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The Faculty of Economics, Business Administration and Information Technology of the University of Zurich hereby authorises the printing of this Doctoral Thesis, without thereby giving any opinion on the views contained therein.

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Contents

Chapter 1

Introduction

1.1 Microdata and Household Surveys

Microdata provide subjective and/or objective information on individual units that can be either persons, households, or firms. The common feature of all microdata is that the information is available for each unit and is non-aggregated. The collection of the data can be intentionally related to a specific research project or can avail of official statistics such as census data, or tax or health insurance records. Microdata tend to be observational data, in contrast to data gathered on the basis of an experiment. The information can be organized on either a continuous or a discrete measurement scale. Both of these features – the observational nature of the data and the type of measurement scale – require the application of specific methods when the data is used for empirical research. While the data sources, surveys, or administrative records call into question the random sampling assumption, the potential use of a discrete scale for measurement challenges the appropriateness of the linear model. The dimension of microdata can either be cross-sectional or longitudinal. Cross-sectional data consist of a sample of persons, households, or firms taken at a given point in time. Panel or longitudinal data consist of time series for each cross-sectional unit. If the cross-sectional dimension is large compared to the time dimension, then longitudinal data can be considered as microdata (Winkelmann and

Boes, 2006).

Microdata can be used to empirically test microeconomic models, to investigate the determinants of social phenomena, or to evaluate policy programs that have been implemented. In addition to cross-sectional data, longitudinal data can also be used to test life-course models. The main purpose is to determine a causal relationship for the population between a variable of interest and an outcome variable. This can be achieved using a linear regression model. To determine causality using a linear model, one crucial assumption must be met, namely that of the mean independence of the error term and the variables in the model. Other assumptions usually made are linearity in the parameters, no multicollinearity, homoscedasticity, and the randomness of the sample so as to permit inferences from the regression sample to the population (Wooldridge, 2003). In practice, the analysis of microdata with a linear model is not straightforward. First, the data may be a non-random sample of the population. A sample drawn from the labor force survey may include only observations within the labor force and the estimates would therefore be biased due to selection. A second concern in application is unobserved heterogeneity. Because we are only observing the data, we do not know all the information about individuals. Unobserved characteristics and attributes may be correlated with variables, and the assumption of mean independence may be violated, resulting in biased estimates. With longitudinal data where we observe each unit several times, the parameters can be consistently estimated, even in the presence of unobserved heterogeneity. A final problem with using the linear model concerns discrete outcome variables. If the outcome is binary, the estimated probabilities can be outside the unit interval. In the case of a multinomial or ordered outcome variable, the linear model cannot be applied. The expectation of the outcome given the control variables is not defined. Special regression models are available to overcome the violation of the linear regression model caused by the characteristics of microdata (see, for example, Winkelmann and Boes, 2006, or Wooldridge, 2002, for further details of the alternative models). The benefits of microdata and especially the collection of data in order to resolve specific research questions in the production of economic knowledge were already recognized in the 1960s (Juster, 1970).

Household surveys have gained some popularity in all economic research fields working on empirical questions. Household surveys are longitudinal data sets providing information on persons and households; they are sampled as a representative sample of the population. Information on family or personal background variables allows the researcher to examine the importance of background for a certain outcome or can also be used to study intergenerational transmission. Another field of use is the analysis of dynamic models related to changes over time or country of residence. Prominent examples of longitudinal household survey data are the Socio-Economic Panel for Germany, the Panel Study on Income Dynamics (PSID) and the National Longitudinal Survey for the U.S.A., the British Household Panel (BHPS) for the U.K., the Household, Income and Labour Dynamics Survey (HILDA) for Australia, the Survey of Labour and Income Dynamics (SLID) for Canada, and the Swiss Household Panel for Switzerland. In this thesis, all of the essays apply data from the German Socio-Economic Panel to research questions in the fields of education and health economics. The following section describes the German Socio-Economic Panel, and the chapter concludes with an outline of the thesis.

1.2 German Socio-Economic Panel

The idea for a German household survey was born in the 1960s when H. J. Krupp was a guest researcher at the University of Wisconsin, Madison. The survey was eventually launched with a project statement in 1981/82 as part of the project "Mikroanalytische Grundlagen der Gesellschaftspolitik" (Microanalytical Basis of Social Politics). The German Socio-Economic Panel (GSOEP) survey was first carried out in 1984 in the former West Germany. Following the reunification of Germany in 1989, eastern Germany was included in the survey for the first time in 1990. The GSOEP was distributed in 1984 to 5900 households, 12000 persons and 3900 children. A problem common to longitudinal household surveys is that of attrition. People may leave the sample because of death, moving abroad, or moving out of a household covered by the survey. In order to avoid a decrease in the sample size, the sample base was enlarged by means of six extensions carried out between 1990 and 2006. Another tactic used to maintain the GSOEP sample size is a follow-up strategy if someone leaves a household in the sample. Following a successful interview, respondents receive a small gift. A mix of interview types, where possible face-to-face, ensures a high degree of identification between the respondents and the interviewer and ultimately also the survey. As a result of these extensive maintenance measures, in 2005 the survey consisted of around 11500 households, 21000 persons and 4900 children. Up to now, the GSOEP has been widely used in research. At the end of 2006, 680 national and 560 international researchers had used data from the survey. The yearly research output of the SOEP Group increased from 8 articles in refereed journals, 3 SSCI articles, and 6 policy reports in 1996, to 11 journal articles, 5 SSCI articles, and 24 policy reports in 2005. To increase the attractiveness of the GSOEP for international comparative studies with the PSID, the BHPS, SLID, and HILDA, equivalent files with standardized measures are made available.

The field name of the survey, "Living in Germany", indicates the themes covered: household composition, labor and family biographies, employment, labor mobility, income histories, education, health, and personal satisfaction. In order to collect this information, the questions in the GSOEP are related to different dimensions of time. They include questions about an actual single point in time, single retrospective questions on certain events, retrospective life-event histories since the age of 15, monthly calendar information on income and labor market issues, questions concerning a period of time in the past, and questions concerning future prospects. The survey participants are asked to respond to different questionnaires. Each person older than age 17 compiles an individual questionnaire requesting personal information, while the head of household also answers an additional, household questionnaire. Young adults participating in the GSOEP answer a youth biography questionnaire regarding topics such as school performance, relationship with parents, and use of leisure time. Similarly, adults are asked to provide biographical data the first time they participate in the survey. This questionnaire includes questions about occupational history between the ages of 15 and 65, family and marital history, and questions concerning migration, where applicable (Frick, 2006).

Further information about the GSOEP can be found in Wagner et al. (2006), who describe the development of the survey, and in Burkhauser et al. (2001) and SOEP Group (2001), which provide a general overview. Frick (2006) presents an overview of the data collected and the content of each data file.

1.3 Outline

The remainder of the thesis is structured in three chapters, each concerned with a different research question and using a particular feature of the GSOEP. The three essays also apply different regression models, each of which is appropriate to the respective research question and suited to the outcome variable. In Chapter 2, we use an ordered probit model to account for the ordered outcome of the dependent variable. In Chapter 3, we use a logit model and sibling difference estimation, while in Chapter 4 we use a log-linear model. Each method is presented in more detail in the respective essay.

The first essay (joint work with R. Winkelmann) asks whether being raised in a single-mother household affects adolescents' choice of secondary school. The dependent variable is the school in which adolescents enroll at age 14 and can be either Hauptschule, Realschule, or Gymnasium. We use the long panel of the GSOEP to construct the family situation during childhood. We can identify for each observation whether a subject was living in a single-mother household or not. Thanks to the nature of the long-running panel we do not need to rely on retrospective information. This makes the information more reliable, which is an advantage of this type of data. Interpreting the regression results, we conclude that being raised in a single-mother household reduces respondents' likelihood of enrolling in a Gymnasium and that this can be explained by the lower income found in single-mother households. Chapter 3 examines the relationship between family background during childhood and the probability of being obese as a young adult. We use the labor biography data from the GSOEP to obtain information about the labor market participation of respondents' mothers as a possible determinant for obesity in later life. Then we use the respondent's birth date to synchronize the mother's labor history and the first 15 years of childhood. Finally, we sum up the years the mother spent in full-time work when her child was aged between 0 and 15. Our analysis shows that the more years a mother worked during a person's childhood, the higher that person's probability of being obese in young adulthood (between 18 and 25 years). We also use the GSOEP feature that allows us to link children's and parents' data. This makes it possible to identify siblings and to apply a sibling estimation approach. Using this estimation strategy, we can control for unobserved family heterogeneity. We find that the Body Mass Index difference between siblings can be explained by a difference in the mother's labor market participation.

In the final chapter, we are interested in the relationship between obesity and wages. Our hypothesis is that the obese earn lower wages either because they are discriminated or because they are less productive than their non-obese peers. Here we use the longitudinal structure of the GSOEP to collect information from the past. The idea is to overcome potential unobserved heterogeneity and reverse causality using lagged measures of obesity. Using this strategy, we are able to consistently estimate the parameters. We find that being obese reduces wages only for female workers in Germany and that it is more due to discrimination than to productivity differences. Since all three essays concern different research questions, concluding remarks and literature references are provided separately at the end of each chapter.

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Chapter 2

Family Background and School Choice

(This chapter has been published, with Rainer Winkelmann as co-author, under the title "Secondary School Track Selection of Single-Parent Children - Evidence from the German Socio-Economic Panel," *Schriften des Vereins für Socialpolitik*, 313, 39-54.)

2.1 Introduction

Equal opportunity education is one of the founding principles of any just society. However, a look at reality shows that the intergenerational transmission of educational attainment is high and that the ideal of a meritocracy remains quite elusive even in advanced economies. A child's education is highly correlated with the income and schooling of his or her parents. Opportunities may not be so equal after all.

For Germany, these linkages have been well investigated. In the German school system, only the first four years in primary school are shared by a cohort of pupils. After that, pupils are sorted into different tracks in a three-tiered secondary-school system. Only the highest secondary-school track – Gymnasium – allows direct entry to university. The other two tracks, Hauptschule and Realschule, mainly prepare pupils for entering the labor market through the apprenticeship system. The enrollment decision regarding choice of secondary school is typically made relatively early – at the age of 10 or 11. This distinguishes Germany from the U.K., where the decision for or against a university entrance qualification is made at the age of 16, and from the U.S.A., where a large majority of each cohort completes high school.

Children's secondary-school choices and subsequent educational attainment has been shown to be strongly influenced by parental education (Dustmann, 2004). Although parental education and household income are strongly correlated, controlling for both characteristics shows that parental education has a greater influence on children's educational attainment than household income (Schneider, 2004). A more detailed analysis of the income effects reveals that permanent income, measured between the ages of 6 and 13, is more important than transitory income at age 13 (Buechel et al., 2001). Splitting childhood up into early and late childhood periods shows that household income in late childhood is more important for secondary-school choice than household income in early childhood (Jenkins and Schluter, 2002).

Apart from these two main factors, other reasons for inequalities in children's educational opportunities have been identified in the literature. One such additional factor is the break-up of families. The analysis of family instability and children's educational opportunities in Germany has been given only scant attention so far.

Previous evidence for the U.S.A. and U.K. shows that growing up in a broken family has negative consequences for children's educational attainment. For the U.S.A., a comprehensive review of methods and findings concludes, among other things, that growing up in a single-parent or step-parent family, or experiencing parental separation or divorce, has a negative effect on educational attainment (Haveman and Wolfe, 1995). Moreover, high-school drop-out rates in the U.S.A. are higher for children living in single-parent households than for children living in intact, two-parent families. The negative effect of growing up in a single-parent household on high-school drop-out rates is stronger if the child experienced an episode of single parenthood during preschool age (Gransky, 1995). Living under disadvantaged family circumstances during early childhood has also been shown to adversely affect a child's educational attainment in the U.K. (Ermisch and Francesconi, 2001a, 2001b, 2002). Parental disruption during early childhood causes substantial reductions in children's later educational attainment (Fronstin et al., 2001). Evidence for the Netherlands confirms the negative effect of single motherhood on children's educational attainment (Dronkers, 1994).

In this paper, we extend the existing literature for Germany in three ways. First, we investigate the effects of single parenthood on children's educational opportunities, measured by the type of school attended at age 14. The second novelty is that we study whether this effect is childhood stage dependent, that is, if the effect of living in a single-parent family in early childhood is stronger than that of living in a single-parent family during late childhood. Third, we identify the channels through which single parenthood affects children's secondary-school choice. Is this an effect *per se* or are factors *related* to single parenthood – less income and less time – responsible for the children's lower educational attainments?

The data used in this study are drawn from the German Socio-Economic Panel (GSOEP). While the outcome variable – educational attainment at age 14 – is cross-sectional, the annual panel information is used for reconstructing the social and economic environment of the children during early and later childhood.

2.2 Theoretical and Empirical Framework

In order to model the relationship between educational attainment and single parenthood, we assume the existence of an education production function

$$edu = f(p, r) + u, \tag{2.1}$$

where edu is the child's educational attainment measured by the type of secondary school at age 14, p is the child's psychological well-being, r is the amount of household resources spent in the upbringing of the child, be it money or time, and u is an independently and identically distributed (i.i.d.) error term. We assume that education is an increasing function of household resources and psychological well-being, that is, $\partial edu/\partial r > 0$ and $\partial edu/\partial p > 0$.

In this framework, the effect of parental separation is mediated by the psychological and the material well-being variables. On the one hand, we can write

$$p = g(s, x), \tag{2.2}$$

where s is an indicator for single parenthood and x is a vector of socio-economic characteristics, excluding resource variables. We take it as evident that $\partial g/\partial s < 0$, based on a large literature that links a child's psychological well-being to the interaction between parents and their children and hence to the family structure (cf., e.g., Boggess, 1998; Coleman, 1988; Seltzer, 1994). On the other hand, single parenthood clearly also has an adverse effect on resources:

$$r = h(s, x), \tag{2.3}$$

with $\partial h/\partial s < 0$, since single parenthood reduces household income as well as the time available for the child if the single parent needs to start working – or increase working hours – in order to support the family. After substitution, the education production function can therefore be written as

$$edu = f(g(s, x), h(s, x)) + u = \tilde{f}(s, x) + u. \tag{2.4}$$

The reduced-form equation (2.4) reveals the crucial dependence of a child's educational attainment on single parenthood. Under the assumptions made above, we hypothesize a negative effect of separation on education, both because resources are diminished and because psychological well-being is compromised. However, based on (2.4), we cannot decompose the overall effect of separation $\partial \tilde{f}/\partial s$ into its two constituent parts. Therefore, in order to identify the relative contributions of the resources and psychological effects, respectively, we consider the alternative model:

$$edu = f(g(s, x), r) + u = \hat{f}(s, x, r) + u. \tag{2.5}$$

Since the resources effect is controlled for in this specification, $\partial\hat{f}/\partial s$ is now the pure psychological effect, and a comparison of $\partial\tilde{f}/\partial s$ and $\partial\hat{f}/\partial s$ gives us the relative importance of the two channels.

While the two equations (2.4) and (2.5) capture the essence of our empirical approach, there are two additional aspects that complicate the interpretation of these models. The first aspect is the issue of timing of events, while the second aspect refers to the selection problem and the potentially non-random assignment of separation. According to this hypothesis, the incidence of single parenthood does not arise randomly, rather it is systematically related to other family-specific factors that diminish educational outcomes.

We start with the first aspect. In order to address questions of dynamics such as "Does it matter whether separation occurred during early or late childhood?" we can generalize the static equations by conceptualizing the relevant psychological well-being p and resources r as accumulated stock variables. In this interpretation, p is the stock of psychological capital an adolescent is endowed with at time T. The accumulation process can be expressed as follows:

$$p = \int_0^T p(t)w_p(t)\mathrm{d}t = \int_0^T g(s(t), x)w_p(t)\mathrm{d}t$$

and similarly for r:

$$r = \int_0^T r(t)w_r(t)\mathrm{d}t = \int_0^T h(s(t), x)w_r(t)\mathrm{d}t$$

The relative importance of early and late childhood events is then captured by the two weighting functions $w_p(t)$ and $w_r(t)$.

With respect to the selection problem, we can distinguish between *selection on observables*, which arises if s and x are correlated, and *selection on unobservables*, which arises if s and u are correlated. In this paper, we control for selection on observables by including as many relevant variables in the regression as possible. Selection on unobservables, such as the "quality" of the partnership, that is, whether it is a happy or an unhappy one, will tend to cause an upward bias of the estimated effect of single motherhood on a child's educational attainment.

One possible approach for addressing selection on unobservables would be to compare the children's educational attainments before and after parental separation. In this spirit, Piketty (2003) shows for France that children of divorced parents already have lower educational attainment before their parents' separation. De Galdeano and Vuri (2004) show similar results for the U.S.A. Alternative methods require either the availability of an instrument (such as state-level variation in divorce laws, as in Gruber, 2005), or the availability of siblings' data in order to remove the family effect through differencing (see, e.g., Björklund and Sundström, 2002, and Ginther and Pollak, 2000). But in Germany there is neither regional variation in divorce law – and thus in the probability of single parenthood – nor are there sufficient siblings in the GSOEP data to allow any kind of reasonable analysis. With our data, therefore, we cannot satisfactorily address selection due to unobservables and it is possible that our estimates overstate the causal effect of single motherhood. However, if it turns out that no effect is found once we control for selection on observables, this whole issue can be safely ignored.

For the empirical implementation, we must first understand the hierarchical structure of the German school system. In Germany, compulsory school attendance begins at the age of 6 and ends at the age of 16. Primary school provides basic education, which is identical for all pupils. After four years of primary school, pupils continue their education in a secondary school. The secondary-school level is divided into three main tracks: lower-level secondary school (Hauptschule), intermediate-level secondary school (Realschule) and upper-level secondary school (Gymnasium). After Hauptschule, graduates often start a career as a blue-collar worker. At the higher level of Realschule, pupils are prepared for a white-collar track or have the possibility to enroll in schools for further education. Pupils from both Hauptschule and Realschule often start an apprenticeship after leaving school. Only graduates from a Gymnasium are entitled to enter university directly.

We therefore model educational attainment as a standard ordered probit model (see Greene, 1997, Ch. 19.8, for further details):

$$y^* = \eta + u, \quad u|\eta \sim Normal(0,1)$$

$$y = \begin{cases} 0 & \text{if } y^* \leq \alpha_1 & \text{"Hauptschule"} \\ 1 & \text{if } \alpha_1 < y^* \leq \alpha_2 & \text{"Realschule"} \\ 2 & \text{if } y^* > \alpha_2 & \text{"Gymnasium"}, \end{cases}$$

where y^* describes a latent variable dependent on a linear index function of the form $\eta = x'\beta$, and u is an i.i.d. error with a standard normal distribution. For the reasons described in our discussion above, we want to decompose the overall effect into a resources effect and a psychological effect, controlling for selection as well as we can with the data at hand. Therefore, we consider three alternative models that differ in the assumptions regarding the index function:

Model 1: $\eta = x_1'\beta_1$

Model 2: $\eta = x_1'\beta_1 + x_2'\beta_2$

Model 3: $\eta = x_1'\beta_1 + x_2'\beta_2 + x_3'\beta_3$

In Model 1, the vector x_1 includes indicators for living in a single-parent household, differentiated by when this status occurred. These are incidence indicators that are equal to 1 if any episode of single parenthood is recorded in the data, regardless of its length, and otherwise are equal to 0. We distinguish between two childhood periods – early childhood from age 0 to 6, and late childhood from age 7 to 14. A third indicator is equal to 1 if at least one single-parent episode was recorded during both childhood periods. These three dummy variables are therefore mutually exclusive, in the sense that a child lives in a single-parent household either in early, in late, or in both childhood periods.

The additional regressors in x_2 in Model 2 control for a potential selection or family effect. These include the mother's schooling, an indicator for a foreign household head, and the mother's age on the birth of the child. As mentioned above, we are only able to control for selection on observables. To control for the resources effect, we include additional regressors in x_3 in Model 3 with information on the family's average per-capita equivalent household income and the mother's labor supply separately for each child's early and late childhood.

The empirical reasoning is as follows. If we compare the educational attainment of children from intact and non-intact families, the difference gives us a combination of the psychological, selection, and resources effects (Model 1). In order to decompose the overall effect into its constituent parts, we need to include the vectors containing the controls for the selection and resources effects x_2 and x_3, respectively, in addition to the vector containing the single-parenthood indicator x_1. The coefficient of the latter then measures the psychological effect, in other words, the specific effect of single parenthood keeping resources constant and controlling for selection on observables. If the parameter related to the psychological effect becomes insignificant after controlling for selection and resources, whereas the resource effect is significant, we can conclude that single parenthood causally affects children's educational attainment, and that the reasons for this effect are diminished economic resources rather than adverse psychological effects.

2.3 Data

The data used for this study are drawn from the German Socio-Economic Panel (GSOEP), an annual panel survey of a random sample of households in Germany (see Burkhauser et al., 2001, and Haisken-DeNew and Frick, 2002, for further details). The survey was first conducted in the former West Germany in 1984, and since 1990 eastern German households have also been included. The GSOEP contains a wealth of information about the households and personal characteristics of its participants. Each participant aged older than 16 answers his or her own personal questionnaire. For younger children, basic information such as current schooling is provided by the household head in a separate questionnaire. This information is essential for the following analysis.

For each year between 1994 and 2001, records for 14-year-old children were extracted from the GSOEP and checked for school status. All children attending either a Hauptschule, Realschule, or Gymnasium were kept in the sample. The few children attending a so-called Gesamtschule (integrated school) (less than 8.5 percent) had to be dropped because the ordering of this school type relative to the other three dominant types is ambiguous. The age of 14 was chosen because the final decision about the secondary-school track has effectively been made by then.

These children live in households with either a western German or "foreign" household head. Observations from the former East Germany are excluded from the sample because the school system was different there. In order to analyze specific childhood period effects, childhood is divided into two periods – early childhood from 0 to 6 years before children enter school, and late childhood from 7 to 14 years after schooling has started.

For each wave, family structure, average household income, mother's labor force participation, mother's highest educational attainment, mother's age on birth of child, average number of members in household for both childhood periods, and birth order were determined and merged with the information from the children's sample. A full description of the variables is given in the Appendix. Family structure here means whether the child ever lived in a single-mother household as opposed to a two-parent household. Single-father households, while a theoretical possibility, are empirically irrelevant. Incidentally, we cannot be sure for two-parent families whether the partner is the biological father or not. Unfortunately, this potentially important distinction cannot be made on the basis of the GSOEP data. In future work, we plan to refine our measure of family structure by using the share of childhood years (or months) spent with one parent only, similarly, for instance, to Björklund and Sundström (2002).

Income is measured as an average over the respective childhood periods, that is, early childhood from age 0 to 6 or late childhood from age 7 to 14. The basis is the annual household income after taxes and government transfers provided in each wave, deflated to 1995, and on a per-capita equivalence scale where the following weights were used:

The first adult in a household has a weight of 1, each additional adult a weight of 0.7, and each child in the household a weight of 0.5 (Buhmann et al., 1988). The mother's labor force participation history is measured as average working hours per weekday, again averaged over the two childhood periods, and the mother's highest educational attainment can be "no degree," "compulsory school degree," "completed apprenticeship," or "tertiary education." It was not possible to include the highest educational degree of the father or partner; because of the large amount of missing data for this variable, the sample size would have been reduced too much to have been of any value.

Finally, the eight subsamples for the years 1994 to 2001 were pooled together. Controlling for missing values, the final data set consists of 704 children. Note that due to the panel structure of the GSOEP and its annual survey, we do not need to rely on retrospective information. The information about the constructed variables stems from the particular year rather than from retrospective answers. We consider this a great strength of our analysis in that it should allow us to gain new insights into the link between parental separation and educational attainment.

2.4 Results

A first impression of the data is offered by some basic descriptive statistics in Table 2.1.

– Table 2.1 here –

First of all, we notice that the incidence of single motherhood is relatively low. Of the 704 14-year-olds observed in our sample, only 94 (or 13.4 percent) have ever experienced an episode of single motherhood. Of those 94 cases, 18 concern single motherhood during early childhood only, the majority of 43 cases concern single motherhood only during late childhood, and the remaining 33 cases concern single motherhood during both early and late childhood.

The remainder of the table shows some bivariate associations between family situation during childhood and the main variables of interest, namely children's educational attainment and the main confounding variable – highest educational attainment of mother, income, and work. First, the type of school attended at age 14 seems indeed to vary as a function of family situation. Among those children who never experienced single motherhood, 37 percent attend a Hauptschule, 28 percent a Realschule and 35 percent a Gymnasium. On the other hand, children who had single-motherhood periods during both early and late childhood are more likely to attend a Hauptschule (49 percent) and less likely to attend a Gymnasium (21 percent). However, the standard errors are quite large so that neither the +11 percentage-point difference for Hauptschule nor the -14 percentage-point difference for Gymnasium are significantly different from zero at conventional levels of significance. If one compares the difference between single motherhood during early childhood and single motherhood during late childhood, one finds that the early childhood experience matters more. Indeed, there is hardly any difference in educational attainment between children who experience single motherhood during late childhood only and those who never experience it.

Next, we consider the association between family situation and the educational attainment of the mother. We know that the intergenerational transmission rates of education are quite high. In Table 2.1, we find no simple relationship between single motherhood and level of formal education. The educational attainment of mothers is measured not by school type – which makes sense when considering 14-year-olds – but by highest qualification, including compulsory school, and vocational or tertiary education. As these women went to school some decades ago, we also find women who left school without graduating at all, something that would be very rare today. Consider again the contrast between "never single" mothers and mothers with episodes of single parenting during both early and late childhood. We see that none of the mothers in the latter group left school without a qualification, whereas 10 percent of the mothers in the former group did (possibly a cohort effect). The university graduation rate is higher among the "never single" mothers, albeit at a very low level (6 percent as opposed to 3 percent – the difference is insignificant). All in all, the two groups of mothers are quite similar with respect to their schooling. Considering mothers who were single parents either during early or late childhood, the main differences are higher rates of university graduation and lower rates of vocational training. Again, these may be cohort effects. Taken together, it seems unlikely that the mother's education is responsible for the lower educational attainment of children who grew up with single mothers.

By contrast, the income effect points in the expected direction. Single motherhood tends to go along with lower disposable household income, and the effect is most pronounced for the "always" category. During early childhood, the income gap was DM 5200, that is, single mothers earned 26 percent less than the average equivalent income of the "intact family" comparison group. During late childhood, the income gap is slightly narrower at DM 4800, or 22 percent. Table 2.1 also contains a justification for our implicit assumption that income is a resources effect (single motherhood leads to lower income) rather than a selection effect (lower income families are more likely to separate). In particular, we find that the early childhood income of children where the separation occurred in late childhood is the highest among all categories and, in particular, also higher (although not statistically significantly so) than the early childhood income of children who never experienced single motherhood.

The working-hours effect also goes in the expected direction. Single mothers spend more time working than do mothers with a partner, and this translates into time that is not available for the child. The effect is most pronounced in late childhood, where single mothers spend on average about 4.8 hours working per day (the weighted average of 4.89 hours and 4.63 hours), whereas partnered mothers spend only 3 hours a day in market work.

The regression results are displayed in Table 2.2.

– Table 2.2 here –

The ordered dependent variable is the secondary-school track at age 14, with categories (in this order) Hauptschule, Realschule, and Gymnasium. A positive regression coefficient means that an increase in the corresponding regressors increases the probability of attending a Gymnasium and reduces the probability of attending a Hauptschule. The direction of the effect on the middle category is ambiguous – it depends on the other regression coefficients as well as on the values of the regressors. While it would be possible to compute the correct marginal probability effects for all three categories, for simplicity's sake we concentrate in our discussion on the signs (i.e., the direction of the change in the probability of attending a Gymnasium), the significance, and the relative magnitudes of the coefficients.

We estimated the three different models mentioned in Section 2. Apart from a set of time-dummy variables common to all three models, the first specification only includes three additional indicator variables describing family structure – single motherhood during early childhood only, single motherhood during late childhood only, and single motherhood during both early and late childhood. In the second specification, we added controls for selection on observables – education and age of the mother – and an indicator for foreign household head. The third specification includes the main resource variables, namely income and time spent working, plus family size, birth order, and the child's gender.

From a statistical point of view, Model (3) is the preferred model. A likelihood ratio test of Model (2) against Model (1) has a test statistic of 156 with p-value of 0, while a likelihood ratio test of Model (3) against Model (2) has a test statistic of 110, again with p-value of 0. Nevertheless, we will consider the two other models in turn first, mainly because the changes to the estimated single-motherhood coefficients across the three models can tell us something about the nature of the relationship between single motherhood and children's educational attainment.

Model (1) allows us to answer the first two questions raised in this paper. Is there an effect of single motherhood on children's educational attainment and, if so, is this effect childhood stage dependent? The regression results show that children who spent both childhood periods with a single mother are significantly (at the 5 percent level of significance) less likely to attend a Gymnasium than children from intact families. We can therefore answer the first research question with a "yes." But is this effect stage dependent? The point estimate for the "only early childhood" group is similar to that of the children who spent both childhood stages in single motherhood, although the standard error is now larger and the hypothesis of no effect cannot be rejected. Children with a single-motherhood episode only in later childhood are practically identical to children from intact families with respect to school track. The second research question therefore only has an inconclusive answer. Based on point estimates, the early childhood effect is larger.

As we move to Model (2), we see that there is indeed a very strong transmission of educational attainment from mother to child. The coefficient of "mother has a tertiary education" is very high. Statistically significant positive effects on the probability of attending a Gymnasium are also observed for the mother's age and for living in a non-foreign household. Interestingly, these selection variables cannot explain away the single-motherhood effect. On the contrary, the effect of having lived in a single-mother household during both childhood periods now has stronger negative effects on the probability of attending a Gymnasium, and the t-statistic increases to 2.4.

Now consider the results for Model (3), our preferred specification. The main additional variables of interest are the resource variables, that is, average household income and the mother's working hours specific to the two different childhood periods. This model answers our third research question: "What are the channels through which single motherhood affects children's educational attainment?" The effects are as expected – the probability of attending a Gymnasium depends positively on income. The effect is significant for both periods but, as already reported by Jenkins and Schluter (2002), it is stronger for the later period. On the other hand, a child's educational attainment is negatively affected by the mother's working hours during childhood. Here, the time pattern is the reverse of that for income, that is, working during early childhood matters more. The later childhood coefficient is lower by about one third and is only marginally significant (the p-value is 6.8 percent for a one-sided test). Finally, and importantly, all three coefficients of the family structure variables are very close to zero and statistically insignificant in this extended model. Therefore, we find as conjectured that the observed correlation between single motherhood and secondary-school track is mostly attributable to the resources effect. According to the evidence in our data, both selection and psychological effects play subordinate roles only.

2.5 Conclusions

This paper examines the effect of family structure – defined as single motherhood – on children's secondary-school track at the age of 14 in Germany, using data from the *German Socio-Economic Panel* and ordered probit regression models. An innovative aspect of the paper is the fact that these effects are investigated separately for two childhood periods, namely early childhood (between 0 and 6 years) and late childhood (between 7 and 14 years).

There are three main findings. First, the observed correlation between single motherhood and secondary-school track is mostly attributable to the resources effect. When controlling for household income and mother's labor force participation, the estimated coefficients for the variable "single mother" become insignificant for both childhood periods. The lower educational attainment of children growing up in single-mother households appears therefore to be due to the diminished resources associated with single motherhood. Second, there is no systematic evidence that resources during early childhood are more important than resources during later childhood. While this is the case for the mother's working hours, the opposite holds for income. Third, and finally, as shown by previous, related research, the single most important explanatory factor for secondary-school track choice is the mother's educational background.

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2.7 Tables

Table 2.1: Sample Means by Single Motherhood

Single motherhood	never	in early childhood	in late childhood	always
Hauptschule	0.37	0.50	0.37	0.49
	(0.020)	(0.121)	(0.075)	(0.088)
Realschule	0.28	0.22	0.30	0.30
	(0.018)	(0.101)	(0.071)	(0.082)
Gymnasium	0.35	0.28	0.33	0.21
	(0.019)	(0.109)	(0.072)	(0.072)
Mother's highest education				
None	0.10	0.11	0.05	0.00
	(0.012)	(0.076)	(0.033)	(0.000)
School	0.26	0.33	0.28	0.36
	(0.018)	(0.114)	(0.069)	(0.085)
Apprenticeship	0.58	0.44	0.49	0.61
	(0.020)	(0.121)	(0.077)	(0.086)
Tertiary	0.06	0.12	0.18	0.03
	(0.010)	(0.076)	(0.060)	(0.030)
Early childhood				
Income[1]	1.99	1.95	2.29	1.47
	(0.031)	(0.192)	(0.190)	(0.155)
Work[2]	2.13	4.28	3.32	2.82
	(0.111)	(0.749)	(0.397)	(0.527)
Late childhood				
Income[1]	2.23	2.17	2.14	1.75
	(0.037)	(0.192)	(0.106)	(0.118)
Work[2]	3.00	3.86	4.89	4.63
	(0.116)	(0.783)	(0.449)	(0.601)
N	610	18	43	33

Data from GSOEP, author's calculations.
Standard errors in parentheses.
1: Equivalence income per capita in DM 10000 (1995). 2: Average hours per weekday.

Table 2.2: Ordered Probit Regression Results

Variable	Model 1	Model 2	Model 3
Single mother, child's age 0 - 6	-0.313 (0.278)	-0.249 (0.298)	-0.125 (0.306)
Single mother, child's age 7 - 14	-0.028 (0.180)	-0.297 (0.191)	-0.150 (0.203)
Single mother, child's age 0 - 14	-0.415†† (0.208)	-0.511†† (0.213)	0.129 (0.254)
Mother's edu: School		0.706††† (0.192)	0.568††† (0.199)
Mother's edu: Apprenticeship		1.123††† (0.195)	0.717††† (0.205)
Mother's edu: Tertiary		2.336††† (0.296)	1.672††† (0.314)
Foreigner HH		-0.275†† (0.118)	-0.063 (0.124)
Mother's age at childbirth		0.036††† (0.009)	0.045††† (0.012)
Income,[1] child's age 0 - 6			0.452†† (0.214)
Income,[1] child's age 7 - 14			0.988††† (0.225)
Work,[2] child's age 0 - 6			-0.048†† (0.022)
Work,[2] child's age 7 - 14			-0.033 (0.022)
Log avg # of persons in HH child's age 0 - 6			0.275 (0.211)
Log avg # of persons in HH child's age 7 - 14			-0.071 (0.295)
Child is female			0.140 (0.093)
Birth order			-0.287††† (0.075)
Log likelihood	-760.9	-682.9	-628.3
χ^2	15.4	171.4	280.6

Notes: Standard errors in parentheses.

Significance levels: † 5 percent, †† 1 percent.

$N = 704$. All models include a time trend and two cut points.

[1] Equivalence income per capita in DM 10000 (1995).

[2] Average hours per working day.

2.8 Appendix

Table 2.3: Description of Variables

Variable	Definition
School	Secondary-school type when the child is 14 years old, either Hauptschule (0), Realschule (1), or Gymnasium (2).
Single mother	Dummy variable which equals 1 if the child ever lived in a single-mother household during the respective childhood period.
Log avg # of persons in household	Natural logarithm of the average number of persons living in the household during the respective childhood period.
Child is female	Dummy variable which equals 1 if the child is female and 0 otherwise.
Foreigner HH	Dummy variable which equals 1 if the child lives in a household with a foreign household head and 0 otherwise.
Mother's age at childbirth	Age of mother at child's birth.
Birth order	Constructed assigning the value 1 to the first-born child, value 2 to the second-born child, and so on.
Mother's highest education	Highest educational qualification achieved by the mother: No qualification (reference category), a school qualification, completed an apprenticeship, completed tertiary education.
Income	Equivalence income per capita after taxes and government transfers in DM 10000 deflated to 1995 using the annual average CPI published by the Federal Statistical Office, Germany. The first adult in a family is weighted by 1, each additional adult by 0.7, and each child by 0.5.
Work	Mother's average working hours per working day during the respective childhood period.

Chapter 3

Female Labor Supply and Obesity

(Another version of this chapter has been published under the title ”I’m not fat, just too short for my weight – Family Child Care and Obesity in Germany,” *SOI Discussion Paper*, 0707.)

3.1 Introduction

> Overweight and obesity may not be infectious diseases, but they have reached epidemic proportions in the United States. ... Approximately 300,000 deaths a year in this country are currently associated with overweight and obesity. Left unabated, overweight and obesity may soon cause as much preventable disease and death as cigarette smoking. (*D. Satcher, M.D., Ph.D., U.S. Surgeon General 1998-2002*)

The above quotation from former U.S. Surgeon General David Satcher documents the importance and tragedy of overweight and obesity. In the U.S.A., the share of obesity in the population increased from 15 percent in the late 1970s, to 23 percent in the period 1988 to 1994, and to 27 percent in 1999 (U.S. Department of Health and Human Services, 2001). The obesity epidemic is not only restricted to the U.S.A. According to the World Health Organization (WHO, 2000), the prevalence of obese people has grown worldwide.

– Table 3.1 here –

Table 3.1 shows obesity trends for some selected countries. Most of the countries show dramatic increases in obesity for men and women. Only Canada, the Netherlands, and Japan report small decreases in the shares of obese women in the years observed. Another striking observation is the sharp difference in obesity across countries.

The increase in obesity is worrisome because obesity is associated with negative health and economic consequences. Obese people have a higher mortality risk from coronary heart diseases and higher morbidity risks from chronic diseases such as diabetes mellitus, hypertension, several cancer types, musculoskeletal disorder, sleep apnea, and gallbladder disease (Finkelstein et al., 2004; Pi-Sunyer, 1993). The higher risk of chronic diseases and the required medical treatment increase personal and public health costs.

If the increase in obesity is to be slowed down, then first the reasons behind its rise and their respective importance must be identified. If the determinants of obesity are not known, then policy reform cannot be fruitful. Unfortunately, obesity is caused by multiple determinants, including genetic, cultural, socio-economic, and behavioral factors.

A factor behind the increase in obesity over the last two decades that can be defined as cultural, socio-economic and behavioral in nature may be a change in family structures. On the one hand, culture and behavior is lived and experienced within the family and is transmitted from one generation to the next; on the other, family structure influences each family member's socio-economic background. The importance of family background for children's development and later life achievements is a field that has been the subject of extensive research. It is well documented that growing up in a disadvantaged family has significant negative effects on children's later life outcomes.

One aspect of the change in family structure seen in recent decades is the increase in mothers' working hours (Merz, 2006). The increase in female labor supply in traditional families – with consequential reduced possibilities for child care – raises the question of adverse effects on children's later life outcomes. This paper answers the question as to whether an increase in mothers' working hours has an effect on young adults' probability of being obese.

The basic idea is that different amounts of time dedicated by mothers to gainful employment result in different potential hours of child care. Less child-care time is assumed to lead to a higher probability of being obese as a young adult. To answer this question, we partly replicate the study of Anderson et al. (2003) and adopt it to German data. The authors show for the U.S.A that the more hours a mother works per week over a child's life, the more likely the child is to be obese. The more hours a mother works a day, the less time she has for child care, cooking, and organizing leisure activities, and in general for providing a day-to-day routine for her child. This in turn may lead to higher probabilities of being obese. Furthermore, the data show that this negative effect is stronger in families with a more solid socio-economic background. Mothers with a weaker socio-economic background may not provide healthy food or opportunities for active play time to their children because of the insecure neighborhood they live in. In this case, the time constraints imposed by employment have no effect on the child's probability of being obese. Mothers with a strong socio-economic background may provide their children with healthy food or active play time given their better financial possibilities and the fact that they live in more secure neighborhoods (Anderson et al., 2003). Due to data limitations we were not able to replicate this interesting result for Germany.

The working hypothesis in this paper is that the absence of the mother while she is at work reduces child-care time in childhood and increases the probability of being obese as a child and subsequently also as a young adult. To identify this effect, we use only two-parent families, based on the fact that in recent years more married women have worked. In families where the mother works, potential supervision time is reduced compared to families where the mother does not work. Less parental supervision may lead to obesity through a lack of activity which may be caused by two factors. First, through a direct impact in childhood in the form of less sport and more high-calorie food; and, second, the child may adopt a more sedentary lifestyle and be less physically active as a young adult and therefore be more likely to be obese. The following section presents selected related literature and findings. We explain the empirical approach in greater detail in Section 3. The analysis is based on a sample drawn from the German Socio-Economic Panel (GSOEP) and is restricted to young adults who were raised for their entire childhood in a two-parent family. The data, selected sample, and variables used are presented in Section 4. We find that potentially reduced supervision time by the mother, measured as her absence due to employment, increases the probability of her child being obese as a young adult. Unfortunately, because of a lack of data, it is not possible to control for other forms of child care such as external child-care facilities, or a nanny or other family member looking after the child. Section 5 presents a comprehensive discussion of the results. We believe that this finding is important because it shows, first, the relevance of child care and, second, because it may stimulate further research into the causes of the rise in obesity.

3.2 Obesity

In this section, the prevalence and development of obesity, its consequences at both the personal and social level, and its potential determinants are presented on the basis of an overview of studies conducted on the issue.

As already noted in the introduction (see table 3.1), the prevalence of obese people has increased worldwide, and Germany is no exception. Between 1985 and 2002, moderate obesity (Body Mass Index $\geq$ 30) increased from 16.2 to 22.5 percent for German men and from 16.2 to 23.5 percent for German women. The increase in pronounced obesity (BMI $\geq$ 35) increased over the same period from 1.5 to 5.2 percent for German men and from 4.5 to 7.5 percent for German women (Helmert and Strube, 2004). Toschke et al. (2005), using data on 19-year-old Germans obtained during their medical examinations for military service, show that obesity increased between 1989 and 1998 from 3.4 to 5.7 percent. They comment that the prevalence of obesity is inversely related to educational level, but that the increase is unrelated to education.

Obese people have higher medical costs. Estimates for Germany show that the expenditure of obese people on in- and outpatient health care is 36 percent higher than for people of normal weight. Moreover, obesity-related health costs account for 4 percent of total health-care expenditure in Germany (Schneider, 1996; Sturm, 2002). Estimates for the U.S.A. show that total obesity-related public health costs account for around 6 percent of total medical expenditure (Finkelstein et al., 2004). Moreover, besides having higher health risks and costs, obese people are also discriminated in the labor market.

On top of higher individual medical costs, the obese also have to contend with lower individual labor market outcomes. U.S. studies on the return on investments in appearance-related human capital reveal lower earnings for the obese. A body-weight difference of 65 pounds (29 kg) is equivalent to a wage effect of roughly 1.5 years of education or three years of work experience (Cawley, 2004). A study by Hamermesh and Biddle (1994) shows an earnings penalty of 5 to 10 percent for plain people and a beauty premium of between 4 and 5 percent for good-looking people. Using a sample of persons aged 23 to 31, Averett and Korenman (1996) find – among other results – robust evidence of labor market discrimination against obese women. A comparison of the U.S.A. and Germany reveals that only U.S. women have a BMI penalty on labor earnings (Cawley et al., 2005). A comparison of nine European countries shows a reduction in earnings of 3.3 percent and 1.9 percent for men and women, respectively, for a BMI increase of 10 percent. This effect is stronger in southern European than in northern European countries for cultural and labor market reasons (Brunello and D'Hombres, 2007). Obese people generally have a low educational status, low occupational status, and low household incomes (Helmert and Strube, 2004).

What can explain the drastic increase in obesity over the last two decades? In the Introduction we mentioned genetic, cultural, socio-economic, and behavioral factors as possible reasons for an increase in obesity. It is certainly not possible for human beings' underlying genetic disposition to have changed to such an extent in just 20 years as to explain the increase in obesity on its own. Genetic disposition may favor or hinder the occurrence of obesity in different persons with different lifestyles and different environmental influences, but no more than that. Therefore, the increase over the last two decades must be due to structural and behavioral changes in people's lives (Rössner, 1998).

The demographic trend towards longer-living populations could, on the other hand, be responsible on its own for the increase in obesity. The rise in average BMI and in obesity could be due to the higher share of old people in the population, given that BMI increases naturally with age. Another source of increase is technological change. Technological advances lead to the substitution of physically strenuous work by sedentary work, which in turn reduces energy expenditure. Nowadays people pay for the privilege of engaging in physical activity in the form of gym fees or forgone leisure time. In the past, jobs were physically more demanding and people were paid for burning calories at work. Thus, obesity can be avoided when the benefits of not being obese are greater than the costs of the behavioral change associated with combating obesity (Philipson and Posner, 2003). Lakdawalla and Philipson (2002) support the technological change hypothesis, also looking at the question of technological change in agriculture. Agricultural innovations lower food prices and the costs of energy intake. Together with more sedentary jobs, this may explain the long-run growth in body weight. The increasing division of labor in food preparation reduces the time price of food. Centralized food preparation allows rapid consumption (microwave meals, preprocessed food) and increases the quantity of consumed meals (Cutler et al., 2003). The transformation of the urban structure is another possible explanation for the increase in obesity. More homogeneous districts make it almost impossible to find grocery stores within walking distance compared to mixed-used neighborhoods. The reduction in walking time in exclusive residential neighborhoods has a significant positive effect on the likelihood of being obese (Ewing et al., 2003). Mela (2001) shows that food choice is important for the probability of being obese. Differences in food likes and dislikes develop during the lifetime on the basis of food experiences and learned eating habits. Overweight and obese individuals show a tendency to favor energy-dense food, which contributes to the development and maintenance of their physical condition.

The balance between individual consumption preferences today and concerns about health tomorrow is another explanation for obesity. Weight control requires forgoing current consumption and making investments in physical activity in the interests of future health. The higher valuation of consumption today over health tomorrow leads therefore to weight gain (Komlos et al., 2004).

Another factor explaining the rise in obesity could be family structure. For the U.S.A., studies show that being raised in non-intact families is associated with above-average levels of emotional, behavioral, and academic problems, and with lower self-rated health (Gorman et al., 2006; Kovar, 1991). Family structure can limit economic and social resources, such as parents' availability to spend time with their children – for instance, supervising their homework – or their possibilities for spending money on their children's needs. Time spent with children has positive educational and social effects (Schneider et al., 2005). An example of economic constraints is shown by Mahler and Winkelmann (2006), who present evidence that children raised in single-parent households have lower educational attainments than children raised in intact families. In traditional families, defined as families with two biological parents where the father works and the mother stays at home, child care is mostly the job of the mother and is available 24 hours a day. In recent years, this traditional family structure has been challenged by other types of families, such as single women or divorced women living alone with their child, or other family arrangements such as apartment-sharing communities or patchwork families. The biggest change has taken place in traditional families, where more and more married women have started working. The share of working married women aged between 25 and 45 increased from just over 40 percent in 1970 to almost 70 percent in 2000, with a steep rise occurring in the mid-1980s. The increase is highest for wives with young children, and the type of employment is more likely to be in part-time than full-time work (Merz, 2006). In these families, the time spent by the mother on child care is clearly reduced, and child-care time is reduced in general if no other person takes care of the child when the mother is working. This increase in female labor supply is also an answer to demographic challenges such as the need for more high-skilled workers.

3.3 Empirical Model

A person's weight is mostly determined by diet, physical activity, and – to some degree – genetic disposition. To visualize the interaction between these factors, think of a weighing scales. One side of the scales represents a person's energy intake and the other side that same person's energy expenditure. When the person eats, then the energy-intake side is filled up and becomes heavier than the empty energy-expenditure side. As time goes by, the body uses the stored energy and the balance returns to the initial equilibrium. If a person's energy intake is higher than his/her energy expenditure, then there is excess weight on the energy-intake side, the energy balance becomes positive, and the excess energy is stored in the body as fat. When the energy balance of a person is positive over a lengthy period of time, then the stored energy remains in the body and the person gains weight. If the ratio of body weight to body height squared (kg/m^2) – the so-called BMI – is now ≥ 30, then that person is considered obese (WHO, 2000).

In childhood, physical activity and diet depend mostly on parental decisions. In the above weighing-scales model, a mother's absence from home may influence a child's energy balance through a related lack of physical activity. This effect can influence child's probability of being obese in two ways. The first is a short-term effect (during childhood), while the second can be seen more as a long-term effect (transmission of behavior). In the short term, the absence of the mother affects both the child's energy intake and his/her energy expenditure. In the absence of the mother, the child may watch television (Andersen et al., 1998; Proctor et al., 2003) or may be unable to play sport because the nearest sports facility is too far away to reach independently. Another reason may be that the neighborhood is not suitable for unsupervised outdoor play. In these cases, when a mother is working, her child must stay at home. This decreases energy expenditure because of the child's low level of physical activity. To use our picture of the weighing scales, given a constant energy intake, the pointer moves toward energy storage because the energy cannot be burned. Again on the energy-intake side, the mother may return tired from work and have little time or desire to prepare proper cooked meals. The alternative may be fast food or preprocessed meals heated up in the microwave. Both substitutes are more energy dense than properly cooked meals and the energy intake is therefore higher. Again, the pointer on the weighing scales moves toward energy storage. These effects taken together increase the probability of a child being overweight or obese in childhood (Anderson et al., 2003), and these children are also at higher risk of being obese as adults (Whitaker et al., 1997; Wright et al., 2001).

The long-term aspect of the model is that the child learns and adopts a behavioral pattern of eating habits and physical activities. On the one hand, a parent's sedentary lifestyle may be transmitted to young adults who did not experience a more active childhood. On the other hand, a young adult may stick to preprocessed or fast food because of a lack of knowledge of how to cook proper meals.

Energy intake and expenditure, and therefore a person's BMI and probability of being obese, $P(O)$, depend on that person's childhood family background, CFB, and on socio-demographic factors, X:

$$BMI = f(CFB, X)$$
$$P(O) = f(CFB, X).$$

The controls can be grouped into two categories. The first group includes variables related to a person's childhood and are summarized in the vector CFB. These variables control for the living area, whether the person grew up in an urban area, if the person lived as child in the former GDR, and for parental labor supply during childhood. They also control for potential differences in the labor supply, availability of child-care facilities, and parental time for child care. The availability of child-care facilities, especially in eastern Germany, may compensate for a mother's absence. A working mother is a proxy for potentially reduced child care if no other person or institution is available to compensate for the absence. If two families are compared, and in one family the mother is working and in the other she is not, then this variable should measure the effect of reduced child care. This vector also includes information about childhood family living conditions. We control for parental education as a proxy for childhood household income and for parental BMI to control for genetic disposition and family lifestyle. A higher BMI may indicate a more sedentary lifestyle. We also proxy the quality of family life with a dummy indicating whether that person had conflict as a 15-year-old with his father or mother. The second group of controls concerns actual (as a young adult) personal characteristics, such as age and gender, and is summarized in the vector X.

For the econometric analysis of the binary dependent variable obesity, we use a standard logit model (Wooldridge, 2003). The probability of being obese is represented in the latent function:

$$O^* = \beta_0 + \beta_1 CFB + \beta_2 X + u,$$

where CFB includes childhood family background controls, X is a vector of socio-demographic variables, and u is a standard logistic distributed error term. Obesity is equal to 1 if the latent variable O^* is greater than 0 and otherwise is equal to 0:

$$O = \begin{cases} 1 & \text{if } O^* > 0 \quad \text{"obese"} \\ 0 & \text{if } O^* \leq 0 \quad \text{"otherwise"} \end{cases}$$

The ordinary least squares (OLS) regression model for young adults' BMI is specified as follows:

$$BMI = \alpha_0 + \alpha_1 CFB + \alpha_2 X + v,$$

where CFB and X represent the same variables as in the latent obesity function and v is a standard error term.

In the pooled sample, an observation may appear in both years. Ignoring this would lead to biased standard errors due to the correlation of the two observations. For this reason, the standard errors are corrected for this within-group correlation.

Both specifications may suffer from unobserved family heterogeneity. Unobserved factors such as parental involvement or the quality of the time spent with the children may be correlated with parental schooling. When more highly educated parents spend time with their children, then this time may be more productive than the time spent with children by less well educated parents. This correlation leads to biased estimators. Two well-known ways to deal with unobserved heterogeneity – instrumental variables estimation and fixed effects models – are not appropriate here. For example, a plausible instrument is not available for the former method. A possible instrument might be the average female labor supply in the same city or federal state and the age or age group for the actual labor supply of the mother. This variable is certainly correlated with the actual labor supply of the mother and is probably uncorrelated with potential unobserved heterogeneity. But the information required is either not available or difficult to come by. A fixed effects approach would erase all the constant information regarding a person's childhood and would delete the variables of main interest in this paper. This can be avoided using a sibling setup. If parental behavior is independent of the characteristics of the individual children, then omitted family effects can be captured in a family-specific error term ω_j. The BMI of siblings can then be expressed as

$$BMI_{1j} = \alpha_0 + \alpha_1 CFB_{1j} + \alpha_2 X_{1j} + \omega_j + \epsilon_{1j} \tag{3.1}$$

$$BMI_{2j} = \alpha_0 + \alpha_1 CFB_{2j} + \alpha_2 X_{2j} + \omega_j + \epsilon_{2j}, \tag{3.2}$$

where BMI_{ij} is the BMI for child i in family j, CFB_{ij} is a vector including childhood family background controls, X_{ij} is a vector including socio-demographic control variables, ω_j is a family-specific error term, and ϵ_{ij} is a standard error term, assumed to be orthogonal to CFB_{ij}, X_{ij} and ω_j. Estimates of Equations (3.1) and (3.2) are biased when the family-specific error term, ω_j, correlates with CFB_{ij} or X_{ij}, which is very likely. For example, family lifestyle may be correlated with parental schooling.

Taking the difference between Equations (3.1) and (3.2) eliminates the family-specific error term ω_j and leaves the reduced form

$$\Delta BMI_j = \lambda_1 \Delta CFB_j + \lambda_2 \Delta X_j + \xi_j,$$

where $\Delta BMI_j = (BMI_{1j} - BMI_{2j})$ is the BMI of the older sibling minus the BMI of the younger sibling. Analogously, $\Delta CFB_j = (CFB_{1j} - CFB_{2j})$ and $\Delta X_j = (X_{1j} - X_{2j})$ are the differences between the family background and socio-demographic control variables of the siblings, and $\xi_j = (\epsilon_{1j} - \epsilon_{2j})$ is a standard error term.

The idea of the sibling estimator is to eliminate family-specific unobserved heterogeneity and therefore to control for endogeneity by using two children living in the same family. Taking the difference between the variables of the two siblings eliminates the unobserved family heterogeneity ω_j from the regression equation. If the mother's labor force participation now differs from one sibling to another, then the difference in labor force participation can be used to estimate the effect of the mother's labor supply on the BMI difference of the siblings.

Some caveats must be mentioned in regard to the sibling estimator. First, we consider unobserved family heterogeneity. The environment (outside stimuli) may change from one sibling to the next. The father may become unemployed or the family structure may change. To reduce this problem and to ensure as stable a family environment as possible, we focus only on families where the parents have been married for at least 15 years.

The second caveat is the difference between the observable variables of siblings who are close in age. Think of twins as the extreme example – the family environment does not vary between the two. The closer the distance between siblings, the smaller will be the variation in the variables.

3.4 Data

The data for this analysis are drawn from the German Socio-Economic Panel (GSOEP). The information about the actual demographic life situation and body height and weight of the respondents stems from the 2002 and 2004 surveys, whereas for the information about the childhood-specific life situation and the socio-economic background, the biography files are used (see Haisken-DeNew and Frick, 2002, and SOEP Group, 2001, for further details). We transformed the information from the spell data into variables measuring the duration of the full-time or part-time work of both parents. In Germany everything less than 80 percent work is defined as part-time work. For each observation, we constructed a time window of 16 years, when the young adult was between 0 and 15 years old, and matched the beginning of this window – that is, the young adult's birth year – to the respective year in the parental job trajectory. This procedure allows us to count the years of the parents' full- and part-time labor supply during the young adult's childhood. The other variables are taken directly from the respective data files. In the Appendix, a full description of the variables used for the analysis is given for the full sample and the sibling sample.

As outlined above, we only kept observations about respondents who spent their entire childhood, from 0 to 15 years of age, with both biological parents. Moreover, we restricted the sample to respondents in the age range 18 to 25, which we define as young adulthood. The two files for 2002 and 2004 were then pooled and merged with the respective childhood information. Finally, observations with missing values in one of the variables were dropped. The final sample consists of 1641 observations, where for 519 observations information is available for both years, and for 603 observations information is either available for 2002 or for 2004. A total of 47 of the 1641 observations, or around 3 percent of the sample, are obese. This is slightly lower than the share given in the official statistics. According to the official data, 3.7 percent of the people in this age range are obese (Statistisches Bundesamt, 2005, author's calculations).

In the case of the sibling sample, the age was not restricted to 25 with a view to increasing the size of the sample. When a family had more than two children, we only included the two youngest siblings. The sample has 818 observations, 33 of whom are obese. The sample includes not only same-gender siblings, but also mixed siblings, again with a view to increasing the sample size. Around 49 percent are same-gender and around 51 percent are mixed-gender siblings.

Table 3.2 shows the means of the parental labor supply variables. The upper panel shows the means for the full sample, while the lower panel shows the means for the sibling sample.

– Table 3.2 here –

The data show that 72 percent of the mothers of obese young adults worked at least once during their child's childhood, compared to only 61 percent in the non-obese sample. Moreover, the mothers of obese young adults worked an average of 5.96 years of full-time work, compared to 4.0 years for the non-obese group. This difference is statistically significant (t-statistic of -2.54). There is no difference between the two groups as regards the fathers' working histories. Fathers in the obese and non-obese groups worked 12.66 and 12.04 years, respectively. Mothers of obese young adults worked 2.87 years in part-time employment, whereas mothers of non-obese young adults worked an average of 3.21 years part time. This difference is statistically insignificant. Part-time employment on the part of fathers is negligible at 0.13 and 0.18 years, on average, for the obese and non-obese groups, respectively. To sum up, we conclude that mothers of obese young adults have higher labor force participation, on average, and work more full-time years than mothers of non-obese young adults. Fathers' full- and part-time employment does not differ between the two groups. This underlines the above hypothesis that a lack of child-care time may affect the probability of being obese as a young adult.

Comparing obese young adults with non-obese young adults in a siblingship test, we do not find a different pattern compared to the full sample. Comparing the labor force participation of mothers of both obese and non-obese siblings in young adulthood, we see that the mothers of the obese siblings have a higher labor force participation – at 79 percent – during the childhood of the obese sibling, compared to 54 percent labor force participation during the childhood of the non-obese sibling. The mother of siblings may work more years full-time in the childhood of one sibling and reduce their labor force participation during the childhood of the other sibling. This pattern underlines the hypothesis that a higher labor force participation has a deleterious effect on young adults' probability of being obese. The average number of years spent in full-time work by mothers in the obese group is 6.8, compared to 4.0 years in the non-obese group. This difference is statistically significant (t-value 2.91). Mothers in the obese group spend less time in part-time work than mothers of non-obese young adults, at 2.6 and 3.2 years, respectively, but the difference is not statistically significant. Fathers' full-time and part-time work does not differ across the groups.

– Table 3.3 here –

Table 3.3 presents the means of the other control variables. The first two columns present the means for the full sample and the next two columns those for the sibling sample. First, we describe the full sample. The socio-demographic variables we use show that males are more obese than females, while age is slightly higher in the obese group. The duration of the mother's schooling is 11.6 years and 12.6 years for the obese and non-obese groups, respectively. The father's schooling lasted 11.5 and 13 years in the respective two groups. Parental education is statistically higher in the group of the non-obese young adults, with t-statistics of 2.25 and 3.33 for the mothers and fathers, respectively. Better education may lead to better nutrition and more physical activity, or the family may, due to potentially higher household income, be able to afford to live in a better neighborhood, eat better food, and hire a nanny. The conflict potential is slightly higher in the obese group, with 21 percent of the obese young adults having problems with their parents and 17 percent and 14 percent of the non-obese young adults having problems with their mothers and fathers, respectively. The BMI of the parents of obese young adults is higher than that of the parents of non-obese young adults, and there is also a higher incidence of obesity amongst the parents of the obese. These data may support the assumption made above that BMI may, on the one hand, be closely related to genetic disposition and, on the other, be a result of intergenerational transmission of lifestyle. A dramatically higher share of obese parents in the group of obese young adults underlines this assumption. The two groups do not differ, by contrast, according to their living areas.

In the sibling sample, the pattern is similar. The mean BMI and age in the sibling sample are higher than in the full sample because we dropped the age restriction in the sibling sample. The age range in this sample is 17 to 47 years. As in the full sample, the father's education is statistically significant between obese and non-obese young adults (t-value 1.84), whereas the mother's education has no statistical significance. The conflict potential with parents is slightly lower in the sibling sample and is similar for the two groups.

As mentioned above, the sibling sample allows us to show the differences between the siblings in the case of non-constant variables. The means are shown in Table 3.4.

– Table 3.4 here –

The mean difference in BMI is roughly 0.6 points, with a minimum of 16 and a maximum of 24 points of difference between the older and the younger sibling. The difference in the mother's full-time labor supply is roughly one month. The extremes go from -14 to 10 years. We note that the first born is heavier and that the mother's labor supply is slightly higher for the first born. The mother's part time labor supply for the second born is roughly six months longer than for the first born. This underlines again the hypothesis that increased child-care time has a negative effect on the probability of being obese. The higher part-time and lower full-time labor supply indicates higher potential child-care time for the second born and should result in a lower BMI for the second born, which is indeed supported by the data. The mean age difference between the two siblings is 3 years, with a minimum of 0 and a maximum of 12 years, which could also explain to some extent the higher BMI found for the first-born siblings.

3.5 Results

The results are discussed with respect to their direction and significance and the focus is on the variables defining parental working time. The descriptive statistics show that mothers of obese young adults work more years in full-time employment than do mothers of non-obese young adults and that the former therefore have less potential time to spend with their children. The question now is whether mothers' working time has a causal effect on young adults' probability of being obese. We therefore include additional controls for childhood family background and socio-demographic factors to meet the mean independence assumption.

– Table 3.5 here –

Table 3.5 presents the regression results. We estimate two specifications of the logit model. In Model (1), we consider only parental labor supply as the years spent in full-time work. In Model (2), we additionally include the years spent by parents in part-time work. We first discuss the results of Model (1) and then the additional findings of Model (2).

In Model (1), maternal full-time labor supply is statistically significant and positive. The longer a mother works full time, the higher is the probability of her young adult child being obese. An additional year of full-time work increases the probability of the child being obese as young adult by 0.003 percentage points. In the logit model, the marginal effect can be calculated as $\beta_j * p(1-p)$, where p is the probability of being obese as a young adult. The marginal effect of an additional year of full-time labor supply by the mother is equal to one year less of parental schooling. Full-time work on the part of fathers has no significant effect.

Fathers' educational attainment, however, has a significant negative effect on young adults' probability of being obese. The negative effect of fathers' education may point to the importance of income and education in the prevention of obesity. The negative, but not significant, effect of mothers' schooling points in the same direction. The quality of family life does not significantly affect the probability of being obese. The positive but not significant point estimate indicates that conflicts at home in childhood may increase the probability of being obese. Genetic disposition and parental lifestyle, measured on the basis of parental BMI, have a positive and significant effect on young adults' probability of being obese. The channel through which parental BMI affects young adults' obesity cannot be determined here. It could be interesting to analyze the potential of behavioral transmission from parent to child and how strong genetic disposition is transmitted from parent to child. Male young adults have a higher probability of being obese than female young adults. The controls for living area, residence in the former GDR before 1989, and living in an urban area all have no effect on a person's probability of being obese. The results of the socio-demographic factors are in line with research for the U.S.A. (Classen and Hokayem, 2005).

In Model (2), we added years spent in part-time work in order to control for potential influences of increased child-care time when working part time. Unfortunately, we cannot determine whether part-time work was more common when the children were young, which would have been useful for analyzing a potential timing effect. On the basis of the data at hand, we find no significant effect of part-time work. The positive but not significant estimate for the mother underlines the importance of child care. The argument here is as follows. When the mother works in the morning and the child is at school, the mother may take care of the child in the afternoon. In this case part-time work has no effect on the child's probability of being obese. The negative sign given to the father's value can be interpreted as the effect of additional child-care time. The effect is not significant but could point to the argument that the father may take care of the child when he is at home and that this may reduce the child's probability of being obese. The other controls have the same sign and significance as in Model (1).

In Model (3), we regress respondents' BMI on the usual set of control variables. We find a statistically significant positive effect of potential child-care time on young adults' BMI. One additional year of full-time work by a mother increases the BMI by 0.04 points. This effect is small compared to fathers' schooling or parental BMI. In contrast to Models (1) and (2), in Model (3) age and living in the GDR prior to 1989 are statistically significant. The positive effect of age is in line with previous research that BMI increases with age. The negative sign of living in the former GDR points to the possibility that better child-care facilities there compensated for the hours spent by the mother at work.

– Table 3.6 here –

Table 3.6 presents the results of the sibling difference estimation. In the first place, we cannot reject the zero result for the overall significance of the regression. The difference in mother's full-time labor supply is the only significant parameter besides the gender difference. A decrease in mother's full-time work for the second born - labor supply for the first born as given - would increase the size of the variable Δ*Mother full time*. ΔBMI would then increase by 0.228 BMI points. This in turn means that the BMI of the second born - given the BMI of the first born - has decreased. This result underlines the observation already made above that an increase in mother's labor supply as a proxy for reduced child-care time has a deleterious effect on young adults' BMI and increases their probability of being obese.

3.6 Conclusion

In this paper we analyze the effect of mothers' child care on young adults' probability of being obese. The absence of the mother at home may favor the increase in obesity in the population. Using data from the German Socio-Economic Panel, we conclude that mothers' absence from home while working when no other child care is available increases the probability of children being obese as young adults. Including part-time work in order to control for more potential child-care time does not change the effect. A sibling estimation approach using the difference in siblings' BMI as the dependent variable underlines the relationship found between mothers' labor supply and body weight in young adulthood, again when no other child care has been provided. The results show that the difference in siblings' BMI can be explained by a difference in the amount of time spent by the mother in full-time employment. The siblings estimation approach allows us to control for unobserved heterogeneity and increases the credibility of the results.

On the basis of the data at hand, we cannot control for actual child-care time or for other persons taking care of the child during childhood. This is a limitation of the study, but it should not affect the result that the amount of child-care time given by the mother or other persons may influence obesity in later life. This could be a point where further research could step in, but a detailed data set of child-care history would be required. The question as to whether child care by another person can substitute child care by one's mother is important for policy conclusions. On the one hand, one could argue that if a mother's child care is more effective than child care provided elsewhere, then, for example, an increase in day-care facilities would not help to combat the obesity epidemic. On the other hand, one could argue that for children aged 0 to 6, for example, the quality of child care may not be so important. The important thing is that the child is supervised. In order to be able to reach such conclusions, it would be important to know the relevant timing effects. Unfortunately, due to data limitations, we are not able to do this. The low number of obese individuals in the sample prevents us from further disaggregating the sample.

Despite this limitation, this study still reveals that the demographic challenge – the greater need for skilled labor and the consequently increased female labor supply – may be a determinant of the increase in obesity. The results show that the negative effect of mother's absence during childhood on young adult's health could be reduced. This can be achieved either with more child-care facilities or with the help of the family as carers, as the results for part-time workers and the eastern German dummy indicate.

Again, notwithstanding this limitation, we believe that we have provided a preliminary insight into the relationship between obesity in young adulthood and mothers' potential child-care time in Germany on the basis of a large-scale data set. Another innovation in our work is the application of a sibling estimation approach using the German Socio-Economic Panel.

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3.8 Tables

Table 3.1: Increase in Obesity in Selected Countries Worldwide

Country	Men	Women	Years	Reference
Brazil	3.1 - 5.9	8.2 - 13.3	1975 - 1989	WHO, 2000
Canada	6.8 - 9	9.6 - 9.2	1978 - 1988	
England	6 - 15	8 - 16.5	1980 - 1995	
Finland	10 - 14	10 - 11	1978 - 1993	
Netherlands	6 - 8.4	8.5 - 8.3	1987 - 1995	
Italy	7.9 - 9	6.6 - 7.4	1998 - 2001	De Galdeano, 2005
Spain	12.9 - 14	11.8 - 13	1998 - 2001	
Greece	9.8 - 10.1	9.3 - 10.2	1998 - 2001	
Austria	10.8 - 11.4	9.9 - 10.9	1998 - 2001	
Australia	9.3 - 11.5	8 - 13.2	1980 - 1989	WHO, 2000
Japan	0.7 - 1.8	2.8 - 2.6	1976 - 1993	

Table 3.2: Obesity and Potential Child-Care Time, Means

Full sample Variable	Obese	Non-obese
Mother full time (dummy)	0.72 (0.066)	0.61 (0.012)
Mother full time	5.96 (0.829)	4.00 (0.130)
Father full time	12.66 (0.684)	12.04 (0.130)
Mother part time	2.87 (0.601)	3.29 (0.112)
Father part time	0.13 (0.072)	0.18 (0.023)
N	47	1594
Sibling sample Variable	**Obese**	**Non-obese**
Mother full time (dummy)	0.79 (0.072)	0.54 (0.018)
Mother full time	6.82 (1.000)	4.00 (0.194)
Father full time	13.39 (0.684)	13.11 (0.149)
Mother part time	2.55 (0.780)	3.22 (0.168)
Father part time	0.12 (0.084)	0.11 (0.026)
N	33	785

Standard errors in parentheses.

Table 3.3: Means by Obesity and Sample

	Full sample		Sibling sample	
Variable	Obese	Non-obese	Obese	Non-obese
Socio-demographic variables				
BMI	32.56	21.83	33.26	22.01
	(0.599)	(0.069)	(0.893)	(0.102)
Age	21.15	20.38	23.30	21.96
	(0.352)	(0.054)	(0.666)	(0.137)
Male	0.74	0.51	0.76	0.54
	(0.064)	(0.013)	(0.076)	(0.018)
Family background variables				
Mother's schooling	11.63	12.55	11.74	12.53
	(0.382)	(0.069)	(0.454)	(0.102)
Father's schooling	11.54	13.03	12.12	13.18
	(0.294)	(0.076)	(0.455)	(0.117)
Conflict w/ mother	0.21	0.17	0.12	0.14
	(0.060)	(0.009)	(0.058)	(0.012)
Conflict w/ father	0.21	0.14	0.15	0.13
	(0.060)	(0.009)	(0.063)	(0.012)
BMI mother	29.25	25.13	29.47	25.24
	(0.934)	(0.117)	(1.048)	(0.180)
BMI father	30.23	26.78	29.81	26.63
	(0.629)	(0.088)	(0.531)	(0.114)
Mother obese	0.40	0.12	0.45	0.11
	(0.072)	(0.008)	(0.088)	(0.011)
Father obese	0.47	0.16	0.48	0.13
	(0.074)	(0.009)	(0.088)	(0.012)
Urban	0.55	0.65	0.61	0.61
	(0.073)	(0.012)	(0.086)	(0.017)
East	0.28	0.27	0.36	0.22
	(0.066)	(0.011)	(0.085)	(0.015)
N	47	1594	33	785

Standard errors in parentheses.

Table 3.4: Mean Sibling Differences

Variable	Mean	Min	Max
Δ BMI	0.555	-16.38	24.73
	(0.222)		
Δ Mother full time	0.099	-14	10
	(0.109)		
Δ Father full time	-0.003	-14	15
	(0.151)		
Δ Mother part time	-0.453	-14	14
	(0.131)		
Δ Father part time	-0.059	-12	2
	(0.035)		
Δ Age	2.96	0	12
	(0.099)		
Δ Conflict w/ mother	0.015	-1	1
	(0.022)		
Δ Conflict w/ father	0.020	-1	1
	(0.022)		
Δ Male	0.005	-1	1
	(0.036)		
Δ Urban	-0.036	-1	1
	(0.012)		
Δ East	0.003	0	1
	(0.003)		
N	393		

Standard errors in parentheses.

Δ = Older - Younger Sibling.

Table 3.5: Regression Results Full Sample, Dependent Variable: Obesity (Logit, Models 1 and 2), BMI (OLS, Model 3)

Variable	Model 1	Model 2	Model 3
Mother full time	0.102†††	0.107†††	0.039†
	(0.037)	(0.041)	(0.023)
Father full time	0.017	0.012	-0.005
	(0.041)	(0.043)	(0.0189)
Mother part time		0.011	0.018
		(0.044)	(0.020)
Father part time		- 0.070	-0.018
		(0.167)	(0.099)
Mother's schooling	- 0.069	- 0.067	0.001
	(0.096)	(0.097)	(0.039)
Father's schooling	- 0.114†	- 0.116†	-0.079††
	(0.063)	(0.064)	(0.035)
Conflict w/ mother	0.387	0.390	0.015
	(0.423)	(0.422)	(0.256)
Conflict w/ father	0.306	0.292	-0.029
	(0.431)	(0.438)	(0.286)
BMI mother	0.089†††	0.090†††	0.139†††
	(0.026)	(0.026)	(0.026)
BMI father	0.158†††	0.157†††	0.167†††
	(0.036)	(0.037)	(0.027)
Urban	- 0.079	- 0.072	-0.308
	(0.381)	(0.384)	(0.203)
Male	1.051†††	1.051†††	1.553†††
	(0.414)	(0.415)	(0.187)
Age	0.089	0.091	0.138†††
	(0.075)	(0.076)	(0.037)
East	- 0.148	- 0.152	-0.434†
	(0.414)	(0.416)	(0.236)
Intercept	- 11.396†††	- 11.399†††	11.806†††
	(2.456)	(2.481)	(1.185)
Log likelihood	-174.525	-174.441	
χ^2	59.99	60.11	
F (15, 1121)			15.98
R^2			0.187

Notes: Adjusted (1122 clusters) standard errors in parentheses.

Significance levels: † 10 percent, †† 5 percent, ††† 1 percent.

N = 1641, time dummy included in all models

Table 3.6: Regression Results Sibling Differences, Dependent Variable: BMI

Variable	Model 4	
Δ Mother full time	$0.228^{\dagger}$	
	(0.135)	
Δ Father full time	0.009	
	(0.062)	
Δ Mother part time	0.090	
	(0.081)	
Δ Father part time	0.114	
	(0.223)	
Δ Conflict w/ mother	0.004	
	(0.786)	
Δ Conflict w/ father	-0.637	
	(0.923)	
Δ Urban	0.656	
	(1.178)	
Δ Male	$1.198^{\dagger\dagger\dagger}$	
	(0.409)	
Δ Age	0.106	
	(0.114)	
Intercept	0.296	
	(0.421)	
F (9, 243)		1.72
R^2		0.064

Notes: N = 393, Adjusted (244 clusters) standard errors in parentheses.
Significance levels: † 10 percent, †† 5 percent, ††† 1 percent.

3.9 Appendix

Table 3.7: Description of Variables, Full Sample

Variable	Description
Mother full time (dummy)	Equal to 1 if mother worked at least one year full time, child aged 0 to 15
Mother full time	Mother's full-time work measured in years, child aged 0 to 15
Father full time	Father's full-time work measured in years, child aged 0 to 15
Mother part time	Mother's part-time work measured in years, child aged 0 to 15
Father part time	Father's part-time work measured in years, child aged 0 to 15
BMI	BMI of young adult, BMI = kg/m^2
Age	Age of young adult, measured in years
Male	Gender of young adult, equal to 1 if young adult is male, otherwise 0
Mother's schooling	Schooling of mother, measured in years
Father's schooling	Schooling of father, measured in years
Conflict w/ mother	Equal to 1 if young adult had problems with mother during childhood, otherwise 0
Conflict w/ father	Equal to 1 if young adult had problems with father during childhood, otherwise 0
BMI mother	BMI of mother, BMI = kg/m^2
BMI father	BMI of father, BMI = kg/m^2
Mother obese	Equal to 1 if mother's BMI $\geq$ 30, otherwise 0
Father obese	Equal to 1 if father's BMI $\geq$ 30, otherwise 0
Urban	Equal to 1 if childhood spent in a village, city, or big city, otherwise 0
East	Equal to 1 if young adult lived in East Germany before 1989, otherwise 0

Table 3.8: Description of Variables, Sibling Sample

Variable	Description
Δ BMI	Difference in sibling's BMI
Δ Age	Difference in sibling's age
Δ Mother full time	Difference in sibling's full-time work by mother
Δ Father full time	Difference in sibling's full-time work by father
Δ Mother part time	Difference in sibling's part-time work by mother
Δ Father part time	Difference in sibling's part-time work by father
Δ Conflict w/ mother	Difference in sibling's problems with mother
Δ Conflict w/ father	Difference in sibling's problems with father
Δ Male	Difference in sibling's gender

Chapter 4

Obesity and Wages in the German Labor Market

4.1 Introduction

Obesity has become a major health issue over the last two to three decades, and it has also been added to the research agenda of economists. On the one hand, economists are interested in the potential consequences of obesity and, on the other, they are keen to identify its determinants. Awareness of the consequences of obesity on public health costs, the society and finally on individual economic success is the first step to the design and implementation of policy measures to improve public and individual utility. And knowing the determinants of obesity is essential so that intervention can become possible. This essay is intended as a contribution to the field of research on the potential consequences of obesity in that it seeks an answer to the question, "Does obesity affect labor market success?" The obese are subject to numerous prejudices, such as the idea that they are slow, untidy, not particularly intelligent, and so on. Moreover, obese people are often the butt of jokes. It is easy to imagine that being constantly beleaguered in this manner can debilitate one's self-esteem. Given these prejudices about the performance of obese workers and the related mental stress, the question as to whether the labor market and employers go along with the popular thinking about the obese and perhaps reward their work differently to that of non-obese employees is straightforward. This is reflected in Figure 4.1, a histogram of gross monthly income for obese and non-obese workers (with female workers on the left and male workers on the right), where we see that there is a higher share of obese (red) among low earners and that their earnings do not reach the levels of the non-obese (green). This pattern is similar for men and women, but is stronger for female workers.

In the economic literature, two strands of explanation as to why obese people may earn less than their non-obese peers can be found. On the one hand, obese people may be less productive. Employers pay wages on the basis of marginal productivity and lower productivity leads to lower wages. On the other hand, obese people may earn less because they are discriminated by employers, meaning that there is no objective reason why the obese should earn less. In this essay we follow up both ideas, finding different results for males and females as regards the explanation as to why obese workers earn less. We address the problem by adopting the theoretical approach used by Judge and Cable (2004) to examine the effect of body height on income, applying their method instead to the effect of obesity on income. These authors devised a psychologically based model to link body height and social esteem, self-esteem, performance, and career success. The taller one is, the higher is one's social esteem and self-esteem, and this leads in turn to labor market success. We argue that obesity likewise leads to lower social esteem and self-esteem and therefore to lower performance and less labor market success. The lower level of performance can be attributed to the lower productivity argument, whereas the lower degree of social esteem might explain the lower wages due to discrimination. Our empirical approach is to partly replicate a previous study of Cawley et al. (2005) with recent German data. To control for potential endogeneity, we do not apply IV estimation or sibling differences, rather use a lagged measure of obesity at point $t-1$, which we assume does not correlate with the actual error term in t. This approach is used in Cawley (2004) with U.S. data. It is difficult to find appropriate instruments because if it is to be successful, the instrument used must satisfy two requirements. First, it must be highly correlated with the endogenous variable; second, it must be uncorrelated with the error term. The authors use the weight of a family member as an instrument, which, in our view, is also likely to be correlated with the error term. If we think about personal will or discipline, it is possible that this may be passed on from generation to generation either genetically or through learned behavior in childhood and subsequently also affect one's degree of labor market success.

Empirical studies on the effect of obesity on labor market earnings are rare for Germany. Cawley et al. (2005) find that for German men BMI has no effect on earnings, whereas it does for German women. The negative effect of BMI on female earnings disappears with IV estimation. With regard to obesity, the authors find negative effect on earnings for men and women, but they do not control for the potential endogeneity of obesity. We find that obesity does not carry a wage penalty for male German workers after controlling for health status, but that it does for female workers. We argue that the negative effect for female workers is due to employer discrimination, whereas for male workers the effect is explained by lower productivity.

The following section presents models of thoughts on the two possible explanatory approaches. An empirical framework is outlined in Section 3, whereas Section 4 presents the data and the sample used. In Section 5, the results are discussed, while the final section concludes the essay.

4.2 Thought models

Do the obese earn less because they are less productive or because they are discriminated on the labor market? We outline two toy models explaining why lower productivity and discrimination might lead to a wage differential between obese workers and their non-obese peers.

The first argument, that obese people may earn less because they are less productive than their non-obese peers, is straightforward. It is known that the obese are at higher risk for health problems such as diabetes mellitus, hypertension, musculoskeletal disorder, sleep apnea, and gallbladder disease (Finkelstein et al., 2004; Pi-Sunyer, 1993). The medical treatment of these diseases requires visits to a doctor or a hospital and the obese therefore have less potential working days at their disposal. This in turn reduces their productivity and ultimately their wages. Another reason why the obese may be less productive are physical limitations such as lower endurance or lower flexibility, both of which restrict their work effort. Furthermore, in jobs requiring a lot of contact with customers, the obese may be less efficient on the basis of what is seen to be an unfavorable physical appearance and also in this sense are therefore less productive than their non-obese peers.

Research on the U.S.A., for example, shows that body height and body weight have negative effects on wage levels and wage growth (Loh, 1993) and that obese females tend to have lower family incomes (Averett and Korenman, 1996). Data from the National Longitudinal Survey of Youth show that for white females, a body-weight difference of 29 kg is associated with a 9 percent difference in wages (Cawley, 2004). There is some similarity in the results for Europe. Obesity has no effect on wages in northern Europe, but there is a substantial negative effect in southern Europe, where an increase of 10 percent on the average BMI reduces real earnings by 3.3 percent and 1.9 percent for men and women, respectively (Brunello and D'Hombres, 2007; D'Hombres and Brunello, 2005). In Germany, taller male workers – though not those taller than 195 cm – enjoy a wage premium of about 4 percent for each additional standard deviation increase in height (Heineck, 2005). A comparison between the U.S.A. and Germany shows – using instrumental variables (IV) estimation – that body weight lowers labor earnings only for U.S. women and not for German women or for men in both countries. Ordinary least square (OLS) estimations of the impact of obesity on earnings shows a positive effect only for U.S. men and a negative effects for U.S. women and for German men and women (Cawley et al., 2005).

The discrimination argument brings us to the research strand investigating physical appearance and wages from the perspective of underdeveloped self-esteem, which translates into insecure behavior in life. The latter argument is developed by Persico et. al (2004). They argue that being tall relative to others has a positive effect on labor market earnings. But when they control for body height in youth, this effect disappears. The authors conclude that social discrimination on the basis of being small relative to others in childhood impedes the development of self-esteem. Women's BMI can be related to general attractiveness. Women with a BMI of between 18 and 25 are viewed as being most attractive (Tovee et al., 1998). The popular wisdom that pretty people have easier lives and are more successful in the labor market seems confirmed. Plain people face a wage penalty of between 5 and 10 percent, and this applies to both sexes. Better-looking people appear to sort into jobs where beauty may be more productive (Hamermesh and Biddle, 1994). Harper (2000) investigates the effect of both beauty and obesity on wages for the U.K. He estimates plainness penalties of 15 and 11 percent for men and women, respectively, and a 5 percent wage reduction for being short (male and female) and for being obese (female).

Persico et al. (2004) and Behrman and Rosenzweig (2001) stress the importance of childhood and pre-birth environment in the determination and impact of anthropometrics on labor market outcomes. The observed wage penalty on small people in adulthood can be explained as a teen penalty in body height. The hypothesis is that relatively small teens were excluded from opportunities for social contact, such as playing in a football or ice hockey team, and therefore could not develop the same self-esteem as their taller peers (Persico et al., 2004). Behrman and Rosenzweig (2001) argue, besides other findings, that the effect of BMI on earnings reflects the correlation between unmeasured earnings endowments and also that body height increases earnings. This results are found on the basis of sibling estimations to control for the effect of childhood endowments.

4.3 Obesity and Wages

In this section we present the empirical model we used to analyze the relationship between obesity and wages. We focus on blue- and white-collar employees because they are subject to more or less similar labor market conditions (such as wages, working hours, and institutional aspects like trade unions) compared to people working either in the military or the civil service, the self-employed, or apprentices. Just by looking at a specific group of workers we assume we are analyzing a homogeneous group, and this should allow us to relate differences in wages to differences in obesity and not to general labor market and institutional differences.

We start our analysis with a wage equation representing worker i's wage at time t, where the wage depends only on a dummy variable if i is obese at time t or not, Ob_{it}, and an idiosyncratic error term ϵ_{it}:

$$ln(wage)_{it} = \beta_0 + \beta_1 Ob_{it} + \epsilon_{it}$$

We treat male and female workers separately because they differ so much with respect to labor market characteristics like wage structure and employment types. This first, rather naive approach shows only a possible correlation between wages and obesity rather than the desired causal effect. The necessary exogeneity condition of the error term $E(\epsilon_{it}|Ob_i) = 0$ for a causal interpretation of obesity on wages is likely to be violated. The estimates of β_1 would be biased because of the omitted variables. Too many factors that influence obesity and wages simultaneously remain in the error term affecting both the probability of being obese and wages earned. Personal attributes such as age, education, or having children may influence a person's employment and ultimately the associated wage and may also affect a person's BMI. We therefore include personal characteristics such as age and education in the following step. The vector X_{it} includes age, education, civil status, region, and whether or not there are children in the household. With these variables we can control for wage differences due to educational level and also regional differences in wages. Our modified wage equation now has the form

$$ln(wage)_{it} = \beta_0 + \beta_1 Ob_{it} + \beta_2 X_{it} + \epsilon_{it}.$$

Given the personal characteristics X_{it}, the estimated parameter β_1 still may be biased due to the violated mean independence assumption. As argued above, obese workers may have lower productivity. As research shows, the obese face higher risks of health problems. This may result in more absent working days and lower productivity. The obese may also have physical limitations on the job, such as lower endurance than their non-obese peers. Another aspect could be lower productivity because of mental stress. To control for possible productivity effects related to physical or mental health, we include two controls – a cumulative measure for physical and mental health status (for details, see Nübling et al., 2006). The important assumption behind the use of these measures is that they are exogenous, that is, they are not caused by obesity. We assume that the indices described above can be viewed as exogenous. These controls are captured in the vector HS_{it}:

$$ln(wage)_{it} = \beta_0 + \beta_1 Ob_{it} + \beta_2 X_{it} + \beta_3 HS_{it} + \epsilon_{it}$$

An obvious remaining source of heterogeneity, then, are labor market characteristics. The obese may sort into labor markets with lower wages, or different labor market characteristics may favor non-obese workers whereas others favor obese workers. The vector LMC_{it} includes controls for tenure, industry, firm size, type of employment, and type of job.

$$ln(wage)_{it} = \beta_0 + \beta_1 Ob_{it} + \beta_2 X_{it} + \beta_3 HS_{it} + \beta_4 LMC_{it} + \epsilon_{it}$$

The development to the final equation is interesting because we can test the validity of the two explanations as to why the obese earn lower wages. Assuming that the parameter associated with obesity affects wages negatively, in the second equation this could be because of differences in health status. If, after including health status controls, obesity still lowers wages in one group but not in the other (male/female workers), then this results supports the discrimination approach because given the same productivity in one group, the obese still earn less than the non-obese workers. One could still argue that not only productivity influences wages rather also job characteristics. Assuming the same level of productivity, an obese worker may generate lower returns in industries or jobs with customer contact. The discrimination approach is then supported if, after controlling for labor market characteristics, in the last equation the obese still earn less in one group.

The above model still has two apparent weaknesses. It could still suffer from endogeneity because the expectation of the error term given the controls is not equal to 0, $E(\epsilon_{it}|Ob_i, X_i, HS_i, LMC_i) \neq 0$. The second problem here could be reverse causality. Obesity may affect wages but, at the same time, wages may affect the probability of being obese. We discuss a possible solution to both problems in the next paragraph.

If we assume that motivation or self-esteem are left in the error term, then it follows that these estimates are not causal and instead represent the correlation between obesity and wages. Motivation and self-esteem change from day to day and year to year. Therefore, it is reasonable to assume that motivation and/or self-esteem may influence wages at a particular moment in time, t, but not at another moment in time, $t-1$. Therefore the assumption of contemporaneous exogeneity $E(\epsilon_{it}|Ob_{it}, X_{it}, HS_{it}, LMC_{it}) = 0$ (Wooldridge, 2003) can be justified. We then replace obesity in t, Ob_{it}, with obesity in $t-1$, Ob_{it-1} (Cawley, 2004). Obesity is now no longer endogenous and the estimated effect can be interpreted as causal. We then estimate the following model:

$$ln(wage)_{it} = \alpha_0 + \alpha_1 Ob_{it-1} + \alpha_2 X_{it} + \alpha_3 HS_{it} + \alpha_4 LMC_{it} + \nu_{it}.$$

Using this specification of the wage equation, the problem of reverse causality is also resolved. If we use obesity and wages from the same year, it is unclear whether wages influence obesity or obesity influences wages. When we use the obesity measure from a lagged time period, Ob_{it-1}, it is unlikely, on the one hand, that wages in time period t affect obesity in time $t-1$. On the other hand, obesity in $t-1$ affect wages in period t because wages cannot be adjusted immediately. Negotiations on wages and working conditions are carried out at the beginning of a contract and these conditions normally remain constant for a certain period of time.

The method proposed here to control for endogeneity is not the only possibility. Given the panel structure of our data, the advantage of using fixed-effect methods would seem apparent. In fact, the idea of eliminating fixed, unobserved personal characteristics is very attractive. Unfortunately, we cannot use fixed-effects models, however, because the variation in the variables is too small and would lead to imprecise estimates. Of the 2398 males we observed in 2002 and again in 2006, only 204 (8.5 percent) became obese or lost weight. The figures are similar for the females. We observed 1959 women over the sampling period, but only 135 women (6.9 percent) showed a change in weight. A similar idea to the fixed-effects approach is used by the sibling or twin approach. Here, the unobserved heterogeneity is eliminated by subtracting information about siblings or twins. The assumption here is that both siblings experience a similar family background. As in the case of fixed effects, there must be some variation in the variables between the siblings or twins. We believe that using a sibling difference approach here makes no sense because the similar background is too distant in the past and the siblings have too different a life history after leaving home. A further prominent method for dealing with endogeneity are IV models. As mentioned in the Introduction, finding a reasonable instrument to use in this method is difficult. The instruments proposed so far in the literature are questionable: for instance, family poverty level, health limitations, or indicator variables about self-esteem (Pagan and Davila, 1997), or the weight of a family member (Cawley et al., 2005). We are unable to propose a more plausible instrument here. A recent paper by Kline and Tobias (2007) used a Bayesian approach to estimate the effect of BMI on wages. Using data from the 1970 British Cohort Study, they found that for men the wage penalty for a BMI increase is higher if the men are already obese. For women, the highest wage penalty is paid at relatively low levels of BMI and becomes smaller as the BMI increases.

Another, rather different aspect of the relationship between obesity and wages is the self-selection of workers. A person's working status is not exogenously given. Everyone has to make the decision to work based on personal experience, education, or living situation, and one factor in this decision could arguably be obesity. The obese face a lot of prejudice and this may lower their self-esteem and their willingness to participate in the labor market. The obese and non-obese may have different job-search strategies and expectations regarding their wage. Ignoring these factors could lead to a selection bias (Gronau, 1974). The obese who actually enter the labor market may be positively selected, meaning they are the best educated or the people with the strongest motivation in the group of obese. A possible way to test this hypothesis would be to use a Heckman selection model, that is, to take a subsample of obese people and estimate the possible selection of the obese in the labor force. Unfortunately, we cannot apply this method here because the sample of obese people is too small for a sound analysis of the selection problem. We leave this interesting question, especially in the context of a rise in obesity, to further research, when more data is available.

4.4 Data

We use data from the German Socio-Economic Panel (GSOEP) to analyze the relationship between obesity and the wages of German workers (see SOEP Group, 2001, for more general information on the survey). Beginning in 2002, the GSOEP includes biennial questions on the health status of the respondents. From this information, the BMI, calculated as body weight in kilograms divided by body height in meters squared, is derived. A person is categorized as obese if his/her BMI is ≥ 30 (WHO, 2000). The GSOEP health data also contains information on respondents' physical and mental health. These two summary measures are calculated on the basis of 12 health-related questions from the GSOEP. These 12 items are condensed to eight subindices consisting of one or two items. The subindices are "Physical functioning", "Role physical", "Bodily pain", "General health", "Vitality", "Social functioning", "Role emotional" and "Mental health". These subindices are now combined to two indices measuring physical and mental health. The index "Mental health" consists of the subindices "Vitality", "Social functioning", "Role emotional" and "Mental health". The index "Physical health" is constructed with the subindices "Physical functioning", "Role physical", "Bodily pain" and "General health" (Andersen et al., 2007; Nübling et al., 2006). A table with the items and respective subindices is provided in the Appendix. We interpret this information as a proxy for potential labor market productivity. On the one hand, labor market productivity depends on one's physical health status, which is mirrored in the "Physical health" index. On the other hand, labor market productivity depends on one's mental capabilities to deal with pressure or a new situation, and this is reflected in the "Mental health" index. The information on personal background is taken from the corresponding survey year. For information on the labor market situation and working sector, the respective summary data file is used. The structure of the GSOEP allows us to combine personal and labor-market-related information with health information. Exploiting the panel structure, we are able to combine information from one year with information from another year. We can then construct data samples with lagged information for each respondent's obesity status.

Personal background information includes information on education, age, gender, civil status, number of children in the household, and region of residence. Labor market information includes industry sector, firm size, monthly and yearly wage, type of work, type of employment, and tenure. The sample is restricted to respondents aged between 18 and 65 years. As mentioned above, we only take employees, either blue- or white-collar, into account for the analysis. A description of the variables used and their means and standard errors for the full sample and by gender is given in the Appendix.

For each year between 2002 and 2006 we constructed a cross-section sample with the above variables. We pooled the respective cross-sections in accordance with the time structure of the estimated model. This results in the following sample sizes. In the basic model with gross monthly wage and the obesity information from the same year, the sample consists of 11909 male and 10819 female observations. The sample size of the specification with lagged values for obesity is 6841 male and 6262 female observations.

With gross yearly labor income as the dependent variable and obesity information from the same year, the sample consists of 8232 male and 7492 female observations. Using lagged information, the sample includes 7373 male and 6561 female workers.

The description of the data is based on the setting with gross monthly wage as dependent variable and obesity information from the same year.

– Table 4.1 here –

Table 4.1 shows the relationship between wages and weight for men and women. The average wage of male workers increases up until the overweight group, and is then lower in the obese group. Female workers earn most in the normal weight category and less if they are overweight or obese. This first look at average wages by weight group shows that heavier workers – and especially the obese – earn less. Their average wage is lower than the average wage in the normal weight group for male workers, while the wages of obese female workers are even lower than the average wage of underweight co-workers.

If we split the sample into an obese and a non-obese group, we observe that the obese mostly earn less, irrespective of the labor market characteristics.

– Table 4.2 here –

– Table 4.3 here –

Tables 4.2 and 4.3 show in the first two columns the average wages of obese and non-obese male and female workers by different labor market characteristics. The last two columns in these tables show the share of obese and non-obese workers with the same labor market characteristics. Starting with the male sample, we observe that the share of full- and part-time workers is the same in both groups. Obese part-time workers earn higher average wages than non-obese part-time workers, whereas for full-time workers the pattern is reversed. Regarding job type, we see that of the non-obese workers, 56 percent work in a white-collar job and 44 percent in a blue-collar job. Obese workers are split evenly between the two groups. In the white-collar jobs, the non-obese workers earn more, while the opposite holds true for the blue-collar jobs. This may point to the fact that the obese work more in physically demanding jobs and that their stature signals strength, whereas the non-obese work more in jobs with contact with the public or where obesity signals lower productivity.

In the female sample, the picture is somewhat different. Of the female obese workers, 56 percent have a white-collar job, in contrast to 81 percent of non-obese workers with a white-collar job. This may suggest that non-obese workers are in jobs where physical appearance is worth more than physical strength. Only 8 percent of the obese females work in the banking and insurance sector, compared to 30 percent of the non-obese. The opposite holds for physically more demanding industries such as energy or mining. These findings indicate that female workers are selected on the basis of their physical appearance.

In Table 4.4 we compare the personal characteristics of obese and non-obese subsamples.

– Table 4.4 here –

We see that the educational levels of the obese are lower than those of the non-obese for both genders. Average tenure is higher for obese workers than for the non-obese. This may indicate that the obese are less mobile in the labor market, which may lead to lower wages (Gronau, 1974). Regarding the mental and physical health status measures, the pattern is identical for male and female workers. Obese workers have a higher score on the mental measure, whereas the non-obese have higher scores on the physical measure. Interpreted as productivity proxies, this would mean that the obese are less productive than non-obese workers.

The labor market participation of female non-obese workers is higher than for obese workers – 69 percent and 58 percent, respectively. For male workers, the difference between non-obese and obese workers is not all that large. The labor force participation of non-obese workers is 84 percent, compared to 79 percent of the obese workers. This distribution of labor force participation underlines a potential selection into the labor market on the basis of physical appearance.

4.5 Results

We estimated each of the above models twice, once with the gross monthly wage and once with the gross yearly labor income as dependent variables. Tables 4.5, 4.6, 4.7, and 4.8 are structured as follows. The upper panel of each table shows the results for controls and obesity measured in the same year, while the lower panel shows the results with the lagged obesity variable. In the model with gross monthly wages, the lag is two years, whereas in the model with gross yearly labor income, the lag is one year. The results are discussed table by table and summarized at the end of the section.

– Table 4.5 here –

The upper panel of Table 4.5 shows the results for male workers and the gross monthly wage as dependent variable. Starting from Model 1 and moving to Model 4, we see that obesity only has a significant negative effect in Model 2, where the personal characteristics are included. In this model an obese worker faces a wage penalty of around 4 percent. As soon as the productivity proxies are included in Model 3, obesity becomes insignificant, and it remains so in Model 4, where labor market controls are included. The results in this specification are puzzling. The lower wage of obese male workers can hardly be explained by productivity and labor market characteristics. Only the significance in Model 2 does not boost confidence in the specification of the model. The lower panel of Table 4.5 shows the results when the obesity measure is replaced by a lagged measure of obesity. In Model 1, we observe that the obese face a wage penalty of around 5 percent. Including personal attributes does not explain this wage penalty. After including the productivity proxies in Model 3, the negative effect of obesity is no longer significant. In Model 4, where labor market controls are included, the negative effect of being obese is not significant. We interpret this evidence in the sense that the lower wages of the obese can be explained by their potentially lower productivity according to the mental and physical health measures. The obese, especially, have lower scores in the physical health measure.

For female workers, the story is a little bit different. Table 4.6 reveals that obesity is significant in all four specifications.

– Table 4.6 here –

Female workers are subject to a wage penalty for being obese that amounts to 7 percent in Model 4. Because neither productivity nor labor market characteristics can explain the wage penalty, we interpret it as strong evidence of discrimination. This result may be biased, however, by unobserved heterogeneity. Replacing the obesity measure with the lagged information, we observe the same pattern. The significant and negative effect of obesity does not vanish in Models 3 and 4, which include the productivity and labor market controls, respectively. From these results we conclude that the lower wages cannot be explained by the personal labor market characteristics of the workers. Our conclusion is that the lower wages are due to employer discrimination of obese female workers.

Tables 4.7 and 4.8 show the results with gross yearly labor income as dependent variable. These results can be viewed as robustness checks of the above results. The upper panel of Table 4.7 shows the same puzzling pattern as the upper panel of Table 4.5.

– Table 4.7 here –

Obesity has a significant and negative effect only in Model 2, where only personal characteristics are controlled for. The lower panel with the lagged obesity measure shows that with respect to the gross yearly labor income, our productivity proxies cannot explain the wage difference. When labor market characteristics are included in Model 4, the effect of obesity is insignificant.

The estimates for female workers are presented in Table 4.8.

– Table 4.8 here –

Again in the upper panel we see the results for the specification with obesity and gross yearly labor income measured in the same year. In all models, obesity has a negative and significant effect on gross yearly labor income. In Model 4, with all controls included, the wage penalty is 6 percent. In the lower panel, the results with the lagged obesity measure are presented. Here again, in all models obesity has a negative and significant effect. The penalty here for the obese is around 5 percent in Model 4. We interpret the result as above in the case of gross monthly wage. These results underline the above conclusion that there is evidence of employer discrimination against obese female workers.

Finding the same pattern with different dependent variables and different subsamples increases the credibility of the estimations under the assumption that our estimation equation is correctly specified. If we compare the R^2 of all estimated models, we observe that the personal characteristics of male workers explain around 30 percent, whereas the same model specification of female workers explains only 10 percent of labor income. Comparing the final models, we find that for all models and both genders, between 40 and 50 percent of labor income is explained. Obviously, labor market characteristics are more important for determining female workers' wages, whereas for male workers, personal characteristics appear to be more important. Taking both analyses together, we conclude that female workers are subject to a wage penalty of between 5 and 7 percent, in contrast to male workers, where there is no evidence of such a penalty. We interpret these findings as evidence of discrimination of female workers because of obesity or in a broader sense because of their physical appearance.

4.6 Conclusion

Thus, the answer to the question "Do obese workers earn less in Germany?" is "It depends." We arrived at this conclusion using a sample of German workers from the German Socio-Economic Panel, GSOEP. We restricted our analysis to blue- and white-collar dependent employees only so as to be able to better isolate the effect of obesity on earnings and not to confound it with other effects associated with self-employment or with an apprenticeship. Starting with a standard wage equation, we extended the analysis and used lagged information on obesity to overcome methodological caveats. Exploiting the time-series aspect of the GSOEP allows us to deal with reversed causality and possible endogeneity.

We looked at two possible explanations as to why obese workers earn less: productivity and discrimination. We conclude that the productivity argument is valid for German workers. We could not find a relationship between obesity and earnings for male German workers. The negative effect of obesity on earnings vanishes as soon as we control for physical and mental health. This is in line with the finding from Hamermesh and Biddle (1994), who claim that better-looking workers may self-select into jobs where obesity does not harm wages, in other words, the obese are as productive as their peers and therefore no wage differential is observed. These search or selection phenomena seem not to play a role for women. We found a negative effect of obesity on the earnings of female German workers. Being obese reduces average earnings by between 7 and 5 percent for monthly and yearly labor market income, respectively. On the one hand, this result can be interpreted as discrimination against female obese workers. On the other hand, obese females may self-select into industries or jobs with lower earnings than those where non-obese women tend to work. Due to data limitations, we could not investigate this question of self-selection any further and now leave it as an idea for future research in this field. At any rate, we interpret it as support for the employer discrimination argument.

The results are in line with research for the U.S.A. and other European countries and enrich this strand of research with interesting results for Germany.

4.7 References

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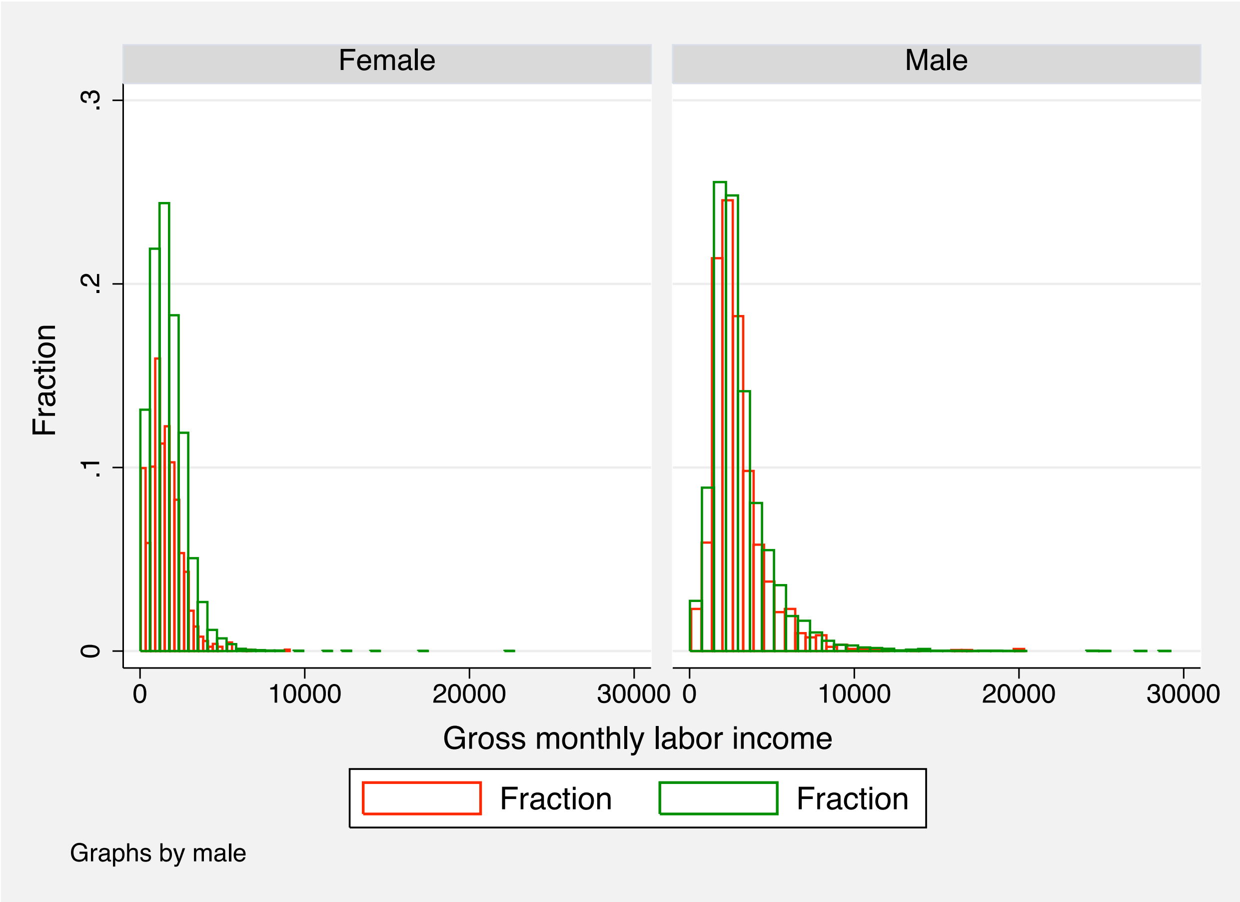
4.8 Figures

Figure 4.1: Wage Distribution by Gender and Obesity



4.9 Tables

Table 4.1: Mean Gross Monthly Wage

Variable	Male	N	Female	N
Underweight	2638.60	57	1640.80	308
	(348.30)		(73.60)	
Normal weight	2938.40	4669	1726.30	6440
	(29.00)		(13.80)	
Overweight	3083.90	5440	1620.70	2797
	(24.70)		(19.10)	
Obese	2885.80	1743	1538.30	1274
	(41.10)		(26.80)	

Standard errors in parentheses.

Table 4.2: Mean Gross Monthly Wage and Shares of Workers, Male

	Mean wage		Share	
Variable	Obese	Non-obese	Obese	Non-obese
Employed	2885.80	3014.50	—	—
	(41.10)	(18.90)	(—)	(—)
Full-time	3003.40	3161.60	0.89	0.89
	(43.90)	(20.10)	(0.008)	(0.003)
Part-time	1973.30	1782.00	0.11	0.11
	(94.20)	(38.50)	(0.008)	(0.003)
White-collar	3587.40	3732.10	0.50	0.56
	(70.10)	(29.30)	(0.012)	(0.005)
Blue-collar	2188.20	2108.90	0.50	0.44
	(27.30)	(11.40)	(0.012)	(0.005)
Industry				
Agriculture	2689.70	2658.60	0.04	0.04
	(161.80)	(81.70)	(0.005)	(0.002)
Banking, insurance	2504.70	3050.50	0.06	0.08
	(142.60)	(71.30)	(0.006)	(0.003)
Trade	3473.70	3441.20	0.13	0.12
	(180.60)	(60.30)	(0.008)	(0.003)
Mining	3218.80	3345.50	0.14	0.13
	(105.50)	(51.50)	(0.008)	(0.003)
Services	3023.70	2936.30	0.06	0.05
	(217.50)	(105.80)	(0.006)	(0.002)
Energy	2777.80	3033.40	0.24	0.23
	(63.20)	(33.90)	(0.010)	(0.004)
Manufacturing	2366.60	2498.20	0.11	0.12
	(64.10)	(37.10)	(0.007)	(0.003)
Construction	2327.90	2351.50	0.10	0.11
	(94.00)	(43.40)	(0.007)	(0.003)
Transportation	3211.30	3414.20	0.12	0.12
	(111.70)	(68.00)	(0.008)	(0.003)
Firm size				
< 20	2164.90	2239.20	0.19	0.19
	(73.50)	(39.70)	(0.009)	(0.004)
20 to 200	2547.10	2783.90	0.29	0.30
	(61.20)	(32.00)	(0.011)	(0.005)
200 to 2000	2972.10	3276.00	0.27	0.25
	(65.60)	(37.80)	(0.011)	(0.004)
> 2000	3725.20	3611.30	0.25	0.26
	(104.40)	(37.50)	(0.010)	(0.004)

Standard errors in parentheses.

Table 4.3: Mean Gross Monthly Wage, Female

	Mean wage		Share	
Variable	Obese	Non-obese	Obese	Non-obese
Employed	1538.30	1692.60	—	—
	(26.80)	(11.10)	(—)	(—)
Full-time	1994.70	2227.20	0.52	0.52
	(36.90)	(15.80)	(0.014)	(0.005)
Part-time	1039.80	1124.80	0.48	0.48
	(26.90)	(10.50)	(0.014)	(0.005)
White-collar	1728.10	1831.00	0.56	0.81
	(32.50)	(12.60)	(0.005)	(0.004)
Blue-collar	1077.90	1096.80	0.44	0.19
	(37.50)	(17.10)	(0.005)	(0.004)
Industry				
Agriculture	1207.10	1504.40	0.04	0.03
	(66.90)	(52.60)	(0.002)	(0.002)
Banking, insurance	1628.70	1695.10	0.08	0.30
	(50.20)	(17.00)	(0.003)	(0.005)
Trade	1913.20	2238.10	0.12	0.09
	(116.10)	(45.10)	(0.003)	(0.003)
Mining	1839.70	1945.70	0.13	0.05
	(128.40)	(50.50)	(0.003)	(0.002)
Services	1254.40	1332.10	0.05	0.07
	(90.60)	(39.00)	(0.002)	(0.003)
Energy	1771.40	2050.20	0.23	0.08
	(82.80)	(42.40)	(0.004)	(0.003)
Manufacturing	1857.10	1817.10	0.12	0.02
	(215.00)	(70.10)	(0.003)	(0.002)
Construction	1229.30	1253.60	0.11	0.20
	(49.40)	(19.80)	(0.003)	(0.004)
Transportation	1457.10	1811.30	0.12	0.16
	(59.10)	(31.40)	(0.003)	(0.004)
Firm size				
< 20	1147.10	1215.20	0.28	0.30
	(41.00)	(16.80)	(0.013)	(0.005)
20 to 200	1531.60	1636.10	0.33	0.29
	(46.90)	(17.30)	(0.013)	(0.005)
200 to 2000	1838.10	1984.80	0.21	0.21
	(60.70)	(22.20)	(0.011)	(0.004)
> 2000	1797.70	2189.80	0.18	0.20
	(62.20)	(30.90)	(0.011)	(0.004)

Standard errors in parentheses.

Table 4.4: Means for Personal Characteristics

	Male		Female	
Variable	Obese	Non-obese	Obese	Non-obese
Education (more than high school)	0.17 (0.009)	0.26 (0.004)	0.17 (0.011)	0.23 (0.004)
Age	44.8 (0.232)	41.6 (0.102)	44.9 (0.269)	41.3 (0.105)
Tenure	13.2 (0.262)	10.9 (0.094)	10.8 (0.262)	9.4 (0.088)
Children 0-1	0.03 (0.004)	0.04 (0.002)	0.01 (0.002)	0.01 (0.001)
Children 2-4	0.09 (0.007)	0.12 (0.004)	0.03 (0.005)	0.06 (0.002)
Married	0.77 (0.010)	0.65 (0.005)	0.69 (0.013)	0.62 (0.005)
Region				
North	0.14 (0.008)	0.13 (0.003)	0.13 (0.009)	0.13 (0.003)
South	0.35 (0.011)	0.37 (0.005)	0.33 (0.013)	0.35 (0.005)
East	0.23 (0.010)	0.24 (0.004)	0.29 (0.013)	0.27 (0.005)
West	0.28 (0.011)	0.26 (0.004)	0.25 (0.012)	0.25 (0.004)
Health status				
Mental (MCS)	51.31 (0.217)	50.88 (0.088)	49.30 (0.280)	48.95 (0.098)
Physical (PCS)	49.86 (0.196)	53.25 (0.074)	48.37 (0.242)	52.67 (0.082)

Standard errors in parentheses.

Table 4.5: Regression Results, Dependent Variable: Log Gross Monthly Wage, Male

	Model 1	Model 2	Model 3	Model 4
Obese	-0.026	-0.042††	-0.020	-0.014
	(0.020)	(0.017)	(0.017)	(0.014)
Age		0.098†††	0.100†††	0.066†††
		(0.006)	(0.006)	(0.005)
Age squared		-0.001†††	-0.001†††	-0.001†††
		(0.000)	(0.000)	(0.000)
Education		0.429†††	0.405†††	0.275†††
		(0.015)	(0.015)	(0.014)
Tenure				0.012†††
				(0.002)
Tenure squared				-0.001†††
				(0.000)
Health controls	No	No	Yes	Yes
Personal controls	No	Yes	Yes	Yes
Labor market controls	No	No	No	Yes
R^2	0.0002	0.297	0.310	0.501
Obese_{t-1}	-0.048††	-0.048††	-0.032	-0.014
	(0.024)	(0.021)	(0.020)	(0.017)
Age		0.090†††	0.092†††	0.058†††
		(0.007)	(0.007)	(0.006)
Age squared		-0.001†††	-0.001†††	-0.001†††
		(0.000)	(0.000)	(0.000)
Education		0.438†††	0.419†††	0.288†††
		(0.017)	(0.017)	(0.017)
Tenure				0.014†††
				(0.002)
Tenure squared				-0.001†††
				(0.000)
Health controls	No	No	Yes	Yes
Personal controls	No	Yes	Yes	Yes
Labor market controls	No	No	No	Yes
R^2	0.0008	0.301	0.310	0.508

Cluster-corrected standard errors in parentheses.

All models include a constant. Additional Models 2, 3, and 4 include time and regional dummies.

Table 4.6: Regression Results, Dependent Variable: Log Gross Monthly Wage, Female

	Model 1	Model 2	Model 3	Model 4
Obese	-0.108†††	-0.098†††	-0.084†††	-0.071†††
	(0.030)	(0.029)	(0.029)	(0.022)
Age		0.062†††	0.062†††	0.051†††
		(0.006)	(0.006)	(0.005)
Age squared		-0.001†††	-0.001†††	-0.001†††
		(0.000)	(0.000)	(0.000)
Education		0.384†††	0.379†††	0.232†††
		(0.022)	(0.022)	(0.016)
Tenure				0.022†††
				(0.002)
Tenure squared				-0.001†††
				(0.000)
Health controls	No	No	Yes	Yes
Personal controls	No	Yes	Yes	Yes
Labor market controls	No	No	No	Yes
R^2	0.002	0.113	0.116	0.506
Obese$_{t-1}$	-0.092†††	-0.091†††	-0.078††	-0.072†††
	(0.036)	(0.34)	(0.034)	(0.026)
Age		0.058†††	0.058†††	0.053†††
		(0.007)	(0.007)	(0.006)
Age squared		-0.001†††	-0.001†††	-0.001†††
		(0.000)	(0.000)	(0.000)
Education		0.369†††	0.364†††	0.229†††
		(0.024)	(0.024)	(0.018)
Tenure				0.019†††
				(0.003)
Tenure squared				-0.001†††
				(0.000)
Health controls	No	No	Yes	Yes
Personal controls	No	Yes	Yes	Yes
Labor market controls	No	No	No	Yes
R^2	0.002	0.107	0.110	0.504

Cluster-corrected standard errors in parentheses.

All models include a constant. Additional Models 2, 3, and 4 include time and regional dummies.

Table 4.7: Regression Results, Dependent Variable: Log Yearly Wage, Male

	Model 1	Model 2	Model 3	Model 4
Obese	- 0.030	-0.041††	-0.016	-0.012
	(0.023)	(0.020)	(0.020)	(0.017)
Age		0.104†††	0.105†††	0.076†††
		(0.007)	(0.007)	(0.006)
Age squared		-0.001†††	-0.001†††	-0.001†††
		(0.000)	(0.000)	(0.000)
Education		0.432†††	0.403†††	0.268†††
		(0.017)	(0.017)	(0.016)
Tenure				0.017†††
				(0.002)
Tenure squared				-0.001†††
				(0.000)
Health controls	No	No	Yes	Yes
Personal controls	No	Yes	Yes	Yes
Labor market controls	No	No	No	Yes
R^2	0.0003	0.281	0.298	0.461
Obese_{t-1}	-0.051††	-0.056†††	-0.036†	-0.017
	(0.024)	(0.022)	(0.022)	(0.018)
Age		0.093†††	0.094†††	0.064†††
		(0.007)	(0.007)	(0.006)
Age squared		-0.001†††	-0.001†††	-0.001†††
		(0.000)	(0.000)	(0.000)
Education		0.421†††	0.399†††	0.255†††
		(0.018)	(0.018)	(0.018)
Tenure				0.018†††
				(0.002)
Tenure squared				-0.001†††
				(0.000)
Health controls	No	No	Yes	Yes
Personal controls	No	Yes	Yes	Yes
Labor market controls	No	No	No	Yes
R^2	0.0008	0.258	0.270	0.433

Cluster-corrected standard errors in parentheses.

All models include a constant. Additional Models 2, 3, and 4 include time and regional dummies.

Table 4.8: Regression Results, Dependent Variable: Log Yearly Wage, Female

	Model 1	Model 2	Model 3	Model 4
Obese	-0.116†††	-0.105†††	-0.087††	-0.060††
	(0.035)	(0.034)	(0.034)	(0.025)
Age		0.077†††	0.078†††	0.066†††
		(0.008)	(0.008)	(0.006)
Age squared		-0.001†††	-0.001†††	-0.001†††
		(0.000)	(0.000)	(0.000)
Education		0.372†††	0.366†††	0.223†††
		(0.026)	(0.026)	(0.021)
Tenure				0.025†††
				(0.003)
Tenure squared				-0.001†††
				(0.000)
Health controls	No	No	Yes	Yes
Personal controls	No	Yes	Yes	Yes
Labor market controls	No	No	No	Yes
R^2	0.002	0.099	0.103	0.443
Obese$_{t-1}$	-0.103†††	-0.097†††	-0.084††	-0.048†
	(0.035)	(0.034)	(0.033)	(0.026)
Age		0.067†††	0.068†††	0.059†††
		(0.008)	(0.008)	(0.006)
Age squared		-0.001†††	-0.001†††	-0.001†††
		(0.000)	(0.000)	(0.000)
Education		0.349†††	0.344†††	0.221†††
		(0.025)	(0.025)	(0.020)
Tenure				0.020†††
				(0.003)
Tenure squared				-0.001†††
				(0.000)
Health controls	No	No	Yes	Yes
Personal controls	No	Yes	Yes	Yes
Labor market controls	No	No	No	Yes
R^2	0.002	0.092	0.096	0.435

Cluster-corrected standard errors in parentheses.

All models include a constant. Additional Models 2, 3, and 4 include time and regional dummies.

4.10 Appendix

Table 4.9: Items and Subindices Physical and Mental Health Indices

Index	Subindex	Item
Physical health	Physical functioning	State of health affects ascending stairs
		State of health affects tiring tasks
	Role physical	Accomplished less due to physical problems
		Limitations due to physical problems
	Bodily pain	Physical pain last 4 weeks
	General health	Current health
Mental health	Vitality	Used lot of energy last 4 weeks
	Social functioning	Limited socially due to health last 4 weeks
	Role emotional	Accomplished less due to emotional problems
		Less careful due to emotional problems
	Mental health	Melancholy last 4 weeks
		Well balanced last 4 weeks

Table 4.10: Description of Variables

Variable	Description
Obese	Equal to 1 if person's BMI > 30, otherwise 0
Gross monthly income	Person's gross monthly income deflated to 2000 Euro
Male	Equal to 1 if person is male, otherwise 0
Age	Person's age in years
Age squared	Person's age in years squared
Education	Equal to 1 if person has a university degree, otherwise 0
Married	Equal to 1 if person is married
Children 0-1	Equal to 1 if person has children aged 0 to 1, otherwise 0
Children 2-4	Equal to 1 if person has children aged 2 to 4, otherwise 0
Blue-collar	Equal to 1 if person works in a blue-collar job, otherwise 0
White-collar	Equal to 1 if person works in a white-collar job, otherwise 0
Full-time	Equal to 1 if person works full time, otherwise 0
Part-time	Equal to 1 if person works part time, otherwise 0
Employment	Equal to 1 if person works either in a blue-collar or a white-collar job, otherwise 0
Tenure	Tenure in actual job in years
Tenure squared	Tenure in actual job in years squared

Table 4.11: Description of Variables, cont.

Variable	Description
Firm size	Measured with four dummies, each equal to 1 if person works in the respective firm, otherwise 0 (less than 20, 20 to 200, 200 to 2000, and more than 2000 employees)
Industry	Measured with nine dummies, each equal to 1 if person works in the respective industry, otherwise 0 (Agriculture, Banking and insurance, Energy, Services, Trade, Transportation, Construction, Mining, and Manufacturing)
Region	Measured with four dummies, each equal to 1 if person lives in the respective region, otherwise 0 (northern, southern, eastern, and western Germany)
Health status	Two cumulative measures, one for the physical status (PCS) and one for the mental status (MCS), both measured on a scale from 0 to 100

Table 4.12: Means

Variable	Full Sample	Male	Female
Obese	0.13 (0.002)	0.15 (0.003)	0.12 (0.003)
Income (gross / month)	2366.70 (11.159)	2995.70 (17.206)	1674.40 (10.310)
Age	41.90 (0.068)	42.10 (0.094)	41.70 (0.099)
Male	0.52 (0.003)	— (—)	— (—)
Education	0.24 (0.003)	0.25 (0.004)	0.22 (0.004)
Tenure	10.4 (0.062)	11.2 (0.090)	9.5 (0.084)
Blue-collar	0.33 (0.003)	0.45 (0.005)	0.20 (0.004)
White-collar	0.67 (0.003)	0.55 (0.005)	0.80 (0.004)
Full-time	0.71 (0.003)	0.89 (0.003)	0.52 (0.005)
Part-time	0.29 (0.003)	0.11 (0.003)	0.48 (0.005)
Agriculture	0.03 (0.001)	0.04 (0.002)	0.03 (0.002)
Banking, insurance	0.18 (0.003)	0.08 (0.002)	0.30 (0.004)
Trade	0.11 (0.002)	0.12 (0.003)	0.09 (0.003)
Mining	0.09 (0.002)	0.13 (0.003)	0.05 (0.002)
Services	0.06 (0.002)	0.05 (0.002)	0.07 (0.002)
Manufacturing	0.07 (0.002)	0.12 (0.003)	0.02 (0.001)
Energy	0.16 (0.002)	0.23 (0.004)	0.08 (0.003)
Construction	0.15 (0.002)	0.11 (0.003)	0.19 (0.004)
Transportation	0.14 (0.002)	0.12 (0.003)	0.16 (0.004)

Standard errors in parentheses.

Table 4.13: Means, cont.

Variable	Full Sample	Male	Female
< 20	0.24 (0.003)	0.19 (0.004)	0.30 (0.004)
20 to 200	0.30 (0.003)	0.30 (0.004)	0.30 (0.004)
200 to 2000	0.24 (0.003)	0.26 (0.004)	0.21 (0.004)
> 2000	0.22 (0.003)	0.25 (0.004)	0.19 (0.004)
North	0.13 (0.002)	0.13 (0.003)	0.13 (0.003)
South	0.36 (0.003)	0.36 (0.004)	0.35 (0.005)
East	0.25 (0.003)	0.24 (0.004)	0.27 (0.004)
West	0.26 (0.003)	0.27 (0.004)	0.25 (0.004)
Married	0.65 (0.003)	0.67 (0.004)	0.62 (0.005)
Child 0-1	0.03 (0.001)	0.04 (0.002)	0.01 (0.001)
Child 2-4	0.09 (0.002)	0.12 (0.003)	0.05 (0.002)
MCS	50.01 (0.062)	50.94 (0.082)	48.99 (0.092)
PCS	52.47 (0.052)	52.76 (0.070)	52.16 (0.079)

Standard errors in parentheses.

Curriculum Vitae

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Education

10/2002–09/2007	Doctoral Studies at the University of Zurich, Switzerland Advisor: Prof. Dr. R. Winkelmann
09/2007	University of Zurich, ”Causal Inference and Program Evaluation” by Guido Imbens
01/2006	University of Zurich, ”Empirical Strategies” by Joshua D. Angrist
08/2004	Study Center Gerzensee, ”Econometric Policy Evaluation” by James J. Heckman
04/2004	7^{th} IZA Summer School in Labor Economics, Ammersee, Germany • ”Behavioral Labor Economics” by Armin Falk • ”Empirical Labor Market Models with Dynamic Self-Selection” by Christian Belzil
09/1999–06/2000	Studies in Economics at the University of Lund, Sweden
10/1997–10/2002	Licentiate in Economics, University of Bern, Switzerland

Working Experience

since 01/2008	Consultant, Polynomics AG
07/2007–12/2007	Consultant, Plaut Economics
10/2002–09/2007	Research Associate, Statistics and Empirical Economics Research Group, Socioeconomic Institute, University of Zurich
03/2004–03/2007	Assistant Representative at the Faculty of Economics

Publications and Working Papers

2007	*Obesity and Wages in the German Labor Market*, unpublished manuscript.
	I'm not fat, just too short for my weight, Family Child Care and Obesity in Germany, SOI Working Paper No. 0707.
2006	*Secondary School Track Selection of Single-Parent Children - Evidence from the German Socio-Economic Panel*, Schriften des Vereins für Socialpolitik, 313, 39-54.
2005	*Single Motherhood and (Un)Equal Educational Opportunities: Evidence from Germany*, SOI Working Paper No. 0512.
	Secondary School Track Selection of Single-Parent Children - Evidence from the German Socio-Economic Panel, SOI Working Paper No. 0415.