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# Parental Impact on Attitude Formation

## A Siblings Study on Worries about Immigration

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# Parental Impact on Attitude Formation – A Siblings Study on Worries about Immigration

Abstract
The existing literature on attitudes towards immigration has not accounted for the potential effect of unobservable *home education* on attitude formation. Yet, factors such as parents' knowledge, their morals, and their *weltanschauung* are likely to influence the attitudes of the next generation. Their omission from the analysis thus threatens to lead to erroneous conclusions. Utilizing siblings data from the German Socio-Economic Panel (GSOEP) this paper analyzes the determinants of worries about immigration controlling for unobserved family specific effects. Our results suggest that benchmark models used in the literature yield inconsistent estimates of the main determinants of attitudes towards immigration.

JEL Classification: C51, F22, J15

Keywords: Subjective data, siblings data, unobserved effects, minorities

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# 1 Introduction

The analysis of attitudes towards immigration continues to gain increasing interest in the economic literature.[1] Reasons to examine this relationship are multifarious. As shown in Figure 1, the share of the foreign-born population is already fairly sizable in most (Western) European countries. Additionally, almost all industrialized countries are confronted with aging societies and an excess demand for high skilled labor. The demographic problem becomes apparent when looking at Figure 2. It depicts the ratio of the population aged 65 and older to the total labor-force in 2005 and estimates of this ratio for 2050 in Europe. In all European countries this figure is expected to roughly double.

The effects of both the demographic change and the shortage of skilled workers could be mitigated by a selective immigration policy that offers young, highly educated foreigners a permanent perspective to work and live in these countries. This, of course, would further increase the population shares of foreigners. Consequently, the societal integration of immigrants is an elementary factor for a successful implementation of any immigration policy. In general, this integration process is most likely facilitated if natives are relatively open to the idea of accepting foreigners permanently among them. Since this public willingness to accept foreign minorities in society can be interpreted as the demand side of immigration policy, it should be of utmost interest to policy makers to understand what drives these opinions.

To evaluate the impact of economic concerns on attitudes towards foreigners, one strand of the literature tries to reconcile individual opinions on immigration taken from survey data to the predictions of stylized economic models on the wage effects of immigration. These effects primarily depend on the skill distributions of native and foreign workers, and are different for native workers with different skill levels. Correspondingly, individual attitudes are also assumed to vary across skill levels reflecting the unequally distributed individual benefits from immigration (see e.g. Mayda, 2006, and Scheve and Slaughter, 2001). Following a similar motivation, Dustmann and Preston (2004b) and Facchiniy and Mayda (2006) investigate the perceived impact of immigration on the national welfare system. Most of these studies interpret educational attainment as a skill proxy, and ask whether attitudes vary across skill levels due to the expectation of different impacts of immigration on the high and low-skilled sectors of the labor market.[2] Additionally, Facchiniy

[1] For a survey of the recent empirical literature and new empirical evidence for 20 European countries see Brenner and Fertig (2006).

[2] Among others Hainmueller and Hiscox (2007) interpret school degrees as a broad education measure, arguing that higher education should be associated with increasing ethnical and racial

and Mayda (2006) use an income measure as a proxy of welfare concerns induced by immigration.[3] The conclusion of this literature is that labor market as well as welfare considerations apparently affect the view of individuals on immigration as predicted by specific economic models.

This paper addresses a severe shortcoming in the study design of virtually all of the received literature on attitudes towards immigration, since it typically neglects the potential impact of parents on the attitude formation of their children.[4] We argue that factors such as parents' knowledge, their morals, and their *weltanschauung* are transmitted to a certain degree to their offspring and hence contribute to shape their view of the world including their worries about immigration. These unobservable factors which we refer to as *home education* are most likely correlated with observable covariates, in particular educational attainment. Since this is in turn the most important determinant discussed in the literature, we should expect to obtain inconsistent estimates of its impact when standard models are applied. In accordance with this reasoning, the analysis in this study illustrates that ignoring *home education* indeed results in inconsistent coefficient estimates, utilizing siblings data from the *German Socio-Economic Panel* (GSOEP).

We exploit the specific structure of our data by controlling for family-specific effects which are assumed to capture parental influences on attitude formation. The estimations are carried out applying two distinct identification strategies, fixed effects ordered logit, suggested by Ferrer-i-Carbonell and Frijters (2004), and Chamberlain's (1980) random effects ordered probit. Results are then compared to and tested against the benchmark models typically employed in the literature, (ordered) logit and (ordered) probit, respectively, which ignore unobservable effects such as *home education*.

The rest of the paper is structured as follows. In **Section 2** the data is summarized. **Section 3** describes the econometric model and the identification strategies in detail. We present our empirical evidence in **Section 4** and draw conclusions in **Section 5**.

tolerance and open-mindedness.

[3] Facchiniy and Mayda (2006) augment a stylized labor market model with a government's budget constraint consisting of lump sum welfare benefits and a redistributive tax system to motivate their empirical analysis. Their *first welfare-state scenario*, which is supported by their empirical findings, assumes that the government maintains the per capita welfare benefits after an immigration shock occurs. To keep the budget constraint balanced, the tax system has to adjust which has a heterogeneous impacts on individuals depending on their position in the wage distribution.

[4] To our knowledge, only Brenner and Fertig (2006) proxy this potential impact by the inclusion of parental educational attainment as an additional explanatory variable.

## 2 Data

In our empirical application we utilize data from the German Socio-Economic Panel (*GSOEP*).[5] In particular, six waves comprising the years 1999 to 2004 are examined. In this period participants were asked to express their worries about immigration on a three point scale reaching from *very concerned* (coded 1) over *somewhat concerned* (2) to *not concerned at all* (3). We focus on a sub-sample of siblings which are identified via the identity of their parents, including only respondents in our sample if we find at least one more individual associated with the same mother and father. If only mother or father coincide the observations are discarded since it is unclear whether the respondents were raised jointly in the same household, which we assume if both parents match. We further restrict our sample to non-immigrant German nationals aged 16 or older who have finished their education. In total we end up with 8,780 complete person-year observations of 2,040 individuals from 931 families. The distribution of these observations over the years is shown in Table 1.

As our principal explanatory factor we include the most emphasized determinant in the literature, the educational attainment of the respondents. We expect higher educated individuals to exhibit a more informed view of the world and a higher level of ethnical and racial tolerance than lower educated individuals. Alternatively, one might reconcile the measured attitudes-education-association with concerns about the effects of immigration on the labor market. In the German case, low-educated individuals might display a higher propensity to consider immigrants as direct competitors for jobs because they are close substitutes in the production process[6]. High-educated individuals, on the other hand, benefit from low-skilled immigration since their skills become relatively more scarce and thus they are more inclined to favor immigration. In any case, we include three dummy variables for the highest level of education covering *Hauptschule* (lower secondary

[5]The data used in this paper was extracted from the SOEP Database provided by the DIW Berlin (http://diw.de/soep) using the ADD-ON package SOEPMENU v2.0 (Jul 2005) for Stata(R). SOEPMENU (http://soepmenu.de) was written by Dr. John P. Haisken-DeNew (john@soepmenu.de). See Haisken-DeNew (2005) for details. The following authors supplied SOEPMENU Plugins used to ensure longitudinal consistency, John P. Haisken-DeNew (15), John P. Haisken-DeNew and Markus Hahn (16), Mathias Sinning (2). The SOEP Menu generated DO file to retrieve the SOEP data used here and any SOEPMENU Plugins are available upon request. Any data or computational errors in this paper are my own.

[6]In Germany the bulk of immigrants is actually low-skilled (according to SOPEMI (2004) 47.7 % on average in 2001-2002).

degree or less), *Abitur* (qualification for universities), and university degree, leaving *Realschule* (intermediate secondary school) as the base group.

Furthermore, we include individual labor earnings. Assuming that low-skilled workers earn on average less than high-skilled workers, following the same arguments as above we would expect a positive impact of earnings on worries about immigration. If, however, labor income reflects concerns about the welfare impact of immigration, as suggested by Facchiniy and Mayda (2006), a negative sign of the coefficient should be found. Since most respondents live in multiple-person households, their personal incomes are not necessarily the only source of income. Therefore we add the equivalent household income, computed by using the *OECD* scale. This variable should to some extent capture the social status of the respondents' household.[7]

An additional labor market variable considered is the employment status (employed/not employed) which we include along with a dummy indicating whether the respondent lives in Eastern Germany to test the two popular hypotheses that on the one hand people from the East of Germany and on the other hand unemployed workers display more negative perceptions of immigrants. Since attitudes might change over life time due to personal experience but also due to national and global developments, we control for respondents' age by the inclusion of age group dummies. Further controls are gender and marital status. Table 2 contains summary statistics of the dependent and the independent variables.

# 3 The Empirical Framework

We begin this section with a description of the econometric model used in our study. In the remainder of the section we discuss the different identification restrictions imposed and conclude with the discussion of some robustness tests of these assumptions.

## 3.1 Econometric Model

Our sample consists of $i = 1, \dots, N$ families which comprise $j = 1, \dots, J_i$ brothers and sisters. $J_i$, the number of siblings in family $i$, can vary over families but has to be at least equal to two. For each individual we observe the categorical dependent variable $y_{ij}$ which can take the values $\{1, 2, 3\}$ and a $K \times 1$ vector of

[7]Dustmann and Preston (2004a,b) use household income, yet in a categorized metric, stressing the importance of the relative position in the income distribution.

socio-economic variables $X_{ij}$, containing, among others, gender, age, labor income, educational attainment, employment and marital status.

We assume that an underlying true opinion $y^*_{ij}$ on the item exists that is unobservable. This latent variable is modeled to depend on $X_{ij}$ in the following linear fashion

$$y^*_{ij} = X'_{ij}\beta + \epsilon_{ij} \qquad \forall\ j = 1, \ldots, J_i,\ i = 1, \ldots, N, \tag{1}$$

with $\epsilon_{ij}$ a regression error term. Due to the latent nature of $y^*_{ij}$ we assume the following link to the observable counterpart $y_{ij}$

$$y_{ij} = \begin{cases} 1 & \text{if } y^*_{ij} \leq \tau_1 \\ 2 & \text{if } \tau_1 < y^*_{ij} \leq \tau_2 \\ 3 & \text{if } \tau_2 < y^*_{ij} \end{cases} \tag{2}$$

where $\tau_1$ and $\tau_2$ are unknown threshold parameter such that $\tau_2 > \tau_1$. They will have to be estimated along with $\beta$, the parameter vector of interest that measures the impact of the socio-economic factors on $y^*_{ij}$.

In the received economic literature of attitudes towards immigration a specific distribution of the error term (standard normal or logistic) along with non-correlation with the regressors $X_{ij}$ is assumed. Thus, Equation (1) is estimated by Maximum Likelihood (*ML*) as ordered probit or ordered logit, the benchmark models in this study. Taking into account the siblings structure of the data, we however assume that the compound regression error term is given by

$$\epsilon_{ij} = f_i + u_{ij}, \tag{3}$$

where $f_i$ denotes the family component being identical for each member of family $i$ and $u_{ij}$ is a mean zero i.i.d. error term. Allowing the family specific unobservable effect $f_i$, assumed to capture the impact of *home education*,[8] to be correlated with $X_{ij}$, the benchmark estimates are inconsistent.

Since the single year samples admitting to estimate family effects are rather small,[9] we will pool our data over time. This involves further identifying assumptions. Most importantly, we have to assume that the family effects $f_i$ are constant

[8]Further potential unobservables affecting siblings similarly that might be captured by $f_i$ are the contact to and influence of a similar group of friends and neighbors, as well as community specific characteristics, e.g. the ethnical mix of the local population.

[9]The maximum number of observations in any given year is 1,342 for the random effects model and 735 for the fixed effect model due to lacking variation in the outcome within families (see **Section 3.2**). This intra-family variation is increased considerably by pooling observations over time.

over time. Furthermore, we impose the assumption that all parameters are constant over the considered time horizon of six years. Finally, we add year dummies to the models to capture varying answering behavior which might be induced by exogenous changes that affect each respondent in the same fashion.

## 3.2 Identification Strategies

Ordered probit ($OP$) and ordered logit ($OL$), the common estimation techniques utilized in the literature on attitudes towards immigration, are well-known textbook procedures and need no further discussion (see e.g. Greene, 2003). The other estimators, fixed effects ordered logit ($FE$) and Chamberlain's random effects ordered probit ($CHOP$), however, are less common and will be described in some more detail.

Both procedures model the family relations of respondents by the inclusion of a family effect $f_i$. They further impose one important common identification assumption. The observed answers within each family $i$, $y_i = [y_{i1} \ \ldots \ y_{iJ_i}]'$, are statistically independent conditional on $f_i$ and $X_i = [X'_{i1} \ \ldots \ X'_{iJ_i}]'$. It follows that the joint density of $y_i$ conditional on $f_i$ and $X_i$ is the product of the marginal densities of $y_{i1}$ to $y_{iJ_i}$ conditional on $f_i$ and $X_i$, respectively. If $f_i$ was observable, this would enable us to estimate the resulting likelihood straight-forwardly. However, since $f_i$ is latent, further identification assumptions are necessary which vary over the two approaches considered.

*Fixed Effects Ordered Logit*
Our first identification approach, fixed effects ordered logit, is an extension of the conditional logit model (Chamberlain, 1984) for dependent variables with more than two categories.[10] To implement this model, a binary variable $w_{ij}$ is generated that relates to the original outcome $y_{ij}$ as follows:

$$w_{ij} = \begin{cases} 0 & \text{if } y_{ij} < \bar{y}_i \\ 1 & \text{if } y_{ij} \geq \bar{y}_i, \end{cases} \tag{4}$$

where $\bar{y}_i = 1/J_i \sum_{j=1}^{J_i} y_{ij}$. Using $w_{ij}$ instead of $y_{ij}$ as the new dependent variable, the traditional conditional logit model can be estimated by $ML$. The resulting

[10] This version of the model slightly deviates from Ferrer-i-Carbonell and Frijters (2004). The author is very grateful to Ada Ferrer-i-Carbonell and Paul Frijters to hint at this version of their model and its easy implementation in Stata. Jones and Schurer (2007) apply both versions in the context of health satisfaction and find that parameter differences are negligible.

likelihood for each family $i$ is given by

$$L[w_{i1},\ldots,w_{iJ_i}|\sum_{j=1}^{J_i} w_{ij}=W_i]=\frac{\exp\{\sum_{j=1}^{J_i} w_{ij}X'_{ij}\beta\}}{\sum_{w_i\in S(W_i)}\exp\{\sum_{j=1}^{J_i} w_{ij}X'_{ij}\beta\}}, \tag{5}$$

where $w_i = [w_{i1} \ \ldots \ w_{iJ_i}]'$ and $S(W_i)$ denotes the set of possible realizations of $w_i$ such that $\sum_{j=1}^{J_i} w_{ij} = W_i$. This specification is attractive since no assumptions about the correlation structure between $f_i$ and $X_{ij}$ are necessary as the conditional likelihood is free of the unobservable factor. Unfortunately, it is impossible to estimate marginal effects for the original outcome measure $y_{ij}$ which are more naturally interpreted in the non-linear models at hand than their parameters.[11] Hence, to test the appropriateness of this specification we are only able to compare the parameter estimates of $FE$ with those of $OL$ by performing a Hausman test.

Finally one should mention that the well known problems of the original conditional logit model for binary dependent variables carry over to this adjusted version, i.e. we lose all units $i$ that have no variation in the dependent variable over the $j$ realizations. However, since we analyze a family panel, the drawback that unit-invariant regressors $X_i$ drop out of the likelihood is not present. In typical panel applications where an individual is observed at several points in time variables such as gender usually do not vary over time and hence cannot be included. Since our 'time dimension' are the different family members, we have sufficient variation in all regressors over $j$, even if not for every family $i$.

*Chamberlain's Random Effects Ordered Probit*

The second approach, Chamberlain's random effects ordered Probit (Chamberlain, 1980) extents the standard random effects approach by suggesting a linear relationship between $f_i$ and $X_i$. We adopt the specification of Mundlak (1978), assuming that

$$f_i = \bar{X}_i{}'\gamma + r_i \tag{6}$$

with $r_i|X_i \sim N(0,\sigma_r^2)$ and $\bar{X}_i = 1/J_i\sum_{j=1}^{J_i} X_{ij}$. Combining (3) and (6) with Equation (1) yields

$$y_{ij}^* = X'_{ij}\beta + \bar{X}_i{}'\gamma + r_i + u_{ij}, \tag{7}$$

which is estimable by $ML$ as a standard random effects ordered probit model.

The implication of Assumption (6) is that we explicitly account for a potential correlation between the family effect $f_i$ and observable characteristics $X_i$. The

[11] Even in the case of a binary outcome additional undesirable assumptions about $f_i$ are necessary, typically that $f_i = 0 \ \forall \ i = 1,\ldots,N$, to be able to estimate marginal effects.

chosen specification restricts this correlation to be identical for each family member. Similar to the $FE$ approach, an important limitation to $CHOP$ is that each regressor needs to vary over the $J_i$ realizations for at least some units $i$ in the sample. Otherwise, the average over $J_i$ would be perfectly collinear to the regressor itself and could not be estimated. However, as mentioned above, in the present case of a family panel there is sufficient variation in all considered independent variables.

A benefit of the normality assumption of $u_{ij}$ is that it enables us to compute marginal effects. As highlighted by Wooldridge (2002) for the binary probit case, this is feasible since for a particular realization $\tilde{x}$ of the regressors $X_{ij}$,

$$E[P(y_{ij}^* \leq \tau_j)] = E[\Phi(\tau_j - \tilde{x}'\beta - \bar{X}_i{}'\gamma - r_i)]$$

for $j = \{1, 2\}$. Using the law of iterative expectations,

$$\begin{aligned} E\{E_X[\Phi(\tau_j - \tilde{x}'\beta - \bar{X}_i{}'\gamma - r_i)|X_i]\} &= E\{\Phi[(\tau_j - \tilde{x}'\beta - \bar{X}_i{}'\gamma)(1 + \sigma_r^2)^{-1/2}]\} \\ &= \Phi[(\tau_j - \tilde{x}'\beta - \bar{X}_i{}'\gamma)(1 + \sigma_r^2)^{-1/2}]. \end{aligned}$$

This result can be exploited to compute predicted probabilities of observing the three outcomes by plugging the $ML$ estimates and the sample mean $\bar{X}$ (as the realization $\tilde{x}$ of interest) into the probability expressions. Using those, marginal effects of the regressors $X$ are obtained straightforwardly averaging over $\bar{X}_j{}'\hat{\gamma}$.[12]

To test whether omitting the family effect yields consistent estimates of $\beta$ we perform a Hausman test comparing the Chamberlain approach with the benchmark specification. Choosing $u_{ij}$ to be standard normal the adequate comparison model is ordered probit.[13]

## 3.3 Robustness Tests

To verify the robustness across the two different strategies of modeling the family effects we re-estimate Equation (7), however, this time assuming that $u_{ij}$ follows a logistic distribution. The parameter estimates from the resulting *Chamberlain's random effects ordered logit* ($CHOL$) model are then tested against the $FE$ parameters, again by a Hausman test. If this statistic indicated that there was no significant difference between the two estimates of $\beta$, i.e. that the linear correlation

[12] Ordered probit marginal effects are evaluated at the sample mean as well. The discrete nature of changes of dummies is taken into account when computing marginal effects.

[13] In general any other distribution for $u_{ij}$ (as well as $\epsilon_{ij}$ in Equation (1)) could be applied to compare the two modeling approaches, in particular the logistic distribution, a fact we will exploit later on.

assumption between $f_i$ and $\bar{X}_i$ was a sufficiently close approximation to the true correlation structure, this would massively increase our confidence in the marginal effects obtained from $CHOP$.

A further issue is the pooling of observations over time which, as argued above involves the extra assumptions of time-invariant parametric relations and family effects. To relax these assumptions to some extent, we re-estimate all models using only the last three waves of data, comprising the years 2002 to 2004. Furthermore, we estimate the following *hierarchical random effects ordered probit* model ($HI$):[14]

$$y^*_{ijt} = X'_{ijt}\beta + \bar{X}_i{}'\gamma + \delta_t + r_i + p_{ij} + u_{ijt}. \tag{8}$$

with subscript $t$ denoting the time index, $\delta_t$ are time dummies, and $p_{ij}$ is an individual-specific random effect satisfying $p_{ij}|X_i, r_i \sim N(0, \sigma^2_p)$. In this fashion we control for the additional individual-specific correlation over time which otherwise is absorbed in the family specific-random effect $r_i$. We again choose the normal distribution to be able to compute marginal effects. Finally, we test whether the consistency of $CHOP$ is called into question by the inclusion of $p_{ij}$.

# 4 Results

The results of the models assuming logistic error terms are reported in Table 3.[15] Whereas the parameter estimates of the two models taking account of *home education* are very close in magnitude and significance, substantially different results are obtained for the benchmark model. In particular, the impacts of the indicators of welfare and labor market concerns, individual labor income and educational attainment, respectively, appear to be overstated in magnitude in the $OL$ model compared to $FE$ and $CHOL$. Furthermore, we find differences concerning the significance and magnitude of the East Germany indicator[16] and the age-attitude profile, respectively. These findings are backed up by the results of Hausman tests reported in the first two rows of Table 4.[17] While consistency of $OL$ is rejected

[14] *Chamberlain's random effects ordered logit* as well as the *hierarchical random effects ordered probit* model are estimated using the *gllamm* command in Stata written by Rabe-Hesketh, Skrondal, and Pickles (2002, 2005).

[15] Due to missing variation in the original independent variable within the family, 493 observations from 79 families have to be discarded when estimating $FE$.

[16] One need to bear in mind that in the family component model *East* is only identified by individuals who move from East to West (or vice versa) over time or by siblings who live in both parts of Germany. This is only the case for 69 families or 447 person-year observations, respectively. Hence, we do not want to overemphasize this finding.

[17] All Hausman tests follow a $\chi^2$ distribution under the null hypothesis. The degrees of freedom are identical to the impacts on the latent outcome, i.e. 18 for all tests but the last which tests $HI$ against $CHOP$ and has 31 degrees of freedom.

against both alternatives at any reasonable significance level, we further find no systematic differences between the point estimates of $CHOL$ and $FE$. This latter result implies that the linear approximation of the correlation structure between $f_i$ and $X_i$ given in Equation (6) is appropriate for our data and underlines the robustness of our findings across identification strategies.

In Table 5 we show the parameter estimates of the three models assuming normal regression errors. The results of $OP$ and $CHOP$ are virtually identical to $OL$ and $CHOL$, yet differently scaled, a well-understood empirical regularity.[18] The last two columns report the results of the hierarchical model. Those are much closer to the $CHOP$ estimates than to the benchmark model. The significant and comparatively large point estimate of $\sigma_p^2$ suggests that a considerable amount of correlation is present for individuals over time. The somewhat reduced point estimate of the family-specific variance component compared to the $CHOP$ parameter further implies that this intra-person correlation is partly captured by $\sigma_r^2$ when $p_j$ is omitted from the regression. However, a Hausman test, depicted in the bottom right corner of Table 4, comparing $HI$ and $CHOP$ rejects the necessity of adding the individual-specific random effect to obtain consistent estimates at the 5 % significance level. Additionally, the consistency of $OP$ is clearly rejected compared to both alternatives.

Finally, depicted in Tables 6 and 7, we compare the marginal effects of $OP$, $CHOP$ and $HI$ for the two extreme answer categories.[19] The marginal effects of the benchmark model differ substantially from the suggested alternatives. Firstly, $OP$ supports the popular claim that citizens living in Eastern Germany are more likely to be *very concerned* and less likely to be *not concerned about immigration at all*, though at moderate levels. It is, however, rebutted by the family-effect models. With respect to age, the benchmark model indicates that the least worried part of the population are the very young. $CHOP$ and $HI$, however, suggest that worries decrease monotonically in age. The effects of equivalent household income, included as a proxy for social status, are almost identical in all models. With respect to gender as well as marital status and unemployment status the models exhibit similarly small and insignificant effects.

We now turn to the most emphasized impacts in the literature, educational attainment and labor income. The benchmark model seems to substantially exaggerate their importance in explaining variation in attitudes towards immigration.

[18]The sole exception is the significance of *Hauptschule* in the $OP$ specification which is insignificant in the $OL$ case.

[19]Results of the middle category are available upon request.

Whereas the income effects are very close to zero for the more complex models (and insignificant for $HI$) , $OP$ finds two to three times larger effects in line with the *first welfare-state scenario* predictions of Facchiniy and Mayda (2006). Furthermore, while sign and significance of the education indicators coincide in all models[20], $OP$ suggests significantly stronger impacts of the two highest educational classes, in particular on being *not concerned about immigration at all*. The impacts of having finished high school (*Abitur*) or completed a university degree are again roughly twice as large as the $CHOP$ effects and even three times as large as the $HI$ impacts.

In Tables 8 to 12 of the Appendix we depict our findings using the subsample from 2002 to 2004 only. In this way, we want to relax the assumption of time-invariance of parameters imposed on all models. Although point estimates (in particular for the age profiles) and significance vary to some extent, the latter probably partly induced by the loss of efficiency, the general pattern remains unchanged. In particular, all Hausman tests give rise to the same conclusions. Hence, we are confident that pooling six waves of data and assuming constant parametric relationships over this time horizon is adequate for the data at hand.

# 5 Conclusions

In this study we illustrate how the special structure of siblings data can be exploited to control for unobservable factors when analyzing the determinants of attitudes towards immigration. In particular, we argue that *home education*, the parental impact on attitude formation of their children via the transmission of their knowledge, their morals, and their *weltanschauung* is correlated with observable factors. This in turn renders estimates of benchmark models applied in the literature inconsistent.

Utilizing six waves of the *GSOEP* we find support for this concern. Hausman tests indicate that compared to two alternative identification strategies the typically used ordered logit and probit models yield inconsistent parameter estimates. Furthermore, we find no systematic difference between point estimates obtained from the alternative approaches, fixed effects ordered logit and Chamberlain's random effects ordered probit/logit, according to a Hausman test.

Finally, we assess how the omission of the family specific characteristics affects the estimation results in terms of the interpretation of the determinants. To this

[20]The exceptions are the significant marginal effects of the lowest education group in the $CHOP$ model.

end, we compare the marginal effects of the benchmark ordered probit model with the Chamberlain estimates. With respect to several regressors the benchmark model yields misleading results. Furthermore, impacts of variables supposed to proxy labor market and welfare concerns caused by immigration are strongly exaggerated compared to marginal effects obtained from the models controlling for unobservable effects such as *home education*.

To summarize, all our evidence suggests that the standard models employed in most of the empirical literature analyzing the determinants of attitudes towards immigration yield inconsistent estimates of their impacts. The results of existing studies should therefore be interpreted cautiously as long as they do not control for *home education*.

## References


BRENNER, J., AND M. FERTIG (2006): "Identifying the Determinants of Attitudes towards Immigrants - A Structural Cross-Country Analysis," *IZA Discussion Paper no. 2306.*

CHAMBERLAIN, G. (1980): "Analysis of Covariance with Qualitative Data," *Review of Economic Studies*, 47, 225–238.

——— (1984): "Panel Data," p. 1247–1318, in Handbook of Econometrics, Volume 2, ed. Z. Griliches and M.D. Intriligator. Amsterdam: North Holland.

DUSTMANN, C., AND I. PRESTON (2004a): "Racial and Economic Factors in Attitudes to Immigration," *CReAM Discussion Paper no. 01/04.*

——— (2004b): "Is Immigration Good or Bad for the Economy? Analysis of Attitudinal Responses," *CReAM Discussion Paper no. 06/04.*

FACCHINIY, G., AND A. M. MAYDA (2006): "Individual Attitudes towards Immigrants: Welfare-State Determinants Across Countries," *IZA Discussion Paper no.2127.*

FERRER-I-CARBONELL, A., AND P. FRIJTERS (2004): "How important is Methodology for the Estimates of the Determinants of Happiness?," *The Economic Journal*, 114, 641–659.

GREENE, W. H. (2003): "Econometric Analysis," Fifth Edition, New Jersey: Prentice Hall Press.

HAINMUELLER, J., AND M. J. HISCOX (2007): "Educated Preferences: Explaining Attitudes Toward Immigration in Europe," *International Organization*, 61(2), TBA.

HAISKEN-DENEW, J. P. (2005): "SOEP Menu: A Menu-Driven Stata/SE Interface for Accessing the German Socio-Economic Panel," (http://soepmenu.de).

JONES, A. M., AND S. SCHURER (2007): "How Does Heterogeneity Shape the Socioeconomic Gradient in Health Satisfaction?," *Ruhr Economic Papers no. 8.*

MAYDA, A. M. (2006): "Who Is Against Immigration? A Cross-Country Investigation of Individual Attitudes toward Immigrants," *Review of Economics and Statistics*, 88, 510–530.

MUNDLAK, Y. (1978): "On the Pooling of Time Series and Cross Section Data," *Econometrica*, 46, 69–85.

OECD (2007): "OECD Factbook 2007: Economic, Environmental and Social Statistics," Paris: OECD.

Rabe-Hesketh, S., A. Skrondal, and A. Pickles (2002): "Reliable estimation of generalized linear mixed models using adaptive quadrature," *The Stata Journal*, 2, 1–21.

——— (2005): "Maximum likelihood estimation of limited and discrete dependent variable models with nested random effects," *Journal of Econometrics*, 128, 301–323.

Scheve, K., and M. Slaughter (2001): "Labor Market Competition and Individual Preferences over Immigration Policy," *The Review of Economics and Statistics*, 83, 133–145.

SOPEMI (2004): "Trends in International Migration 2003 Edition," Paris: OECD.

Wooldridge, J. M. (2002): "Econometric Analysis of Cross Section and Panel Data," Cambridge: MIT Press.

# Tables and Figures

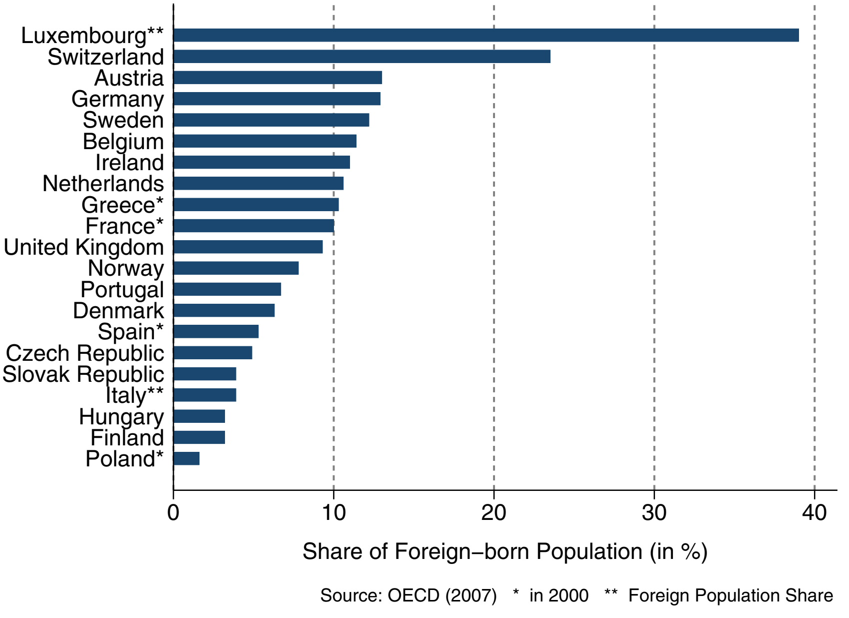


FIGURE 1 - SHARES OF FOREIGN-BORN POPULATION IN EUROPE (2004)

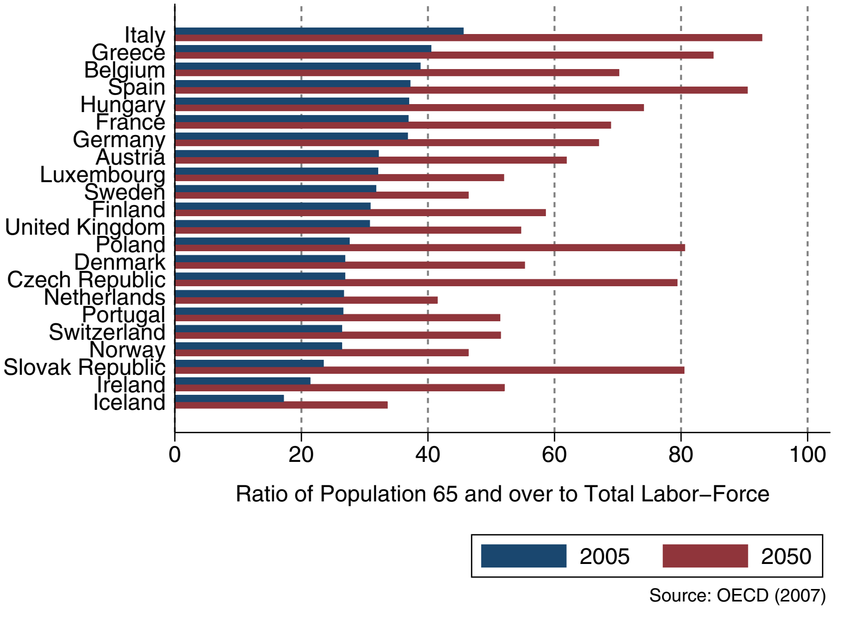


Figure 2 - Ratios of Population aged 65 and over to Total Labor -Force in Europe - 2005 compared to Estimates for 2050

Table 1.—Distribution of Observations by Family Size and Year

| | Family Members Observed per Year | | | | | | Total |
|---|---|---|---|---|---|---|---|
| Year | 1 | 2 | 3 | 4 | 5 | 6 | |
| 1999 | 166 | 840 | 156 | 52 | 10 | 6 | 1,230 |
| 2000 | 204 | 1,018 | 192 | 52 | 15 | 12 | 1,493 |
| 2001 | 233 | 984 | 171 | 48 | 20 | 6 | 1,462 |
| 2002 | 204 | 1,072 | 186 | 44 | 30 | - | 1,536 |
| 2003 | 206 | 1,054 | 204 | 36 | 30 | 6 | 1,536 |
| 2004 | 181 | 1,042 | 225 | 44 | 25 | 6 | 1,523 |
| Total | 1,194 | 6,010 | 1,134 | 276 | 130 | 36 | 8,780 |

TABLE 2.—SUMMARY STATISTICS

| Dependent Variable | Frequency | Percent |
|---|---|---|
| Worries about immigration | | |
| *Very Concerned* | 2,355 | 26.82 |
| *Somewhat Concerned* | 4,040 | 46.01 |
| *Not Concerned At All* | 2,385 | 27.16 |
| Regressors | Mean | Std. Dev. |
| East | 0.26 | 0.44 |
| Female | 0.46 | 0.50 |
| Age | 26.95 | 6.59 |
| Married | 0.23 | 0.42 |
| Unemployed | 0.05 | 0.21 |
| Household Equivalent Income (HEI) | 18,017 | 13,304 |
| Individual Labor Income (ILI) | 15,277 | 17,581 |
| Educational Attainment | | |
| *Hauptschule* (or less) | 0.24 | 0.43 |
| *Realschule* | 0.39 | 0.49 |
| *Abitur* | 0.25 | 0.43 |
| University Degree | 0.12 | 0.32 |
| Observations | 8,780 | |

Table 3.—Determinants of Worries about Immigration - Logistic Error Models

| Regressor | OL | FE | CHOL | |
|---|---|---|---|---|
| | | | $\hat{\beta}$ | $\hat{\gamma}$ |
| East | -0.2310** | -0.0822 | -0.0264 | -0.3822 |
| | (0.0488) | (0.2703) | (0.1684) | (0.2139) |
| Female | 0.0448 | 0.0436 | 0.0347 | -0.0217 |
| | (0.0427) | (0.1058) | (0.0687) | (0.1651) |
| Age Groups | | | | |
| 16 to 20 | 0.2178** | 0.0541 | 0.0763 | 0.3497 |
| | (0.0653) | (0.1028) | (0.0810) | (0.3105) |
| 26 to 30 | -0.0867 | 0.2379* | 0.1971* | -0.7459* |
| | (0.0570) | (0.1107) | (0.0819) | (0.3262) |
| 31 to 35 | -0.0041 | 0.4228* | 0.3538** | -0.2033 |
| | (0.0732) | (0.1749) | (0.1191) | (0.3406) |
| 36 to 55 | 0.1401 | 0.6839** | 0.6191** | -0.5151 |
| | (0.0837) | (0.2379) | (0.1539) | (0.3823) |
| Married | -0.0776 | -0.1002 | -0.0943 | 0.0507 |
| | (0.0584) | (0.1305) | (0.0833) | (0.2517) |
| Unemployed | 0.0032 | 0.0288 | -0.0774 | 0.3681 |
| | (0.0966) | (0.1331) | (0.1161) | (0.5244) |
| HEI/$1,000$ | 0.0054** | 0.0117* | 0.0092** | -0.0053 |
| | (0.0019) | (0.0048) | (0.0031) | (0.0052) |
| ILI/$1,000$ | -0.0091** | -0.0065 | -0.0054* | -0.0161** |
| | (0.0015) | (0.0035) | (0.0022) | (0.0062) |
| Educational Attainment | | | | |
| *Hauptschule* (or less) | -0.1102* | -0.1305 | -0.1909* | 0.1369 |
| | (0.0550) | (0.1432) | (0.0919) | (0.2046) |
| *Abitur* | 0.7745** | 0.4561** | 0.4828** | 0.8152** |
| | (0.0538) | (0.1463) | (0.0910) | (0.2027) |
| University Degree | 1.2761** | 0.7798** | 0.8275** | 1.4041** |
| | (0.0736) | (0.2065) | (0.1234) | (0.2838) |
| Family Variance $\hat{\sigma}_r^2$ | - | - | 1.8630** | |
| | | | (0.1278) | |
| Observations | 8,780 | 8,287 | 8,780 | |

Abbreviations refer to different estimation strategies: OL: Ordered Logit, FE: Fixed effects ordered logit, CHOL: Chamberlain's random effects ordered logit. ** significant at 1%, * significant at 5% level. Standard errors in parentheses (robust for $OL$ and $FE$). Year dummies included.

TABLE 4.—HAUSMAN TESTS

| | FE vs. OL | CHOL vs. OL | FE vs. CHOL |
|---|---|---|---|
| $\chi^2(18)$ | 151.39 | 95.82 | 5.18 |
| Prob$>\chi^2$ | 0.0000 | 0.0000 | 0.9986 |
| | CHOP vs. OP | HI vs. OP | HI vs. CHOP |
| $\chi^2(18)$ | 98.90 | 73.30 | 43.60[§] |
| Prob$>\chi^2$ | 0.0000 | 0.0000 | 0.0660 |

[§] This test has 31 degrees of freedom.

Abbreviations refer to different estimation strategies: OL: Ordered logit, FE: Fixed effects ordered logit, CHOL: Chamberlain's random effects ordered logit, OP: Ordered probit, CHOP: Chamberlain's random effects ordered probit, HI: Hierarchical random effects ordered probit.

Table 5.—Determinants of Worries about Immigration - Normal Error Models

| Regressor | OP | CHOP | | HI | |
|---|---|---|---|---|---|
| | | $\hat{\beta}$ | $\hat{\gamma}$ | $\hat{\beta}$ | $\hat{\gamma}$ |
| East | -0.1371** | -0.0012 | -0.2316 | 0.0201 | -0.2868 |
| | (0.0290) | (0.0980) | (0.1243) | (0.1371) | (0.1656) |
| Female | 0.0273 | 0.0180 | -0.0149 | 0.0348 | -0.0213 |
| | (0.0253) | (0.0367) | (0.0956) | (0.0719) | (0.1275) |
| Age Groups | | | | | |
| 16 to 20 | 0.1303** | 0.0446 | 0.1957 | 0.0542 | 0.2317 |
| | (0.0382) | (0.0469) | (0.1798) | (0.0586) | (0.2184) |
| 26 to 30 | -0.0519 | 0.1150* | -0.4425* | 0.1306* | -0.5783* |
| | (0.0342) | (0.0478) | (0.1890) | (0.0629) | (0.2308) |
| 31 to 35 | -0.0035 | 0.2065** | -0.1081 | 0.2594** | -0.1747 |
| | (0.0432) | (0.0692) | (0.1975) | (0.0978) | (0.2449) |
| 36 to 55 | 0.0814 | 0.3587** | -0.3019 | 0.3830** | -0.3176 |
| | (0.0496) | (0.0894) | (0.2219) | (0.1317) | (0.2777) |
| Married | -0.0493 | -0.0572 | 0.0332 | -0.0460 | -0.0053 |
| | (0.0347) | (0.0484) | (0.1459) | (0.0712) | (0.1808) |
| Unemployed | 0.0005 | -0.0540 | 0.2290 | -0.0280 | 0.2373 |
| | (0.0572) | (0.0678) | (0.3046) | (0.0772) | (0.3686) |
| HEI/1,000 | 0.0033** | 0.0054** | -0.0030 | 0.0054* | -0.0030 |
| | (0.0011) | (0.0018) | (0.0031) | (0.0022) | (0.0037) |
| ILI/1,000 | -0.0055** | -0.0032* | -0.0096** | -0.0028 | -0.0121** |
| | (0.0009) | (0.0013) | (0.0036) | (0.0018) | (0.0044) |
| Educational Attainment | | | | | |
| *Hauptschule* (or less) | -0.0597 | -0.1098* | 0.0856 | -0.0332 | 0.0161 |
| | (0.0324) | (0.0528) | (0.1183) | (0.0863) | (0.1534) |
| *Abitur* | 0.4624** | 0.2874** | 0.4736** | 0.2593** | 0.6713** |
| | (0.0318) | (0.0532) | (0.1176) | (0.0863) | (0.1535) |
| University Degree | 0.7638** | 0.4892** | 0.8208** | 0.3190** | 1.3342** |
| | (0.0438) | (0.0717) | (0.1642) | (0.1156) | (0.2133) |
| Family Variance $\hat{\sigma}_r^2$ | - | 0.6262** | | 0.5331** | |
| | | (0.0421) | | (.0640) | |
| Individual Variance $\hat{\sigma}_p^2$ | - | - | | 0.9148** | |
| | | | | (0.0670) | |

Abbreviations refer to different estimation strategies: OP: Ordered probit, CH: Chamberlain's random effects ordered probit, HI: Hierarchical random effects ordered probit. 8,780 Observations. ** significant at 1%, * significant at 5% level. Standard errors in parentheses (robust for OP). Year Dummies included.

Table 6.—Marginal Effects for 'Being very concerned about Immigration'

| Regressor | OP | CH | HI |
|---|---|---|---|
| East | 0.0452** | 0.0003 | -0.0041 |
| Female | -0.0088 | -0.0044 | -0.0070 |
| Age Groups | | | |
| 16 to 20 | -0.0409** | -0.0107 | -0.0109 |
| 26 to 30 | 0.0169 | -0.0275* | -0.0260* |
| 31 to 35 | 0.0011 | -0.0485** | -0.0506** |
| 36 to 55 | -0.0257 | -0.0815** | -0.0728** |
| Married | 0.0160 | 0.0140 | 0.0093 |
| Unemployed | -0.0002 | 0.0132 | 0.0057 |
| HEI/1,000 | -0.0011** | -0.0013** | -0.0011* |
| ILI/1,000 | 0.0018** | 0.0008* | 0.0006 |
| Educational Attainment | | | |
| *Hauptschule* (or less) | 0.0194 | 0.0270* | 0.0067 |
| *Abitur* | -0.1371** | -0.0674** | -0.0510** |
| University Degree | -0.1949** | -0.1080** | -0.0613** |

Abbreviations refer to different estimation strategies: OP: Ordered probit, CHOP: Chamberlain's random effects ordered Probit. 8,780 Observations. ** significant at 1%, * significant at 5% level. Year dummies included.

Table 7.—Marginal Effects for 'Being not concerned at all about Immigration'

| Regressor | OP | CH | HI |
|---|---|---|---|
| East | -0.0437** | -0.0003 | 0.0041 |
| Female | 0.0089 | 0.0044 | 0.0072 |
| Age Groups | | | |
| 16 to 20 | 0.0435** | 0.0110 | 0.0112 |
| 26 to 30 | -0.0167 | 0.0286* | 0.0273* |
| 31 to 35 | -0.0011 | 0.0521** | 0.0550** |
| 36 to 55 | 0.0270 | 0.0925** | 0.0826** |
| Married | -0.0159 | -0.0140 | -0.0094 |
| Unemployed | 0.0002 | -0.0131 | -0.0057 |
| HEI/1,000 | 0.0011** | 0.0013** | 0.0011* |
| ILI/1,000 | -0.0018** | -0.0008* | -0.0006 |
| Educational Attainment | | | |
| *Hauptschule* (or less) | -0.0192 | -0.0266* | -0.0068 |
| *Abitur* | 0.1599** | 0.0725** | 0.0546** |
| University Degree | 0.2810** | 0.1282** | 0.0684** |

Abbreviations refer to different estimation strategies: OP: Ordered probit, CHOP: Chamberlain's random effects ordered Probit. 8,780 Observations. ** significant at 1%, * significant at 5% level. Year dummies included.

## Appendix (not to be included in the paper)

Table 8.—Determinants of Worries about Immigration - Logistic Error Models

| Regressor | OL | FE | CHOL | |
|---|---|---|---|---|
| | | | $\hat{\beta}$ | $\hat{\gamma}$ |
| East | -0.1831** | -0.0042 | 0.0710 | -0.4390 |
| | (0.0678) | (0.3430) | (0.2375) | (0.2807) |
| Female | -0.0077 | -0.0868 | -0.0848 | 0.1353 |
| | (0.0591) | (0.1276) | (0.0905) | (0.1897) |
| Age Groups | | | | |
| 16 to 20 | 0.2629** | 0.1561 | 0.1481 | 0.1939 |
| | (0.0957) | (0.1553) | (0.1277) | (0.3247) |
| 26 to 30 | -0.0864 | 0.3630* | 0.3683** | -1.0196** |
| | (0.0785) | (0.1476) | (0.1213) | (0.2952) |
| 31 to 36 | -0.0590 | 0.1735 | 0.2131 | -0.1409 |
| | (0.1008) | (0.2396) | (0.1771) | (0.3302) |
| 36 to 55 | 0.0325 | 0.4349 | 0.4673* | -0.5584 |
| | (0.1078) | (0.2983) | (0.2233) | (0.3687) |
| Married | -0.0459 | 0.0445 | 0.0231 | -0.0418 |
| | (0.0812) | (0.1736) | (0.1257) | (0.2592) |
| Unemployed | 0.0011 | -0.0170 | -0.1050 | 0.4243 |
| | (0.1251) | (0.1857) | (0.1658) | (0.4905) |
| $HEI/1,000$ | 0.0039* | 0.0133* | 0.0103** | -0.0083 |
| | (0.0018) | (0.0058) | (0.0037) | (0.0056) |
| $ILI/1,000$ | -0.0077** | -0.0048 | -0.0037 | -0.0131* |
| | (0.0018) | (0.0038) | (0.0029) | (0.0061) |
| Educational Attainment | | | | |
| *Hauptschule* (or less) | -0.1024 | -0.2466 | -0.2551 | 0.1975 |
| | (0.0780) | (0.1855) | (0.1416) | (0.2439) |
| *Abitur* | 0.7534** | 0.3535 | 0.4173** | 0.8606** |
| | (0.0733) | (0.1825) | (0.1315) | (0.2335) |
| University Degree | 1.1666** | 0.6959** | 0.8461** | 1.0559** |
| | (0.0957) | (0.2470) | (0.1753) | (0.3049) |
| Family Variance $\hat{\sigma}_r^2$ | - | - | 1.9445** | |
| | | | (0.1664) | |
| Observations | 4,595 | 4,022 | 4,595 | |

Abbreviations refer to different estimation strategies: OL: Ordered Logit, FE: Fixed effects ordered logit, CHOL: Chamberlain's random effects ordered logit. ** significant at 1%, * significant at 5% level. Standard errors in parentheses (robust for $OL$ and $FE$). Year dummies included.

Table 9.—Hausman Tests

| | FE vs. OL | CHOL vs. OL | FE vs. CHOL |
|---|---|---|---|
| $\chi^2(15)$ | 103.46 | 75.14 | 2.98 |
| Prob>$\chi^2$ | 0.0000 | 0.0000 | 0.9996 |
| | CH vs. OP | HI vs. OP | HI vs. CH |
| $\chi^2(15)$ | 80.35 | 47.14 | 27.77[§] |
| Prob>$\chi^2$ | 0.0000 | 0.0000 | 0.4766 |

[§] This test has 28 degrees of freedom.

Abbreviations refer to different estimation strategies: OL: Ordered logit, FE: Fixed effects ordered logit, CHOL: Chamberlain's random effects ordered logit, OP: Ordered probit, CHOP: Chamberlain's random effects ordered probit, HI: Hierarchical random effects ordered probit.

Table 10.—Determinants of Worries about Immigration - Normal Error Models

| Regressor | OP | CHOP | | HI | |
|---|---|---|---|---|---|
| | | $\hat{\beta}$ | $\hat{\gamma}$ | $\hat{\beta}$ | $\hat{\gamma}$ |
| East | -0.1107** | 0.0450 | -0.2562 | -0.0531 | -0.2018 |
| | (0.0402) | (0.1370) | (0.1621) | (0.2197) | (0.2460) |
| Female | -0.0043 | -0.0515 | 0.0786 | -0.0515 | 0.0823 |
| | (0.0350) | (0.0521) | (0.1098) | (0.0936) | (0.1551) |
| Age Groups | | | | | |
| 16 to 20 | 0.1526** | 0.0826 | 0.1104 | 0.1105 | 0.1537 |
| | (0.0559) | (0.0737) | (0.1876) | (0.1013) | (0.2427) |
| 26 to 30 | -0.0491 | 0.2147** | -0.5942** | 0.2220* | -0.7207** |
| | (0.0470) | (0.0704) | (0.1712) | (0.0994) | (0.2243) |
| 31 to 35 | -0.0338 | 0.1224 | -0.0771 | 0.1428 | -0.1095 |
| | (0.0592) | (0.1024) | (0.1913) | (0.1505) | (0.2574) |
| 36 to 55 | 0.0171 | 0.2609* | -0.3161 | 0.2245 | -0.2725 |
| | (0.0639) | (0.1286) | (0.2137) | (0.1955) | (0.2944) |
| Married | -0.0278 | 0.0086 | -0.0151 | -0.0221 | 0.0137 |
| | (0.0479) | (0.0726) | (0.1500) | (0.1133) | (0.2035) |
| Unemployed | -0.0006 | -0.0719 | 0.2722 | -0.0438 | 0.3012 |
| | (0.0745) | (0.0962) | (0.2847) | (0.1155) | (0.3636) |
| HEI/1,000 | 0.0024* | 0.0061** | -0.0048 | 0.0078** | -0.0063 |
| | (0.0011) | (0.0022) | (0.0033) | (0.0027) | (0.0041) |
| ILI/1,000 | -0.0048** | -0.0022 | -0.0078* | -0.0011 | -0.0123** |
| | (0.0011) | (0.0017) | (0.0035) | (0.0025) | (0.0047) |
| Educational Attainment | | | | | |
| *Hauptschule* (or less) | -0.0568 | -0.1424 | 0.1080 | -0.1049 | 0.0510 |
| | (0.0458) | (0.0811) | (0.1409) | (0.1450) | (0.2057) |
| *Abitur* | 0.4478** | 0.2419** | 0.4995** | 0.3140* | 0.6453** |
| | (0.0434) | (0.0765) | (0.1354) | (0.1298) | (0.1933) |
| University Degree | 0.7004** | 0.4999** | 0.6163** | 0.6273** | 0.8227** |
| | (0.0571) | (0.1015) | (0.1765) | (0.1711) | (0.2523) |
| Family Variance $\hat{\sigma}_r^2$ | - | 0.6527** | | 0.6146** | |
| | | (0.0544) | | (0.0891) | |
| Individual Variance $\hat{\sigma}_p^2$ | - | - | | 1.1189** | |
| | | | | (0.1079) | |

Abbreviations refer to different estimation strategies: OP: Ordered probit, CH: Chamberlain's random effects ordered probit, HI: Hierarchical random effects ordered probit. 4,595 Observations. ** significant at 1%, * significant at 5% level. Standard errors in parentheses (robust for OP). Year Dummies included.

TABLE 11.—MARGINAL EFFECTS FOR 'BEING VERY CONCERNED ABOUT IMMIGRATION'

| Regressor | OP | CH | HI |
|---|---|---|---|
| East | 0.0353** | -0.0107 | 0.0099 |
| Female | 0.0013 | 0.0123 | 0.0096 |
| Age Groups | | | |
| 16 to 20 | -0.0458** | -0.0195 | -0.0202 |
| 26 to 30 | 0.0155 | -0.0496** | -0.0401* |
| 31 to 35 | 0.0107 | -0.0287 | -0.0260 |
| 36 to 55 | -0.0053 | -0.0594* | -0.0404 |
| Married | 0.0087 | -0.0021 | 0.0041 |
| Unemployed | 0.0002 | 0.0175 | 0.0082 |
| HEI/1,000 | -0.0008* | -0.0015** | -0.0015** |
| ILI/1,000 | 0.0015** | 0.0005 | 0.0002 |
| Educational Attainment | | | |
| *Hauptschule* (or less) | 0.0179 | 0.0347 | 0.0197 |
| *Abitur* | -0.1288** | -0.0561** | -0.0565* |
| University Degree | -0.1765** | -0.1075** | -0.1049** |

Abbreviations refer to different estimation strategies: OP: Ordered probit, CHOP: Chamberlain's random effects ordered Probit. 4,595 Observations. ** significant at 1%, * significant at 5% level. Year dummies included.

TABLE 12.—MARGINAL EFFECTS FOR 'BEING NOT CONCERNED AT ALL ABOUT IMMIGRATION'

| Regressor | OP | CH | HI |
|---|---|---|---|
| East | -0.0364** | 0.0115 | -0.0105 |
| Female | -0.0014 | -0.0131 | -0.0102 |
| Age Groups | | | |
| 16 to 20 | 0.0526** | 0.0213 | 0.0223 |
| 26 to 30 | -0.0163 | 0.0562** | 0.0451* |
| 31 to 35 | -0.0112 | 0.0318 | 0.0289 |
| 36 to 55 | 0.0058 | 0.0690* | 0.0458 |
| Married | -0.0093 | 0.0022 | -0.0044 |
| Unemployed | -0.0002 | -0.0181 | -0.0087 |
| HEI/1,000 | 0.0008* | 0.0016** | 0.0016** |
| ILI/1,000 | -0.0016** | -0.0006 | -0.0002 |
| Educational Attainment | | | |
| *Hauptschule* (or less) | -0.0188 | -0.0357 | -0.0207 |
| *Abitur* | 0.1578** | 0.0632** | 0.0640* |
| University Degree | 0.2595** | 0.1363** | 0.1332** |

Abbreviations refer to different estimation strategies: OP: Ordered probit, CHOP: Chamberlain's random effects ordered Probit. 4,595 Observations. ** significant at 1%, * significant at 5% level. Year dummies included.