are transmitted stronger among immigrant families compared to natives. Similar to previous findings, these results conclude that the migration background has an important impact on the transmission rate of religious traits.

3.6 Discussion and Conclusion

This paper studies one important determinant of the formation of religious identity, namely the religious identity of parents, by using datasets from Germany. I first investigate the association between parents' and children's religious identities by using simple intergenerational elasticity models. The main finding of the paper is the importance of parents in the religious identity formation of their children. I find that parents' role is very strong in the development of religious traits. A stronger and significant persistence of religious identity among Muslim families is reported by the empirical analysis. In addition, I assume attendance at religious services as indicative of religiosity, and estimate the intergenerational transmission of religiosity among different religious groups. I conclude that not only religion, but also religiosity is strongly transmitted across generations. I find that the persistence of religiosity among Muslim families is stronger than among Protestants and Catholics in Germany. I conclude that persistence of religiosity is as strong as that of height and

stronger than transmission other traits.

The high transmission of religious traits raises questions about the factors behind it.The empirical results reveal that the socio-economic characteristics of families influence the persistence of religious traits across generations. In addition, the role of each parent in the socialization of the child changes according to socio-economic characteristics. The highest variation is observed among Muslim families. Moreover, in line with the theoretical framework, it is shown that immigrants exert more pressure on their children to preserve their religious traits.

This paper is an attempt to understand the religious identity dynamics across religions in Germany. It is not always easy to find appropriate dataset for studying the persistence of religious traits across generations, yet further analysis is needed to understand the transmission mechanism. The findings can be very interesting and may have further important economic implications regarding the integration process of immigrants in Europe.

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Table 3.1: Sample Selection in the GSOEP

Variables	Sample	GSOEP
Age	23.63	41.84
	(6.243)	*(17.842)*
Religiosity	4.31	6.33
	(10.647)	*(13.852)*
Height	175.02	172.42
	(9.404)	*(9.277)*
Weight	74.57	76.67
	(15.986)	*(17.108)*
Trust	2.02	2.03
	(.313)	*(.316)*
Years of Education	12.14	11.83
	(2.553)	*(2.673)*
Gender	.54	.51
	(.498)	*(.500)*

The number in the first row is the mean of corresponding variable and the number in the second row in parenthesis is the standard deviation for each group.
All variables in the above table are the lifetime measures of the respondents.Age refers to the average age that the respondents are present in the survey. Religiosity refers to the average attendance to religious services that is reported by the respondents. Height refers to the maximum height that is reported by the respondents. Weight refers to the average weight that is reported by the respondents. Trust refers to the average trust that is reported by the respondents. The answers range from 1 to 4 where 1 indicates everyone is trustworthy, 2 refers to depends, 2 refers to not always and 4 indicates No. Years of Education refers to the maximum years of education that is reported by the individuals. Females are denoted by 0 and males are denoted by 1.

Table 3.2: Distribution of Religions in the Sample

Religions	Number of Observations	Percentage
Catholics	2,771	*33.35*
Protestants	2,833	*34.10*
Muslims	532	*6.4*
No Religion	2,173	*26.15*
Total	8,309	*100.00*

The reported numbers are distribution of religions for children.

Table 3.3: Descriptive Statistics According to Religious Groups in Germany

	Germany			
Religions	Catholic	Protestant	Muslim	No Religion
Age	23.69	23.92	23.29	23.25
	(6.229)	*(7.087)*	*(4.234)*	*(5.425)*
Gender	53.88	51.78	58.46	56.74
	(.499)	*(.500)*	*(.493)*	*(.496)*
Years of Education	12.04	12.42	10.53	12.31
	(2.556)	*(2.570)*	*(2.098)*	*(2.479)*
Religiosity	7.10	3.45	9.57	.59
	(13.318)	*(9.412)*	*(14.308)*	*(3.218)*
Trust	2.01	2.00	2.09	2.04
	(.314)	*(.296)*	*(.447)*	*(.297)*
Height	174.84	175.59	171.69	175.20
	(9.756)	*(9.026)*	*(8.864)*	*(9.422)*
Weight	74.35	75.38	74.76	73.78
	(16.032)	*(16.488)*	*(15.038)*	*(15.457)*
% Immigrant	22.70	7.87	100.00	9.20
	(.419)	*(.269)*		*(.289)*
% Foreign Born	44.36	46.64	48.12	33.5
(among immigrants)	*(.497)*	*(.500)*	*(.500)*	*(.473)*

The number in the first row is the mean, the number in the second row in parenthesis is the standard deviation. All variables in the above table are the lifetime measures of the respondents.Age refers to the average age that the respondents are present in the survey. Religiosity refers to the average attendance to religious services that is reported by the respondents. Height refers to the maximum height that is reported by the respondents. Weight refers to the average weight that is reported by the respondents. Trust refers to the average trust that is reported by the respondents. The answers range from 1 to 4 where 1 indicates everyone is trustworthy, 2 refers to depends, 2 refers to not always and 4 indicates No. Years of Education refers to the maximum years of education that is reported by the individuals. Females are denoted by 0 and males are denoted by 1.

Table 3.4: Transition Probabilities in Germany

Parents	Children					
	Catholics	Protestants	Muslims	No Religion	Total	Sample Size
Catholics	83.67	10.53	0.04	5.76	100.00	2,793
Protestants	8.86	79.70	0.11	11.33	100.00	2,640
Muslims	0	0.54	91.06	8.41	100.00	559
No Religion	8.63	18.64	0.82	71.90	100.00	2,317

Note. The probabilities are given conditional on parents' religion.
The numbers that are given in the last column are the sample size for the parents.

Table 3.5: Parent-Child Religion Regression Results

	Catholics	Protestants	Muslims	No Religion
Intergenerational Elasticity	.74***	.65***	.84***	.63***
in Germany	*(.007)*	*(.009)*	*(.006)*	*(.008)*
	[.729-.757]	[.632-.666]	[.832-.856]	[.612-.645]
Sample Size	*8,309*	*8,309*	*8,309*	*8,309*
Controlled for				
Cohort fixed effects	✓	✓	✓	✓
Country Fixed Effects	✓	✓	✓	✓
Gender	✓	✓	✓	✓
Age	✓	✓	✓	✓
Parents' Education	✓	✓	✓	✓

Equation 3.1 is estimated. The dependent variable is the child's dummy for the corresponding religion.
Note. * *significant at* 10%; ** *significant at* 5%; *** *significant at* 1%.
Note. controls for gender, birth cohort, age, immigrant, foreign born, years of education of mother, years of education of father, and country of origin.
The number in the first row is the transmission coefficient measured by OLS (β in Equation 3.1), the number in the second row in parenthesis is the standard deviation, the interval in the third row is the 95% confidence interval, and the number in the fourth row is the sample size for each group.

Table 3.6: Parent-Child Regression Results for Several Traits

	Intergenerational Elasticity	Standard Error	Observation
Religiosity	.42***	*(.008)*	6,616
Trust	.17***	*(.016)*	5,442
Years of Education	.44***	*(.012)*	7,217
Height	.52***	*(.013)*	6,024
Weight	.38***	*(.014)*	6,012
Controlled for			
Cohort fixed effects	✓		
Country Fixed Effects	✓		
Gender	✓		
Age	✓		
Parents' Education	✓		

Equation 3.1 is estimated. The dependent variable is the corresponding child's variable.
Note. * *significant at* 10%; ** *significant at* 5%; *** *significant at* 1%.
Note. controls for gender, birth cohort, age, immigrant, foreign born, years of education of mother, years of education of father, and country of origin. While measuring education, height, and weight, years of education of mother and years of education of father are excluded from the regression.
The number in the first column is the transmission coefficient measured by OLS (β in Equation 3.1), the number in the second column in parenthesis is the standard deviation and the number in the third column is the sample size for each cell in the table.
The unreported coefficients are due to low number of observations.

Table 3.7: Intergenerational Elasticity Measures in Germany

	Germany			
Religions	Catholic	Protestant	Muslim	No Religion
Religiosity	.39***	.45***	.51***	.37***
	(014)	*(.016)*	*(.038)*	*(.022)*
	[.364-.417]	[.423-.487]	[.437-.588]	[.327-.415]
Sample Size	*2,337*	*2,104*	*509*	*1666*
Trust	.23***	.11***	.20***	.14***
	(.031)	*(.026)*	*(.063)*	*(.029)*
	[.174-.296]	[.061-.164]	[.080-.329]	[.085-.199]
Sample Size	*1,699*	*1,882*	*294*	*1,567*
Years of Education	.48***	.47***	.15***	.42***
	(.023)	*(.021)*	*(.077)*	*(.023)*
	[.437-.525]	[.431-.513]	[.002-.303]	[.374-.463]
Sample Size	*2,425*	*2,426*	*466*	*1900*
Height	.53***	.52***	.49***	.51***
	(0.025)	*(.022)*	*(.070)*	*(.024)*
	[.479-.576]	[.481-.569]	[.349-.624]	[.467-.561]
Sample Size	*1,897*	*2,085*	*327*	*1,715*
Weight	.35***	.47***	.15***	.34***
	(0.025)	*(.024)*	*(.065)*	*(.023)*
	[.298-.396]	[.428-.521]	[.020-.276]	[.297-.388]
Sample Size	*1,894*	*2,080*	*326*	*1,712*

Equation 3.1 is estimated. The dependent variable is the corresponding child's variable.

*Note. * significant at* 10%; ** *significant at* 5%; *** *significant at* 1%.

Note. controls for gender, birth cohort, age, immigrant, foreign born, years of education of mother, years of education of father, and country of origin. While measuring education, height, and weight, years of education of mother and years of education of father are excluded from the regression.

The number in the first row is the transmission coefficient measured by OLS (β in Equation 3.1), the number in the second row in parenthesis is the standard deviation, the interval in the third row is the 95% confidence interval, and the number in the fourth row is the sample size for each religious group.

The unreported coefficients are due to low number of observations.

Table 3.8: Intergenerational Elasticity Measures in Germany, Father and Mother

	Germany			
	Catholic	Protestant	Muslim	No Religion
Father Religion	.32***	.29***	.50***	.20***
	(.009)	*(.010)*	*(.023)*	*(.012)*
Mother Religion	.60***	.55***	.37***	.48***
	(.009)	*(.009)*	*(.023)*	*(.013)*
Sample Size	*6,576*	*6,576*	*6,576*	*6,576*
R^2	.7596	.6423	.8782	.5859
Father Religiosity	.22***	.24***	.26***	.08***
	(.020)	*(.023)*	*(.038)*	*(.016)*
Mother Religiosity	.19***	.22***	.25***	.12***
	(.018)	*(.021)*	*(.054)*	*(.017)*
Sample Size	*2,210*	*2,196*	*487*	*1,683*
R^2	.3162	.3044	.3302	.2020

Equation 3.1 is estimated. The dependent variable is the corresponding child's variable. Sample is restricted to parent-child pair where both mothers' and fathers' outcomes are identified.

Note. * *significant at* 10%; ** *significant at* 5%; *** *significant at* 1%.

Note. controls for gender, birth cohort, age, immigrant, foreign born, years of education of mother, years of education of father, and country of origin. While measuring education, height, and weight, years of education of mother and years of education of father are excluded from the regression.

The number in the first row is the transmission coefficient measured by OLS (β in Equation 3.1), the number in the second row in parenthesis is the standard deviation, the number in the third and the 4th rows report the sample size for each religious group and R^2.

The unreported coefficients are due to low number of observations.

Table 3.9: Intergenerational Elasticity Measures in Germany According to Gender of the Child

	Catholic		Protestant		Muslim		No Religion	
	Males	Females	Males	Females	Males	Females	Males	Females
Father Religion	.32***	.31***	.28***	.31***	.26***	.64***	.21***	.18***
	(.012)	*(.012)*	*(.013)*	*(.014)*	*(.039)*	*(.028)*	*(.017)*	*(.017)*
Mother Religion	.59***	.60***	.55***	.56***	.61***	.21***	.46***	.49***
	(.012)	*(.013)*	*(.013)*	*(.014)*	*(.039)*	*(.028)*	*(.018)*	*(.019)*
Sample Size	*3,578*	*2,998*	*3,578*	*2,998*	*3,578*	*2,998*	*3,578*	*2,998*
R^2	.7466	.7773	.6384	.6455	.8793	.8789	.5877	.5861
Father Religiosity	.23***	.20***	.25***	.22***	.40***	.02	.13***	.02
	(.025)	*(.031)*	*(.030)*	*(.036)*	*(.054)*	*(.043)*	*(.016)*	*(.044)*
Mother Religiosity	.15***	.23***	.21***	.23***	.19**	.33***	.02*	.28***
	(.024)	*(.029)*	*(.029)*	*(.032)*	*(.077)*	*(.062)*	*(.015)*	*(.038)*
Sample Size	*3,045*	*3,171*	*1,141*	*1,055*	*288*	*199*	*952*	*731*
R^2	.3045	.3171	.3328	.2851	.3733	.2412	.2517	.2547

Equation 3.1 is estimated. The dependent variable is the corresponding child's variable. Sample is restricted to parent-child pair where both mothers' and fathers' outcomes are identified.

Note. * *significant at* 10%; ** *significant at* 5%; *** *significant at* 1%.

Note. controls for gender, birth cohort, age, immigrant, foreign born, years of education of mother, years of education of father, and country of origin. While measuring education, height, and weight, years of education of mother and years of education of father are excluded from the regression.

The number in the first row is the transmission coefficient measured by OLS (β in Equation 3.1), the number in the second row in parenthesis is the standard deviation, the number in the third and the 4th rows report the sample size for each religious group and R^2.

The unreported coefficients are due to low number of observations.

Table 3.10: Intergenerational Elasticity Measures in Germany According to Homogeneous Marriage

	Catholic		Protestant		Muslim		No Religion	
	Homogeneous	Heterogeneous	Homogeneous	Heterogeneous	Homogeneous	Heterogeneous	Homogeneous	Heterogeneous
Father Religiosity	.21***	.19***	.27***	.05	.26***		.10***	.17***
	(.023)	*(.045)*	*(.028)*	*(.043)*	*(.039)*		*(.021)*	*(.030)*
Mother Religiosity	.21***	.13***	.19***	.25***	.25***		.12***	−.05***
	(.022)	*(.031)*	*(.027)*	*(.031)*	*(.055)*		*(.018)*	*(.032)*
Sample Size	*1,753*	*457*	*1,538*	*658*	*481*		*1,414*	*269*
R^2	.3207	.1054	.3453	.1762	.3276		.2243	.1713

Equation 3.1 is estimated. The dependent variable is the corresponding child's variable. Sample is restricted to parent-child pair where both mothers' and fathers' outcomes are identified.

Note. * *significant at* 10%; ** *significant at* 5%; *** *significant at* 1%.

Note. controls for gender, birth cohort, age, immigrant, foreign born, years of education of mother, years of education of father, and country of origin. While measuring education, height, and weight, years of education of mother and years of education of father are excluded from the regression.

The number in the first row is the transmission coefficient measured by OLS (β in Equation 3.1), the number in the second row in parenthesis is the standard deviation, the number in the third and the 4th rows report the sample size for each religious group and R^2.

The unreported coefficients are due to low number of observations.

Table 3.11: Intergenerational Elasticity Measures in Germany According to Education Level of Children

	Catholic		Protestant		Muslim		No Religion	
	Low	High	Low	High	Low	High	Low	High
Father Religion	.30***	.32***	.31***	.28***	.32***	.58***	.18***	.21***
	(.015)	*(.010)*	*(.015)*	*(.013)*	*(.057)*	*(.025)*	*(.019)*	*(.015)*
Mother Religion	.60***	.59***	.52***	.57***	.51***	.30***	.47***	.48***
	(.016)	*(.010)*	*(.014)*	*(.012)*	*(.057)*	*(.025)*	*(.021)*	*(.017)*
Sample Size	*2,072*	*4,504*	*2,947*	*3,629*	*1,242*	*5,334*	*2,447*	*3,629*
R^2	.7854	.7459	.6460	.6356	.8874	.8676	.5964	.5895
Father Religiosity	.27***	.20***	.32***	.21***	.23***	.29***	.07***	.17***
	(.032)	*(.025)*	*(.042)*	*(.028)*	*(.058)*	*(.053)*	*(.020)*	*(.029)*
Mother Religiosity	.11***	.22***	.22***	.22***	.29***	.21***	.06***	.10***
	(.030)	*(.023)*	*(.037)*	*(.026)*	*(.095)*	*(.070)*	*(.018)*	*(.027)*
Sample Size	*788*	*1,422*	*841*	*1,355*	*211*	*276*	*725*	*958*
R^2	.3244	.3175	.3377	.3055	.2204	.3672	.2079	.2265

Equation 3.1 is estimated. The dependent variable is the corresponding child's variable. Sample is restricted to parent-child pair where both mothers' and fathers' outcomes are identified.

Note. * *significant at* 10%; ** *significant at* 5%; *** *significant at* 1%.

Note. controls for gender, birth cohort, age, immigrant, foreign born, years of education of mother, years of education of father, and country of origin. While measuring education, height, and weight, years of education of mother and years of education of father are excluded from the regression.

The number in the first row is the transmission coefficient measured by OLS (β in Equation 3.1), the number in the second row in parenthesis is the standard deviation, the number in the third and the 4th rows report the sample size for each religious group and R^2.

The unreported coefficients are due to low number of observations.

Table 3.12: Intergenerational Elasticity Measures in Germany According to Neighborhood Characteristics

	Catholic		Protestant		Muslim		No Religion	
	City	Countryside	City	Countryside	City	Countryside	City	Countryside
Father Religion	.29***	.32***	.26***	.33***	.43***	.72***	.14***	.23***
	(.015)	*(.012)*	*(.017)*	*(.013)*	*(.045)*	*(.032)*	*(.021)*	*(.018)*
Mother Religion	.60***	.60***	.56***	.54***	.43***	.17***	.50***	.48***
	(.015)	*(.012)*	*(.017)*	*(.013)*	*(.045)*	*(.032)*	*(.023)*	*(.016)*
Sample Size	*2,272*	*3,236*	*2,272*	*3,236*	*2,272*	*3,236*	*2,272*	*3,236*
R^2	.7189	.7826	.6044	.6672	.8524	.9025	.5897	.6199
Father Religiosity	.23***	.21***	.37***	.18***	.20***	.24***	.11***	.08***
	(.044)	*(.025)*	*(.039)*	*(.033)*	*(.069)*	*(.086)*	*(.028)*	*(.025)*
Mother Religiosity	.23***	.16***	.11***	.29***	.26***	.33***	.03***	.11***
	(.039)	*(.024)*	*(.037)*	*(.031)*	*(.096)*	*(.115)*	*(.029)*	*(.024)*
Sample Size	*615*	*1,181*	*720*	*1,143*	*198*	*136*	*739*	*776*
R^2	.3517	.2890	.4007	.2909	.3070	.2719	.1123	.3284

Equation 3.1 is estimated. The dependent variable is the corresponding child's variable. Sample is restricted to parent-child pair where both mothers' and fathers' outcomes are identified.

Note. * *significant at* 10%; ** *significant at* 5%; *** *significant at* 1%.

Note. controls for gender, birth cohort, age, immigrant, foreign born, years of education of mother, years of education of father, and country of origin. While measuring education, height, and weight, years of education of mother and years of education of father are excluded from the regression.

The number in the first row is the transmission coefficient measured by OLS (β in Equation 3.1), the number in the second row in parenthesis is the standard deviation, the number in the third and the 4th rows report the sample size for each religious group and R^2.

The unreported coefficients are due to low number of observations.

Table 3.13: Descriptive Statistics of Samples from Germany and Indonesia

Country	Germany			Indonesia		
	Children	Mother	Father	Children	Mother	Father
Age	23.33	50.07	52.29	22.62	48.73	53.28
	(6.461)	*(8.229)*	*(7.571)*	*(6.776)*	*(9.010)*	*(9.536)*
Gender	.54			.54		
	(.498)			*(.498)*		
Years of Education	12.14	11.20	10.35	9.90	4.99	4.98
	(2.553)	*(3.111)*	*(5.006)*	*(3.090)*	*3.807)*	*(4.367)*
Religiosity	4.31	8.84	8.09	4.47	5.23	5.25
	(10.646)	*(15.217)*	*(15.076)*	*(1.846)*	*(1.876)*	*(2.006)*
Parent Identified		.99	.89		.94	.77
		(.121)	*(.314)*		*(.233)*	*(.418)*

The number in the first row is the mean, the number in the second row in parenthesis is the standard deviation.
All variables in the above table are the lifetime measures of the respondents in Germany.Age refers to the average age that the respondents are present in the survey. Religiosity refers to the average attendance to religious services that is reported by the respondents. Years of Education refers to the maximum years of education that is reported by the individuals. Females are denoted by 0 and males are denoted by 1. Parent Identified refers to percentage of parents whose outcomes are identified in the sample.

Table 3.14: Intergenerational Elasticity Measures of Religious Traits in Indonesia

Variable	Religon	Religious	Religiosity(Numerical)	Religiosity(Categorical)
Coefficient	.97***	.25***	.14***	.30***
Standard Deviation	.008	.023	.031	.041
No. of Observations	5,605	4,991	4,242	4,996
R^2	06326	.0553	.0529	.0624
Controlled for				
Cohort fixed effects	✓	✓	✓	✓
Country Fixed Effects	✓	✓	✓	✓
Gender	✓	✓	✓	✓
Age	✓	✓	✓	✓
Parents' Education	✓	✓	✓	✓

Equation 3.1 is estimated. The dependent variable is the corresponding child's variable.
Note. *** *significant at* 1%.
The number in the first row is the transmission coefficient measured by OLS (β in Equation 2.1*), the number in the second row in parenthesis is the standard deviation, the sample size is in the third row, and the number in the fourth row is the* R^2.
Note. controls for gender, birth cohort, age, years of education of mother, years of education of father.
Note. Religiosity refers to "How religious are you?". Possible answers to this question vary from 1 to 4 where 1 refers to "very religious" and 4 refers to "not religious"; Religiosity(Numerical) refers to "How many times do you pray each day?". The question is answered by a numerical value that the respondents pray each day which ranges from 1 to 81. iii Religiosity(Categorical) refers to"How many times do you pray each day (categorical)?". Respondents can choose from three different answers which are 1 "given times", 2 "not everyday" 3 "do not practice".

Table 3.15: Parent-Child Birth Cohorts from the WVS

Parent Cohort	No. of Obs	Child Cohort	No. of Obs.
Cohort 1920 - 1925	36	Cohort 1940 - 1945	239
Cohort 1925 - 1930	75	Cohort 1945 - 1950	289
Cohort 1930 - 1935	120	Cohort 1950 - 1955	411
Cohort 1935 - 1940	180	Cohort 1955 - 1960	624
Cohort 1940 - 1945	239	Cohort 1960 - 1965	741
Cohort 1945 - 1950	289	Cohort 1965 - 1970	740
Cohort 1950 - 1955	411	Cohort 1970 - 1975	842
Cohort 1955 - 1960	624	Cohort 1975 - 1980	883
Cohort 1960 - 1965	741	Cohort 1980 - 1985	613
Cohort 1965 - 1970	740	Cohort 1985 - 1990	172

Note. Cohorts are constructed according to birth years of respondents. The average religiosity of cohorts is calculated by taking the average value of all respondents born in the specific birth cohort.

Table 3.16: Parent-Child Religion Regression Results Based on Constructed Generations

	Catholics	Protestants	Muslims
GSOEP (Equation 2.1)	.39***	.45***	.51***
Standard Deviation	*(.014)*	*(.016)*	*(.038)*
Sample Size	2,337	2,104	509
GSOEP (Equation 2.6)	.53***	.44***	.51***
Standard Deviation	*(.003)*	*(.002)*	*(.004)*
Sample Size	144,612	18,466	18,466
WVS (Equation 2.6)			.17***
Standard Deviation			*(.015)*
Sample Size			1,209

Note. *** *significant at* 1%.

Equation 3.6 is estimated where the dependent variable is the average religiosity of child cohort.

Table 3.17: Intergenerational Elasticity Measures of Different Traits According to Immigrant Status

	Catholics		Protestants	
	Native	Immigrant	Native	Immigrant
Religiosity	.37***	.46***	.44***	.62***
	(.015)	*(.027)*	*(.017)*	*(.055)*
	[.340-.401]	[.408-.514]	[.402-.469]	[.511 - .727]
Sample Size	*1,772*	*565*	*1,944*	*160*
Years of Education	.50***	.40***	.47***	.46***
	(.026)	*(.045)*	*(.022)*	*(.074)*
	[.452-.554]	[.314-.492]	[.432-.518]	[.310-.601]
Sample Size	*1,822*	*603*	*2,218*	*208*
Height	.53***	.52***	.52***	.59***
	(.028)	*(.055)*	*(.023)*	*(0.113)*
	[.478-.586]	[.408-.623]	[.477-.566]	[-.367-.814]
Sample Size	*1,586*	*311*	*1,929*	*156*

Equation 3.1 is estimated. The dependent variable is the corresponding child's variable. Sample is restricted to parent-child pair where both mothers' and fathers' outcomes are identified.

Note. * *significant at* 10%; ** *significant at* 5%; *** *significant at* 1%.

Note. controls for gender, birth cohort, age, foreign born, years of education of mother, years of education of father, and country of origin.

The number in the first row is the transmission coefficient measured by OLS (β in Equation 3.1), the number in the second row in parenthesis is the standard deviation, the number in the third and the 4th rows report the sample size for each religious group and R^2.

The unreported coefficients are due to low number of observations.