Three Essays on Empirical Labor Economics

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Meiner Familie.

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Contents

List of Tables

List of Figures

Summary

This dissertation addresses different issues from the field of empirical labor economics and comprises three stand-alone research papers. The thesis is organized as follows: the first two chapters deal with the inclusion of personality traits in labor economic research. In recent years, it has been shown that apart from observable socio-demographic factors, personality traits can contribute considerably to explaining individual behavior on the labor market. The focus is thereby on female labor force participation and on the determinants of job satisfaction. The third chapter investigates misclassification in register data. The analysis of the determinants for job separation with transition to unemployment illustrates the relevance of measurement errors for empirical research.

The first chapter of the thesis is joint work with Winfried Pohlmeier and aims at assessing the effect of personality traits in the labor force participation decision of women. While research on the role of cognitive skills for individual labor market success has a long tradition in economics, comparatively little is known about the channels through which non-cognitive skills affect individual labor market behavior. We find strong evidence that aside from differences in cognitive skills, a large proportion of individual earnings differentials can be attributed to personality traits. Consequently, we expect two possible channels of personality traits having an influence on female labor force participation: First, personality traits that are favorable to higher wages might increase the probability of a women participating in the labor market simply because she faces higher wages. Second, there can also be a direct effect of personality traits if they influence preferences that determine labor force participation. For our analysis, we use the Big Five personality concept of personal psychology. The data is taken from the German Socio-Economic Panel (SOEP) that includes self-reported measurements of the Big Five Traits in addition to rich information about the socio-economic background as well as the employment history. Our results show that personality traits play an important role for female labor force

participation. In particular, we find that ignoring personality traits exaggerates the effect of education. The study expands the understanding of the heterogeneity of individual decisions. We find strong evidence that the Big Five personality concept is closely related to preference parameters and that this effect is rather stable over different age groups compared to other socio-economic variables. However, future research has to shed more light on the role of personality traits for preference formation. Moreover, our results show the need to include personality traits also in other economic analyses since we do not expect that the impact of personality traits is only limited to the marginal rate of substitution between leisure and consumption.

The second chapter investigates the determinants of job satisfaction. In the last decade, research on happiness in general and on satisfaction with special domains has received special attention in economics. Job satisfaction has been found to be a strong predictor of productivity and job stability as well as of physical and mental health. Increasing or maintaining job satisfaction should therefore be of interest for employers as well as for employees. Hence, this chapter analyzes which factors drive job satisfaction. We are especially interested in the role of the own wage as well as in the effect of comparison wages, i.e. the own wage compared to others. We follow two approaches to incorporate these comparison wages: first, we use the fitted wages of an additional age-specific wage equation to model the expected wage of individuals with similar characteristics. This comparison effect is called social comparison. Second, we include past wages in order to capture the effect of the development of the own wage. In addition to the comparison wages, we introduce personality traits in the analysis. Results from psychology show that personality traits affect satisfaction directly but also indirectly through a different weighting of certain individual and job characteristics. In this chapter, we analyze these direct and indirect effects of personality traits on overall job satisfaction and compare the results with those for satisfaction with pay. We find comparatively little direct and no indirect effects for the Big Five personality traits. The Locus of control affects overall job satisfaction directly and indirectly. Individuals with an internal Locus of Control are on average more satisfied with their job in general than individuals with an external Locus of Control. Moreover, comparison wages do not matter for the first group as much as for the latter group. This difference cannot be found in the determinants of satisfaction with personal income which is more determined by observable characteristics than by personality. Robustness checks show no evidence for reverse causality of job satisfaction on personality traits. Furthermore, more flexible estimation methods indicate that comparison wages have an especially strong effect for very satisfied and very unsatisfied individuals with an external Locus of Control.

The third chapter of the thesis is joint work with Ralf Wilke and deals with misclassification in register data. We analyze the main determinants for job separation with transition to unemployment using individual administrative data from Germany. While the sample size is large and the information in target variables is often highly accurate, non-target variables are subject to considerable measurement errors due to a lack of relevance for the data generating process. We apply comprehensive logical editing and imputation rules for the education and citizenship variables and use validation information to determine misclassification probabilities. Our results suggest the presence of considerable measurement errors that strongly affect our estimation results. In particular, we observe that the effect of education halves in magnitude when using the imputed data instead of the original data. The effect of not being German changes its sign. Our results therefore illustrate that standard results for classical measurement error do not hold for nonlinear models with non-classical measurement errors, because there would be no change in the sign of the estimated coefficients and their magnitude would increase after editing and imputing the data. Our findings demonstrate that measurement errors in register data can lead to misleading conclusions about the effect of education or foreign nationality on individual labor market outcomes even if the data are large and partly precise. Our application shows that even though individual labor market outcomes are strongly associated with individual skills, it is mainly the length of tenure that eliminates the unemployment risk. The choice of educational qualification seems to be far less important than is commonly thought and suggested by previous evidence for Germany based on household survey data, although higher education is related to safer jobs.

Zusammenfassung

Die vorliegende Dissertation beschäftigt sich mit verschiedenen Aspekten der empirischen Arbeitsmarktforschung und besteht aus drei eigenständigen Forschungsarbeiten. Der Aufbau der Arbeit setzt sich wie folgt zusammen: in den ersten beiden Kapiteln wird untersucht, wie sich die zusätzliche Berücksichtigung von Persönlichkeitsmerkmalen in Fragestellungen der Arbeitsmarktforschung auswirkt. In den vergangenen Jahren wurde gezeigt, dass Persönlichkeitsmerkmale neben den traditionellen sozio-ökonomischen Hintergrundvariablen wesentlich zur Erklärung des Verhaltens von Menschen auf dem Arbeitsmarkt beitragen können. Besonderes Interesse gilt im Rahmen dieser Arbeit dem Zusammenhang von Persönlichkeit und der Erwerbsbeteiligung von Frauen und den Einfluss von Persönlichkeit auf die Arbeitszufriedenheit. Das dritte Kapitel beschäftigt sich mit Misklassifikation in amtlichen Daten. Am Beispiel des Übergangs von Beschäftigung in Arbeitslosigkeit wird erörtert, wie entscheidend Messfehler die Ergebnisse beeinflussen können.

Das erste Kapitel ist eine gemeinsame Arbeit mit Winfried Pohlmeier und untersucht den Einfluss von Persönlichkeit auf die Erwerbsbeteiligung von Frauen. Während die Forschung über den Effekt von kognitiven Fähigkeiten auf den individuellen Arbeitsmarkterfolg eine lange Tradition hat, gibt es bisher relativ wenig Erkenntnisse über die Wirkmechanismen von nicht-kognitiven Fähigkeiten auf das individuelle Verhalten am Arbeitsmarkt. In diesem Kapitel finden wir eindeutige Belege dafür, dass nicht-kognitive Fähigkeiten wesentlich dazu beitragen, individuelle Lohnunterschiede zu erklären. Basierend auf diesen Erkenntnissen erwarten wir zwei mögliche Kanäle, über die Persönlichkeit die Erwerbsbeteiligung von Frauen beeinflussen kann: Zum einen können bestimmte Persönlichkeitsmerkmale zu höheren Löhnen führen, was wiederum die Wahrscheinlichkeit erhöht, dass Frauen mit diesen Persönlichkeitsmerkmalen aus diesem Grund erwerbstätig werden. Zum anderen gibt es die Möglichkeit, dass die individuellen Präferenzen direkt von der Persönlichkeit beeinflusst werden. In unserer Arbeit verwenden wir das Big Five-Konzept aus der

Persönlichkeitspsychologie. Die Daten stammen aus dem Sozio-Ökonomischen Panel (SOEP), das neben umfangreichen Informationen zum sozio-ökonomischen Hintergrund auch Informationen zu den Big Five-Persönlichkeitsmerkmalen sowie der Erwerbshistorie bietet. Die Ergebnisse zeigen, dass Persönlichkeit in der Entscheidung über die Erwerbsbeteiligung bei Frauen eine wesentliche Rolle spielt. Darüber hinaus können wir zeigen, dass der Einfluss von Bildung überschätzt wird, wenn Persönlichkeit in der Analyse ignoriert wird. Zusammenfassend tragen unsere Ergebnisse dazu bei, die Heterogenität individueller Entscheidungen besser zu verstehen. Wir können zeigen, dass die Persönlichkeitsmerkmale des Big Five-Konzepts einen Einfluss auf individuelle Präferenzen haben und dass dieser Einfluss in verschiedenen Altersklassen im Gegensatz zu dem anderer sozio-ökonomischer Faktoren relativ stabil ist. Trotzdem gibt es auf diesem Gebiet noch viele offene Forschungsfragen. Insbesondere die Rolle von Persönlichkeit in der Ausbildung von Präferenzen muss näher untersucht werden. Außerdem machen unsere Ergebnisse deutlich, dass die Rolle von Persönlichkeit auch in anderen ökonomischen Fragestellungen berücksichtig werden sollte, da nicht davon auszugehen ist, dass nur die hier untersuchte Grenzrate der Substitution zwischen Freizeit und Konsum von individuellen Persönlichkeitsmerkmalen abhängt.

Das zweite Kapitel beschäftigt sich mit den Determinanten von Arbeitszufriedenheit. In den vergangenen Jahren ist die Glücksforschung allgemein und die Forschung zu bestimmten Bereichszufriedenheiten in der ökonomischen Literatur vermehrt behandelt worden. Da Arbeitszufriedenheit als Prediktor sowohl für Produktivität und Jobstabilität als auch für physisches und psychisches Wohlbefinden identifiziert wurde, ist eine hohe Arbeitszufriedenheit sowohl für Arbeitgeber als auch für Arbeitnehmer erstrebenswert. Daher wird in diesem Kapitel untersucht, welche Determinanten die individuelle Arbeitszufriedenheit beeinflussen. Insbesondere wird die Frage behandelt, welchen Effekt Vergleichslöhne zusätzlich zu dem des eigenen Lohns haben. Die Vergleichslöhne werden durch zwei Ansätze modelliert. Zum einen werden geschätzte Löhne basierend auf einer zusätzlichen Lohngleichung verwendet, zum anderen wird das aktuelle Gehalt im Vergleich zu dem früherer Jahre betrachtet. Zusätzlich zum Einfluss von Vergleichslöhnen wird untersucht, inwieweit diese Ergebnisse von Persönlichkeitsmerkmalen abhängen. Psychologische Forschungsergebnisse zeigen, dass Persönlichkeit zum einen einen direkten Einfluss auf Zufriedenheit hat, dass sie zum anderen aber auch die Gewichtung bestimmter individueller und Jobeigenschaften beeinflussen kann. Diese direkten und indirekten Effekte von Persönlichkeit auf die allgemeine Arbeitszufriedenheit werden untersucht und mit denen für die Determinanten der Zufriedenheit mit dem Einkommen verglichen. Neben dem vergleichsweise kleinen direkten Effekt der Big Five- Persönlichkeitsmaße zeigt der Locus of Control hohe direkte und indirekte Effekte auf die Arbeitszufriedenheit. Individuen mit einem internen Locus of Control machen ihre allgemeine Arbeitszufriedenheit weniger von Vergleichseinkommen abhängig als Individuen mit einem externen Locus of Control. Für die Zufriedenheit mit dem Einkommen ist dieser Unterschied nicht feststellbar, diese Zufriedenheit wird mehr durch beobachtbare Eigenschaften beeinflusst als durch Persönlichkeit. Robustheitschecks geben keine Hinweise für ein Endogenitätsproblem. Weiterhin zeigt sich, dass Vergleichslöhne insbesondere eine wichtige Rolle für sehr unzufriedene und sehr zufriedene Individuen mit einem externen Locus of Control spielen.

Das dritte Kapitel dieser Arbeit ist eine gemeinsame Arbeit mit Ralf Wilke und beschäftigt sich mit Misklassifikation in amtlichen Daten. Wir untersuchen die Hauptursachen für die Beendigung von Beschäftigungsverhältnissen mit einem Übergang in die Arbeitslosigkeit. Dabei verwenden wir individuelle deutsche Registerdaten. Ein wesentlicher Vorteil dieser Registerdaten ist der große Stichprobenumfang und die hohe Datenqualität der Kerninformationen. Demgegenüber enthalten diejenigen Variablen, die nur aus statistischen Gründen erhoben werden, sehr viele Messfehler. In diesem Papier werden umfangreiche Editing- und Imputationsverfahren auf die Bildungs- und Nationenvariable angewendet. Anhand von zusätzlichen Validierungsinformationen von höherer Qualität im Datensatz berechnen wir zusätzlich die Misklassifikationswahrscheinlichkeiten. Unsere Ergebnisse zeigen, dass es in den Daten einen erheblichen Anteil an Misklassifikation gibt und dass diese die Ergebnisse wesentlich beeinflusst. Insbesondere kann gezeigt werden, dass sich der Effekt von Bildung gegenüber den Originaldaten halbiert und der Effekt für ausländische Individuen das Vorzeichen wechselt, wenn die Misklassifikation berücksichtigt wird. Somit zeigen unsere Ergebnisse, dass die üblichen Eigenschaften des klassischen Messfehlermodells in diesem Fall nicht gelten. Hierbei wäre kein Vorzeichenwechsel möglich und der Koeffizient nach Korrektur der Daten müsste immer größer sein als der auf den fehlerhaften Daten basierende. Es wird deutlich, dass die Ergebnisse bezüglich des Einflusses von Bildung und Nationalität irreführend sein können, wenn Fehler in den Daten nicht berücksichtigt werden. Unsere Anwendung zeigt, dass Bildung zwar eine Rolle spielt, dass jedoch die Betriebszugehörigkeit die wesentliche Größe ist, die das Arbeitslosigkeitsrisiko senkt. Die Wichtigkeit des Bildungsabschlusses in diesem Zusammenhang wird demnach in früheren Studien, welche auf Umfragedaten beruhen, überschätzt.

Chapter 1

Female Labor Force Participation and the Big Five

1.1 Introduction

This paper investigates the relationship between personality traits and female labor force participation. While research on the role of cognitive skills for individual labor market success has a long tradition in economics, comparatively little is known about the channels through which non-cognitive skills affect individual labor market behavior. There is striking evidence that personality traits play a major role in explaining individual differences in school attendance and school performance (e.g. Jacob (2002), Duckworth and Seligman (2005), Carneiro et al. (2007)). Bowles et al. (2001a) survey the early literature that relates personal characteristics to earnings. There is no longer any doubt that, aside from differences in cognitive skills, a large proportion of individual earnings differentials can be attributed to personality traits. Empirical evidence is provided, for example, for the US (Carneiro and Heckman (2002), Heckman et al. (2006), Mueller and Plug (2006)), for Canada (Green and Riddell (2002)), for Sweden (Zetterberg (2005)), for the Netherlands (Nyhus and Pons (2005)) and Germany (Piatek and Pinger (2010), Heineck and Anger (2008) and Flossmann et al. (2007)). Although there is a growing literature attempting to synthesize the vast body of literature on personality traits and the economic literature on individual labor market performance, a large fraction of these studies focus on earnings. Comparatively little is known about how and which personalty traits affect labor supply decisions.

The channels through which personality traits affect labor supply can be manifold. In a recent paper, Borghans et al. (2008) study the measurement of personality traits in psychology and their relationship to preference parameters in economics. They emphasize the link between personality measures and economic preference parameters such as time preferences, risk aversion, altruism and preferences for leisure. In this paper, we build on their idea and relate personality traits to preference parameters using a conventional structural framework of labor force participation. This allows us to separate the direct effects of personality traits affecting the individual participation decision based on different individual preferences from the indirect effects of wages and / or educational attainment. Empirical support for our strategy is given by the study by Flossmann et al. (2007). Interestingly, they find a rather weak direct effect of non-cognitive skills on female wages compared to the effect for males, suggesting that for females, given their educational attainment and occupational choices, much of the skill effects operate indirectly.

By focusing on the effects of non-cognitive skills on labor supply, our study also relates to the literature on intergenerational transmission of non-cognitive skills. While there is large body of literature in psychology and economics on the effects of mothers' employment patterns on child development (e.g. Bernal and Keane (2006), Gregg et al. (2005), Harvey (1999), Hill et al. (2005), Ruhm (2004)), little is known about the transmission of personalty traits of parents to their children and how the labor supply decision of the mother and the decision of external child care interact with the skill acquisition process. Tavares (2008) finds that personality traits play an important role in the timing of childbearing. Since female labor force participation is closely related to the decision about having children, our results also contribute to this research field.

Disentangling the effects of personalty traits on labor force participation is not trivial and requires strong identifying restrictions. Here, we follow a rigorous structural approach by estimating a structural participation equation which allows us to interpret the estimated effects of personality traits in terms of preference parameters.

Our taxonomy of personality is based on the concept of the Big Five personality scale that maps the multidimensional facets of personality into five distinct factors (McCrae and Costa (1987)). The cross-section of married women and cohabiting women in Germany that we use for our empirical study is taken from the 2005 wave of the German Socio-Economic Panel (SOEP), which contains fifteen qualitative self-assessments on the Big Five.

The outline of the paper is as follows. Section 2 reviews the Big Five taxonomy and its relevance to the labor force participation decision. In Section 3, we work out our econometric approach, where we relate the Big Five to preference parameters of the labor supply function. Section 4 contains the relevant information on our sample, while in Section 5 the empirical findings are presented. Section 6 concludes and provides an outlook on future research.

1.2 The Big Five Personality Traits

In the subsequent analysis, we use the Big Five personality concept to image the various dimensions of personal traits. This concept, widely used in psychology, provides a solution to the problem of how to measure the complex structure of the personality of an individual and offers a consensus for researchers from different fields that are researching personality (John and Srivastava (1999)). The Big Five model states that the personality of an individual can be grouped into five personality domains which can be each divided into six subgroups, the facets. Table 1.1 summarizes the Big Five Personality Traits and the corresponding facets.

Table 1.1: Description of the five main personality traits (McCrae and Costa (1987))

Extraversion:	Friendliness, Gregariousness, Assertiveness, Activity Level, Excitement-Seeking, Cheerfulness
Agreeableness:	Trust, Morality, Altruism, Cooperation, Modesty, Sympathy
Conscientiousness:	Self-Efficacy, Orderliness, Dutifulness, Achievement-Striving, Self-Discipline, Cautiousness
Neuroticism:	Anxiety, Anger, Depression, Self-Consciousness, Immoderation, Vulnerability
Openness:	Imagination, Artistic Interest, Emotionality, Adventurousness, Intellect, Liberalism

In general, we can distinguish two types of traits: Extraversion and Agreeableness describe the interindividual behavior, meaning that these traits describe how an individual interacts with others. On the other hand, Conscientiousness, Neuroticism, and Openness to Experience deal with the intraindividual habitude of a person. These traits characterize how an individual deals with intellectual and emotional tasks.

The trait Extraversion captures how an individual behaves among others. A person with a high level of extraversion is friendly, likes having company, knows how to prevail, is active, likes impulses from new experiences and has positive emotions. Seibert and Kraimer (1995) find that extraverted people earn more, have more success in their working career and are more satisfied with their private and working live. We therefore expect that Extraversion has a positive effect on labor force participation. However, Fahr and Kusche (2008) find a positive relationship between Extraversion and absenteeism for females. They argue that extraverted individuals value additional leisure time more to recover from their work environment and to meet with friends and family.

A person with a high score on the trait Agreeableness is considered to be selfless, helpful, and cares for others. Less agreeable individuals, on the other hand, are egoistical, selfish and uncooperative. Erdheim et al. (2006) find a positive relationship between Agreeableness and normative commitment. However, Seibert and Kraimer (1995) show that individuals with a high score on Agreeableness have lower job satisfaction. Fahr and Kusche (2008) find a negative influence of Agreeableness on absenteeism for males and no effect for females. In the light of the present analysis, we could expect that agreeable women tend to be altruistic towards their spouse and children and therefore resign from their own career ambitions.

Conscientiousness describes the way how people deal with problems. Conscientious people show a high level of responsibility for themselves as well as for others. Furthermore, they are organized, hard working and ambitious. Barrick and Mount (1991) show a positive effect of Conscientiousness on job performance, which leads us to expect a positive effect on the likelihood of participating in the labor force as well.

The domain Neuroticism characterizes how people experience strong positive and negative emotions, i.e. their emotional stability. Individuals with a high score on Neuroticism cannot cope with stress and get frustrated and nervous easily. In contrast to the facets of the other Big Five traits, the facets of the domain Neuroticism reflect negative characteristics. Therefore, a very strong markedness of Neuroticism has a negative connotation while a high score on the other traits is socially desirable. Vearing and Mak (2007) find that a high score on Neuroticism leads to a high work commitment (even an over-commitment) on the one hand, but that this can often lead to physical and mental illness on the other hand as well. We hypothesize that the hurdle to start working is higher for neurotic women and that they are thus less likely to participate in the labor force.

The personality trait Openness to Experience describes how needy somebody is for changes, novelty, and complexity. The dimension “Experience“ includes the aspects fantasy, aesthetics, feelings, ideas, as well as values. Several facets of this domain are very abstract and difficult to operationalize. A highly open person may enjoy a complex job but may also cherish self-determination. Hence, it is difficult to estimate whether or not this domain influences the probability of a women taking part in the labor market. Fahr and Kusche (2008) do not find any effect of Openness to Experience on job absenteeism.

1.3 Empirical Approach

In our empirical strategy, we relate the Big Five personality traits to the individual preference parameters of a labor supply equation, which can be derived from an life-cycle labor supply decision sticking to the traditional assumption of explicit additivity of the intertemporal utility function and intertemporal additivity of the budget constraint. For the within-period preference function, we postulate parallel preferences of the form:[1]

$$U_{it}(C_{it}, L_{it}) = G_{it}(C_{it} + V_{it}(L_{it})), \tag{1.1}$$

where C is consumption and L denotes leisure. $G_{it}(\cdot)$ represents an increasing function. For parallel preferences, labor supply is independent of the marginal utility of

[1]See König et al. (1995) and Laisney et al. (1993) for two female labor supply studies using this preference function.

wealth, i.e. the Frisch labor supply equation coincides with the Marshallian and the Hicksian form (see Koebel et al. (2008) for details). In the context of our analysis, this admittedly restrictive parametric specification is a useful starting point because labor supply is independent of the time preference parameter so that personality traits enter the labor supply equation only through the parameters of the preference function (1.1). Therefore, the model is consistent with both hyperbolic discounting, as suggested by experimental evidence from psychology (e.g. Ainslie and Monterosso (2004), Rachlin (2006)), and exponential discounting, as the dominant specification strategy in economics. A more flexible preference function would cause an additional identification problem because personality traits affecting preferences for leisure and those affecting time preferences would have to be identified by additional functional form assumptions. A similar argument holds for risk preference (Green and Myerson (2004)). In a general framework, separate preference parameters for risk aversion and the consumption-leisure trade-off cannot be identified without additional functional form assumptions. If the individual overall preference for risk is reflected by the curvature of $G_{it}(\cdot)$, the curvature of $V_{it}(\cdot)$ may be interpreted as representing predominantly the preferences with respect to the consumption-leisure trade-off.

Assuming a Box-Cox specification $V_{it}(L_{it}) = \gamma_{it}(L^{\alpha_L} - 1)/\alpha_L$ with $0 < \alpha_L < 1$ yields a leisure demand equation of the form

$$\ln L_{it} = \frac{\ln \gamma_{it}}{1-\alpha_L} - \frac{1}{1-\alpha_L} \ln W_{it}, \tag{1.2}$$

where W_{it} is the wage. Note that the labor supply equation is log linear in the preference parameter γ, which determines the marginal rate of substitution between leisure and consumption. This parameter is a natural candidate to link personalty traits P_i with labor supply parameters. Let γ be given by the second order approximation

$$\ln \gamma_{it} = \gamma_0(t) + \gamma_z(t) Z_{it} + \gamma_p(t) \ln P_i + \gamma_{zz}(t) Z_{it}^2 + \gamma_{pp}(t)(\ln P_i)^2 + \gamma_{zp}(t) Z_{it} \ln P_i + \nu_{it},$$

where Z_{it} denotes other observable socio-economic factors capturing individual heterogeneity in the marginal rate of substitution between consumption and leisure, while the error term ν_{it} captures unobserved heterogeneity.

Note that the preferences are allowed to vary over the life-cycle. In particular, we want to allow for life-cycle context related effects of personal factors (personality traits, age, family characteristics, such as e.g. age of children) to affect the labor force participation decision. Borghans et al. (2008) review empirical evidence concluding that traits are sufficiently stable across situations to support the claim that traits exist. Traits, however, evolve over the life-cycle and their manifestation is contextual dependent. To our knowledge, little is known about traits with relation to the labor force participation decision. Obviously, our approach implicitly assumes that traits are sufficiently stable over the life-cycle such that individual responses on questions reflecting personality traits as provided by the SOEP can be treated as proxies for unobserved personalty traits. The question whether or not this assumption about the stability of the traits is valid, has been widely discussed in the literature (e.g. Conley (1985), Gustavsson et al. (1997), Costa et al. (2000), Caspi and Roberts (2001), Svrivastava et al. (2003) and Costa et al. (2006)). Although the authors admit that there can be small changes in some of the personality traits during the life-cycle, they all conclude that the traits can be seen as mostly stable after the age of 30.

1.4 The Data

Our sample is taken from the 2005 wave of the German Socio-Economic Panel (SOEP). It contains women living together with their partner. We do not condition on being married, i.e. we look at married couples and cohabiting couples, but we include a dummy for being married in our regression analysis. Women with partners who are not covered by the survey are excluded from our analysis. Furthermore, we restrict our analysis to women in the prime working years between age 25 to 54. This is done to avoid issues such as school and/or university enrollment as well as early retirement. Table A.1.1 in Appendix A contains the definitions of the variables used in the following analysis. Observations with missing information on one of the characteristics are excluded from the sample. This leaves us 3,390 observations for 2005. The summary statistics of the overall sample and by participation status are displayed in Table A.1.2.

Our variable of interest is *PARTIC*, a dummy variable indicating whether or not a woman participates in the labor market. We define this variable so as to come as close as possible to the notional participation concept by counting those as participating who are in fact participating in the labor force and those who intend to participate. Thus, we also consider a woman as participating if she is marginally or irregularly employed and looking for a full- or part-time employment at the same time. In addition, women in maternity protection ("Mutterschutz") or on parental leave ("Erziehungsurlaub") are also counted as participating. Finally, women who are officially registered at the Employment Office as being unemployed and intend to engage in paid part- or full-time employment as soon as possible and have been actively looking for work within the last four weeks are also treated as participating. Table 1.2 shows the composition of our sample with respect to the employment status. All states except the first one are treated as participation states, which corresponds to a labor force participation rate of 75.2%. The share of women working either full- or part-time is about 62.8%, this seems to be reasonable and representative for this population. Merz (2005) presents comparable results for the women's employment-to-population ratio in Germany in 2000. 12.2% of the women in the sample are counted as participating in the labor market even though they are not gainfully employed at the time.

Table 1.2: Employment status of the women in the sample (SOEP, Wave 2005, Number of obs. = 3,389)

Employment status	Nobs.	Percentage
Not participating	839	24.8
Full-time employed	1,125	33.2
Part-time employed	1,002	29.6
Marginally employed and looking for a regular job	7	0.2
Maternity protection	84	2.5
Parental leave	210	6.1
Registered unemployed and willing to work	123	3.6
Total	3,390	100.0

One third of the women in our sample are full-time and 29% part-time employed. Overall, 84% have at least one child, 18% of the women in our sample have three or more children. Comparing the two groups of participating women on the one hand and those not participating in the labor force on the other hand shows that in the former group, 81% of the women have at least one child, while this share is 93% in the latter group. Table A.1.3 gives more details about the children situation of the women in the sample. Another important difference between the two groups is the education level: one fourth of the non-participating women did not exceed the lowest vocational degree, this share is only 10% in the participating group. Compared with this, 25% of the participating women reached the highest education level, that is an university degree, while only every tenth women in the other group attained this level. Thus, the average education level in the group of participating women is higher.

The Big Five personality traits that we use as a proxy for non-cognitive skills in this paper is a psychological concept used to describe and study personality. In the 2005 wave of the SOEP, this concept was first introduced in the panel. Originally, the Big Five is measured using a long questionnaire. Since this is not tractable in the SOEP, a short item scale, the BFI-S, with 15 instead of originally 25 items has been developed (see Gerlitz and Schupp (2005) for a detailed description). Dehne and Schupp (2007) review the Big Five measurement in the SOEP and show its validity and reliability. The BFI-S consists of 15 statements that have to be assessed by the respondents on a 7-tier Likert-Scale, “1” meaning “I strongly disagree” and “7“ meaning “I strongly agree“. Each three of these statements belongs to one trait, the ordering of the statements during the interview is not clustered. Each statement can be classified into one of two possible groups: either an agreement with the statement belongs to a strong markedness of the trait in question (+); or an agreement with the statement can be seen as a sign for a strong opposition to the trait (-). Table 2.3 illustrates the measurement of the Big Five Index in the SOEP.

Table 1.3: The Big Five Personality Traits in the SOEP (2005)

“I see myself as someone who ...	
	... is communicative, talkative” (+)
Extraversion:	... is outgoing, sociable” (+)
	... is reserved” (-)
	... has a forgiving nature” (+)
Agreeableness:	... is considerate and kind to others” (+)
	... is sometimes somewhat rude to others” (-)
	... does a thorough job” (+)
Conscientiousness:	... does things effectively and efficiently” (+)
	... tends to be lazy” (-)
	... is relaxed, handles stress well” (-)
Neuroticism:	... gets nervous easily” (+)
	... worries a lot” (+)
	... is original, comes up with new ideas” (+)
Openness:	... has an active imagination” (+)
	... values artistic experiences” (+)

Table A.1.4 in Appendix A displays the correlation between the different personality traits of the Big Five Concept, where all correlation coefficients are significantly different from zero ($p < 0.01$). All traits except Neuroticism show positive correlation coefficients. Therefore, the measurement of the trait Neuroticism should be treated inversely to the others. The opposite of Neuroticism is often called Emotional Stability. In order to construct a measure for each trait, we add up the answers of the three questions for each trait, where "I strongly disagree" is worth one point and "I strongly agree" seven points in a positive question, in a negative question, we give one point for "I strongly agree" and seven for "I strongly disagree". The points of the three questions are added to get a single score for each trait, ranging from 3 to 21. We also construct a unidimensional Big Five-Index as the sum of the five traits. Here, we have to take into account that Neuroticism has a negative weight, we therefore recode this variable and use Emotional Stability[2] instead. The Big Five-Index is then given by Big Five-Index $= CONSC + OPEN + EXT + AGREE + EMOSTAB$. The scores for each trait as well as the Big Five-Index are standardized with mean set to zero and variance equal to one for the following analysis.

In order to compare the relevance of the Big Five for the two groups in Table A.1.2, we perform a t-test to check whether differences in the Big Five scores between participating and non participating women exist: For the traits Extraversion, Neuroticism and Conscientiousness, we find that the mean difference is highly significant ($p < 0.01$). Moreover, we can say that the mean score in the group of participating women is significantly higher for the traits Extraversion and Conscientiousness, whereas the score for Neuroticism is significantly smaller in this group. The traits Openness to Experience and Agreeableness do not show a significant difference ($p > 0.10$). The overall Big Five-Index gives a significantly higher score in the group of the participating women ($p < 0.01$). We therefore observe higher non-cognitive skills in women that participate in the labor force. Figure B.1.1 in Appendix B illustrates the distribution of the five traits and the Big Five-Index by participating status. In the following section, we will estimate whether these observed differences in the personality traits influence women in their decision regarding labor force participation.

A final issue that needs to be addressed is the question of whether or not personality traits are stable over time and wether personality traits and their self assessments are influenced by previous labor market participation. If the traits are influenced by changes in the labor force participation status and dynamic feedbacks occur causal

[2] $EMOSTAB = 24 - NEU$

effects are difficult to identify. Using information on the previous participation history we provide some evidence that the assumption of constant personality traits is not too unrealistic.

1.5 Empirical Results

A number of empirical studies using the Rotter scale (Flossmann, Piatek, and Wichert (2007)), the Big Five concept (e.g. Mueller and Plug (2006), Nyhus and Pons (2005)) or both (Heineck and Anger (2008)) show that non-cognitive skills have some explanatory power in explaining individual wage differences. Bowles et al. (2001b) argue that theses skills contribute to production by providing a service that appears as an argument in the production function. In the light of a principle agent problem, non-cognitive skills as an argument of the preference function are incentive enhancing, which implies that an employee's work ceteris paribus is more productive at every wage rate. Thus, employers are willing to set wages higher for those workers who reveal such incentive-enhancing preferences. The evidence though is not too striking if the wage equation includes control variables for human capital and/or cognitive skills.

Since there is no generally agreed-upon estimation strategy for the estimation of a labor force participation equation, we follow a simple two-stage approach where wages are imputed from a Becker-Mincer type earnings function and account for sample selectivity via a Heckman type of control function. The selection equation we use is a reduced form specification of the participation equation. It uses information on the proximity of the parents' home (*PAR_COLSE*) and the woman's personal assessment of the child care conditions (*NOT_SATISFIED*) as proxies for the time costs and monetary cost of labor force participation, which do not enter the wage equation and are not element of the structural participation equation. A similar approach is taken by Heim (2007) in his labor supply study for the US and is described there in more detail.

Table 1.4 contains the least squares estimates of the wage equation for the sample of working women which gives a first impression of the role of personality traits for wage determination. We use the natural log of the hourly net wage as the dependent variable. Since this information is not directly available in the SOEP, we compute the wage from information on the monthly net wage and the agreed upon work time per week[3]. Moreover, only women are included in the sample who work part- or full-time and report a monthly net wage of at least 400 Euro. Observations on wages of women who are marginally or irregularly employed are excluded from our study, because we think that this information is not reliable because the hourly wage rates for these observations suffer from a serious bias.

Inclusion of the Big Five as additional controls does not improve the explanatory power of the wage equation in terms of the adjusted R^2 (column 1 and 2) substantially. The joint exclusion of the five regressors is rejected by the F-statistics ($p < 0.01$), only Extraversion and Agreeableness turn out to have a significant effect on wages ($p < 0.01$). As expected, Extraversion has a positive effect on wages, while for Agreeableness we observe a negative one. Since these two personal traits relate to interindividual behavior, we can state that the interindividual traits seem to matter more for wages than the intraindividual skills described by the three other traits. Our result for Agreeableness supports the notion that agreeable persons are weaker wage negotiators and may have a more egalitarian attitude towards payment. But the negative sign may also reflect job choice aspects. More agreeable employees may be found in low wage sectors, in particular in the service sector or in health care services. Our finding is somewhat more pronounced than comparable findings by Nyhus and Pons (2005) for the Netherlands, who find a significant negative coefficient at the 10 percent level, while Mueller and Plug (2006) find no significant effect of this trait at all using US data. Neither Mueller and Plug (2006) nor Nyhus and Pons (2005) find a significant influence of Extraversion on female wages. The latter find a positive effect of emotional stability on wages, which would correspond to a negative effect of Neuroticism on wages in our model that we cannot confirm. Moreover, a comparison of the augmented wage equation (column 2) with the standard wage equation (column 1) reveals that the Big Five regressors are close to being orthogonal to the included explanatory variables because the coefficient estimates change only slightly when we augment the wage equation by the Big Five regressors.

[3] The hourly wage was calculated by $\text{HOUR\_WAGE} = \frac{\text{monthly wage}}{(\text{weekly working hours}) * \frac{52}{12}}$.

Table 1.4: Estimates of Wage Equation
Least squares estimates based on part- or full-time employed women without selectivity correction, p-values in parenthesis.
Dependent variable: log hourly wages. Standardized values of the Big Five Traits.

	without Big 5	with Big 5	Big 5-Index	without Education	Cross-section
			2005		2007
EAST	-.2303	-.2289	-.2303	-.1632	-.2328
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
AGE	.0128	.0107	.0127	0.0130	.0018
	(0.19)	(0.28)	(0.19)	(0.24)	(0.87)
$AGE^2 * 0.01$	-.0085	-.0055	-.0084	-0.0058	.0037
	(0.49)	(0.65)	(0.49)	(0.67)	(0.79)
GERMAN	.1567	.1531	.1568	0.2320	.1564
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
MID_VOC	.0569	.0568	.0567		.0487
	(0.04)	(0.04)	(0.04)		(0.14)
HIGH_VOC	.1734	.1726	.1732		.1684
	(0.00)	(0.00)	(0.00)		(0.00)
HIGH_EDU	.4735	.4717	.4733		.4691
	(0.00)	(0.00)	(0.00)		(0.00)
CONST	1.5094	1.5499	1.5104	1.5578	1.7818
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
EXT (2005)		.0262		.0152	.0206
		(0.00)		(0.12)	(0.04)
AGREE (2005)		-.0247		-.0290	-.0181
		(0.00)		(0.00)	(0.06)
CONSC (2005)		-.0083		-.0340	-.0113
		(0.42)		(0.00)	(0.32)
NEU (2005)		-.0040		-.0162	-.0134
		(0.63)		(0.08)	(0.15)
OPEN (2005)		-.0054		.0264	.0045
		(0.55)		(0.01)	(0.66)
Big Five Index (2005)			0.0011		
			(0.89)		
Nobs.	2,127	2,127	2,127	2,127	1,668
$\bar{R}^2$	.2572	.2622	.2569	.0802	.2620
$F_{(5)}$ Big 5		3.82		6.99	2.47

In column 3 of Table 1.4 we also present the results when including the Big Five-Index into the wage equation. This strategy is unsuccessful, which confirms the previous results that, if at all, only a few traits contribute to the explanation of individual earnings differentials and that using an aggregate measure swallows the channels through which non-cognitive skills affect wages. Column 4 shows the estimation results of a wage equation without controlling for education. This also leads to significant effects for Conscientiousness, Openness, and Neuroticism but at the expense of a loss in explanatory power of more than two thirds. In this case, Extraversion is no longer significant. One possible explanation for this is that the intraindividual traits Conscientiousness, Openness, and Neuroticism affect wages only indirectly through a higher education attainment and are, therefore, only significant when not controlling for education.

Finally, in order to alleviate a potential bias due to endogeneity of the Big Five we also present estimates for the wage equation based on the 2007 cross-section using the Big Five regressors of 2005 as predetermined variables (column 5). The estimation results are very similar. Extraversion and Agreeableness are still the only personality traits having a significant effect on wages: The size of the effect stays almost the same and the significance level is slightly lower in both cases. These results support our implicit assumption that the self-assessments of the traits are not suffering from reverse causation and are not affected by the current wage situation. Most of the effects of the Big Five on wages are indirect ones affecting wages by higher educational attainment. This robustness exercise points out that the Big Five personalty traits can be treated as time constant individual effects. Our estimation results for the other specifications of the wage equation also do not change when using the cross-section of 2007 (not displayed here).

A potential endogeneity problem arises from the fact that the self-assessments of personality traits are context related and may result from status in the labor force. In this case, we would have to find appropriate instruments for the participation equation. In order to address this potential endogeneity problem, we run a regression of the Big Five measured in 2005 on the participation status of the previous years and their interaction terms. Table A.1.5 displays the regression results for the Big Five traits where we also include age in order to control for possible changes over the life cycle. The explanatory variables in this setting are dummy variables that take on the value “1” if the women was participating in the labor force at the time of the interview in the corresponding year. Note that the sample size of these regressions are smaller due to missing values in the panel. The setting of the regression allows us to test whether or not a change from participating to not participating in the labor market has a different effect on a women's personality traits than a change from not participating to participating. If this were the case, we would have evidence for a non negligible endogeneity issue. However, the corresponding tests show that these two effects are not significantly different ($p > 0.5$), which again supports our assumption of exogenous personality traits in the labor force participation decision. Moreover, it is worth noting that some personality traits show some life-cycle pattern. In particular, Conscientiousness and Extraversion increase over the lifetime but with diminishing rates. However, since we only have one cross section, we cannot identify, whether this is an age or an cohort effect.

Table 1.5: Heckit Estimates of the Wage Equation
Dependent variable: log hourly wages, p-values in parenthesis.
Standardized values of the Big Five Traits.

	Wage equation		Selection equation	
EAST	-.2310	(0.00)	.1217	(0.04)
AGE	.0175	(0.08)	.0323	(0.00)
$AGE^2 * 0.01$	-.0148	(0.23)		
GERMAN	.1107	(0.00)	.3473	(0.00)
MID_VOC	.0410	(0.15)	.0872	(0.23)
HIGH_VOC	.1404	(0.00)	.3675	(0.00)
HIGH_EDU	.4257	(0.00)	.5736	(0.00)
CONST	1.5690	(0.00)	-1.3393	(0.00)
MARR			-.3868	(0.00)
NOT_SATISFIED			-.1375	(0.07)
PAR_CLOSE			.1297	(0.01)
logHH_INC			-.0300	(0.04)
ONE_CHILD			-.5554	(0.00)
TWO_CHILD			-.7477	(0.00)
THREE_CHILD			-1.1521	(0.00)
EXT (2005)	.0212	(0.02)	.0971	(0.00)
AGREE (2005)	-.0175	(0.05)	-.0638	(0.02)
CONSC (2005)	-.0230	(0.04)	.2009	(0.00)
NEU (2005)	.0010	(0.90)	-.0677	(0.01)
OPEN (2005)	-.0024	(0.79)	-.0480	(0.08)
λ	-.1366	(0.00)		
Nobs.	2,127		3,390	

The results of the wage equation corrected for sample selectivity are given in Table 1.5 (further specifications of the wage equation are given in Tabel A.1.6). The variables *MARR*, *NOT_SATISFIED*, *PAR_CLOSE*, *logHH_INC*, and the number of children are used as instruments entering the selection equation but are excluded from the wage equation. Except for the effect of Conscientiousness, which is now significantly negative, there are no substantial differences to report compared to the conventional OLS results on the sample of working women. The negative sign on Conscientiousness is somewhat surprising because we would expect that this personality trait is valued by employers. Since the existence of sample selectivity, cannot be rejected at conventional significance levels, we use the estimates of the Heckit to compute the imputed wages for the structural participation equation. The estimates used for the imputation procedure including the selection equation are displayed in Table 1.5 (same model specification as in column 2 of Table A.1.6). Figure B.1.2 in

Appendix B illustrates the distribution of the imputed wages for participating and non-participating women.

The results of the structural participation equation using imputed hourly wages for all women are given in Table 1.6 where the average marginal effects are displayed. In the following analysis, we exclude household income from our model since it turned out to be insignificant ($p > 0.9$) in all specifications. This finding is in line with many previous labor supply studies for Germany and other countries and provides support for our choice of a parallel preference function. The results in column 2 show that all personality traits except Agreeableness significantly influence the participation decision. Women with high self-regulatory skills, as captured by the overall factor Conscientiousness, are more likely to participate in the labor force. This trait has the strongest impact on the participation probability. The effect of Extraversion is also positive, but the corresponding coefficient is not even half the size of that for Conscientiousness. Openness to Experience and Neuroticism have a negative impact on the probability of participating in the labor market. The positive effect of Conscientiousness and the negative effect of Neuroticism are in line with our expectations as outlined in the discussion of the Big Five and labor force participation in Section 1.2.

The statistically insignificant coefficient on Agreeableness can be explained by the strong impact of this trait on wages. If we exclude wage from the participation equation (column 4), Agreeableness turns out to be negative and significant, at least at the 10%-level. Given wages, more agreeable women may face a larger conflict in the choice between work and family. Unconditionally, they work less due to lower wages. Contrary to the findings for the wage equation, the Big Five-Index is significant in the participation equation (column 3). The loss of explanatory power in terms of the McFadden's Pseudo R^2 is comparatively small which implies that the use of unidimensional measures of personality traits may be a reasonable research strategy in this context. Since four out of five personality traits have an affect, the aggregate measure has explanatory power in the direction we expected: The higher the non-cognitive skills as measured by the index, the higher is the probability that a women will participate in the labor market. In order to illustrate the effect of the personality traits, Table 1.7 displays the change in the predicted participation probability given certain changes in the different traits. If we take Conscientiousness as the most important of the five traits, the expected difference in the participation probability between two women one with maximum and one with minimum score equals 42 percentage points (keeping all other explanatory variables constant at their mean). If we only look at change of half a standard deviation around the mean, this difference is only 5 percentage points. However, the results of Table 1.7 illustrate that the effects of non-cognitive skills are not negligible in the labor force participation decision of women.

Column 1 gives the estimates of a conventional structural participation equation excluding measures of personality traits. If we compare column 1 and column 2, we find that, similar to the findings for the wage equation, significant coefficients remain significant and do not change sign. Interestingly, the only exception is the coefficient on education that drops dramatically and even becomes insignificant. This means that labor supply and labor force studies ignoring personality traits are likely to exaggerate the effect of education on labor supply. In these studies, education simply proxies the omitted personality traits to a large extend.

The wage effect is not significant in any of the model specifications given in Table 1.6. This is in line with the finding that wage effects for the female labor supply have decreased or even vanished over the last decades (Heim (2007)). A comparison of the full model in column 2 with the estimates given in column 4 in which the wage variable is excluded shows that the effects of the Big Five on the participation probability do not change. The coefficient estimates are nearly stable - only Agreeableness becomes more significant - supporting our hypothesis that much of the effects of the Big Five on labor force participation is preference driven rather than wage driven.

Even though the regression of the Big Five on previous labor force participation did not indicate that personal traits are affected by the present employment status, we perform another robustness check by estimating the participation equation based on the 2007 cross-section using the Big Five regressors from 2005 as pre-determined variables. We do not find substantial changes in the results. In fact, the coefficients for the Big Five are now larger and estimated with greater precision: now even the effect of Agreeableness is significantly negative.

Table 1.6: Estimates of the Structural Participation Equation
Average partial effects of the ML logit estimates, p-values in parenthesis. Imputed wages by Heckit estimates given in column 2 of Table 1.5. Standardized values of the Big Five Traits.

	without Big 5	with Big 5	Big 5-Index	without log wage	Cross-section
			2005		2007
EAST	.1173 0.1499	.1354	.1127	-.0530	
	(0.00)	(0.00)	(0.00)	(0.00)	(0.14)
AGE	-.0036	-.0140	-.0066	-.0104	-.0044
	(0.72)	(0.15)	(0.50)	(0.27)	(0.69)
$AGE^2 * 0.01$	.0020	.0130	.0050	.0102	.0020
	(0.87)	(0.26)	(0.67)	(0.38)	(0.88)
GERMAN	.1111	.0870	.0992	.1055	.1558
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
EDUCATION	.0548	.0268	.0382	.0555	.0801
	(0.00)	(0.18)	(0.03)	(0.00)	(0.00)
imp. logHOUR_WAGE	-.0013	.2022	.0871		-.0282
	(0.99)	(0.12)	(0.44)		(0.84)
MARR	-.1244	-.1246	-.1240	-.1248	-.0976
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
ONE_CHILD	-.0718	-.0740	-.0757	-.0751	-.0624
	(0.02)	(0.01)	(0.01)	(0.01)	(0.05)
TWO_CHILD	-.1309	-.1282	-.1325	-.1287	-.1200
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
THREE_CHILD	-.2739	-.2684	-.2767	-.2681	-.2906
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
EXT (2005)		.0278		0.0318	.0394
		(0.00)		(0.00)	(0.00)
AGREE (2005)		-.0112		-0.0145	-.0352
		(0.17)		(0.07)	(0.00)
CONSC (2005)		.0611		0.0557	.0625
		(0.00)		(0.00)	(0.00)
NEU (2005)		-.0196		-0.0194	-.0312
		(0.01)		(0.01)	(0.00)
OPEN (2005)		-.0239		-0.0241	-.0270
		(0.00)		(0.00)	(0.01)
Big Five Index (2005)			.0409		
			(0.00)		
Nobs.	3,390	3,390	3,390	3,390	2,616
McFadden's R^2	.1094	.1314	.1171	.1308	.1367
Correctly classified	75.63%	76.43%	75.96%	76.34%	73.74%
log Lik	-1,689	-1,648	-1,675	-1,649	-1,359

Table 1.7: Effects on participation probability
Changes of the participation probability due to changes in the personality traits. Changes in percentage points, holding all other variables constant at their mean.
*: *insignificant effect*

	min to max	$+\backslash-\frac{1}{2}$std.dev. around mean
EXT	.1629	.0282
*AGREE**	*-0.0555*	*-.0107*
CONSC	.4160	.0537
NEU	-.0983	-.0195
OPEN	-.1145	-.0233
Big 5 Index	.2701	.0392

For the specifications estimated above we have implicitly assumed that the marginal rate of substitution between consumption and leisure changes over the life-cycle but the effects of the other socio-economic factors (e.g. children, education) and the effects of the personality traits remain constant. Our results presented Table 1.6, however, indicate no significant age pattern for the preferences for all specifications.

The assumption of age-invariant effects of these factors on labor force participation is relaxed in the following by allowing for heterogeneity in the preference parameters by age group. We define three age groups: the first one includes women aged from 25 to 34 at the beginning of their work-life and possibly with young children, the second group consists of women between age 35 and 44, and finally the oldest group contains woman aged from 45 to 54. The labor force participation rate for these three age groups are 81%, 75%, and 72%, respectively. Using dummy variables for these three groups, we interact all explanatory variables, where the youngest group is the reference group. The effect of having a child on labor force participation may well decrease over the life-cycle as the child gets older and eventually leaves the parents' house. Similar arguments can be found for other socio-economic factors. The estimates from the structural participation equation allowing for different effects for different age groups are presented in Table 1.8. Almost all interaction terms of the Big Five are insignificant. When testing for joint significance of the interaction terms of the personality traits, we cannot reject the null ($p = 0.13$). Thus, we can conclude that we do not find any significant evidence that the impact of personality traits on the marginal rate of substitution between leisure and consumption changes over the life-cycle. The age heterogeneity for the coefficients on other socio-economic factors, in particular, the variables for the number of children is not very surprising.

Based on the estimated wage equation and the participation equation, we can now identify the direct (or net) effect of the Big Five traits on female labor force participation as well as the indirect effect of the personality traits through wages. Figure B.1.3 illustrates the odds ratios for the five traits, where the solid line represents the net effect based on the participation equation including the imputed log hourly wage (Column 2 in Table 1.6). The dashed line represents the combination of the net effect and the effect through wages using the estimation results of the participation equation excluding the log hourly wage (Column 4 in Table 1.6). We see that difference between the two effects is obvious for the three traits Extraversion, Agreeableness, and Conscientiousness, while the effect through wage is negligible for Neuroticism and Openness where we find almost no difference. In the case of Extraversion, the additional effect through wages is positive such that the odds ratio becomes higher. For Agreeableness and Conscientiousness, we observe a diminishing effect through wages on the participation probability, which reflects the negative sign of these two traits in the wage equation.

Table 1.8: Estimates of the Structural Participation Equation with time varying preferences Average partial effects of the ML logit estimation, p-values in parenthesis. Imputed wages by Heckit estimates given in column 2 of Table 1.5. Standardized values of the Big Five Traits.

	Coefficient	p-value	Coefficient	p-value
EAST	-.0932	(0.30)	-.0289	(0.72)
EAST * Age 35-44	.2243	(0.00)	.2018	(0.00)
EAST * Age 45-54	.2107	(0.00)	.1535	(0.00)
GERMAN	.2952	(0.00)	.2770	(0.00)
GERMAN * Age 35-44	-.2000	(0.01)	-.1920	(0.01)
GERMAN * Age 45-54	-.2464	(0.00)	-.2151	(0.00)
EDUCATION	.1437	(0.00)	.1099	(0.00)
EDUCATION * Age 35-44	-.1398	(0.00)	-.1102	(0.01)
EDUCATION * Age 45-54	-.1553	(0.00)	-.0934	(0.04)
imp. logHOUR_WAGE	-.6506	(0.02)	-.4030	(0.12)
imp. logHOUR_WAGE * Age 35-44	.9101	(0.01)	.6952	(0.02)
imp. logHOUR_WAGE * Age 45-54	1.1711	(0.00)	.7263	(0.02)
MARR	-.0660	(0.17)	-.0696	(0.15)
MARR * Age 35-44	-.0975	(0.17)	-.0973	(0.17)
MARR * Age 45-54	-.0509	(0.47)	-.0465	(0.51)
ONE_CHILD	-.0904	(0.19)	-.0954	(0.17)
ONE_CHILD * Age 35-44	-.0640	(0.46)	-.0610	(0.49)
ONE_CHILD * Age 45-54	.0824	(0.16)	.0894	(0.12)
TWO_CHILD	-.2360	(0.00)	-.2375	(0.00)
TWO_CHILD * Age 35-44	.0585	(0.40)	.0561	(0.40)
TWO_CHILD * Age 45-54	.1760	(0.00)	.1808	(0.00)
THREE_CHILD	-.3555	(0.00)	-.3623	(0.00)
THREE_CHILD * Age 35-44	.0009	(0.99)	-.0005	(0.99)
THREE_CHILD * Age 45-54	.1386	(0.00)	.1466	(0.00)
Age 35-44	-.5583	(0.04)	-.5562	(0.02)
Age 45-54	-.5841	(0.04)	-.5836	(0.02)
EXT	.0529	(0.00)	.0295	(0.00)
EXT * Age 35-44	-.0374	(0.10)		
EXT * Age 45-54	-.0248	(0.27)		
AGREE	-.0204	(0.29)	-.0124	(0.13)
AGREE * Age 35-44	-.0038	(0.87)		
AGREE * Age 45-54	.0229	(0.32)		
CONSC	.0275	(0.17)	.0593	(0.00)
CONSC * Age 35-44	.0293	(0.24)		
CONSC * Age 45-54	.0497	(0.04)		
NEU	.0056	(0.76)	-.0202	(0.01)
NEU * Age 35-44	-.0213	(0.33)		
NEU * Age 45-54	-.0397	(0.07)		
OPEN	-.0396	(0.04)	-.0242	(0.00)
OPEN * Age 35-44	.0264	(0.25)		
OPEN * Age 45-54	.0149	(0.51)		
McFadden's R^2	.1473		.1432	
Correctly classified	76.78%		76.76%	
log Lik	-1,617		-1,625	

1.6 Conclusion

The goal of this paper is to assess the role of non-cognitive skills, defined here as the Big Five personality traits, for female labor market participation. In particular, we are focussing on the channels through which these personality traits affect labor force participation. This is done by estimating a structural labor force participation equation which allows us to interpret the effects of personality traits on labor force in terms of individual heterogeneity in preferences.

Our findings are very much in line with many empirical studies claiming that non-cognitive skills play a non-negligible role in explaining individual behavior in the labor market. In particular, the results of our study exemplify that ignoring personality traits exaggerates the effect of education on labor force participation. Educational attainment and (female) labor force participation are simply two different outcome dimensions driven by personality traits.

We find a strong impact of the interindividual traits Extraversion and Agreeableness, whereby the former has a positive and the latter a negative effect on wages. Since the wage elasticity of labor supply is rather small and not significantly different from zero, the impact of personality traits on labor force participation is largely a direct one. Conscientiousness is the Big Five trait with the strongest positive effect. Why this particular trait plays such a prominent role requires further investigation, which is beyond the scope of the current study. Extraversion shows a positive, albeit smaller, effect, as well. Neuroticism and Openness both have a negative effect of about the same size on female labor market participation probability. The use of a single index to capture the effects of personality traits on female labor force participation is possible but problematic since the specific effects of the traits differ in size and sign.

Our study expands the understanding of preference heterogeneity and, consequently, of the heterogeneity of individual decisions. By endogenizing preference parameters and relating them to personality traits, the approach taken is admittedly a rather simple one. It yields some evidence that the Big Five concept of personal psychology is strongly related to preference parameters as suggested by Borghans et al. (2008). Various robustness checks show that self-assessed personality traits serve well as explanatory variables for labor force participation. Moreover, the effects of personality traits on preferences are much more stable over the life-cycle compared to other socio-economic factors. We find strong evidence that preferences change over the life-cycle. However, we do not observe time varying effects for the Big Five personality traits.

In our study, the Big 5 Five traits turn out to be rather stable over the life-cycle and orthogonal to the individuals labor force history. Future research should take the formation of personality traits and preference formation building on a model of preference formation into account. Another path of future research should be concerned with identification issues. Personality traits not only affect the preferences determining the marginal rate of substitution between leisure and consumption but also preferences towards risk and intertemporal substitution.

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Appendix A.1: Supplementary Tables

Table A.1.1: Definition of Variables (SOEP, Wave 2005)

Variable	Definition
AGE	Age in years
logHOUR_WAGE	ln(Hourly wage (Euro) based on the agreed upon work time per week)
logHH_INC	ln(net household income minus net wage of the women)
GERMAN	Dummy, 1 if German
EAST	Dummy, 1 if living in East Germany
STATE	Indicator for the different Federal States
MARR	Dummy, 1 if women is married
ONE_CHILD	Dummy, 1 if women has one child
TWO_CHILD	Dummy, 1 if women has two children
THREE_CHILD	Dummy, 1 if women has three or more children
PARTIC	Dummy, 1 if women participates in the labor market
FULLTIME	Dummy, 1 if full-time employed
PARTTIME	Dummy, 1 if part-time employed
LOW_VOC	Dummy, 1 if no degree or less or equal than 10 years of schooling (*reference group*)
MID_VOC	Dummy, 1 if high school degree (12 or 13 years of schooling) or vocational training
HIGH_VOC	Dummy, 1 if high school degree and vocational training
HIGH_EDU	Dummy, 1 if highest degree is university degree
EDUCATION	0 if LOW_VOC = 1; 1 if MID_VOC = 1; 2 if HIGH_VOC = 1; 3 if HIGH_EDU = 1
PAR_CLOSE	Dummy, 1 if parents live in the same household or in the same city
NOT_SATISFIED	Dummy, 1 if not satisfied with the child care situation
EXT	Score for Extraversion (from 3 to 21 (very pronounced))
AGREE	Score for Agreeableness (from 3 to 21 (very pronounced))
CONSC	Score for Conscientiousness (from 3 to 21 (very pronounced))
NEU	Score for Neuroticism (from 3 to 21 (very pronounced))
EMOSTAB	$= -(NEU - 24)$, measure for Emotional Stability
OPEN	Score for Openness to Experience (from 3 to 21 (very pronounced))
BigFiveIndex	Score of the Big Five-Index $(CONSC + AGREE + OPEN + EXT + EMOSTAB)$ (from 15 (low noncognitive skills) to 105 (high noncognitive skills))

Table A.1.2: Summary Statistics
SOEP, Wave 2005, Number of obs. = 3,390; Sample means, standard deviation in parenthesis (only for non-dummy variables)

	Full Sample	Participating	Not Participating	t-test for mean diff. p-values
AGE	41.04	40.68	42.12	0.00
	(7.93)	(8.00)	(7.61)	
logHOUR_WAGE	2.16	2.16	−−	
	(0.41)	(0.41)	−−	
Imputed logHOUR_WAGE	2.23	2.24	2.21	0.00
	(0.22)	(0.23)	(0.19)	
logHH_INC	7.30	7.28	7.37	0.17
	(1.59)	(1.48)	(1.89)	
GERMAN	.91	.94	.83	0.00
EAST	.24	.28	.13	0.00
MARR	.82	.79	.93	0.00
ONE_CHILD	.26	.28	.18	0.00
TWO_CHILD	.40	.39	.43	0.08
THREE_CHILD	.18	.14	.32	0.00
PARTIC	.75	1	0	
FULLTIME	.33	.44	0	
PARTTIME	.29	.39	0	
LOW_VOC (*reference*)	.14	.11	.25	0.00
MID_VOC	.48	.47	.51	0.06
HIGH_VOC	.16	.17	.14	0.04
HIGH_EDU	.22	.25	.12	0.00
EDUCATION	1.46	1.57	1.15	0.00
PAR_CLOSE	.30	.31	.27	0.04
NOT_SATISFIED	.10	.11	.09	0.25
EXT	14.85	15.04	14.27	0.00
	(3.37)	(3.32)	(3.44)	
AGREE	16.76	16.75	16.79	0.68
	(2.77)	(2.75)	(2.85)	
CONSC	18.17	18.34	17.67	0.00
	(2.46)	(2.34)	(2.75)	
NEU	12.51	12.37	12.92	0.00
	(3.54)	(3.48)	(3.68)	
OPEN	13.65	13.69	13.50	0.17
	(3.53)	(3.52)	(3.55)	
BigFiveIndex	74.91	75.45	73.31	0.00
	(9.11)	(8.91)	(9.51)	
Nobs.	3,390	2,551	839	

Table A.1.3: Number of Children by employment status (percentage)
SOEP, Wave 2005, Number of obs. = 3,390

	No children	1 child	2 children	3 or more children	Total
Not participating	1.77	4.46	10.59	7.94	24.76
Full-time employed	11.07	9.32	10.00	2.77	33.17
Part-time employed	2.30	7.82	14.28	5.16	29.57
Marginally employed	.00	.15	.03	.03	.21
Maternity protection	.00	.86	1.09	.53	2.48
Parental leave	.00	2.01	3.04	1.15	6.20
Registered unemployed and willing to work	.65	.97	1.21	.80	3.63
Total	15.79	25.58	40.25	18.38	100.00

Table A.1.4: Correlations between the Big Five Personality Traits
SOEP, Wave 2005, Number of obs. = 3,390

	Extra	Agree	Consc	Neuro	Open
Extraversion	1.0000				
Agreeableness	.0793	1.0000			
Conscientiousness	.2178	.3003	1.0000		
Neuroticism	-.1656	-.1229	-.0839	1.0000	
Openness	.3865	.1005	.2002	-.0564	1.0000

Table A.1.5: Dependency of personality traits on previous labor market participation
Least squares estimates regression of the Big 5 Traits on previous labor market participation, p-values in parenthesis.
Dependent variable: Score of the personality trait.

	Conscient.	Open	Extra	Agree	Neuro
Age	.1777	.0861	.1967	-.0939	-.1078
	(0.00)	(0.32)	(0.02)	(0.16)	(0.21)
AGE^2∗0.01	-.2030	-.1033	-.2588	.1281	.1217
	(0.01)	(0.33)	(0.01)	(0.12)	(0.25)
Partic04	.3472	.1086	.9487	.1665	.0800
	(0.13)	(0.74)	(0.30)	(0.52)	(0.81)
Partic03	.1844	.0151	.5747	.0461	-.1931
	(0.49)	(0.97)	(0.12)	(0.88)	(0.62)
Partic02	-.1210	.1295	.0742	-.4999	-.4121
	(0.62)	(0.71)	(0.83)	(0.07)	(0.24)
Partic04∗Partic03	-.1132	-.5133	-1.0142	-.5386	-.3258
	(0.72)	(0.26)	(0.02)	(0.13)	(0.47)
Partic03∗Partic02	.4342	.5310	.2915	.7948	.1894
	(0.16)	(0.24)	(0.50)	(0.02)	(0.67)
Constant	13.9071	11.6806	10.5766	18.3707	15.2676
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
adjust. R^2	.0178	.0009	.0119	.0017	.0047
Nobs.	2,952	2,952	2,952	2,952	2,952

Table A.1.6: Estimates of Wage Equation with Selectivity Correction
Heckit, p-values in parenthesis. Dependent variable: log hourly wages. Standardized values of the Big Five Traits.

Variable	without Big 5	with Big 5	Big 5-Index	without Education	with Big 5
			2005		2007
EAST	-.2332	-.2310	-.2335	-.1821	-.2415
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
AGE	.0181	.0176	.0185	.0305	.0096
	(0.07)	(0.08)	(0.06)	(0.00)	(0.41)
$AGE^2 * 0.01$	-.0158	-.0148	-.0164	-.0299	-.0064
	(0.20)	(0.23)	(0.18)	(0.02)	(0.66)
GERMAN	.1164	.1107	.1146	.0919	.1254
	(0.00)	(0.00)	(0.00)	(0.02)	(0.00)
MID_VOC	.0383	.0410	.0387		.0149
	(0.17)	(0.14)	(0.17)		(0.66)
HIGH_VOC	.1392	.1404	.1390		.1216
	(0.00)	(0.00)	(0.00)		(0.00)
HIGH_EDU	.4273	.4257	.4270		.4090
	(0.00)	(0.00)	(0.00)		(0.00)
CONST	1.5613	1.569	1.6085	1.5771	1.7852
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
EXT (2005)		.0212		.0054	.0130
		(0.02)		(0.61)	(0.20)
AGREE (2005)		-.0175		-.0094	-.0083
		(0.05)		(0.37)	(0.42)
CONSC (2005)		-.0230		-.0650	-.0259
		(0.04)		(0.00)	(0.03)
NEU (2005)		.0010		.0007	-.0072
		(0.90)		(0.94)	(0.44)
OPEN (2005)		-.0024		.0269	.0104
		(0.79)		(0.01)	(0.32)
Big Five Index (2005)			-.0068		
			(0.43)		
λ	-.1387	-.1366	-.1437	-.3419	-.1395
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Nobs.	3,390	3,390	3,390	3,390	2,616
Log Lik	-2,713	-2,705	-2,713	-2,861	-2,050

Appendix B.1: Figures

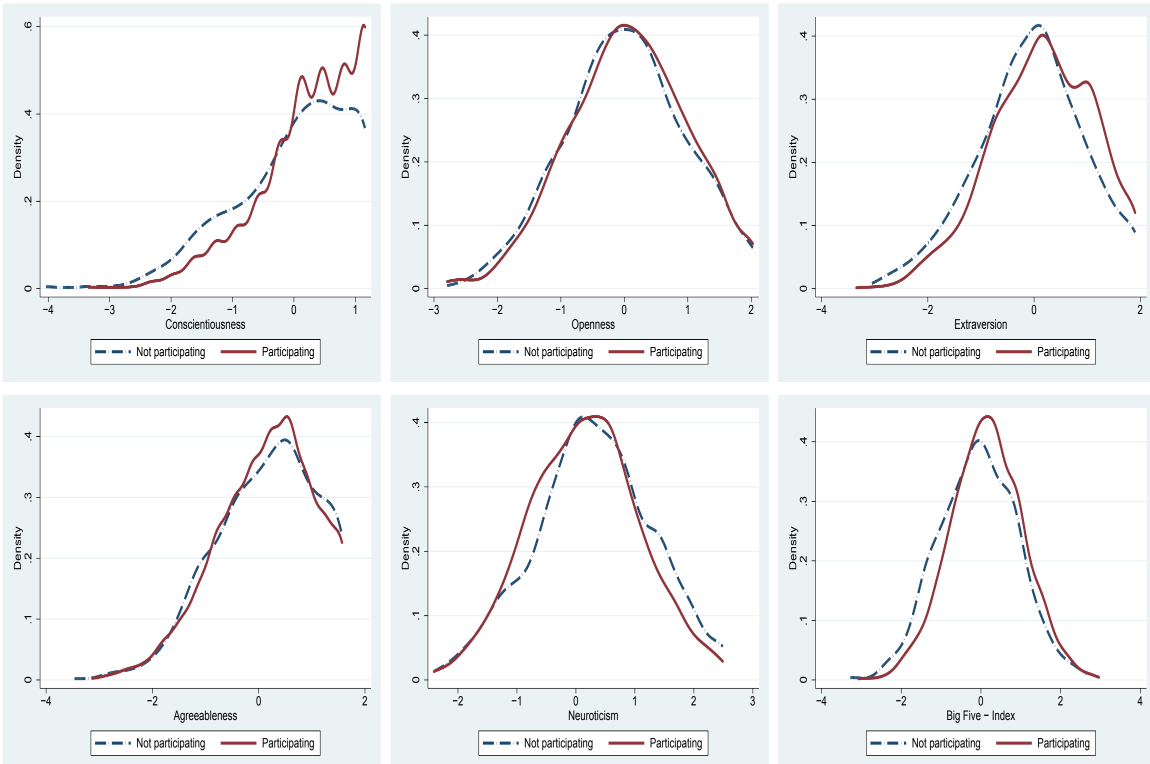

Figure B.1.1: Distribution of the standardized Big Five Personality Traits in the Sample (SOEP, 2005) using a Gaussian Kernel with a bandwidth chosen by Silverman's rule of thumb.

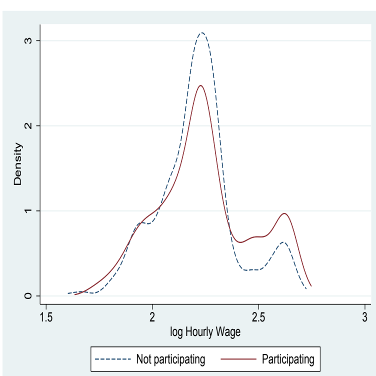

Figure B.1.2: Distribution of the imputed hourly wages in the Sample (SOEP, 2005) using a Gaussian Kernel with a bandwidth chosen by Silverman's rule of thumb.

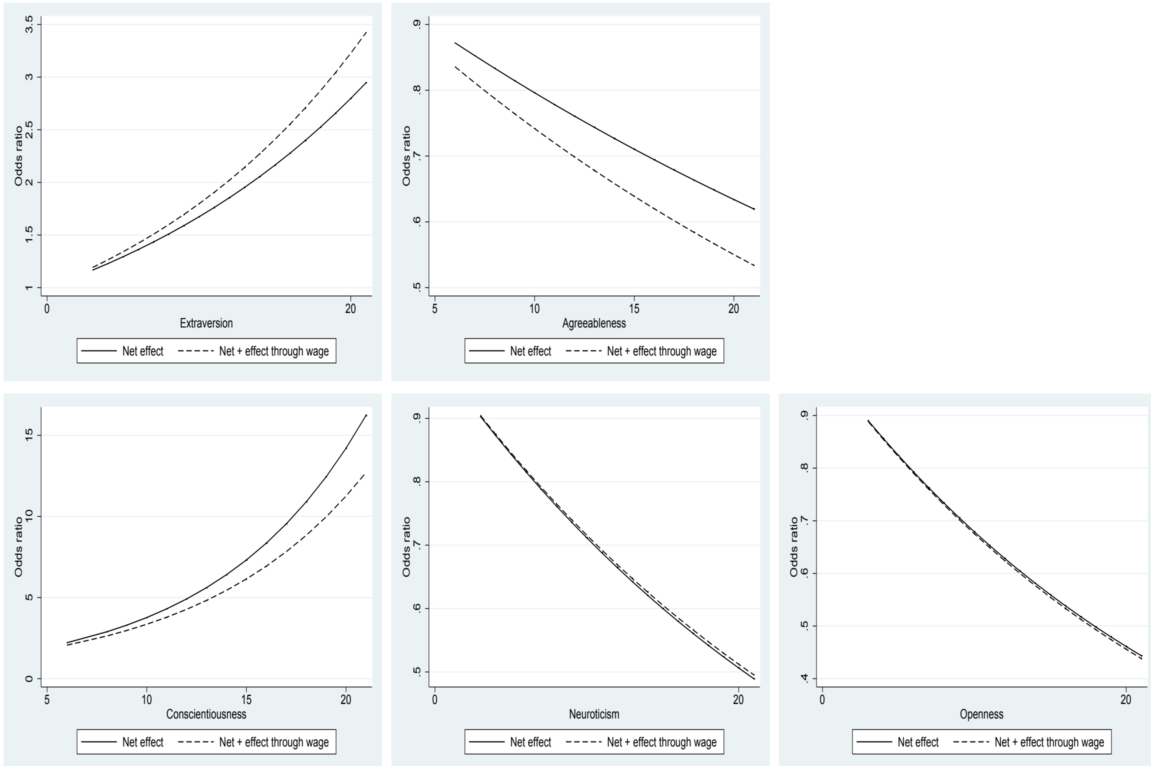

Figure B.1.3: Direct and indirect effects of the Big Five Personality Traits on the participation probability (SOEP, 2005)

Chapter 2

Job satisfaction and comparison wages revisited: Introducing personality traits

2.1 Introduction

Research on satisfaction has become a topic of special interest in economics in the last decade. Since the late 1990's, economists have started to analyze the measurement and the determinants of happiness[1] on a large scale and the body of literature is still evolving (e.g. Frank (1997), Ng (1997), Oswald (1997), Frey and Stutzer (2000), Frey and Stutzer (2002b), Boes and Winkelmann (2006a) and Frey (2008)). Even though economic research on job satisfaction has already been done rarely some decades ago, e.g. the work by Hamermesh (1977), Freeman (1978), Borjas (1979) and Akerloff, Rose, and Yellen (1988), job satisfaction as one specific subdomain of the overall life satisfaction is nowadays a growing field of interest (e.g. Clark (1997), Lévis-Garboua and Montmarquette (2004), Gazioglu and Tansel (2006), Böckerman and Ilmakunnas (2007) and Cornelissen (2009)). It has been shown in the psychological as well as in the economic literature that job satisfaction is an important predictor for subjective well-being, health, job stability and work performance (e.g. Wall et al. (1978), Freeman (1978) and Argyle (1989)). This justifies the interest in the determinants of job satisfaction in order to be able to improve job satisfaction. However, the recent economic literature on job satisfaction has mainly focused on the effects of observable individual and job characteristics on job satisfaction. Even though psychological research has shown that personality matters for life and

[1] In the related literature, the expressions subjective well-being, happiness and satisfaction are often used synonymously even though they denote separable concepts in psychology. In the present paper, we will use the three terms interchangeably.

job satisfaction apart from observable socio-economic variables, there is to our knowledge no economic study that investigates the effect of personality on job satisfaction.

This paper attempts to fill this gap by introducing personality traits into the question what determines job satisfaction. Moreover, we investigate the role of comparison wages, i.e. the own actual wage compared to other wages, apart from the absolute wage in this context. Recent studies have shown that it is not the individual wage level alone that makes people satisfied but the wage level compared to that of others. The aspiration-achievement gap theory states that the satisfaction level depends on the difference between what an individual has planed to achieve and what he actually has achieved. The inclusion of personality traits is therefore a promising strategy to better incorporate aspirations in a model and to shed light on the question of how job satisfaction is determined. Michalos (1980) stresses the importance of looking at the perceived gap rather than the calculated gap. Interacting the calculated gap with personality traits is one possibility to follow this suggestion. In the present paper, we widen the idea of comparison wage. Apart from the comparison with others (social comparison), we also want to look at comparison with one's own past (past comparison).

The psychological literature has found two underlying concepts to the attitude of well-being: cognition and affect. The first is related to the rational and intellectual aspects of subjective well-being, the latter to emotions and moods (Veenhoven (1996)). In this paper, we address the role of satisfaction with income compared to the overall job satisfaction and analyze whether different variables have different effects on both outcomes. There are no explicit results in psychology about differing determinants of satisfaction with pay and overall job satisfaction. Even though the two concepts are closely related, we see important differences in their properties: satisfaction with pay addresses a precise facet of the job. Overall job satisfaction is rather vague and can include anything depending on the individual weighting of the different characteristics of a job. Based on the results from psychology, we expect that satisfaction with pay is rather cognition driven while overall job satisfaction is more influenced by affect.

Even though the recent literature provides a lot of evidence that it is more the relative wage level instead of the absolute wage level that determines job satisfaction, there is lot of discussion about how to model the reference wage level (e.g. Hamermesh (1977), Clark and Oswald (1996), Hamermesh (2001), Lévis-Garboua and Montmarquette (1997), McBride (2001) and Nguyen, Taylor, and Bradley (2003)). With the present analysis, we will contribute to this discussion by comparing social comparison and past comparison. Another important aspect is the question how individuals actually do compare themselves to others and how they evaluate this comparison (Hamermesh (2001)). Moreover, the results about the importance of the relative and the absolute wage level as well as the effect of them are not undisputed in the literature. In this line, the role of personality traits comes into play. We expect that different individuals come to different results about their job satisfaction given the same relative wage difference. It is likely to expect that some individuals weight the relative wage gap differently.

We allow for two different channels through which personality can affect both kinds of satisfaction. First, there can be a direct effect of personality on satisfaction which means that individuals with certain personality traits are more likely to be satisfied with their job or their income on average.[2] Second, we want to investigate whether different personality types weight comparison wages differently in evaluating their own satisfaction level. We find that the answers to these questions are quite different for overall job satisfaction and satisfaction with income and for different concepts of personality traits. While the Big Five personality traits affect satisfaction mainly directly, the effect of an internal Locus of Control is direct as well as indirect through a different importance of comparison wages. Boes and Winkelmann (2006b) analyze the effect of income on life satisfaction and show that the effect differs for satisfied and unsatisfied individuals. In the present paper, we will investigate whether this is also true for the relationship of comparison wages and job satisfaction.

The remaining paper is organized as follows: Section 2 summarizes empirical results of the related literature and presents the underlying theoretical models for the determinants of job satisfaction. The data that we use for our analysis is presented in Section 3 together with the methods that we apply. Section 4 contains the results about the determinants of job and income satisfaction and the role of personality. Section 5 summarizes the results.

[2]It is also possible that personality traits influence the individual answering behavior. If this is the case, it is not possible for us to disentangle this answering difference from the direct effect of personality traits. However, we haven't found any evidence for a differing answering behavior due to different personality traits.

2.2 Job satisfaction in the literature

2.2.1 Empirical findings

Research on the determinants and effects of job satisfaction has grown considerably in the last 15 years. As a consequence, an increasing number of surveys contain measures of job satisfaction nowadays. We can distinguish two main strands of literature, one of them concentrating on job satisfaction as a predictor, the other one analyzing the determinants of job satisfaction. The need for the latter approach can be justified by the results of the former. In what follows, we will present the main results of both strands of the literature, starting with the consequences of job satisfaction.

Job satisfaction as a predictor

First, job satisfaction affects individual well-being since it is a strong predictor of mental and physical health: People who are unsatisfied with their job are more likely to develop mental diseases, to live shorter and their risk for coronary heart disease is higher (e.g. Palmore (1969), Sales and House (1971), Wall, Clegg, and Jackson (1978) and Argyle (1989), chapter 9). Moreover, Campbell et al. (1976) show that job satisfaction affects overall life satisfaction, even though its effect is smaller than those of satisfaction with family life and marriage. Second, from an employer's point of view, job satisfaction has an important impact on work performance and job stability. Job satisfaction increases work attendance and productivity (e.g. Vila and Garcia-Mora (2005)). Additionally, if employees are unsatisfied with their job, they are more likely to be searching for a new position and to eventually change the job as well (e.g. Freeman (1978), Akerloff, Rose, and Yellen (1988), Clark (2001), Lévis-Garboua, Montmarquette, and Simonnet (2001), Böckerman and Ilmakunnas (2007), Cornelissen (2009)).

The determinants of job satisfaction

The numerous consequences of job satisfaction show the importance of job satisfaction since it affects several outcome dimensions. Consequently, it is necessary to know which factors drive job satisfaction. There are two main groups of determinants of job satisfaction: job characteristics and individual characteristics. The most prominent job characteristic is without any doubt the wage. However, it is not only the own wage level that is important but also the wage compared to others.

Studies analyzing the role of the absolute wage compared to the effect of relative wages are e.g. Hamermesh (1977), Clark and Oswald (1996), Hamermesh (2001), Lévis-Garboua and Montmarquette (1997), McBride (2001) and Nguyen, Taylor, and Bradley (2003). All authors show that the effect of the relative wage is important and can therefore not be ignored. However, the studies differ in a way that they model the relative wage which makes it difficult to compare the results. Moreover, especially Nguyen, Taylor, and Bradley (2003) point out that the size of this effect is relatively small compared to the effect of the own income. Apart from wages, there are also other job characteristics that have been found to influence job satisfaction, e.g. working hours, tenure, firm size, shift work, job autonomy, self-employment, job status, and union activity (e.g. Borjas (1979), Freeman (1978), Clark and Oswald (1996), Nguyen, Taylor, and Bradley (2003) and Cornelissen (2009)).

In addition to job characteristics, the literature has also found that individual characteristics matter for job satisfaction. The effect of age on job satisfaction is most often found to be U-shaped, meaning that job satisfaction reaches a minimum at a certain age (e.g. Clark et al. (1996)). Another rather undisputed finding in the literature is the positive effect of being married on job satisfaction (e.g. Clark (1997)). Moreover, Clark (1997) shows that women are in general more satisfied than men. He offers the presumption that women have lower expectations from their job due to their traditional poorer position in the labor market and are therefore more easily positively surprised as a possible explanation for this fact. For the case of Germany, we could expect that the comparatively low female labor force participation of married women in the last decades leads to some sort of selection meaning that women don't work if they are not satisfied. However, with increasing female labor force participation, this effect should vanish in the younger age groups. Argyle (1989) shows that pay and feelings of control are important determinants of male job satisfaction while women enjoy job complexity and the social aspects of the job more. The role of education in determining job satisfaction has not been found to be that clear. Clark and Oswald (1996) show that education has a negative effect on job satisfaction once controlling for income. They suggest that this is due to the fact that higher educated individuals have higher aspiration that are less likely met in the job which leads to dissatisfaction. Moreover, mismatches between a job and education and/or skills are more likely to occur for higher skilled jobs which can also lead to a lower expected job satisfaction level for the higher educated (Allen and van der Velden (2001), Fleming and Kler (2008)). Vila and Garcia-Mora (2005) find a positive direct effect of the worker's educational level on job satisfaction after controlling for a mismatch between education and employment, wages and other individual and job related characteristics. They also show positive indirect effects of the educational level on job satisfaction through its impacts on observable job characteristics (e.g. wages and promotion) and on the individual health status.

Job satisfaction and personality traits

The relationship between personality traits and job satisfaction has a long tradition in psychology, e.g. Locke (1976) for an extensive overview. The top-down theory of subjective well-being (Diener (1984)) states that personality traits cause a global tendency to experience life positively or negatively. Additionally, this underlying tendency leads to a different evaluation of situations and events and their effect on one's well-being. We are therefore interested in the two channels, by which personality can influence the satisfaction level: on the one hand, certain personality traits may lead to a tendency to be more or less satisfied in general. We call this a direct effect of personality traits. On the other hand, individuals with different personality traits may react differently to certain events or situations, this would be an indirect effect of personality. For the following analysis, we are interested, which one of the personality trait measures used is more likely to have a direct effect and which one is more likely to affect job satisfaction indirectly. For the indirect effect, we focus especially on the role of wages and comparison wages. In the present paper, we will concentrate on two measures of personality: the Locus of Control and the Big Five personality traits. A detailed description of these two personality concepts used in this paper together with related findings in the literature will be given in Section 2.3.1.1.

Overall job satisfaction and satisfaction with pay

So far, job satisfaction has been mostly analyzed as overall job satisfaction. One of the few exceptions in the recent economic literature is Gazioglu and Tansel (2006) who analyze four different domains of job satisfaction among these also satisfaction with the amount of pay. The authors show that the different domains of job satisfaction are influenced by different characteristics. Clark and Oswald (1996) analyze the effect of comparison income on overall job satisfaction and satisfaction with pay and find no important differences in the determinants of both variables. The paper by Nguyen, Taylor, and Bradley (2003) concentrates on satisfaction with pay only and finds significant but small effects of comparison income on this satisfaction dimension. Veenhoven (1996) distinguishes two possible sources of an individuals' judgement about his satisfaction level: affective experience and cognitive comparison. He states that tangible domains of satisfaction are rather influenced by cognitive comparison than more general domains. If we combine these findings with personality traits, this would imply that personality is important for affective experience and not so much for cognitive comparison. For our application, we therefore expect that affective experience and with that personality traits are more important for overall job satisfaction while self-reported satisfaction with pay is stronger based on cognitive comparison and thus less influenced by personality traits.

The aim of the present paper is to combine the different strands of economic and psychological literature. On the one hand, we will concentrate especially on the effect of the own wage and comparison wages. On the other hand, we extend the individual characteristics by including personality traits in addition to the usual socio-economic background variables. We will further investigate whether the results differ if we analyze overall job satisfaction or satisfaction with pay.

2.2.2 Theoretical Background and the role of comparative wages

The study of satisfaction is originally a province of psychology. Traditional economic theory focuses rather on the utility level of an individual. Even though satisfaction and utility are not exactly the same, they are closely related concepts. Satisfaction measures can be a useful proxy to model individual utility which is not directly measurable.[3] We therefore assume that job satisfaction can be seen as a proxy for the utility of a job. Taking the conventional utility framework, we can write an individual's utility from work as

$$U = U(y, h, i, j), \tag{2.1}$$

where U is the utility level, y is the income, h are the hours worked, i are individual characteristics and j job characteristics. In this framework, we assume that the individual utility depends positively on income and negatively on the working hours. If we add comparison income to this function, we get the utility from work as

$$U = U(y, y^*, h, i, j), \tag{2.2}$$

where y^* represents the comparison wage level.

[3] Frey and Stutzer (2002a), (2002b) (2004) and Clark, Frijters, and Shields (2007) present an extensive discussion about reported happiness as a measure for individual utility.

The inclusion of comparison wages can be seen as an attempt to incorporate the goal-achievement gap theory by Michalos (1980) into the economic literature. Clark and Oswald (1996) call this the relative deprivation theory. The reasoning for the inclusion of comparison wages in addition to the individual wage originates from findings from the field of life satisfaction research. The Easterlin Paradox (Easterlin (1995)) states that the average happiness level of a population stays relatively stable over a given period even though the overall GNP per capita increases considerably during this time. This is in contrast to other findings that income increases individual happiness at the micro level (e.g. Frey and Stutzer (2000), Shields and Price (2005)). One frequently cited explanation for this phenomenon is the fact that the comparison effects matter in determining happiness and that therefore an overall income increase does not have any significant impact on the average happiness. Several economic papers have consequently proposed different approaches to test the validity of this relative income hypothesis given in Equation 2.2 against the traditional utility theory in Equation 2.1. The main question that arises when analyzing comparison wages is how to model comparison wages. It is easy to claim *that* individuals compare themselves to others but it is almost impossible to answer the question *with whom* they compare themselves and *how* this comparison is done. In the existing literature, we find several approaches how to deal with this issue.

Clark and Oswald (1996) suggest two possibilities to model comparison wages. The first one is to take individuals with similar (observable) characteristics and use the fitted wage of an underlying wage equation as the comparison wage. Their second approach is the use of representative wages from an earnings survey to compute reference earnings according to gender and the weekly hours of work. Neumark and Postlewaite (1995) and McBride (2001) follow a different approach to model reference wages. They argue that individuals might compare themselves rather with individuals that are close to them, e.g. family and friends, than with some unknown reference group with similar characteristics. A third strand of literature follows the idea that individuals compare their attainment with their former expectations. According to this reasoning, an individual will be satisfied with his job if he earns as much as or more than he expected when he started his career. This modeling of the expected wage, however, is not trivial. Lévis-Garboua and Montmarquette (2004) and Hamermesh (2001) use fitted past wages. Hamermesh (2001) additionally allows for the possibility that individuals may update their expectations during their career. Nguyen, Taylor, and Bradley (2003) dispose of explicit information about the expected wages and include it in their analysis. Another approach to model comparison wages is to look at individual's wages from the past. It is plausible to think that individuals not only compare themselves with external reference groups (however defined) but also with their own past. Clark, Frijters, and Shields (2007) suggest to include own past income in order to capture this comparison effect. In what follows, we will present our model that we will use to analyze the role of comparison income and personality on job satisfaction.

Based on the utility function given in Equation 2.1, we can write the utility, proxied by the self reported job satisfaction, S of individual i at time t as

$$S_{it} = \alpha + \beta y_{it} + Z_{it}\delta + \eta_{it}, \tag{2.3}$$

where Z_{it} contains socio-economic factors as well as job characteristics of individual i at time t. Existing studies include education, gender, the disutility of work and satisfaction with other domains of life. For the present analysis, Z_{it} is a natural candidate to pick up the direct effect of personality traits on job satisfaction. A significant effect here would mean that individuals with a certain personality structure are more likely to be (un)satisfied with their job overall. In order to allow for an effect of comparison wages on job satisfaction, we follow Lévis-Garboua and Montmarquette (1997) and use a modified version of equation 2.3, using the fact that the wage, y_{it}, can be rewritten as $y_{it} = \hat{y}_{it} + e_{it}$, with $\hat{y}_{it}$ as the fitted wage from an additional wage equation:

$$S_{it} = \alpha + \beta_1 \hat{y}_{it} + \beta_2 e_{it} + Z_{it}\delta + \eta_{it}. \tag{2.4}$$

If we find that $\beta_1 = \beta_2$, Equation 2.4 is identical to Equation 2.3. Other authors, e.g. Clark and Oswald (1996), include the observed wage and the fitted wage in order to analyze the role of comparison wages explicitly and in order to write the equation in terms of the arguments of Equation 2.2. This is just another way of writing Equation 2.4:

$$\begin{aligned} S_{it} &= \alpha + \beta_1 \hat{y}_{it} + \beta_2 e_{it} + Z_{it}\delta + \eta_{it} \\ &= \alpha + \beta_2 y_{it} + (\beta_1 - \beta_2)\hat{y}_{it} + Z_{it}\delta + \eta_{it} \\ &= \alpha + \gamma_1 y_{it} + \gamma_2 \hat{y}_{it} + Z_{it}\delta + \eta_{it}. \end{aligned} \tag{2.5}$$

The writing of Equation 2.5 seems more intuitive to us, therefore, we will use it in the following. Testing for social comparison, i.e. testing whether comparison wage apart form the own wage has an significant effect on job satisfaction, corresponds in this setting to testing whether $\beta_1 = \beta_2$, i.e. $\gamma_2 = 0$.

In addition to the inclusion of the fitted wages we also want to incorporate comparison with the past. Clark, Frijters, and Shields (2007) suggest to use a weighted average of past income, $y_{i,past} = y_{it} - \sum_{s=1}^{S} \lambda_s y_{i(t-s)}$. For the following analysis, we include the past three years and weight them equally, i.e. $S = 3$ and $\lambda_s = 1/3$ for $s = 1, 2, 3$.[4] Finally, we will estimate a complete model including the external reference group together with the comparison with the own past:

$$S_{it} = \alpha + \gamma_1 y_{it} + \gamma_2 \hat{y}_{it} + \gamma_3 y_{i,past} + Z_{it}\delta + \eta_{it}. \tag{2.6}$$

Apart from the effect of comparison wages on job satisfaction, we are also interested in the role of personality traits in this setting, and therefore allow for an indirect effect of personality via the comparison wage and allow for different coefficients of the variables γ_1 to γ_3 for different personality types. This leads to the following equation:

$$\begin{aligned} S_{it} = {} & \alpha + \gamma_1 y_{it} + \gamma_2 \hat{y}_{it} + \gamma_3 y_{i,past} + \\ & + \gamma_4 (P_{itp} \cdot y_{it}) + \gamma_5 (P_{itp} \cdot \hat{y}_{it}) + \gamma_6 (P_{itp} \cdot y_{i,past}) + Z_{it}\delta + \eta_{it}, \end{aligned} \tag{2.7}$$

where P_{itp} is an indicator for a high markedness of a certain personality trait, p, for individual i at time t. The main interest lies then on the coefficients γ_4 to γ_6. If we find significant effects for the personality interaction terms, this implies that different individuals in terms of personality react differently to comparison wages.

2.3 Empirical Approach

2.3.1 The Data

The sample for the analysis is taken from the 2005 wave of the German Socio-Economic Panel (SOEP). While most of the relevant information about job satisfaction as well as individual and job characteristics is gathered every year in this panel, the questions about personality are only asked in some waves. In 2005, the questionnaire contains items about the Big Five personality traits and the Locus of Control that we will use to include personality in the analysis. In the following, we will present the variables that were included in the sample. Our sample consists of male

[4] This modeling of past comparison might seem rigorous. However, we also tried different weighting of the past wages and found no important differences. We decided not to include each past year separately since we assume that individuals evaluate their past wage history as one overall phenomenon and do not distinguish between the wages in each year.

and female individuals aged from 30 to 55, either fulltime or parttime employed. Keeping only those observations that have full information on socio-demographic background variables, job characteristics and personality measures leaves us a sample size of 2,776. The definition of the variables together with the descriptive statistics are displayed in Table A.2.1 and A.2.2 in the Appendix.

Job satisfaction in the data

For the present analysis, self reported job satisfaction of individuals is used. In the SOEP, people were asked to assess the question "How satisfied are you with your job?" from "0" (totally unhappy) to "10" (totally happy). One may argue that self reported information about one's satisfaction with the job might not be valid and, even if valid, not comparable between individuals. However, the psychological literature has accepted the use and the validity of this information already long ago. The main interest in satisfaction research lies not in the comparison of absolute levels of satisfaction but rather in the analysis of the determinants of satisfaction. For this issue, the subjective data can be treated ordinally, simply using the notion of "higher" and "lower" satisfaction instead of interpreting the absolute values. There is a vast body of psychological evidence that self-reported satisfaction meets these assumptions and is therefore a valid instrument to capture satisfaction (e.g. Argyle (1989), chapter 4 and 9, Andrews and Robinson (1991), Larsen and Fredrickson (1999) and Schwarz and Strack (1999)).

The use of self-reported satisfaction measures in microeconometric analyses of happiness is accepted even though one has to be aware of some problems: it is likely that self-reported satisfaction measures contain a considerable amount of measurement error. This is not problematic for estimation if it can be assumed to be a random error which is questionable. However, a detailed analysis of this issue is beyond the scope of this paper. An additional problem could be unobserved heterogeneity. This can be captured up to some degree by including other measures of satisfaction and checking how this affects the results. Our approach to include personality traits addresses this issue especially since personality traits are one source of unobserved heterogeneity often cited in the literature (e.g. Lévis-Garboua and Montmarquette (2004), Bertrand and Mullainathan (2001) and Ravallion and Lokshin (2001)). Endogeneity is certainly also an issue in self-reported satisfaction variables. In order to control for reverse causality, we will use lagged personality measures as a robustness check in our analysis.

The left part of Figure 2.1 illustrates the distribution of the job satisfaction variable in our sample. One striking result is the fact that the distribution is heavily skewed towards the left, the mean job satisfaction in the sample is 7.06. This finding is in line with a lot of results in the literature about satisfaction (e.g. Clark and Oswald (1996), Lévis-Garboua and Montmarquette (2004), Hamermesh (2001)). Table 2.1 illustrates differences in the mean job satisfaction by age and gender. Contrary to other studies, we do not find any evidence for an unconditional increase in the average job satisfaction with age. Since the data is taken from a cross section, it is not possible to detect a true age effect in job satisfaction because we cannot differentiate the age effect from a cohort effect. Women are on average slightly less satisfied than men, only in the age group from 45-49 years, women show a higher job satisfaction on average. However, these purely descriptive statistics do not allow to conclude about any effects of age or sex on job satisfaction but offer the possibility to compare the sample with that from other studies.

Table 2.1: Mean overall job satisfaction by age and sex
SOEP 2005, own calculation.

	Mean overall job satisfaction			
Age group	overall	men	women	Nobs.
overall	7.06	7.10	6.99	2,776
30 - 34 years	7.05	7.20	7.01	307
35 - 39 years	7.21	7.38	6.90	521
40 - 44 years	6.96	6.99	6.92	649
45 - 49 years	6.97	6.90	7.05	642
50 - 55 years	7.08	7.10	7.04	657
Nobs.	2,776	1,654	1,122	

In addition to the overall job satisfaction, the SOEP also offers information about satisfaction with pay. Since one of the goals of this paper is to assess the role of wages and relative wages on job satisfaction, we will also look at satisfaction with pay as a dependent variable. The right part of Figure 2.1 illustrates the distribution of the satisfaction with pay variable in the sample. At the first inspection, there are no obvious differences in the distribution of the two variables.

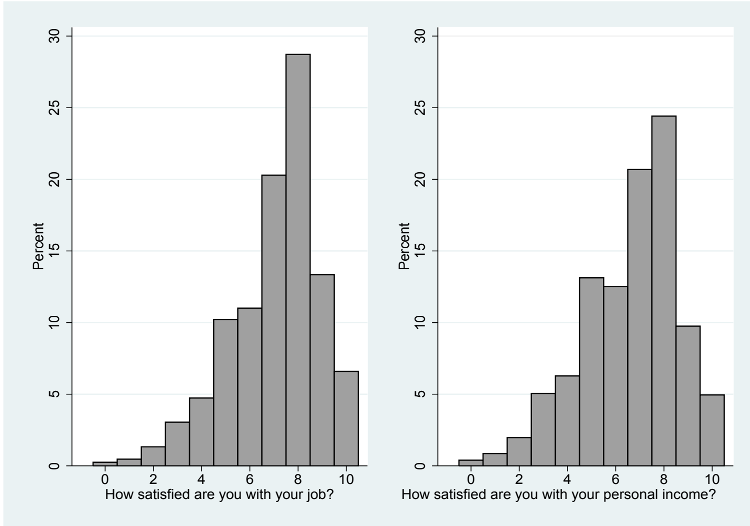

Figure 2.1: Comparison of the distribution of job satisfaction and satisfaction with personal income (SOEP, 2005).

2.3.1.1 Personality traits

Even though the present paper is to our knowledge the first economic paper to explain job satisfaction using personality traits, there is a growing literature on the effect of personality traits on economic outcomes. It has been shown that personality traits affect wages, job search behavior, work attendance, unemployment duration and female labor force participation (e.g. Heckman, Stixrud, and Urzua (2006), Fahr and Kusche (2008), Heineck and Anger (2008), Caliendo, Cobb-Clark, and Uhlendorff (2010), Uysal and Pohlmeier (2010), Piatek and Pinger (2010), Wichert and Pohlmeier (2010)). In the following, we will present the two measures for personality that we use for our analysis. First, we introduce the Locus of Control proposed by Rotter (1966). Second, we present the Big Five personality traits concept introduced by McCrae and Costa (1987).

The Locus of Control

The concept of the Locus of Control was developed by Rotter (1966). It originates from social psychology and describes an individual's beliefs about his control over life. More specifically, it distinguishes two extreme characters: Internalisers and Externalisers. While the first one believes that he controls success and failure in his life, the latter thinks that this is a matter of luck and fate which he cannot influence. Internalisers are thought to be self-confident, assertive and motivated, Externalisers are the opposite and get frustrated easily. The 1999 and the 2005 waves of the SOEP contain ten items that can be attributed to the Locus of Control. Individuals where asked to assess ten statements on a 7tier Likert scale from "1" ("I totally disagree") to

"7" ("I totally agree"). Table 2.2 displays all the statements concerning the Locus of Control in the data together with their relation to the Internaliser/Externaliser concept, $\oplus$ means that this statement is most likely supported by Internalisers, $\ominus$ most likely supported by Externalisers. The bold written statements are those that are used for the following analysis. We chose the included items based on a factor analysis. The result of the factor analysis is given in Figure 2.2 which provides evidence that we have two underlying factors. Based on the ranking of Table 2.2, we can say that Factor 1 is the "Externaliser-Factor" and Factor 2 the "Internaliser-Factor". In their analysis of the impact of personality on job search behavior, Caliendo, Cobb-Clark, and Uhlendorff (2010) also perform such a factor analysis and get a very similar result. Based on the factor analysis, they include nine out of the ten items in their analysis, dropping statement 4 because of its isolated position with respect to the two factors. For our analysis, we have discussed the relevance of those nine items for our application with psychologists and have tried several combinations of the items. Item 10 and item 5, e.g., measure almost exactly the same fact. Since none of the other questions is doubly represented, we chose only the one of the two that led to the most clear results. Finally, we include five items in our analysis, three of which are most likely supported by Externalisers and two by Inernalisers. If we look at the position of our five items in Figure 2.2, we see that we use those that are the most clearly attributed to the two factors.

Table 2.2: Locus of Control statements in the SOEP (2005)
Only the bold statements are used in the empirical analysis.

	Statement	Score
S1	**I decide the way my life is run**	$\oplus$
S2	**Compared to others, I haven't attained what I deserve**	$\ominus$
S3	What you achieve in life is mainly a matter of fate or luck	$\ominus$
S4	Social and political active influence social conditions	$\oplus$
S5	**Experience that others determine my life**	$\ominus$
S6	**One has to work hard to achieve success**	$\oplus$
S7	**In case of difficulties doubts about own abilities**	$\ominus$
S8	Possibilities limited by social conditions	$\ominus$
S9	Abilities are more important than effort	$\ominus$
S10	Little control over life	$\ominus$

The variables are ranked on a seven point scale. In order to construct a unidimensional index that measures "how much Internaliser an individual is", we follow the

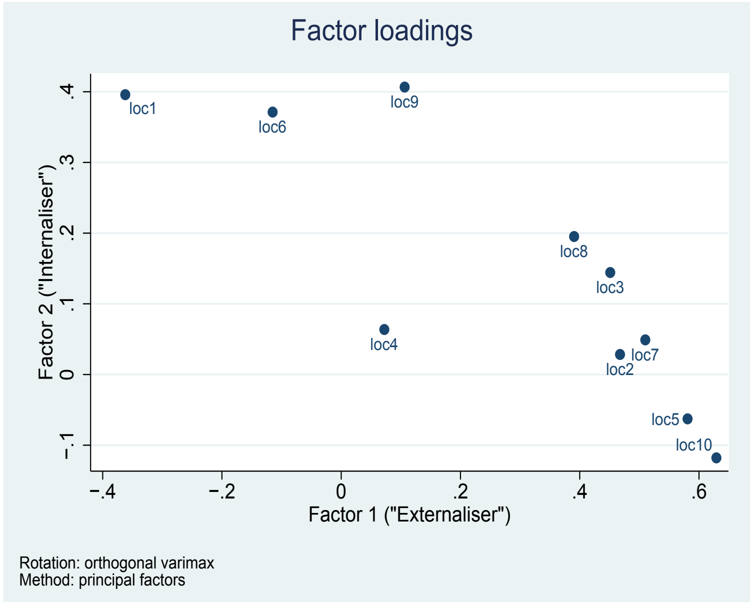

Figure 2.2: Factor analysis of the 10 statements of the Locus of Control (SOEP, 2005).

principle of the Rosenberg scale (Rosenberg (1965)). We assign a score for each item corresponding to the assessed value of the Likert scale. Since we want to obtain an index that has high values for Internalisers and low values for Externalisers, we add the scores of the Internaliser-statements directly, whereas the scores of Externaliser-statements are transformed as (8 − (score)). The score range is then from 5 to 35 (five questions each with a minimum score of 1 and a maximum score of 7). In order to be able to analyze interaction effects of the Locus of Control, we introduce a dummy variable for individuals with a score above the average, i.e. the Internalisers. We then standardize the index to have zero mean and variance equal to one. In the regression, we include the standardized measure and use the dummy for Internalisers for the interaction terms.

DeNeve and Cooper (1998) and Diener (1984) show that an internal Locus of Control is positively correlated with subjective well-being, measured by overall life satisfaction. Andrisani and Nestel (1976) investigate the effect of internal vs. external control (following the concept of the Locus of Control) on several job related outcomes, among others also job satisfaction. They find that Internalisers tend to be more satisfied with their job than Externalisers. Argyle (1987) also confirms the finding that Internalisers are more likely to report higher job satisfaction. We therefore expect a positive direct effect for Internalisers. As for the indirect effect of the Locus of Control, we hypothesize that comparative wages have a smaller effect on job satisfaction for Internalisers since they see themselves as responsible for their success in live and therefore do not compare themselves so much with others.

The Big Five Personality Traits

The Big Five personality traits model that we use as a second way to measure personality is a psychological concept used to describe and study personality, the Big Five personality traits first introduced by McCrae and Costa (1987). In the 2005 wave of the SOEP, this concept was first introduced into the panel. Originally, the Big Five is measured using a long questionnaire. Since this is not tractable in the SOEP, a short item scale, the BFI-S, with 15 instead of originally 25 items has been developed (see Gerlitz and Schupp (2005) for a detailed description). Dehne and Schupp (2007) review the Big Five measurement in the SOEP and show its validity and reliability. The BFI-S consists of 15 statements that have to be assessed by the respondents on a 7-tier Likert-Scale, “1” meaning “I strongly disagree” and “7“ meaning “I strongly agree“. Each three of these statements belong to one trait, the ordering of the statements during the interview is not clustered. Each statement can be classified into one of two possible groups: either an agreement with the statement belongs to a strong markedness of the trait in question (⊕); or an agreement with the statement can be seen as a sign for a strong opposition to the trait (⊖). Table 2.3 illustrates the measurement of the Big Five Index in the SOEP. All traits except Neuroticism can be seen as socially desirable (at least to some extent). Therefore, the measurement of the trait Neuroticism should be treated inversely to the others.[5] In order to construct a measure for each trait, we add up the answers of the three questions for each trait, where “I strongly disagree” is worth one point and “I strongly agree“ seven points in a positive question, in a negative question, we give one point for “I strongly agree” and seven for “I strongly disagree“. The points of the three questions are added to get a single score for each trait, ranging from three to 21. The scores for each trait standardized with mean set to zero and variance equal to one for the following analysis.

[5]The opposite of Neuroticism is often referred to as “Emotional Stability”.

Table 2.3: The Big Five Personality Traits in the SOEP (2005)

"I see myself as someone who ...	
	... is communicative, talkative" (⊕)
Extraversion:	... is outgoing, sociable" (⊕)
	... is reserved" (⊖)
	... has a forgiving nature" (⊕)
Agreeableness:	... is considerate and kind to others" (⊕)
	... is sometimes somewhat rude to others" (-)
	... does a thorough job" (⊕)
Conscientiousness:	... does things effectively and efficiently" (⊕)
	... tends to be lazy" (⊖)
	... is relaxed, handles stress well" (⊖)
Neuroticism:	... gets nervous easily" (⊕)
	... worries a lot" (⊕)
	... is original, comes up with new ideas" (⊕)
Openness:	... has an active imagination" (⊕)
	... values artistic experiences" (⊕)

In general, we can distinguish two types of traits: Extraversion and Agreeableness describe the interindividual behavior, meaning that these traits describe how an individual interacts with others. On the other hand, Conscientiousness, Neuroticism, and Openness to Experience deal with the intraindividual habitude of a person. These traits characterize how an individual deals with intellectual and emotional tasks.

The trait Extraversion captures how an individual behaves among others. A person with a high level of extraversion is friendly, likes having company, knows how to prevail, is active, likes impulses from new experiences and has positive emotions. Extraversion can be seen as the interindividual trait related to the quantity of relationships. DeNeve and Cooper (1998) and Costa and McCrae (1980) find a positive effect of this trait on positive affect and happiness in general. Morris (1979), Vittersø and Nilsen (2002) and Judge, Heller, and Mount (2002) find a positive effect of Extraversion on job satisfaction but Morris (1979) also points out that individuals with a high score on Extraversion are easily bored.

A person with a high score on the trait Agreeableness is considered to be selfless, helpful, and caring for others. Less agreeable individuals, on the other hand, are egoistical, selfish and uncooperative. Analogous to Extraversion, Agreeableness can be connected with the quality of relationships. This trait is a strong predictor for positive affect (DeNeve and Cooper (1998)). Seibert and Kraimer (1995) find that individuals with a high score on Agreeableness have lower job satisfaction. In contrast, Judge, Heller, and Mount (2002) find in their meta-analysis some support for a positive effect of Agreeableness on job satisfaction. However, this result is not consistent over all studies.

DeNeve and Cooper (1998) argue that the effect of Extraversion and Agreeableness on subjective well-being is twofold: first, individuals with a high markedness on these traits have a tendency to be more satisfied in general. Second, the positive effect of these traits on relationships leads to an increase in interindividual relationships which again makes individuals more satisfied.

Conscientiousness describes the way how people deal with problems. Conscientious people show a high level of responsibility for themselves as well as for others. Furthermore, they are organized, hard working and ambitious. According to DeNeve and Cooper (1998), Conscientiousness is the trait with the strongest positive association with life satisfaction. There is some evidence for a positive correlation of Conscientiousness and job satisfaction (Judge, Heller, and Mount (2002)).

The domain Neuroticism characterizes how people experience strong positive and negative emotions, i.e. their emotional stability. Individuals with a high score on Neuroticism cannot cope with stress and get frustrated and nervous easily. DeNeve and Cooper (1998) find that Neuroticism is the strongest predictor of life satisfaction among the Big Five personality traits. They explain the negative effect of Neuroticism by the fact that neurotic individuals are less able to feel positive experiences and thus show lower satisfaction and and a lack of positive emotions. For the domain of job satisfaction, Argyle (1989) finds that individuals with a high markedness of this trait cannot handle stress well and therefore tend to work inefficiently and suffer from health problems. This leads to a lower job satisfaction also found by Judge et al. (2002).

The personality trait Openness to Experience describes how needy somebody is for changes, novelty, and complexity. The dimension 'Experience' includes the aspects fantasy, aesthetics, feelings, ideas, as well as values. Several facets of this domain are very abstract and difficult to operationalize. A highly open person may enjoy a complex job but may also cherish self-determination. Contrary to the other four traits, DeNeve and Cooper (1998) find no significant effect of Openness on subjective well-being. Their explanation is the fact that this fifth factor is the broadest and the least understood within the Big Five model and that it is not really clear which dimension is captured by the respective measurement items used. Judge et al. (2002) only find a very weak correlation of Openness to Experience and job satisfaction.

The psychological studies presented are mostly based on small samples and investigate pure correlations without controlling for additional variables. Moreover, they do not interact personality traits with other explanatory variables.

2.3.2 Methods

Self reported job satisfaction is measured as an ordinal variable. In our data, individuals were asked to assess their level of job satisfaction from "0" (not satisfied at all) to "10" (totally satisfied). The previous literature suggests several methods to deal with ordered dependent variables. The first and most obvious approach is to simply use OLS. Hamermesh (2001), using the same SOEP data as we do, argues that the fact that there are eleven response categories justifies the use of OLS since the variable can be seen as almost continuous. However, there are some limitations to using OLS instead of methods like ordered response models. Clark and Oswald (1996) and Nguyen, Taylor, and Bradley (2003) therefore apply ordered probit in their analysis. Contrary to the SOEP data, their measure of satisfaction consists of only four categories which makes it more suitable to use ordered response models. Another possibility would be to construct a binary measure whether people are satisfied or not or to pool some of the categories to be able to apply ordered response methods. In our application, we apply two methods: The Probit-adapted OLS which is rather simple and restrictive but uses all the information available in the data. The second method, the sequential Logit, relaxes the restrictive assumptions of the first method but will be applied to pooled job satisfaction data.

The Probit-adapted OLS

In their book on happiness research, van Praag and Ferrer-i-Carbonell (2007) propose an alternative method to analyze ordered information about satisfaction, the Probit-adapted OLS (P-OLS). This modification of the simple OLS method is preferable to the ordered Probit method since the presentation of the marginal effects for the dependent variable with eleven categories would be very hard to handle for the ordered Probit. Moreover, a linear approach allows us to use and interpret interaction terms without any problems (e.g. Ai and Norton (2003) for a discussion of interaction terms in nonlinear models). Additionally, using generated regressors as we do to analyze the effect of comparison wages, is for our setting less problematic in linear models than in nonlinear models. We have also checked whether the results in our analysis depend on the method used. We did not find any evidence that the results based on Ordered Probit differ substantially, neither in terms of the size nor the significance of the parameters. Despite the advantages of this method compared to OLS, to our knowledge, Cornelissen (2009) is the only paper that applies this method. The basic idea of the P-OLS is the following: assume we can write the job satisfaction analogue to Equation 2.6 as

$$S = \omega X + \eta, \tag{2.8}$$

where X contains all the explanatory variables, y, $\hat{y}$, $y_{,past}$ and Z, and ω contains all the corresponding coefficients of α, δ, γ. If we estimate this model by OLS, we assume that the dependent variable, S, is continuous and not bounded. Taking the self reported job satisfaction information in the data, we face the problem, that we have an ordinal variable with eleven categories. Therefore, we need to apply a monotonic transformation $f(S) = s$ such that the new dependent variable, s, can be assumed to lie on the real line $(-\infty, +\infty)$. Van Praag and Ferrer-i-Carbonell (2007) propose to use the standard normal distribution for this purpose. In order to get the corresponding threshold values of a standard normal distribution for the dependent variable, we thus use the corresponding Z-values of the cumulative distribution of the ordinal job satisfaction variable to construct the intervals for the eleven categories, $(\mu_{k-1}, \mu_k)_{k=1}^{11}$. The new dependent variable is then derived by taking the conditional expectation of a standard normally distributed variable given that it lies in between the two corresponding Z-values of the original ordinal dependent variable:

$$E(s|\mu_{k-1} < s_k \leq \mu_k) = \frac{\phi(\mu_{k-1}) - \phi(\mu_k)}{\Phi(\mu_k) - \Phi(\mu_{k-1})} = \bar{s}, \tag{2.9}$$

where $\phi(\cdot)$ and $\Phi(\cdot)$ denote the pdf and the cdf of the standard normal distribution, respectively. The model can be estimated using OLS with $\bar{s}$ as the dependent variable.

The Sequential Logit

The second method that we will apply in our analysis is the sequential Logit. Compared to the P-OLS and also to the Ordinal Probit, this approach is especially attractive since it relaxes the single crossing property and the assumption of constant relative marginal probability effects. Its origin lies in duration analysis where it is used to model the transition from one state to another one. The application of this method to microeconomic data is not so prominent. One exception to this is Buis (2009) who models educational choices using sequential Logit. Boes and Winkelmann (2006b) have been the first to apply this method in satisfaction analysis. At first glance, the sequential modeling of the self reported job satisfaction is not straight forward. One could think of a sequential nature in the underlying cognitive process of reporting job satisfaction: an individual that ranks his own satisfaction on a given scale, starting from the lowest satisfaction level and then continuing until he reaches his individual cut-off point. Additionally, we can use the sequential Logit as a flexible tool since it allows the effects of the explanatory variables to change at each category step. Applying this method to the job satisfaction data allows us therefore to analyze whether certain explanatory variables are especially important at different satisfaction levels. For our application, we group the eleven job satisfaction categories, S, into four new categories, $\tilde{S}$, in order to have a reasonable number of observations in each group.[6] Moreover, the underlying decision process is modeled more realistically if we think of fewer larger groups in which an individual can select himself.

The following illustration of the sequential Logit is based on Winkelmann and Boes (2009). Suppose that we have four ordered satisfaction categories $j = 0, 1, 2, 3$ of the individual satisfaction level. Since we assume that the decision about the reported satisfaction level is taken sequentially, we can define conditional transition probabilities from one category to the next given that the previous category has been reached, $\Pr\left[\tilde{S} = j \,\middle|\, \tilde{S} \geq j\right]$, starting with the lowest one. Thus, we can write

$$
\begin{aligned}
\Pr\left[\tilde{S} = 1 \,|X\right] &= \Pr\left[\tilde{S} = 1 \,\middle|\, \tilde{S} \geq 1, X\right] \Pr\left[\tilde{S} \geq 1 \,|X\right] = \Pr\left[\tilde{S} = 1 \,\middle|\, \tilde{S} \geq 1, X\right] \\
\Pr\left[\tilde{S} = 2 \,|X\right] &= \Pr\left[\tilde{S} = 2 \,\middle|\, \tilde{S} \geq 2, X\right] \Pr\left[\tilde{S} \geq 2 \,|X\right] \\
&= \Pr\left[\tilde{S} = 2 \,\middle|\, \tilde{S} \geq 2, X\right] \left(1 - \Pr\left[\tilde{S} = 1 \,\middle|\, \tilde{S} \geq 1, X\right]\right) \\
\Pr\left[\tilde{S} = j \,|X\right] &= \Pr\left[\tilde{S} = j \,\middle|\, \tilde{S} \geq j, X\right] \Pr\left[\tilde{S} \geq j \,|X\right], \qquad (2.10)
\end{aligned}
$$

[6] The definition of the new categories is given in Table A.2.8.

with

$$\begin{aligned}
\Pr\left[\tilde{S} \geq 1\,|X\right] =& 1, \\
\Pr\left[\tilde{S} \geq j\,|X\right] =& \prod_{r=1}^{j-1}\left(1 - \Pr\left[\tilde{S} = r\,\middle|\tilde{S} \geq r, X\right]\right) \qquad\qquad j = 2, 3, 4.
\end{aligned}$$

Since we are interested in the effects of the explanatory variables on these transition probabilities, we have to parameterize the probabilities. Assume that we apply the Logit function, $\Lambda(X'\omega)$, we get

$$\Pr\left[\tilde{S} = j\,\middle|\tilde{S} \geq j, X\right] = F(X'\omega_j) = \Lambda(X'\omega_j), \tag{2.11}$$

which means that we have one set of coefficients per category-step, i.e. $(J-1)k = 3k$ parameters to estimate with k as the length of the coefficient vector ω. The interpretation of the coefficients per se is not very meaningful. Therefore, we look at the marginal effects of a change in the explanatory variable, X_l, on the probability that individual i chooses category j. The individual marginal effects for the sequential Logit can be obtained sequentially, starting with the lowest category:

$$MPE_{i1l} = \frac{\delta \Pr\left[\tilde{S}_i = 1\,|X_i\right]}{\delta X_{il}} = F'(X_i'\omega_1)\omega_{1l}, \tag{2.12}$$

where ω_1 is the vector of coefficients for the transition from the lowest category to the remaining (higher) ones. The marginal effects for the next categories are then given by

$$\begin{aligned}
MPE_{ijl} =& \frac{\delta \Pr\left[\tilde{S}_i = j\,|X_i\right]}{\delta X_{il}} \qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad (2.13)\\
=& F'(X_i'\omega_j)\omega_{jl}\prod_{r=1}^{j-1}[1 - F(X_i'\omega_j)] - F(X_i'\omega_j)\sum_{r=1}^{j-1} MPE_{irk}, \quad j = 2, 3, 4.
\end{aligned}$$

In the following results section, we present the average marginal effects given by $AMPE_{jl} = 1/n\sum_{i=1}^{n} MPE_{ijl}$. The standard errors are obtained using bootstrap.

In the following analysis, we will only display the results for the P-OLS and compare the results of the sequential Logit with the ordered Probit as a robustness check. We also did all the estimation based on simple OLS and ordered Probit in order to avoid results that depend only on the chosen method but did not find any important differences between the methods.

The wage equation

In order to be able to test the social comparison theory, we have to find a measure of comparison income. Following the approach of other studies, e.g. Hamermesh (2001), Nguyen, Taylor, and Bradley (2003) and Clark and Oswald (1996), we estimate a Mincer type log-earnings equation using OLS and take the fitted wages thereof as the social comparison wage. In order to capture remaining age effects in the wage equation, we estimate three different models for three age categories separately to obtain comparable values for the wage residuals.[7] We still include the age variable in the wage equations because we want to capture the remaining age effect within each age group. The results of the wage equation are displayed in Table A.2.3 in the Appendix.

2.4 Results

The presentation of our results starts with a discussion of a traditional job satisfaction equation as a benchmark. This is done in order to compare our results with previous studies and to discuss the model specification. Moreover, we can compare the determinants of overall job satisfaction and of satisfaction with pay. Afterwards, we will present the results of a model including personality traits and the models for the social comparison model and the comparison with pay. The results section will finish with some robustness checks of our models and an extension of the model in which we relax the assumptions of the P-OLS about the single crossing property and the constant marginal effects.

2.4.1 Traditional job satisfaction equation as a benchmark

As a first step, we present the results of an ordinary job satisfaction equation (containing the observed individual wage only) in order to be able to compare our results with those from other studies and to identify the variables that are mostly driving the results. Table 2.4 presents the benchmark model specification only including the absolute wage level. This corresponds to the traditional utility theory given in Equation 2.3. The first three columns contain the results of a regression with the

[7] We did not estimate the wage equations for males and females separately but only included a gender dummy because the number of observations per group becomes too small for reasonable results. We argue that women compare themselves with other employees irrespectively of their gender, therefore this should not be problematic for our application.

overall job satisfaction as the dependent variable, the last three columns present the results for the regression of the self reported satisfaction with personal income, each by gender. The inclusion of additional measures of satisfaction with other domains of life in the job satisfaction equation is questionable. It is obvious that these variables cannot be regarded as exogenous. A structural interpretation of the satisfaction equation including other satisfaction measures is therefor not possible. On the other hand, including a measure for satisfaction with leisure and health anyway is a possibility to control for unobserved heterogeneity. This is a common approach in the literature on satisfaction research (e.g. Lévis-Garboua and Montmarquette (2004), Boes and Winkelmann (2006b) and Hamermesh (2001)). We decided to focus on a model specification without additional measures for satisfaction but display the results of the alternative approach including satisfaction with health and with leisure as additional explanatory variables in the Appendix.

Based on the benchmark model, the monthly income has a significantly positive effect on job satisfaction, the highest coefficient among all explanatory variables. Moreover, we observe that wage plays a more important role for men's overall job satisfaction than for women's. In order to be able to interpret the size of the coefficients in more detail, we follow van Praag and Ferrer-i-Carbonell (2007) who introduce the concept of compensation in their analysis of income satisfaction. They illustrate the effect of different variables on satisfaction with income by calculating how much the income level would have to change in order to compensate for the change in another variable. If we compare the coefficients of the monthly wage and the dummy for fringes[8], we can calculate the wage increase that would be needed to compensate for the absence of fringes. For the first column of Table 2.4, this implies that an individual who receives fringes needs an increase of about 40% in the monthly gross wage to stay at the same expected job satisfaction level if he didn't receive fringes given that everything else stays the same.[9] It is unlikely that an employee receives on average fringes of this value. Most probably, the pure fact that the employee knows that he gets extras of any kind from his employer makes him feel more satisfied about his work because he has the feeling of acknowledgement. We get the same result in the model with additional controls for satisfaction given in the first column of Table A.2.4. Comparing the results for males and females shows that fringes do not have a significant effect on job satisfaction for women. The hours

[8]This dummy is equal to one if an individual receives any kind of fringes, e.g. 13th or 14th month salary, vacation pay.

[9]Calculated using $0.1168/0.3383 = 0.3453$, i.e. an increase by 0.34 log points compensates the change in the fringes dummy from "1" to "0" (ceteris paribus). This equals a raise in wages by $exp(0.3453) = 1.41$, i.e. by 41%.

worked per week show the expected sign for the overall sample, working time decreases job satisfaction. In order to compensate for working one hour per week more, the individual would have to get a wage increase by about 2%. Again, this effect is only significant for men. If we control for satisfaction with leisure, this effect is no longer significant since this measure picks up the effect of working hours (see Table A.2.4). The additional socio-economic background variables are not significant in this setting. This contradicts other findings, especially about the effect of age and education, found by e.g. Cornelissen (2009), Gazioglu and Tansel (2006) and Clark and Oswald (1996). In the following analysis, we will investigate this issue further.

The last three columns of Table 2.4 display the results for satisfaction with personal income. Compared to the results for the overall job satisfaction, we observe considerable differences. First of all, we see that men are on average less satisfied with their wage than women. Fringes do not matter, it seems that the individuals consider their monthly wage only when asked about their satisfaction with personal income. The coefficient of the monthly wage is almost three times the size as for the overall job satisfaction and is by far the most important determinant. The working time per week shows again a significant negative but larger effect in absolute value than for the overall job satisfaction. In order to keep satisfaction with pay constant, wage would have to raise by almost 18% if an individual works one hour more per week. Contrary to the overall job satisfaction, we now also find evidence for a U-shaped effect of age for the overall sample and for females which is in line with other findings (e.g. Gazioglu and Tansel (2006) and Clark and Oswald (1996)). Moreover, we find a positive effect of being married for females. This could be explained by the fact that married women do not have to work for economic reasons but select themselves in the labor market only if they are satisfied with their wage. This should be especially the case for the older women for whom the labor force participation rate is rather low. As in the case of the overall job satisfaction, we do not find a significant effect of education on satisfaction with pay either. The results for satisfaction with personal income do not differ considerably when including other measures of satisfaction (see Table A.2.4).

We regard the differences in the results of the two job related satisfaction measures as evidence that the respondents differentiate between the overall job satisfaction and their satisfaction with personal income. It is therefore likely that the role of comparison wages is different for these two domains of satisfaction. The adjusted R^2 of the overall job satisfaction is much lower than for the satisfaction with pay which means that the latter is better explained by the observable factors included in the benchmark equation. Moreover, we regard this as a justification for the use of self reported satisfaction information in economic analysis. Even though the two questions about overall job satisfaction and satisfaction with personal income are asked successively, the respondents seem to be able to differentiate clearly between the two job related satisfaction domains. In the following, we will analyze both, the determinants of the overall job satisfaction and of satisfaction with personal income in order to get a better understanding about differences in the driving variables for both cases.

2.4.2 Social comparison and personality

For the analysis of the effect of comparison wages, we will first concentrate on the effect of social comparison - i.e. the comparison with other's wages - and personality traits on job satisfaction. Tables 2.5 and 2.6 contain the results for overall job satisfaction and satisfaction with individual pay, respectively. When including the fitted wage and the residual of the wage equation, we no longer include the education variables in the satisfaction equation as in Table 2.4. This is done for identification reasons. In order to get meaningful results, we have to exclude some of the variables that we used in the wage equation from the job satisfaction equation. We chose the education variables because they play an important role in the wage equation but were insignificant in the benchmark equation for job satisfaction in Table 2.4. The inclusion of fitted wages in the satisfaction equation requires special caution when doing inference. Even though this issue has been widely ignored in the job satisfaction literature (one positive exception is Lévis-Garboua and Montmarquette (1997)), using generated regressors can induce inefficient and even inconsistent estimates. Pagan (1984) illustrates the problems in presence of generated regressors in linear models. In our case, we include the fitted value together with the corresponding residual into the job satisfaction equation. Based on the findings of Pagan (1984), we can assume that the estimates of the coefficients of the observed wage and of the fitted wage are consistent. Moreover, the estimator for the observed wage is efficient. The standard errors displayed for the fitted wage are incorrect but the authors show that they understate the true values and therefore do not lead to false inference.

The first columns of Tables 2.5 and 2.6 show the results if including social comparison wage, i.e. the age specific fitted wage from a separate equation (see Table A.2.3), into the model. Testing the traditional view that only the own wage matters corresponds to a significance test of the effect of the fitted wage. For the overall job satisfaction, this can be clearly rejected ($p = 0.01$). However, for the satisfaction with personal income, we do not find a significant effect of the comparison income ($p = 0.48$). The negative sign of the fitted wage in the overall job satisfaction equation implies that individuals are less satisfied with their jobs if they earn less than the estimated wage of an individual with the same (observable) characteristics.[10] These results imply that we cannot ignore the effect of social comparison for the overall job satisfaction, although this doesn't play a role for satisfaction with pay. Again, the results for the two measures of job related satisfaction differ substantially.

Columns 2 of both tables show the results for the direct effect of the six different measures for personality: the Big Five personality traits and a measure for the internal Locus of Control. Personality traits matter considerably more for the overall job satisfaction than for satisfaction with pay. While for the former all traits except Extraversion have a significant - although small - effect, for the latter only Agreeableness and the measure for an internal Locus of Control are significant. In both cases, the measure for Internalisers shows by far the highest coefficient followed by the negative effect of Neuroticsm. The coefficient of the other variables remain unchanged when controlling for personality, i.e. personality traits can be seen as orthogonal, which is in line with previous findings on the Big Five personality traits (e.g. Wichert and Pohlmeier (2010)). However, our results are not in line with the psychological literature that finds that Extraversion and Neuroticism are the most important determinants of job satisfaction when considering the Big Five personality traits (e.g. Costa and McCrae (1980), Vittersø and Nilsen (2002)). One reason for these differences could be the fact that the cited results rely mainly on pure correlations. Multivariate analysis can lead to different effects.

Apart from the direct effect of personality on job satisfaction, we also want to analyze whether the role of comparison wages is the same for different personality traits. Since the Locus of Control measure had the largest effect, we use this trait to define two groups: those with an above average score, i.e. the Internalisers, and those with a lower score, i.e. Externalisers. We then interact the wage measures with a dummy for being Internaliser.[11] The corresponding results are given in the third columns of Tables 2.5 and 2.6. For the overall job satisfaction, the interaction effect for the Internalisers has the opposite sign to the overall effect. This implies that the overall

[10] Clark and Oswald (1996) model comparison wages additionally based on an earnings survey. They use income cell-means by gender and by 28 categories for total usual weekly hours of work as a measure for comparable wages and find no differing results to using fitted wages from a wage equation.

[11] We also included interaction terms for the Big Five personality traits but did not find any significant effects.

job satisfaction of Internalisers depends less on the own wage and that comparison wages have a smaller negative effect (in terms of the absolute value). We can reject the hypothesis that the effect of the wage and the effect of the comparison wage for Internalisers add up to zero for the overall job satisfaction equation ($p = 0.02$ and $p = 0.01$), i.e. we still observe a comparison effect for both groups but a smaller one for Internalisers. For the satisfaction with pay model, we do not find a significant difference for the effect of the own wage and the comparison wage between the two groups of Internalisers and Externalisers.

Overall, we observe that the individual judgement of satisfaction with personal income seems to be much more rational (in terms of observable factors) than the one about the overall job satisfaction. Individuals do not seem to care about others' wages when evaluating their satisfaction with pay, i.e. the traditional view that only the own wage matters applies here. Moreover, the direct effect of personality is very small compared to the overall job satisfaction. Modeling satisfaction with pay in a traditional way, i.e. without comparison wages and without personality traits, does not seem as harmful as in the case of overall job satisfaction. If we compare the increase in the adjusted R^2 by allowing for direct and indirect effects of the personality traits, it is about 14 percentage points for the overall job satisfaction and only about eight percentage points for the satisfaction with pay.

Table 2.4: Benchmark equations with observed wages: overall job satisfaction and satisfaction with personal income
P-OLS estimates, SOEP 2005, Additional controls: dummies for job position (8), industry sector (8), region (15), working fulltime and religion (2).

Dependent variable:	Job satisfaction			Satisfaction with income		
	coeff. (p-value) All	coeff. (p-value) Males	coeff. (p-value) Females	coeff. (p-value) All	coeff. (p-value) Male	coeff. (p-value) Female
ln(wage)	.3383	.4537	.2413	1.0124	1.1438	.8898
	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)
Fringes	.1168	.1149	.1088	.0764	.0804	.0907
	(0.02)	(0.08)	(0.20)	(0.10)	(0.17)	(0.26)
Weekly working hrs.	-.0070	-.0065	-.0039	-.0166	-.0142	-.0146
	(0.01)	(0.09)	(0.38)	(0.00)	(0.00)	(0.00)
Age	-.0378	-.0646	.0115	-.0866	-.0616	-.1393
	(0.30)	(0.15)	(0.85)	(0.01)	(0.13)	(0.02)
$Age^2/100$	.0365	.0632	-.0158	.0938	.0634	.1552
	(0.38)	(0.22)	(0.82)	(0.01)	(0.17)	(0.02)
Mid voc	.0790	-.0268	.2382	-.0118	.0099	-.0359
	(0.28)	(0.78)	(0.05)	(0.86)	(0.91)	(0.75)
High voc	.0317	.0067	.1225	-.0854	-.0625	-.1170
	(0.70)	(0.95)	(0.37)	(0.25)	(0.51)	(0.36)
High edu	-.0023	-.1100	.1843	-.0044	.0075	-.0197
	(0.98)	(0.32)	(0.19)	(0.96)	(0.94)	(0.88)
Male	-.0081			-.1638		
	(0.87)			(0.00)		
Married	.0143	-.0380	.0669	.0596	-.0130	.1514
	(0.75)	(0.53)	(0.33)	(0.15)	(0.81)	(0.02)
German	.0598	-.0006	.1286	.1738	.0739	.3056
	(0.54)	(0.99)	(0.49)	(0.05)	(0.49)	(0.07)
Constant	-1.6780	-1.9416	-1.1318	-5.3606	-7.0512	-3.769
	(0.07)	(0.0)	(0.02)	(0.00)	(0.00)	(0.02)
Adjusted R^2	.0323	.0300	.0520	.1949	.2059	.1818
Nobs.	2,776	1,654	1,122	2,776	1,654	1,122

Table 2.5: Overall job satisfaction
SOEP 2005, Nobs.: 2,776; Additional controls: dummies for job position (8), industry sector (8), working fulltime, East Germany, robust standard errors.

	Social comparison			Past comparison		Combination
	Basic model coeff. (p-value)	Personality traits coeff. (p-value)	Interaction effects coeff. (p-value)	Basic model coeff. (p-value)	Interaction effects coeff. (p-value)	of both coeff. (p-value)
Log monthly gross wage, $ln(y)$	.4055	.3540	.3843	.1754	.1748	.3349
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$ln(y)$·INT			-.1973		.0094	-.1514
			(0.09)		(0.18)	(0.23)
Fitted log wage ($\hat{ln(y)}$)	-.4140	-.4475	-.4999			-.4535
	(0.01)	(0.00)	(0.00)			(0.00)
$\hat{ln(y)}$·INT			.2044			.1604
			(0.08)			(0.20)
Past comparison				.1575	.3385	.2559
				(0.14)	(0.03)	(0.11)
Past comparison·INT					-.3405	-.2420
					(0.09)	(0.26)
Log HH income (net of own wage)	.0045	.0020	-.0051	-.0057	-.0054	-.0053
	(0.49)	(0.74)	(0.36)	(0.32)	(0.34)	(0.35)
Fringes	.1315	.1403	.1227	.1112	.1107	.1213
	(0.01)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)
Weekly working hours	.0008	.0003	.0005	-.0067	-.0067	.0003
	(0.84)	(0.95)	(0.90)	(0.01)	(0.01)	(0.94)
Age	-.0300	-.0333	-.0191	-.0272	-.0277	-.0180
	(0.41)	(0.32)	(0.55)	(0.39)	(0.38)	(0.57)
Age^2/100	.0294	.0331	.0266	.0344	.0349	.0255
	(0.48)	(0.40)	(0.47)	(0.34)	(0.34)	(0.48)
Male	.0688	.0908	.1007	.0377	.0389	.1029
	(0.22)	(0.08)	(0.04)	(0.38)	(0.36)	(0.03)
Married	.0346	.0314	.0572	.0466	.0460	.0571
	(0.45)	(0.46)	(0.15)	(0.24)	(0.24)	(0.15)
German	.1707	.1243	.1193	.1178	.1174	.1166
	(0.05)	(0.11)	(0.09)	(0.09)	(0.09)	(0.10)
Public sector	.0988	.0944	.0843	.0719	.0721	.0834
	(0.10)	(0.08)	(0.09)	(0.15)	(0.15)	(0.09)
EXTstd		.0276	.0250	.0257	.0267	.0259
		(0.16)	(0.18)	(0.17)	(0.15)	(0.16)
AGRstd		.0822	.0573	.0562	.0560	.0566
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
CONstd		.0800	.0582	.0577	.0578	.0579
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
OPEstd		.0608	.0513	.0496	.0510	.0515
		(0.00)	(0.00)	(0.01)	(0.00)	(0.00)
NEUstd		-.1547	-.0762	-.0747	-.0730	-.0755
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
LOCstd		.1939	.1372	.1619	.1385	.1362
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Adjusted R^2	.0250	.1630	.1629	0.1606	0.1610	0.1631

Table 2.6: Satisfaction with personal income
SOEP 2005; Nobs.: 2,776; Additional controls: dummies for job position (8), industry sector (8), working fulltime, East Germany, robust standard errors.

	Social comparison			Past comparison		Combination
	Basic model coeff. (p-value)	Personality traits coeff. (p-value)	Interaction effects coeff. (p-value)	Basic model coeff. (p-value)	Interaction effects coeff. (p-value)	of both coeff. (p-value)
Log monthly gross wage, $ln(y)$	1.0756	1.0227	1.056	.9556	.9628	1.0351
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$ln(y)$·INT			-.1551		-.0069	-.1173
			(0.19)		(0.32)	(0.36)
Fitted log wage ($\hat{ln(y)}$)	-.1011	-.1121	-.1561			-.1325
	(0.48)	(0.42)	(0.28)			(0.36)
$\hat{ln(y)}$·INT			.1467			.1102
			(0.22)			(0.39)
Past comparison				.0183	.1481	.1112
				(0.86)	(0.33)	(0.47)
Past comparison·INT					-.2439	-.1816
					(0.21)	(0.38)
Log HH income (net of own wage)	.0230	.0204	.0155	.0155	.0155	.0156
	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.01)
Fringes	.0829	.0881	.0752	.0752	.0738	.0750
	(0.08)	(0.05)	(0.08)	(0.08)	(0.09)	(0.09)
Weekly working hours	-.0139	-.0141	-.0140	-.0155	-.0156	-.0141
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Age	-.0835	-.0815	-.0723	-.0734	-.0741	-.0723
	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)
$Age^2/100$	.0902	.0884	.0843	.0853	.0859	.0843
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Male	-.1199	-.1145	-.1084	-.1224	-.1229	-.1087
	(0.02)	(0.03)	(0.03)	(0.01)	(0.01)	(0.03)
Married	.0384	.0320	.0483	.0469	.0453	.0477
	(0.37)	(0.43)	(0.22)	(0.23)	(0.25)	(0.23)
German	.2646	.2031	.1986	.1200	.1983	.1979
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Public sector	.1414	.1369	.1320	.1298	.1319	.1328
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
EXTstd		-.0008	-.0025	-.0022	-.0014	-.0002
		(0.97)	(0.89)	(0.90)	(0.94)	(0.92)
AGRstd		.0612	.0454	-.0045	.0456	.0456
		(0.00)	(0.01)	(0.01)	(0.01)	(0.01)
CONstd		.0129	-.0019	-.0023	-.0028	-.0022
		(0.47)	(0.91)	(0.89)	(0.87)	(0.90)
OPEstd		.0226	.0153	.0152	.0152	.0156
		(0.23)	(0.40)	(0.40)	(0.40)	(0.39)
NEUstd		-.0779	-.0261	-.0256	-.0252	-.0255
		(0.00)	(0.16)	(0.37)	(0.17)	(0.17)
LOCstd		.2157	.2198	.1937	.2207	.2192
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Adjusted R^2	.1935	.2717	.2718	.2715	.2719	.2716

2.4.3 Comparison with the past and personality

After having found that social comparison, i.e. comparison with the wages of other individuals with similar characteristics, matters for the overall job satisfaction, we now investigate a second possibility of comparison: the comparison with one's own past. In columns 4 and 5 of Tables 2.5 and 2.6, we show the coefficients of a model specification containing only past comparison without social comparison. Column 4 illustrates that the past comparison term has a significant positive effect for the overall job satisfaction. This is in line with what we would expect: an increase in one's own wage leads to higher job satisfaction. Surprisingly, we do not find a significant effect of this measure for wage history in the model of satisfaction with pay. If we allow for indirect effects of the Locus of Control as we did before for the social comparison, we find that the interaction terms show the opposite sign of the overall variable for wages and comparison with the past. Now, contrary to the social comparison, we even find no significant past comparison effect at all for Internalisers ($p = 0.93$) for the overall job satisfaction.

Columns 6 of Tables 2.5 and 2.6 contain the results for an overall model allowing for social comparison and comparison with the past at the same time. The comparison terms are still significant, however, the interaction terms for the Internalisers are no longer significant. If we estimate the equations separately for Internalisers and Externalisers, we get significant effects of both comparison terms for the Externalisers and insignificant comparison effects for the Internalisers. Comparing the results about social comparison and past comparison so far shows that social comparison has a larger effect on overall job satisfaction than past comparison.

Overall, we can conclude that comparison - with other individuals as well as with one's past - does play an important role in determining the overall job satisfaction. For Internalisers, this comparison does not matter as much as for Externalisers. For the income satisfaction, the comparison with one's past has only a significant effect for the Externalisers. The strong effect of social comparison for Externalisers can be explained by the fact that Externalisers do not see themselves responsible for their course of life, i.e. their wage in this case. They rather believe that this depends on their environment and fate. Since they suppose that this is the case for everybody, they consider wage differences as a sign of good luck if it is positive and as injustice if it is negative. These feelings are then translated into the self reported job satisfaction. Internalisers, in contrast, regard their wage as an outcome of their own effort. Therefore, their satisfaction level is less influenced by comparison with others. Another explanation for the missing effect of social comparison for Internalisers could be cognitive dissonance. This concept states that individuals try to reduce contradictions between their own attitude and observed situations. In case of job satisfaction, this would imply that Internalisers who observe that they earn less than comparison individuals attribute this failure to their own missing effort. Since they believe that they are responsible for this discrepancy they state that they are satisfied with their situation because they are the only ones who could change it. This would imply that Internalisers react differently to negative and positive wage gaps. We have tried to investigate this issue further by allowing for different effects of negative and positive wage differences but did not find any evidence for significant differences. Further and more detailed analysis is necessary to get a better insight in the mechanisms driving our results. For the comparison with one's own past, the explanation is similar. Internalisers see their wage as the consequence of their own effort and ability. Therefore, changes in their wage over time are not surprising but are directly attributed to one's own behavior by Internalisers. Therefore, job satisfaction does not depend on the own wage history. Externalisers don't see the relationship between their own effort and their wage and consider the development of their wage to be more random. Therefore, they do not only react to their own wage level but also to the comparison with the past.

The differing results for overall job satisfaction and satisfaction with pay support the findings by Veenhoven (1996) together with our hypothesis about affective experience and cognitive evaluation. We claim that the first is more influenced by personality and comparison while the latter is closer related to observable characteristics. The judgement about overall job satisfaction seems to be much more influenced by comparison and the direct and indirect effects of personality than satisfaction with pay which can be explained by observable individual and job related characteristics.

2.4.4 Robustness checks

Controlling for possible endogeneity

Due to the fact that the present analysis is based on a cross-section, we cannot rule out the problem of a possible endogeneity bias. Since our measures of personality are taken from the same interview as the information about job satisfaction, we cannot rule out the possibility of reverse causality. Our findings that personality traits matter in determining job satisfaction could easily be reversed to saying that individuals who are satisfied with their job are more likely to report certain personality traits. One often cited argument against this critique are findings from psychology about the stability of personality traits in adulthood (e.g. Conley (1985), Gustavsson et al. (1997), Costa et al. (2000), Caspi and Roberts (2001), Svrivastava et al. (2003) and Costa et al. (2006)). However, even if we assume that the underlying personality traits are stable and thus cannot be influenced by the outcome variable, it might be possible that the answering behavior to the measures of personality traits is not stable. In order to tackle this issue, we profit from the panel structure of our data set. In 1999, the questions about the Locus of Control have been asked for the first time in the SOEP. Unfortunately, alternative measures of the Big Five Personality traits are not available but since we have illustrated the predominant role of the Locus of Control for our application, we think that controlling for possible endogeneity in the Locus of Control is a promising strategy. Exemplary estimation results for the overall job satisfaction using measures of the Locus of Control of 1999 and job satisfaction in 2005 are given in Table A.2.7 in the Appendix. We do not find important differences and can therefore conclude that reverse causality is not a relevant issue in our application.

Alternative estimation methods

The P-OLS method that we have used so far to model the effect of comparison income and personality on job satisfaction is based on quite restrictive assumptions. The P-OLS assumes the single crossing property and constant marginal effects. Boes and Winkelmann (2006b) point out that these restrictive models might produce misleading results in happiness research. In their paper, they suggest alternative models to analyze life satisfaction, among others the sequential Logit. In the following, we aggregated the job satisfaction information into four balanced categories as illustrated in Table A.2.8 in the Appendix. In order to analyze how the results change if we use this method instead of the P-OLS, we also present the estimation results of an ordered Probit for the same model setup. Tables 2.7 and 2.8 present the estimation results for the two models including social comparison and past comparison separately for Internalisers and Externalisers. We only display the results for the overall job satisfaction since we did not find important differences between the two groups for the satisfaction with pay model. Since we are mainly interested whether there are changing results for comparison wages, we only display the corresponding coefficients here. The results are given as average marginal effects. If we look at the overall pattern of the effects first, it is obvious that past comparison does not matter significantly in both models and for both groups. The effect of the fitted wage, i.e. the social comparison, is only significant for Externalisers which is in line with our findings from the P-OLS. The results of the ordered Probit suggest that the monthly wage has a negative effect on the probability that an individual reports one of the two lowest job satisfaction categories. Moreover, we find a positive effect on the probability of choosing the two highest categories. For the comparison wage, the pattern is the opposite. The effects are the largest (in absolute value) for the lowest and the highest categories. The pattern for the own wage is the same in the sequential Logit, except for the fact that the own wage does not matter for Internalisers at a medium satisfaction level. The own wage only plays a role for Internalisers to be very unsatisfied or very satisfied. The coefficients of the sequential Logit model are all higher than those of the ordered Probit. If we take the highest category as an example, an increase of the own wage by 50% leads to an increase of the probability of reporting the highest satisfaction level for Externalisers by 4% points based on the ordered Probit and by about 15% points in the sequential Logit. The effect of social comparison is again higher in the sequential Logit than in the ordered Probit. If the reference wage, i.e. the fitted wage, doubles, this decreases the probability of choosing the highest category for Externalisers by 8% points in the ordered Probit and by 28% points in the sequential Logit. For the average satisfaction level, category "2", social comparison does not matter.[12]

Since the sequential Logit is non-nested in the ordered Probit, we have to use Information Criteria to chose the best model. Boes and Winkelmann (2006b) suggest the AIC for this purpose, the values are given in the tables. In terms of the AIC, the ordered Probit is preferred to the sequential Logit, mainly because of the large number of parameters that have to be estimated in the second case. Overall, we can conclude that the results of the sequential Logit are not in contrast to our previous findings but offer a sharper picture of the role of wages and social comparison in determining overall job satisfaction. The sequential Logit suggests higher effects of both than the ordered Probit does. Moreover, social comparison matters especially for the Externalisers at very high and low satisfaction levels.

[12] We also estimated the model using different definitions of the categories but did not find any differing results.

Table 2.7: Average marginal effects of the comparison income in the Ordered Probit
SOEP 2005; Nobs.: 1,358 Internaliser and 1,418 Externaliser; p-values (in parenthesis) based on standard errors obtained by Delta-method.
Same additional controls as in Tables A.2.5 and A.2.6.

Category	1	2	3	4
		Overall job satisfaction		
		Internaliser		
Log monthly gross wage	-.0943 (0.00)	-.0345 (0.00)	.0166 (0.01)	.1122 (0.02)
Fitted log wage	.1086 (0.10)	.0398 (0.10)	-.0191 (0.11)	-.1293 (0.10)
Past comparison	.0181 (0.71)	.0066 (0.71)	-.0032 (0.71)	-.0215 (0.71)
Log likelihood	-1,776		AIC	3,626
		Externaliser		
Log monthly gross wage	-.1862 (0.00)	.0057 (0.07)	.0811 (0.00)	.0995 (0.00)
Fitted log wage	.2272 (0.01)	-.0069 (0.12)	-.0989 (0.01)	-.1214 (0.01)
Past comparison	-.1167 (0.10)	.0036 (0.21)	.0508 (0.11)	.0624 (0.11)
Log likelihood	-1,761		AIC	3,596

Table 2.8: Average marginal effects of the comparison income in the Sequential Logit
SOEP 2005; Nobs.: 2,789; p-values (in parenthesis) based on standard errors obtained by bootstrapping.
Same additional controls as in Tables A.2.5 and A.2.6.

Category	1	2	3	4
		Overall job satisfaction		
		Internaliser		
Log monthly gross wage	-.0974 (0.01)	-.0190 (0.66)	.0195 (0.74)	.3037 (0.00)
Fitted log wage	.1141 (0.17)	.0089 (0.92)	-.0250 (0.84)	-.3154 (0.16)
Past comparison	.0133 (0.84)	-.0279 (0.68)	.0835 (0.38)	-.1059 (0.52)
Log likelihood	-1,864		AIC	3,938
		Externaliser		
Log monthly gross wage	-.2477 (0.00)	.0834 (0.06)	.1726 (0.01)	.3669 (0.02)
Fitted log wage	.2908 (0.00)	-.1301 (0.16)	-.1474 (0.09)	-.4102 (0.08)
Past comparison	-.0850 (0.33)	.0202 (0.80)	-.0128 (0.92)	.3899 (0.12)
Log likelihood	-1,710		AIC	3,630

2.5 Conclusion

In this paper, we analyze the determinants of job satisfaction. Even though this topic has recently become quite popular in the economic literature, there are still no results in the economic literature on the role of personality within this issue. Our analysis aims at closing this gap by introducing two measures of personality into the determinants of overall job satisfaction and satisfaction with pay. Given the prominent role of wages and comparison wages, we investigate how personality influences the comparison process in evaluating job satisfaction. Additionally, we estimate direct effects of personality. Our findings suggest that overall job satisfaction is a more complex measure than satisfaction with pay. While the first is strongly affected by personality directly and indirectly through a different weighting of comparison, the latter is stronger determined by observable socio-economic and job related factors. Thereby, the effect of social comparison is stronger than the effect of comparison with one's own past. Individuals with an external Locus of Control compare themselves with others and with their own past in terms of wages and evaluate their job satisfaction according to the discrepancy between others' and past wages. Internalisers attribute wages as an outcome of their own effort and don't value comparison in their evaluation of job satisfaction. The results of the more flexible sequential Logit indicate that social comparison and the own wage matter especially at very high and very low satisfaction levels.

Even though our results suggest that including personality traits into the analysis of satisfaction, also of other domains, is a promising strategy, we can only give a first insight into the channels through which personality traits affect job satisfaction. Our results suggest that satisfaction in a broader sense (like overall job satisfaction) is more influenced by personality traits and comparison than satisfaction with a specific domain (like satisfaction with personal income). We find that the question about what matters more, own income or comparison income, cannot be answered unambiguously since this depends strongly on the individual Locus of Control.

This paper contributes to the existing literature in two ways: First, we show that apart from observable individual and job related characteristics, personality traits influence job satisfaction directly and indirectly. Moreover, our results indicate that there are important differences in the determinants of satisfactions with different domains. Further research should investigate how our results translate to related findings about the consequences of job satisfaction. On the one hand, it is important to investigate which measure of job satisfaction is the more important predictor of observable behavior on the labor market, e.g. performance or job quits. On the other hand, it is likely to expect that personality traits also affect how individuals react to their own job satisfaction level. Given the importance of personality traits for job satisfaction, we also expect interesting results for other domains of satisfaction, e.g. life satisfaction, when including personality traits.

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Appendix A.2: Supplementary Tables

Table A.2.1: Description of the variables
SOEP, Wave 2005, Nobs. 2,776

Variable	Description
Job Satisfaction	overall job satisfaction
	0: totally unhappy, 10: totally happy
Satisfaction with income	satisfaction with personal income
	0: totally unhappy, 10: totally happy
Satisfaction with health	overall satisfaction with health
	0: totally unhappy, 10: totally happy
Satisfaction with leisure	overall satisfaction with leisure
	0: totally unhappy, 10: totally happy
Satisfaction with HH income	satisfaction with household income
	0: totally unhappy, 10: totally happy
ln(wage)	log of the monthly gross wage
ln(hh income)	log of gross monthly household income net of own income
Fringes	Dummy, 1: if any kind of fringes obtained
	(13th or 14th month salary, (christmas) bonus, vacation pay
Fulltime	Dummy, 1: working fulltime
Weekly working hours	Hours actually worked on average per week
Age	Age in years
No degree	Dummy, 1: no educational degree (reference group)
Mid vocational	Dummy, 1: if high school degree or vocational training
High vocational	Dummy, 1: if high school degree and vocational training
High education	Dummy, 1: if university degree
Male	Dummy, 1: if male
Married	Dummy, 1: if married
German	Dummy, 1: if German
Small firm	Dummy, 1: if firm staff 1-199 (reference group)
Medium firm	Dummy, 1: if firm staff 200-1999
Large firm	Dummy, 1: if firm staff $\geq$ 2000
Tenure	Months of tenure
Public sector	Dummy, 1: if working in the public sector
East	Dummy, 1: if living in East Germany
LOCstd	standardized value of the index for the Locus of Control
	High values: Internalisers
EXTstd	standardized value of the measure of Extraversion
AGRstd	standardized value of the measure of Agreeableness
CONstd	standardized value of the measure of Conscientiousness
OPEstd	standardized value of the measure of Openness to Experience
NEUstd	standardized value of the measure of Neuroticism

Table A.2.2: Summary statistics
SOEP, Wave 2005, Nobs. 2,776)

Variable	Mean	Standard Deviation
Job Satisfaction	7.06	1.86
Satisfaction with income	6.63	1.99
Satisfaction with health	6.99	1.85
Satisfaction with leisure	6.43	2.06
Satisfaction with household income	6.69	2.01
ln(wage)	7.91	0.50
ln(hh income)	3.51	3.45
Fringes	0.84	
Fulltime	0.83	
Weekly working hours	41.03	9.20
Age	43.62	6.66
No degree	0.08	
Mid vocational	0.44	
High vocational	0.17	
High education	0.31	
Male	0.60	
Married	0.74	
German	0.95	
Small firm	0.48	
Medium firm	0.25	
Large firm	0.27	
Tenure	162.81	106.17
Public sector	0.32	
East	0.263	
LOC	26.38	4.34
EXT	14.49	3.28
AGR	16.19	2.90
CON	18.18	2.39
OPE	13.55	3.36
NEU	11.29	3.49

Table A.2.3: Age-specific wage equations
SOEP, Wave 2005, additional dummies for job position (8), industrial sector (8) and region (15).

Dependent variable:	Age 30-39	Age 40-49	Age 50-55
Log gross monthly income	coeff.	coeff.	coeff.
	(p-value)	(p-value)	(p-value)
Weekly hours worked	.0167	.0160	.0157
	(0.00)	(0.00)	(0.00)
Fulltime	.2878	.2770	.2904
	(0.00)	(0.00)	(0.00)
Middle vocational	.1526	.0427	.0562
	(0.00)	(0.19)	(0.19)
Higher vocational	.1822	.0799	.1162
	(0.00)	(0.03)	(0.02)
Higher education	.3233	.2308	.2347
	(0.00)	(0.00)	(0.00)
Tenure	.0010	.0009	.0015
	(0.10)	(0.01)	(0.00)
Tenure^2	-.0002	-.0001	-.0002
	(0.33)	(0.10)	(0.01)
Male	.1432	.1707	.1676
	(0.00)	(0.00)	(0.00)
Married	.0550	.0313	.0245
	(0.01)	(0.13)	(0.42)
German	.0481	-.0578	.1646
	(0.24)	(0.16)	(0.01)
Age	.0142	.0008	-.0051
	(0.00)	(0.80)	(0.43)
Medium firm	.0763	.0401	.0727
	(0.00)	(0.06)	(0.01)
Large firm	.1444	.1119	.1009
	(0.00)	(0.00)	(0.00)
Constant	6.6162	6.7491	6.0157
	(0.00)	(0.00)	(0.00)
Adjusted R^2	0.6306	0.6907	0.7180
Nobs.	828	1,291	657

Table A.2.4: Benchmark equations with observed wages (additionally controlling for other domains of satisfaction): overall job satisfaction and satisfaction with personal income
P-OLS estimates, SOEP 2005, Additional controls: dummies for job position (8), industry sector (8), region (15), working fulltime and religion (2).

Dependent variable:	Job satisfaction			Satisfaction with income		
	coeff. (p-value) All	coeff. (p-value) Males	coeff. (p-value) Females	coeff. (p-value) All	coeff. (p-value) Male	coeff. (p-value) Female
ln(wage)	.2721	.3495	.1990	.9671	1.0729	.8329
	(0.00)	(0.00)	(0.03)	(0.00)	(0.00)	(0.00)
Fringes	.0936	.1027	.0583	.0550	.0697	.0415
	(0.04)	(0.07)	(0.45)	(0.20)	(0.19)	(0.58)
Satis. with leisure	.0859	.1057	.0602	.0970	.0929	.1013
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Satis. with health	.2116	.2137	.2010	.1355	.1468	.1193
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Weekly working hours	-.0003	.0019	-.0045	-.0093	-.0068	-.0152
	(0.92)	(0.58)	(0.37)	(0.00)	(0.03)	(0.00)
Age	-.0185	-.0576	.0487	-.0726	-.0580	-.0905
	(0.56)	(0.14)	(0.38)	(0.02)	(0.11)	(0.09)
$Age^2/100$	.0234	.0637	-.0488	.0828	.0648	.1051
	(0.52)	(0.16)	(0.44)	(0.02)	(0.13)	(0.09)
Mid voc	.0197	-.0214	.1047	-.0203	.0178	-.1066
	(0.76)	(0.79)	(0.34)	(0.74)	(0.82)	(0.32)
High voc	.0044	.0267	.0094	-.0962	-.0463	-.1710
	(0.95)	(0.77)	(0.94)	(0.16)	(0.59)	(0.15)
High edu	-.0536	-.1001	.0544	-.0271	.0180	-.0740
	(0.47)	(0.29)	(0.67)	(0.70)	(0.84)	(0.55)
Male	-.0232			-.1864		
	(0.59)			(0.00)		
Married	.0436	.0344	.0479	.0853	.0398	.1537
	(0.27)	(0.51)	(0.44)	(0.02)	(0.42)	(0.01)
German	.0166	-.0031	.0062	.1271	.0639	.2021
	(0.85)	(0.98)	(0.97)	(0.12)	(0.51)	(0.19)
Constant	-3.9523	-3.7221	-3.6037	-7.1837	-8.3937	-5.9875
	(0.00)	(0.0)	(0.02)	(0.00)	(0.00)	(0.00)
Adjusted R^2	.2510	.2685	.2349	.3206	.3403	.2972
Nobs.	2,776	1,654	1,122	2,776	1,654	1,122

Table A.2.5: Overall job satisfaction (additionally controlling for other domains of satisfaction) SOEP 2005, Nobs.: 2,776; Additional controls: dummies for job position (8), industry sector (8), working fulltime, East Germany, robust standard errors.

	Social comparison			Past comparison		Combination
	Basic model	Personality traits	Interaction effects	Basic model	Interaction effects	of both
	coeff. (p-value)	coeff. (p-value)	coeff. (p-value)	coeff. (p-value)	coeff. (p-value)	coeff. (p-value)
Log monthly gross wage, $ln(y)$	.3004	.2844	.3956	.1709	.1712	.3293
	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)	(0.00)
$ln(y)$·INT			-.2131		.0096	-.1549
			(0.07)		(0.17)	(0.21)
Fitted log wage ($\hat{ln(y)}$)	-.4811	-.5169	-.6245			-.5560
	(0.00)	(0.00)	(0.00)			(0.00)
$\hat{ln(y)}$·INT			.2198			.1640
			(0.06)			(0.19)
Past comparison				.2111	.4333	.3439
				(0.05)	(0.01)	(0.03)
Past comparison·INT					-.4169	-.3120
					(0.04)	(0.14)
Log HH income (net of own wage)	-.0050	-.0047	-.0045	-.0057	-.0054	-.0048
	(0.39)	(0.39)	(0.42)	(0.31)	(0.33)	(0.39)
Fringes	.1062	.1181	.1154	.1009	.1001	.1131
	(0.02)	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)
Satis. with leisure	.0881	.0748	.0750	.0767	.0775	.0764
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Satis. with health	.2124	.1779	.1784	.1779	.1778	.1780
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Weekly working hours	.0066	.0047	.0048	-.0019	-.0020	.0046
	(0.08)	(0.19)	(0.18)	(0.54)	(0.52)	(0.20)
Age	-.0033	-.0095	-.0105	-.0255	-.0261	-.0093
	(0.92)	(0.76)	(0.74)	(0.41)	(0.40)	(0.77)
Age^2/100	.0085	.0139	.0151	.0302	.0307	.0139
	(0.82)	(0.70)	(0.68)	(0.40)	(0.39)	(0.70)
Male	.0400	.0787	.0816	.0131	.0140	.0836
	(0.42)	(0.10)	(0.09)	(0.76)	(0.74)	(0.08)
Married	.0922	.0811	.0813	.0607	.0599	.0810
	(0.02)	(0.04)	(0.04)	(0.12)	(0.12)	(0.04)
German	.0916	.0703	.0697	.0614	.0602	.0648
	(0.21)	(0.31)	(0.31)	(0.37)	(0.38)	(0.35)
Public sector	.0853	.0809	.0764	.0641	.0645	.0748
	(0.09)	(0.10)	(0.11)	(0.19)	(0.18)	(0.12)
EXTstd		.0243	.0238	.0237	.0249	.0249
		(0.18)	(0.19)	(0.19)	(0.17)	(0.17)
AGRstd		.0590	.0581	.0569	.0567	.0572
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
CONstd		.0644	.0661	.0671	.0673	.0660
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
OPEstd		.0490	.0505	.0479	.0495	.0507
		(0.01)	(0.00)	(0.01)	(0.01)	(0.00)
NEUstd		-.0724	-.0709	-.0697	-.0676	-.0699
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
LOCstd		.1395	.1172	.1391	.1165	.1154
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Adjusted R^2	.2486	.3049	.3055	0.3031	0.3040	0.3064

Table A.2.6: Satisfaction with personal income (additionally controlling for other domains of satisfaction)
SOEP 2005; Nobs.: 2,776; Additional controls: dummies for job position (8), industry sector (8), working fulltime, East Germany, robust standard errors.

	Social comparison			Past comparison		Combination
	Basic model coeff. (p-value)	Personality traits coeff. (p-value)	Interaction effects coeff. (p-value)	Basic model coeff. (p-value)	Interaction effects coeff. (p-value)	of both coeff. (p-value)
Log monthly gross wage, $ln(y)$	1.0013	.9767	1.0697	.9509	.9594	1.0276
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$ln(y)$·INT			-.1758		-.0067	-.1231
			(0.01)		(0.33)	(0.33)
Fitted log wage ($\hat{ln(y)}$)	-.0520	-.0742	-.1608			-.1147
	(0.75)	(0.64)	(0.32)			(0.49)
$\hat{ln(y)}$·INT			.1670			.1163
			(0.16)			(0.36)
Past comparison			.3439	.0793	.2557	.2203
			(0.03)	(0.45)	(0.09)	(0.16)
Past comparison·INT			-.3120		-.3307	-.2656
			(0.14)		(0.09)	(0.20)
Log HH income (net of own wage)	.0162	.0157	.0157	.0154	.0155	.0156
	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)
Fringes	.0576	.0662	.0632	.0635	.0618	.0621
	(0.20)	(0.12)	(0.14)	(0.14)	(0.15)	(0.15)
Satis. with leisure	.1000	.0869	.0872	.0874	.0881	.0880
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Satis. with health	.1323	.1102	.1105	.1101	.1100	.1102
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Weekly working hours	-.0079	-.0092	-.0091	-.0100	-.0101	-.0092
	(0.03)	(0.01)	(0.01)	(0.00)	(0.00)	(0.01)
Age	-.0702	-.0701	-.0711	-.0716	-.0724	-.0707
	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Age^2/100	.0797	.0790	.0801	.0805	.0813	.0798
	(0.03)	(0.03)	(0.03)	(0.02)	(0.02)	(0.03)
Male	-.1633	-.1431	-.1417	-.1503	-.1509	-.1414
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Married	.0772	.0651	.0642	.0628	.0610	.0635
	(0.05)	(0.09)	(0.10)	(0.10)	(0.11)	(0.10)
German	.1753	.1377	.1360	.1355	.1332	.1334
	(0.01)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Public sector	.1281	.1241	.1229	.1210	.1235	.1229
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
EXTstd		-.0044	.0047	-.0045	-.0034	-.0038
		(0.81)	(0.79)	(0.80)	(0.85)	(0.83)
AGRstd		.0462	.0465	.0456	.0465	.0463
		(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
CONstd		.0080	.0088	.0085	.0080	.0086
		(0.64)	(0.60)	(0.62)	(0.64)	(0.61)
OPEstd		.0135	.0137	.0133	.0135	.0140
		(0.45)	(0.44)	(0.46)	(0.45)	(0.43)
NEUstd		-.0203	-.0200	-.0199	-.0192	-.0192
		(0.27)	(0.27)	(0.28)	(0.29)	(0.29)
LOCstd		.1679	.1956	.1677	.1956	.1942
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Adjusted R^2	.3192	.3533	.3539	0.3534	0.3542	0.3540

Table A.2.7: Overall job satisfaction and satisfaction with personal income with Locus of control measured in 1999
SOEP 2005; Nobs.: 1,554; Additional controls: dummies for job position (8), industry sector (8), working fulltime, East Germany, robust standard errors.

	Overall job satisfaction		Satisfaction with pay	
	coeff.	coeff.	coeff.	coeff.
	(p-value)	(p-value)	(p-value)	(p-value)
Log monthly gross wage, $ln(y)$	.4587	.4549	.9758	.9995
	(0.00)	(0.00)	(0.00)	(0.00)
$ln(y)$·INT	-.3282	-.3811	-.1155	-.1846
	(0.06)	(0.01)	(0.53)	(0.29)
Fitted log wage ($\hat{ln(y)}$)	-.5184	-.5186	-.0646	.0085
	(0.02)	(0.01)	(0.75)	(0.97)
$\hat{ln(y)}$·INT	.3163	.3713	.1219	.1931
	(0.07)	(0.01)	(0.51)	(0.27)
Log HH income (net of own wage)	-.0012	-.0050	.0217	.0191
	(0.88)	(0.49)	(0.00)	(0.01)
Fringes	.0800	.0520	.1542	.1204
	(0.20)	(0.37)	(0.01)	(0.03)
Satis. with leisure		.0806		.0988
		(0.00)		(0.00)
Satis. with health		.1816		.0977
		(0.00)		(0.00)
Weekly working hours	-.0010	.0030	-.0115	-.0057
	(0.85)	(0.55)	(0.02)	(0.21)
Age	-.0640	-.0517	-.0423	-.0460
	(0.14)	(0.19)	(0.31)	(0.25)
Age^2/100	.0644	.0596	.0435	.0511
	(0.20)	(0.19)	(0.37)	(0.27)
Male	.0918	.0599	-.1893	-.2381
	(0.16)	(0.32)	(0.00)	(0.00)
Married	.0521	.0733	.0903	.1006
	(0.34)	(0.14)	(0.08)	(0.04)
German	.1519	.0772	.2064	.1194
	(0.11)	(0.34)	(0.01)	(0.12)
East	-.0924	-.0270	-.0631	.0094
	(0.17)	(0.68)	(0.29)	(0.88)
Public sector	.0651	.0460	.0470	.0281
	(0.34)	(0.45)	(0.49)	(0.66)
EXTstd	.0150	.0039	.0087	-.0014
	(0.54)	(0.87)	(0.70)	(0.95)
AGRstd	.0843	.0702	.0346	.0246
	(0.00)	(0.00)	(0.16)	(0.29)
CONstd	.1158	.1020	.0264	.0254
	(0.00)	(0.00)	(0.23)	(0.23)
OPEstd	.0341	.0196	.0018	-.0060
	(0.18)	(0.40)	(0.94)	(0.79)
NEUstd	-.1834	-.1004	-.0915	-.0348
	(0.00)	(0.00)	(0.00)	(0.13)
LOCstd (1999)	.1243	.0738	.1272	.0808
	(0.00)	(0.03)	(0.00)	(0.01)
Adjusted R^2	.1145	.2775	.2145	0.3540

Table A.2.8: Categories for the Ordered Probit and the Sequential Logit
SOEP 2005

Original satisfaction variable, S	New Category $\tilde{S}$	Share All	Share Internaliser	Share Externaliser
0 - 6	1	31.16 %	20.25 %	41.61 %
7	2	20.32 %	19.29 %	21.30 %
8	3	28.60 %	32.92 %	24.47 %
9 - 10	4	19.92 %	27.54 %	12.62 %
Number of obs.		2,776	1,358	1,418

Chapter 3

Which factors safeguard employment? An analysis with misclassified German register data

3.1 Introduction

We use administrative individual data from Germany to analyze the determinants for job separations with subsequent transition to unemployment. Our analysis aims at contributing to several important questions such as the importance of education decisions, whether there is discrimination against immigrant workers and to identify the most important factors that let the individual transition probability from employment to unemployment shrink or even vanish.

Administrative individual data are gradually becoming a prime resource for policy evaluation and empirical labor market research in many countries. This is because the available data sets are large and contain precise information on target variables such as wages, employment periods and the duration and level of employment subsidies and social security transfers. This makes it a very attractive base for empirical labor market research on the returns to education, wage inequality and the evaluation of labor market programmes, among other things. While the administrative data on target variables are generally precise, non-target variables can be subject to considerable measurement errors. For example in Germany, employers report educational qualifications, nationality and job classifications, among other variables, to the public pension insurer for statistical reasons only, yet these variables are irrelevant for the pension entitlements of their employees. In general, administrative data is generated and collected using manifold methods. These include interviews, self-reports and reports from the employer. In some cases, individuals have to present certificates; in others, their reply is entered without any plausibility check. If information is collected solely for statistical purposes, its quality is likely to be lower, since error-checking is labor intensive, and therefore expensive. At worst, this can result in apparent data inconsistencies in the subsequent observations of an individual, such as changes in their educational qualifications or nationalities. Data inconsistencies are also easily identified if the same variable is available in different registers. While it may only be collected for statistical reasons in one register, it may be highly relevant information in another register. In this case, the high quality information can be used to validate lower quality information and it is possible to determine the degree of misclassification and the size of the nonclassical measurement error. While there is extensive literature on data quality problems in survey data, only few contributions analyze the quality of administrative data. Several studies compare survey and administrative data to determine misclassification. However, these studies often assume that the administrative data is correct and use it as validation information for the survey data. For example, see Benitez-Silva et al. (2004) for self reported disability status. Kapteyn and Ypma (2007) compare information on earnings in US administrative and survey data. By focusing on wage data, they can assume that the administrative information is generally reliable. Johansson and Skedinger (2009) doubt that the disability information in administrative data is always reliable and find evidence that disability status is misreported in Swedish administrative data.

There is a broad literature on different general methodologies to improve data quality. While multiple imputation methods (for example, Little and Rubin (2002), Schafer (1997)) primarily focus on the elimination of missing values, there are also methods for editing and imputing data (see e.g. Fellegi and Holt (1976), Manzari (2004) who use logical rules or information in neighboring observations to eliminate inconsistencies and missing values. In context of German administrative data, both methods have been applied to different variables. Büttner and Rässler (2008) apply multiple imputation methods to impute missing values due to top coding in the wage variable of the German employment records. Fitzenberger et al. (2006) observe many inconsistencies and implausible changes in the educational qualification in the same data and suggest several editing and imputation corrections closely related to the logic-driven Fellegi-Holt methodology. Their editing rules make use of the whole employment trajectory of an individual and employ constraints like the educational qualification cannot decrease over time. Since evident data problems are often eliminated by their approach, we consider it an interesting attempt. In our analysis, we will also apply their editing and imputation procedures and we suggest similar approaches for the nationality variable. As another contribution, we compare the quality of the editing and imputation rules to multiple imputation techniques.

While statistical research has often focused on classical measurement error (for a summary see, for example,Cameron and Trivedi (2005), chapter 26) and regression techniques with incomplete data (Schafer (1997)), here we face an error structure that violates the statistical regularity conditions for classical measurement error. Since we have ordered and non-ordered discrete or binary variables rather than continuous variables, there are natural restrictions on the sign of the measurement error that make it non-classical. By making use of our derived misclassification information for the education and nationality, we apply a misclassification SIMEX (MC-SIMEX, Küchenhoff et al. (2006)) for the estimation of a nonlinear regression model with misclassified discrete variables.

In particular, we are estimating logit regressions for the determinants of unemployment risks. Previous research for Germany and other countries (e.g. Gangl (2003) and Frederiksen (2008)) suggests that attributes associated with individual skills, such as the educational qualification, the wage level, and the labor market experience, have a considerable negative statistical association with the probability of losing a job. Based on monthly household panel survey data, Gangl (2003) finds evidence that a higher educational qualification such as A-levels or higher more than halves the conditional transition rate to unemployment compared to an individual without a completed degree or vocational training. The effect of education is found to be much stronger than the effect of labor market experience, while a very low wage is also associated with a considerably higher risk of unemployment. He finds an insignificant positive effect for individuals with an immigration background. As the household survey data is characterised by considerable recall error regarding the labor market experiences of individuals (Jürges (2006)), we perform a similar analysis with administrative data. By applying comprehensive editing and imputation methods as well as misclassification regressions to account for the measurement error in the education and nationality information, we address the disadvantages of the administrative data to improve the quality of results. Our data correction code and our MATLAB implementation of the MC-SIMEX will be made available to the user community of these data by the research data centre of the German Federal Employment Agency (IAB-FDZ, fdz.iab.de).

The paper is structured as follows. Section two reviews and introduces the editing rules for the education and citizenship information in German administrative employment records. Section three uses validation data from other administrative sources for a misclassification analysis. In section four, we present the estimation results of our application to unemployment risk. The last section summarizes and defines future research needs.

3.2 Data and Editing Rules

Since register data is comprised of highly sensitive information, it is often not easily accessible for independent researchers and the user group is therefore in most cases restricted to government contractors or national research institutes. However, the IAB-FDZ has facilitated access for a wider international user community by offering standardized data products as scientific use files, such as the IAB Employment Sample (IABS) and the Integrated Employment Biographies (IEBS). These data products undergo some preparation and documentation steps before they are released to a growing international user community. Additional data preparation and cleaning tools are available to facilitate work with this data and to improve the quality of research. The IABS contains daily employment records (Beschäftigtenhistorie, BeH) for a 2% random sample of the German workforce subject to social security contributions for the period 1975-2004. In addition to the employment periods, the BeH provides basis information on the individual (such as gender, age, wage, educational qualification, nationality and job title) and the employing firm (the business type and the location of the firm). These spells are linked with daily information on claim spells for unemployment compensation from the German Federal Employment agency (Leistungshistorie, LeH). For more information on the IABS, see Hamann et al. (2004) or Drews (2008). The IEBS contains the same sources of information in the period 1990-2004 but with less or higher aggregated information on the firm or individual. As an advantage, for the years after 1999 it is linked to the job seekers register (Bewerberangebotsdatei, BewA) and the register of training measures (Massnahmeteilnehmer-Gesamtdatenbank, MTG). Information in these registers is reported by individuals to the employment agencies to facilitate the job search process. The IEBS is a 2.2% random sample of the joint population of the four administrative registers. For more information on the IEBS see Zimmermann et al. (2007). The IABS is more commonly used in empirical research because it has an easier data structure and a longer time period and it contains more information related to employment and firms. The IEBS is predominantly used for the evaluation of active labor market programmes. Our empirical analysis uses the IABS.

To improve the quality of our analysis, we apply editing and imputation for the educational qualification and the citizenship variable in German administrative employment records. We restrict our analysis to the information in the BeH, as it is a main data source for the IABS and it is the only informative source for education and citizenship in the scientific use file version of the IABS. Moreover, the BeH is the main source of information in several IAB data products (e.g. IABS and linked employer employee data (LIAB)). Since our variables of interest are non-target variables, we expect them to contain a considerable amount of measurement error. The literature about editing and imputing discusses several approaches to deal with measurement errors. Manzari (2004) reviews methods for data editing and imputing and applies them to population census data. In her paper, she combines two methods: the Fellegi-Holt methodology (Fellegi and Holt (1976)) and the nearest neighbour imputation methodology (Bankier et al. (1997) and Bankier (1999)). While the first method is logic-driven by applying logical editing rules about one individual to detect inconsistencies, the latter is data-driven and uses information from other individuals (called 'donors') to correct the data. In the present analysis, we apply Fitzenberger et al.'s (2006) correction method for the education variable and we introduce an editing rule for the citizenship variable that determines which individuals have an immigration background. Both imputation procedures are closely related to the logic-driven Fellegi-Holt methodology since we only use within-person information. This method has been proven to perform well in cases of random errors while the nearest neighbor method is more appropriate for systematic errors (Manzari (2004)). Even though we find that there is a tendency to understate the educational level in the data, we assume that the errors in the education and the nation variable can be considered as being random since there is no evidence that the false reporting by the employer follows any systematic rule as a whole.

Fitzenberger et al. (2006) introduce different imputation procedures for dealing with missing or inconsistent information about the education in the IABS. Their basic idea is that an individual's educational level cannot decrease over the life cycle; it either remains constant or increases. This reporting rule is used to detect inconsistent information in the data. They introduce four different concepts that differ in the requirements that the educational history has to fulfil to be considered sufficiently valid to overwrite inconsistent information in subsequent spells. The authors state that it is impossible to say which procedure is the best among the four. However, it is better to use any kind of imputation than to use the uncorrected original data. In the initial analysis, we focus on the weakest and the strictest version. The results do not differ substantially, but the comparison of the imputed data with validation data (see Section 3.3) suggests that imputation procedure 1 (IP1) leads to better results in terms of the measurement error. Therefore, we only report the results based on this procedure in what follows. IP1 tends to overstate the educational level, so can be seen as an upper bound. For a detailed description of this imputation procedure, see Fitzenberger et al. (2006).

Table 3.1 presents the transition matrix between education levels before and after IP1. The numbers given are the column shares and display the probability that a value of the original data changes to a certain corrected value. Apparently, the imputation procedure changes information about lower educational qualifications in particular. Almost a quarter of the spells with the original information "No degree" are "Vocational training" spells after the imputation. As already expected, the results show that there is a tendency to understate the true educational level in the population since employers often only report the required degree for a certain position instead of the actual educational level of an individual. Moreover, more than 80% of the "Missings" could be removed by the imputation procedure, being replaced with "No degree" or "Vocational training" in 75% of the cases.

Table 3.1: IP1 vs. original education, column shares, 20,960,096 spells.
no degree at all (ND), vocational training degree (VT), high school degree (HS), high school degree and vocational training degree (HSVT), technical college degree (TC), university degree (UD)

Education	Original data						
IP1	Missing	ND	VT	HS	HSVT	TC	UD
Missing	14.32	.02	.01	.06	.01	.01	.01
ND	24.79	75.12	.27	.68	.10	.05	.01
VT	50.06	23.01	94.51	.05	.03	.01	.01
HS	2.31	.69	.00	73.35	.01	.00	.01
HSVT	4.48	.84	3.46	21.50	87.96	.01	.00
TD	1.83	.18	1.08	1.50	5.77	90.09	.00
UD	2.21	.14	.67	2.86	6.12	9.83	99.96
Total	100.00	100.00	100.00	100.00	100.00	100.00	100.00

Similar to the correction and imputation of the education variable, we apply logical editing rules for the citizenship variable although the number of corrections is very small. Still, there are many multiple nationality changes in the data that appear implausible. These are probably driven by immigrants with dual nationality. To better capture this fact, we propose an alternative concept to define individuals using their immigration background instead of trying to model their actual citizenship in each spell. "Immigration background" in this case means that an individual has or had a nationality other than German. This categorial variable takes the value "1" if a person has more than one non-German nationality spell, provided that there is more than one spell. Otherwise, one single spell is sufficient. The variable has a missing value for people with completely missing information about nationality; otherwise, it is "0". Different modifications of this concept, such as a different number of required non-German spells, did not lead to substantial changes. Based on the scientific use file IABS 2004-R04, we present a cross tabulation for the immigration variable against the original variable (see Table 3.2). Although there are far fewer changes than in the case of the education variable, it is important to note that a large fraction of spells from individuals with immigration background are recorded as German in the original data. Indeed, our data editing rule is relevant as it increases the number of "non German" spells by about 20%, from 1.78m to 2.13m spells.

Table 3.2: Immigration variable vs. original nation, 20,960,096 spells.

Immigration		Original data	
background	Missing	German	Non-German
Missing	99.20	.00	.00
German	.47	98.15	.30
Immigration	.33	1.85	99.70
Total	100.00	100.00	100.00

3.3 Misclassification Analysis

In this section, we determine the distribution of the measurement error in the education and nationality variables and assess the quality of the data correction rules. We determine misclassification with the help of the IEBS by comparing information in the BeH with information in the BewA. If the educational qualification or the nationality in the BeH do not match the information in the BewA, we define this as misclassification. We use for our analysis only spells starting in 1999 or later because BewA information is not systematically available in earlier years. Since information in the BewA is a target variable and is collected for non-statistical reasons, it is considered to be of higher quality than the information in the employment records.

Some research on data quality confirms this view (Bender et al. (2005)). To confirm this assessment, we repeat the editing and imputation analysis of the previous section for the BewA and find indeed a considerably lower share of inconsistent observations than in the BeH (6% versus 20% in case of education). Although this does not suggest that our validation data is free of error, it provides evidence for it being far less erroneous. However, further systematic research is required to check the validity of the validation data by, for example, using information from other linked administrate sources or survey data if they were available.

Our approach to validating BeH information is based on information in BewA spells if these overlap with BeH spells or if other spells follow promptly. When we choose only those BeH spells that overlap with BewA spells as the validation sample, we are left with 651,261 spells, or about 10.5% of all BeH spells in the period 1999-2004. As the event of having overlapping spells may be rather selective, we also allow for a gap of up to two weeks gap between BeH and BewA spells. In this case, we are left with about 1.2m spells, or about 20% of all BeH spells in the period 1999-2004. As the following misclassification results are very similar for the two samples, we only report them for overlapping spells. As we are interested in misclassification of information in the IABS, we make two modifications to the IEBS to make information in the BeH spells comparable. This includes setting the nationality information to "Missing" for all individuals who have one employment record in Eastern Germany and constructing a comparable educational qualification variable for the BewA. See Appendix A.3.2 for more details.

The resulting misclassification matrices can be found in Tables 3.3 to 3.8. It is apparent that both education variables (original and IP1) have a high degree of misclassification. Comparing Tables 3.3 and 3.4 reveals that the imputation procedure has improved the data quality by decreasing the amount of misclassification. The main diagonal elements that reflect the correctly classified values are all higher in Table 3.4 than in Table 3.3.

For further analysis we group the education variable in four categories: "Missing", "No degree", "VT" (Vocational training or any kind of school degree) and "Higher Education" (technical college or university degree). This is done because Tables 3.3 and 3.4 suggest that when VT, HS or HSVT are misclassified, they are likely coded as one of these other categories. The same is true for TD and UD. As these two groups of categories are similar anyway, we can increase the precision of the data by aggregating or pooling them. Tables 3.5 and 3.6 confirm that diagonal elements are now much greater. Only the imputed "No degree" value contains slightly more misclassification than the original variable, which is due to the imputation procedure overestimating the educational level, especially for the low-skilled.

Table 3.3: Misclassification matrix for the original education, 651,261 spells.
no degree at all (ND), vocational training degree (VT), high school degree (HS), high school degree and vocational training degree (HSVT), technical college degree (TC), university degree (UD).

Education	Validation data						
Original	Missing	ND	VT	HS	HSVT	TC	UD
Missing	48.65	43.67	30.80	43.43	29.97	25.97	26.26
ND	16.66	32.61	10.64	19.48	7.24	3.86	3.78
VT	28.50	22.76	56.70	18.25	39.37	23.36	17.64
HS	.30	.34	.25	10.19	3.14	2.49	2.97
HSVT	1.63	.35	.86	4.19	11.14	7.39	5.44
TD	2.24	.13	.55	1.83	4.76	22.52	6.24
UD	2.02	.14	.21	2.63	4.37	14.41	37.67
Total	100.00	100.00	100.00	100.00	100.00	100.00	100.00

Table 3.4: Misclassification matrix for IP1, 651,261 spells.
no degree at all (ND), vocational training degree (VT), high school degree (HS), high school degree and vocational training degree (HSVT), technical college degree (TC), university degree (UD).

Education	Validation data						
IP1	Missing	ND	VT	HS	HSVT	TC	UD
Missing	9.96	5.01	1.62	7.73	1.94	2.99	3.30
ND	23.29	39.93	7.45	19.92	5.75	2.35	2.60
VT	54.13	51.79	84.80	27.53	38.67	14.88	11.52
HS	.17	.63	.14	14.87	3.68	2.45	3.08
HSVT	4.00	1.90	3.69	20.10	29.35	10.94	7.63
TD	4.13	.38	1.61	4.10	10.30	36.15	7.44
UD	4.33	.36	.68	5.75	10.30	30.25	64.43
Total	100.00	100.00	100.00	100.00	100.00	100.00	100.00

Table 3.5: Misclassification matrix for the original education variable, 651,261 spells.

Education	Validation data			
Original	Missing	No degree	VT	Higher Educ.
Missing	48.65	43.67	31.02	26.16
No degree	16.66	32.61	10.55	3.81
VT	30.43	23.46	56.88	28.35
Higher Education	4.26	.27	1.55	41.68
Total	100.00	100.00	100.00	100.00

Table 3.6: Misclassification matrix for IP1, 651,261 spells.

Education	Validation data			
IP1	Missing	No degree	VT	Higher Educ.
Missing	9.96	5.01	1.79	3.20
No degree	23.29	39.93	7.59	2.52
VT	58.30	54.31	86.60	24.16
Higher Education	8.45	.75	4.01	70.12
Total	100.00	100.00	100.00	100.00

For the nationality, Table 3.7 suggests that only 72% of the non Germans are correctly classified in the BeH, while about 27% of the non Germans are wrongly classified as Germans in the BeH. This provides evidence that the measurement error in the citizenship information is greater than commonly believed although information on German nationality is generally reliable. Using the immigration concept instead of the original variable captures the non German information better (Table 3.8), although there is no one-to-one link between the two variables because of dual nationalities. Table 3.8 shows that our immigration concept captures the citizenship information in the validation sample quite well. Now, more than 95% of the spells are correctly classified.

Table 3.7: Misclassification matrix for the original nation variable, 651,261 spells.

Original	Validation data		
Nation	Missing	German	non German
Missing	92.70	.03	.15
German	6.29	98.65	27.48
non German	1.01	1.31	72.37
Total	100.00	100.00	100.00

Table 3.8: Misclassification matrix for the immigration variable, 651,261 spells.

Immigration	Validation data		
background	Missing	German	Migration
Missing	97.59	.00	.01
German	1.99	96.28	3.16
Migration	0.42	3.71	96.83
Total	100.00	100.00	100.00

These misclassification matrices are valid for the population of employment records if our sample of validation spells is a random sample with respect to misclassification error. We check this by investigating in two directions: first, we check whether our alternative sample of validation spells, which is twice as large as the sample of overlapping spells, produces very similar results. In the case of the nationality variable and the imputed education variable, deviations between the misclassification probabilities are very small and less than 1% points in all cases. In the case of the original education variable, the differences are also small, but for few values they are about 5% points. Second, we compare descriptive statistics for all BeH spells and all our validation samples and find that they are often similar, although there are sometimes deviations that are probably attributed to our validation samples consisting of employees who were unemployed in the past or who will become unemployed in the future.

In order to evaluate the quality of our editing and imputation strategies, we follow the guidelines given by Chambers (2006), who presents imputation performance measures for categorical variables used in the EUREDIT project. This measure captures the degree of misclassification in the data by computing a weighted share of misclassified observations in the data, with zero being the optimal value (no misclassification). We compute the measure for the original data and the imputed data and find that it decreases from about 33% to 21% in the case of the education variable. For the nation variable, it decreases from about 3% to 2% for the immigration background concept. We also apply multiple imputation techniques using the *ice*-package in Stata (Royston (2005)) to obtain a benchmark for our imputations. We find that in both cases the quality measure for multiple imputation takes a value that is approximately the average of the original variable and our logically edited values. We regard this as strong evidence that our logic-driven imputation performs better than standard multiple imputation techniques for these variables.

Since misclassification can be more or less pronounced in certain population segments, it is of interest to analyze the partial relationship of worker and firm characteristics with the event of misclassification. This is done by estimating logit regressions with a dependent variable equal to one if an observation is misclassified and equal to zero otherwise. Tables 3.9 and 3.10 present the resulting marginal effects on the probability of misclassification evaluated at the sample means of the other regressors. Although it is apparent that the event of misclassification is related to different variables, it is surprisingly difficult to find a systematic pattern of misclassification determinants that is valid for all values of the misclassified variables. The event of misclassification for the immigration variable is very rare as shown in Table 3.8. Despite this fact, Table 3.9 shows that many variables have a significant effect but all the marginal effects are smaller than 5%. Table 3.10 lists the determinants for misclassification of the education variable. The predicted probability of misclassification of having no educational qualification (IP1) is 61%. Being young or a non German decreases this probability by 31% and 12% respectively, while being employed in the construction sector or in trade increases this probability by 9%. The predicted probability of misclassification of having completed vocational training (IP1) is 12%. Being employed in East Germany decreases this probability by 9%, while being young increases this probability by 17%. The predicted probability of misclassification of having completed university degree (IP1) is 29%. Being employed in East Germany decreases this probability by 17%, while being young or being employed in mining increases this probability by 54% and 44%, respectively. These figures provide evidence that the probability of misclassification in the education variable strongly varies across population segments. We also include the actual length of the BeH spell as a regressor to analyze whether information in shorter spells is more likely to be erroneous than for longer spells, since firms may already anticipate the short duration and devote less care in completing the records. This hypothesis is partly supported by the data. While such a pattern is not present for the nationality, there is some evidence for it in the case of the education variable but only for the "No Degree" category where longer spells have a lower misclassification probability than shorter spells. When comparing the average length of BeH spells in our two validation samples, we observe that it is very similar and about 168 days, while it is on average 237 days for all BeH spells in the same period. This suggests that the average misclassification probability in case of no educational qualification may be considerably lower for an average BeH spell than reported in our tables. Since this deviation is driven by individuals with long employment and no unemployment periods, we have no validation data at hand to investigate this further.

Without reporting the results, we also find a positive correlation between misclassification of the education and the nationality variable. This suggests that the reliability of information is likely to vary across reporting firms or individuals. A more detailed analysis would require, however, the availability of a firm identifier.

Table 3.9: Marginal effects (at the mean) for the determinants of misclassification: validation immigration variable vs. original immigration variable (BeH). (IEBS-SUF V.1)

	Dependent variable		
	Missing	German	Immigration
variable	ME (SE)	ME (SE)	ME (SE)
female	-.0029 (.0005)	.0126 (.0006)	-.0187 (.0033)
aged <25	-.0082 (.0005)	-.0148 (.0007)	.0077 (.0049)
aged >55	.0183 (.0009)	-.0157 (.0008)	.0001 (.0059)
education, ref: no completed degree			
vocational training (orig.)	-.036 (.0012)	-.0258 (.0009)	.0089 (.0033)
university degree (orig.)	-.0150 (.0003)	-.0162 (.0010)	.0349 (.0033)
education unknown (orig.)	-.0033 (.0006)	-.0018 (.0011)	.0506 (.0050)
part time	.0071 (.0005)	.0017 (.0008)	-.0075 (.0037)
high income	.0265 (.0023)	-.0122 (.0011)	-.0072 (.0091)
low income	-.0117 (.0009)	-.0013 (.0009)	.0007 (.0041)
business sector, ref: others			
agriculture	-.0129 (.0007)	-.0106 (.0019)	.0152 (.0092)
mining	-.0013 (.0042)	-.0069 (.0054)	.0619 (.0411)
manufacturing	.0130 (.0010)	.0015 (.0009)	.0007 (.0048)
construction	-.0075 (.0006)	-.0108 (.0010)	.0039 (.0053)
trade	.0080 (.0008)	-.0053 (.0009)	.0097 (.0047)
gastronomy	.0031 (.0009)	.0247 (.0009)	-.0034 (.0055)
minor jobs	.0031 (.0021)	-.0039 (.0024)	.0035 (.0116)
length of BeH spell, ref: 2-9 months			
up to one month	-.0047 (.0006)	-.0016 (.0009)	-.0013 (.0051)
more than 9 months	.0104 (.0006)	-.0001 (.0007)	.0054 (.0035)
predicted probability	.0166	.0337	.0276
Log. likelihood	-28,786.84	-48,305.75	-8,306.75
Number of observations	277,863	312,079	61,319

Table 3.10: Marginal effects (at the mean) for the determinants of misclassification: validation education vs. corrected education (IP1). (IEBS-SUF V.1)

	Dependent variable			
	Education missing	No Degree	VT	Higher Educ.
variable	ME (SE)	ME (SE)	ME (SE)	ME (SE)
female	.0144 (.0009)	.0257 (.0026)	-.0136 (.0011)	.0067 (.0057)
aged <25	.0468 (.0014)	-.3058 (.0032)	.1726 (.0021)	.5367 (.0243)
aged >55	-.0022 (.0016)	-.0166 (.0041)	.0348 (.0018)	-.0530 (.0084)
non German (orig.)	.0062 (.0014)	-.1159 (.0030)	.0569 (.0019)	.1288 (.0103)
part time	-.0431 (.0017)	.0048 (.0028)	-.0039 (.0011)	-.0118 (.0063)
high income	.0014 (.0035)	.0831 (.0086)	.0875 (.0033)	-.0802 (.0073)
low income	-.0573 (.0012)	-.0607 (.0035)	.0373 (.0013)	.1237 (.0069)
business sector, ref: others				
agriculture	.0373 (.0031)	.0517 (.0069)	-.0423 (.0023)	-.0012 (.0237)
mining	-.0939 (.0249)	.0029 (.0258)	.0110 (.0104)	.4417 (.0684)
manufacturing	.0387 (.0013)	-.0391 (.0039)	-.0292 (.0013)	.0507 (.0100)
construction	.0351 (.0016)	.0895 (.0044)	-.0578 (.0013)	.0673 (.0159)
trade	.0273 (.0012)	.0847 (.0036)	-.0354 (.0012)	.1281 (.0105)
gastronomy	.0071 (.0019)	.0510 (.0039)	-.0172 (.0017)	.1321 (.0209)
minor jobs	-.0276 (.0052)	.0793 (.0094)	.0032 (.0039)	.0791 (.0239)
eastern Germany	.0319 (.0016)	.2569 (.0029)	-.0953 (.0019)	-.1730 (.0097)
length of BeH spell, ref: 2-9 months				
up to one month	.0349 (.0015)	.0001 (.0035)	-.0099 (.0014)	.0911 (.0089)
more than 9 months	-.0179 (.0011)	-.0359 (.0029)	.0084 (.0012)	.0110 (.0062)
predicted probability	.9193	.6079	.1205	.2879
Log. likelihood	-3,078.06	-112,256.13	-161,248.65	-17,065.56
Number of observations	10,102	178,857	432,548	29,754

3.4 Application

In this section, we empirically analyze how the educational qualification or the nationality affect the probability of losing a job given everything else equal. We estimate a logit model for unemployment risk with a 2% random sample of workers in the period 1999-2002. In addition to the estimated logit coefficients, we report the relative marginal effect (RME), which is the marginal effect at the mean divided by the predicted transition probability of the reference individual. We report the RME rather than the marginal effect as the level of the latter depends on the longitudinal unit of the data, while the RME is invariant (for more details see Dlugosz et al. (2009)). The data is extracted from the IABS and organized as a monthly panel. The sample consists of about 20m observations with more than 50 covariates, which include individual characteristics of the worker and the employing firm, and dummies for calender time. See Table A.3.1 in the Appendix for the descriptive statistics. We first perform a sensitivity type analysis by estimating the same model with original and corrected variables to identify the effect of the data corrections on the estimated model coefficients:

- A: original data
- B: corrected education, immigration background.

Table 3.11: Results of the logit regression - original data vs. imputation

	Model A				Model B		
variable	coeff.	(SE)	RME		coeff.	(SE)	RME
Original Education, ref: VT				*Imputed Education*, ref: VT			
no degree	.1725	(.0086)	.1876***	no degree	.0831	(.0097)	.0863***
higher educ.	-.2285	(.0186)	-.2037***	higher educ.	-.1124	(.0152)	-.1060***
missing	.1752	(.0091)	.1908***	missing	-.3960	(.0318)	-.3263***
Original nation, ref: German				*Immigration background*, ref: none			
non German	-.0306	(.0109)	-.0300***	Immigration	.0494	(.0099)	.0505***
missing	.1738	(.0130)	.1891***	missing	.1775	(.0131)	.1935***

Note: fully robust standard errors (heteroscedasticity, serial correlation).
***, **, *: marginal effect significant at the 1, 5 and 10% level, respectively

Table 3.11 presents the estimated coefficients together with the RMEs for the original education and nationality variables and the imputed education and the migration background indicator. By comparing the estimates for the original variables and the edited variables, we observe large changes. We find evidence that the magnitude of the education effect drops by about a half if we use the imputed education information rather than the original education. According to the results based on the original education data, having no degree increases the probability of losing a job and becoming unemployed compared to the same individual with vocational training by 19%. This number halves to 9% if we use the imputed education variable instead. Higher education decreases the probability of entering unemployment, but the RME of higher education is only -11% for the imputed education variable compared to -20% for the original variable. This is again a drop by one half. For the original nation variable, the results suggests that non-German individuals have a 3% lower probability of losing their job compared to Germans. The effect changes its sign to 5% if we use the immigration background concept. Missing information on nationality shows the strongest relative effect and increases the unemployment risk by about 19% in both models. As this information is missing for all individuals with at least one employment record in east Germany, it suggests that unemployment risk in East-Germany is considerably higher than in West-Germany.

As Section 3.3 suggests, the presence of considerable non-classical measurement error even in case of corrected education variable, it is likely that estimated coefficients are still biased. For this reason, we also estimate a misclassification logit regression by applying the MC-SIMEX method (Küchenhoff et al. (2006)). Appendix B.3 presents an outline of this method and estimation results for the imputed education variable IP1 based on a smaller sample together with additional simulation results. The results are indicative for the estimated coefficients being still affected by the remaining misclassification.

The RMEs of the remaining variables based on the logit estimator are given in Table 3.12. These results do not differ substantially between the two models, therefore, we only present the RME's for Model B. We do not find important gender differences in unemployment risk. Age shows a strong effect, older individuals aged 55 or more have a 85% higher probability of loosing their jobs than individuals aged between 25 and 50. This could be due to age discrimination or due to the fact that older workers often use unemployment benefits as a convenient exit route out of regular employment to old age pensions. Among the individual background variables, past unemployment has the strongest effect. If an individual has been unemployed before, his risk of reentering unemployment increases by 136%, more than doubling. According to the descriptive statistics in Table A.3.1 in the Appendix, our sample consists of 37.97% observations of individuals who have been unemployed before. This illustrates the prominent role of past unemployment as the main predictor of entering unemployment. As the sample correlation between past unemployment and seasonal jobs is rather low, although positive, we do not find evidence that the huge effect is mainly driven by seasonal employment patterns. Jobs with low income (defined by having a wage in the bottom quantile of the population distribution of daily wages in west or east Germany, respectively) are also rather unsafe as such individuals face a 83% higher risk of unemployment. Interestingly, the sample correlation between past unemployment and low wage is also rather low, although positive. Part time workers, who are mainly female, have a much lower probability of making a transition into unemployment. In our sample, many observations with a part time job are associated with a low wage. This suggest that the high unemployment risk of low wage jobs only applies to male full time workers with a low daily wage. This is likely related to a high wage replacement rate in case of unemployment for this group.

Table 3.12: Results of the logit regression - relative marginal effects for Model B

variable	RME		variable	RME	
female	-.0286	***	*month*, ref: June		
aged <25	.0571	***	January	.2928	***
aged 51-55	.2504	***	February	-.1619	***
aged >55	.8139	***	March	-.0362	***
low income	.8703	***	April	-.3333	***
past unemployment	1.3954	***	May	-.3674	***
previously recalled	.6759	***	July	-.0681	***
seasonal job	.3388	***	August	-.2189	***
white collar	-.2684	***	September	-.0967	***
in vocational training	-.4843	***	October	-.1091	***
parttime	-.4740	***	November	-.0746	***
tenure, ref: < 7 months			December	.9477	***
7 - 12 months	.0293	***	*business sector*, ref: agriculture		
13 - 24 months	-.4329	***	goods production	-.0628	***
2 - 3 years	-.5673	***	manufacturing	-.2860	***
4 - 7 years	-.7880	***	steel & car industries	-.2706	***
8 - 14 years	-.8659	***	consumer goods	.0590	**
> 14 years	-.8674	***	drink and tobacco	-.0335	
additional experience[1], ref: < 7 months			construction	.6126	***
7 - 12 months	.0754	***	finishing	.2801	***
13 - 24 months	.0724	***	wholesale	-.0056	
2 - 3 years	-.0452	***	retail	.0032	
4 - 7 years	-.1570	***	traffic	-.1794	***
8 - 14 years	-.2363	***	private services	-.0871	***
> 14 years	-.3610	***	home services	.1415	***
year, ref: 2001			health services	-.1528	***
1999	-.0405	***	public firms/organisations	-.0577	**
2000	-.0921	***	public administration	-.2649	***
2002	.2307	***			
predicted probability	0.0031				
Log. likelihood	-706,558.37				
number of observations	20,659,889				

[1] *additional experience= total experience - tenure*
***, **, *: corresponding marginal effects significant at the 1, 5 and 10% level, respectively

To disentangle the effects of labor market experience and tenure, we construct an experience variable that is defined as the total labor market experience net of tenure in the present job, which gives us additional experience. Comparing the results for tenure and experience shows that both have a positive effect on job security, both increasing with the number of years. However, the effect of tenure is much larger. Individuals with more than four years of tenure have an unemployment risk that is 79-88% lower than individuals with no tenure, which corresponds to a predicted probability of almost zero. An equivalent amount of additional experience only lowers the risk by 15-37%. In our sample, almost 50% of the observations are generated by individuals with four or more years of tenure. This large share of individuals with extremely low unemployment risk explains why the overall mean predicted monthly probability is just 0.31%. This is in line with the results of Elsby et al. (2009) who show that Germany is among the OECD countries with the lowest unemployment inflow rate. As our evidence has a descriptive nature, we cannot distinguish between two possible explanations: first, the strong effect of long tenure may be due to long tenured jobs having a very high level of employment protection in Germany; second, long tenure is a proxy for the high ability of a worker or for firm specific human capital.

We find strong seasonal unemployment patterns, with far fewer separations in April and May and far more in December and January. The spike in the winter separations is, to some extent, due to firms' planned capacity reductions during the winter period, seasonal employment and many work contracts end et at the end of the calendar year. When comparing business sectors, we find evidence that between 1999-2002, the safest jobs were in manufacturing and in public administration, while the construction and finishing works are characterised by a considerably higher separation rate.

When we compare all these effects, it becomes evident that the effect of education on unemployment risk is rather small compared to other individual factors, especially if we use the imputed data. The main indicator for a safe job is long tenure rather than high education. This is in contrast to previous evidence based on survey data (Gangl (2003)) and for other labor markets with higher dynamics such as Denmark, where the educational qualification appears to be far much more important (Frederiksen (2008)). We do not find evidence for discrimination of females and only weak discrimination evidence for individuals with immigration background.

3.5 Summary and Remarks

We analyze the determinants for job separation with transition to unemployment using German register data, taking into account that non-target variables in the data contain a considerable amount of measurement error. We adapt existing editing and imputation methodologies for the education variable and develop an additional editing rule for the nationality variable. We use validation information from an accompanying administrative register to compute misclassification probabilities for the education and the nationality variables to show that the editing and imputation indeed reduce the amount of measurement error. We also show that these editing rules result in higher-quality data for these variables as standard multiple imputation techniques. We provide evidence that the degree of misclassification varies across data segments and we estimate the determinants for it.

We perform a sensitivity type analysis to determine whether estimated logit coefficients change after the imputation, confirming that the correction rules have a strong effect on empirical results. In particular, we observe that the effect of education halves in magnitude when using the imputed data instead of the original data. The effect of not being German changes its sign. Our results therefore illustrate that standard results for classical measurement error do not hold for nonlinear models with non-classical measurement error, because there would be no change in the sign of the estimated coefficients and their magnitude would increase after editing and imputing the data. When applying a misclassification regression to the imputed data, we obtain further indications for changing results. Our findings demonstrate that measurement error in register data can lead to misleading conclusions about the effect of education or foreign nationality on individual labor market outcomes even if the data are large and partly precise.

Our application shows that even though individual labor market outcomes are strongly associated with individual skills, it is mainly the length of tenure that eliminates the unemployment risk. The choice of educational qualification seems to be far less important than is commonly thought and suggested by previous evidence for Germany based on household survey data, although higher education is related to safer jobs.

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Appendix A.3: Additional information on the data

A.3.1 Descriptive statistics

Table A.3.1: Descriptive statistics

variable	mean	variable	mean
female	.4279	*month*, ref: June	
aged <25	.1450	January	.0822
aged 51-55	.0912	February	.0821
aged >55	.0906	March	.0826
low income	.3543	April	.0829
past unemployment	.3795	May	.0831
previously recalled	.1036	July	.0833
seasonal job	.1507	August	.0840
white collar	.4050	September	.0846
in vocational training	.0616	October	.0844
parttime	.1605	November	.0842
tenure, ref: < 7 months		December	.0833
7 - 12 months	.0914	*business sector*, ref: agriculture	
13 - 24 months	.1311	goods production	.0574
2 - 3 years	.1576	manufacturing	.0910
4 - 7 years	.1656	steel & car industries	.0787
8 - 14 years	.1670	consumer goods	.0528
> 14 years	.1410	drink and tobacco	.0271
additional experience[1], ref: < 7 months		construction	.0351
7 - 12 months	.0299	finishing	.0285
13 - 24 months	.0547	wholesale	.0592
2 - 3 years	.1224	retail	.0822
4 - 7 years	.1905	traffic	.0516
8 - 14 years	.2081	private services	.1450
> 14 years	.1082	home services	.0485
year, ref: 2001		health services	.1084
1999	.2444	public firms/organisations	.0562
2000	.2506	public administration	.0572
2002	.2512		
Original education, ref: Vocational training		*IP1*, ref: Vocational training	
no degree	.1791	no degree	.1397
high education	.0823	high education	.1106
missing	.1065	missing	.0132
Original nation, ref: German		*Immigration background*, ref: German	
non German	.0815	immigration	.1090
missing	.0347	missing	.0343
Number of observations	20,659,889		

[1] *additional experience= total experience - tenure*

A.3.2 Construction of a validation variable for the educational level

The BewA contains two different variables describing the educational level of a person: the schooling level (*schbild*) as well as the professional level (*bild*). In order to compare the imputed values based on the LeH- and the BeH-spells with the information given in the BewA, we first have to recode the two variables of the latter to a corresponding single variable. For this purpose, we chose two rules: first, the "strict version" requires valid information in both sources, and second, the "weak version" relies more on the information in the bild-variable, and accepts missings in the schbild-variable. We think that the latter version is also justifiable, because the employer is not so much interested in the schooling level, but more in the highest completed degree, which is either a vocational training or an university or technical college degree. Since there is no big difference between the two variables (only in about 0.05% of the spells), we only use the "weak version" for the following analysis. Table A.3.2 illustrates the construction of the new validation variable for education.

Table A.3.2: Recoding scheme of the education variable ("weak version") in the BewA for the education validation variable (EDU_val).

	BewA		EDU_val
schbild		*bild*	
No school degree or at most 10 years of schooling or missing	AND	No vocational training degree	ND
No school degree or at most 10 years of schooling or missing	AND	Vocational training degree but no technical college nor university degree	VT
12 or 13 years of schooling	AND	No vocational training degree	HS
12 or 13 years of schooling	AND	Vocational training degree but no technical college nor university degree	HSVT
12 or 13 years of schooling or missing	AND	Technical college degree	TD
12 or 13 years of schooling or missing	AND	University degree	UD
Every value	AND	Missing	Missing

Appendix B.3: The MC-SIMEX

The MC-SIMEX (Küchenhoff et al. (2006)) can be applied to (non)-linear regression models in presence of measurement error in discrete variables. It is a modification of the SIMEX algorithm for additive measurement error (Cook and Stefanski (1994) and Carroll, Küchenhoff, Lobard, and Stefanski (1996)). The idea behind this algorithm is to use the relationship of the size of the measurement error to the bias in the estimators when ignoring the measurement error. This is done in two steps: the first step consists of a simulation of an additional adding of measurement errors. If we consider the observed variable as containing one "degree" of misclassification, new variable sets are simulated with an increasing degree of misclassification based on the observed variable: the misclassification is applied to the observed variable to get a variable with more misclassification. Using this new variable with a higher degree of misclassification, we re-estimate the model. Afterwards, the misclassification is again applied to this new variable to get further degrees of misclassification, we estimate the model with the new variable, and so on. These simulation and estimation steps are repeated several times in order to allow for the uncertainty in the misclassification. We then keep the mean of all the estimated coefficients at each simulation step.

In the second step, the estimator in the case of no measurement error, is extrapolated from the simulation results. Sticking to the notation that the observed misclassified variable contains one degree of misclassification, the case of no misclassification can be seen as degree zero of misclassification. Accordingly, we fit a curve to the mean of coefficient estimates of each simulation step (i.e. each degree of misclassification) using OLS. We are then interested in the estimated value of the coefficient in absence of misclassification that we get by extrapolating the fitted curve to the value of zero. The MC-SIMEX algorithm can be applied to measurement errors in discrete variables, either in the regressors, or in the response. In the following, we briefly present the estimation procedure for the case of a general regression problem with response Y and a discrete regressor X, as well as additional explanatory variables Z. Let Y, X and Z denote the true values of the variables. However, we do not observe (Y, X, Z) but (Y, X^*, Z), where X^* is the misclassified but observable counterpart to X. The corresponding misclassification matrix $\pi_{ij} = P(X^* = i|X = j)$ is either known or has to be estimated. Π is a $k \times k$-matrix, with k as the number of possible outcomes for X. The parameter of interest is β. The naive (biased) estimator $\beta_{naive} = \beta^*$ is obtained if we ignore the measurement error and use X^* instead of X. We assume that

$$\beta^*(\Pi) := \text{plim}\hat{\beta}_{naive}, \quad \beta^*(I_{k\times k}) = \beta$$

and define

$$\lambda \longrightarrow \beta^*(\Pi^\lambda).$$

Now the following relationships hold:

$$\Pi^0 = I_{k\times k}, \quad \Pi^{\lambda+1} = \Pi^\lambda * \Pi \quad \text{(for integer values of } \lambda), \quad \text{and} \quad \Pi^\lambda := E\Lambda^\lambda E^{-1}$$

$$\text{with} \quad E := \text{Matrix of eigenvectors of } \Pi$$

$$\text{and} \quad \Lambda := \text{Diagonal matrix of corresponding eigenvalues.}$$

Let X^* be the misclassified value of X with misclassification matrix Π, and X^{**} is related to X^* by the misclassification matrix Π^λ, then X^{**} is related to X by $\Pi^{\lambda+1}$. Küchenhoff et al. (2006) show that the fact that $\ln(\Pi) := E\ln(\Lambda)E^{-1}$ has only positive off-diagonal elements is sufficient for the misclassification matrix to be valid for this method, where $\ln(\Lambda)$ is the diagonal matrix of logarithms of the eigenvalues. Please refer to Küchenhoff et al. (2006) for a detailed discussion of the properties of and the requirements for Π.

The first step of the estimation procedure is a simulation step. We generate B new pseudo data sets for a fixed grid $\lambda_1, \ldots, \lambda_m$:

$$X^*_{b,i}(\lambda_k) := MC[\Pi^{\lambda}_k](X^*_i), \quad \text{i=1,...,n; b=1, ..., B}$$

where $MC[M](X^*_i)$ is simulated from X^* using the misclassification matrix M. Thus, each λ-step corresponds to simulating a different degree of misclassification in X. Then, we estimate $\hat{\beta}_{naive}$ for each of the B data sets. At every λ step we calculate the mean of the B estimators to get one value of $\hat{\beta}(\lambda_k)$ for every λ:

$$\hat{\beta}(\lambda_k) := B^{-1}\sum_{b=1}^{B}\hat{\beta}_{na}[(Y_i, X^*_{b,i}(\lambda_k))^n_{i=1}], \quad \text{k=1, ...,m.}$$

Küchenhoff et al. (2006) show that $\lambda = (1, 1.5, 2, 2.5, 3)$ is a good choice for the λ grid.

In the second step, we assume a parametric model for the relationship between $\beta(\Pi)$ and λ: $\beta(\Pi^{\lambda}) = F(1+\lambda, \Gamma)$. The parameter we are interested in is then $\hat{\beta}_{SIMEX} := F(0, \hat{\Gamma})$. We get this value by extrapolating the OLS-estimates of $[1+\lambda_k, \hat{\beta}(\lambda_k)]^m_{k=0}$. The goodness of the estimate of $\hat{\beta}_{SIMEX}$ depends crucially on the form of $F(\cdot)$, the estimator is consistent if the extrapolation function is correctly specified. In general, the MC-SIMEX is approximately consistent, if $F(\lambda, \Gamma)$ is a good approximation of $\beta^*(\Pi^{\lambda})$. Küchenhoff et al. (2006) present simulation results for a linear, quadratic and log-linear form. Their results suggest that the fit of the quadratic, the linear and the log-linear form are at least as good as other functional forms of the extrapolants. While standard errors of the estimator can be generally obtained by the bootstrap, Küchenhoff et al. (2006b) propose an asymptotic variance estimator.In our application, we have tried the implementation in R offered by Küchenhoff et al. (2007) and our own Matlab implementation but the computing time of this method (in Matlab as well as in R) turned out to be too long on our 64 Bit Quad-Core Xeon. Since it takes about one day to obtain the point estimate, the bootstrap is also not a feasible alternative in this case. Therefore, we were not able to apply the MC-SIMEX method to our whole sample but used a 30% random sample instead. Even for this smaller sample with about 6m observations, standard errors are not available. Thus, our results are only indicative for further considerable changes in the estimated coefficients. In the following, we will present exemplary results for the imputed education variable in Model B as an illustration of the method. Table B.3.1 contains the misclassification matrix for IP1 in our application and Figure B.3.1 contains a graphical illustration of the estimation procedure where we plot $\hat{\beta}(\lambda_k)$ against λ. In the case of the imputed education, the ordinary logit estimate for "no degree" is about 0.1 and -0.15 for "higher education". The coefficients obtained by using the quadratic extrapolant are then 0.26 and -0.35, respectively.

Table B.3.1: Misclassification matrix for IP1 in Model B, 462,560 spells.

Education	Validation data		
IP1	No degree	VT	HE
No degree	42.81	7.67	2.62
VT	56.42	88.17	24.89
HE	0.77	4.16	72.49
Total	100.00	100.00	100.00

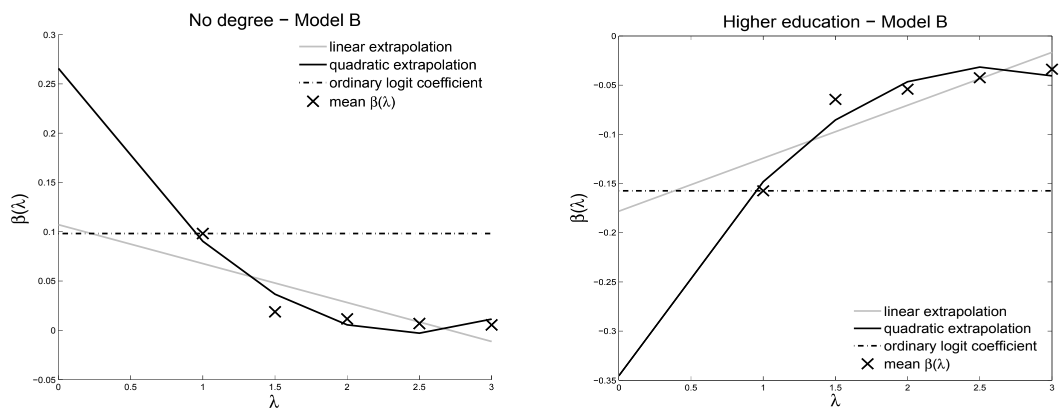

Figure B.3.1: Fitted extrapolants and ordinary logit estimator.

In order to assess the properties of the MC-SIMEX method for our application, we carried out some Monte Carlo simulations. For the first model (Model I), we use the misclassification matrix for IP1 in Model B given in Table B.3.1 with "Vocational training" (VT) as the reference group, i.e.:

$$\Pi_I = \begin{pmatrix} 0.8817 & 0.5642 & 0.2489 \\ 0.0767 & 0.4281 & 0.0262 \\ 0.0416 & 0.0077 & 0.7249 \end{pmatrix}.$$

We create three dummy variables, X_0^*, X_1^* and X_2^* and X_0, X_1 and X_2 for the three possible outcomes of the observed and the true values of the misclassified variable, respectively. In the setup of the simulation, we follow mainly the simulation by Küchenhoff et al. (2006) for the case of a binary misclassified regressor. We use two sample sizes ($n = 5,000$ and $n = 20,000$) in order to capture the influence of the number of observations on the properties of the estimator. We then set $P(X_0 = 1) = P(X_1 = 1) = P(X_2 = 1) = 1/3$. Since Küchenhoff et al. (2006) show that the performance of the estimator depends on the presence of additional (correctly specified) regressors, we use two additional covariates, Z_1 and Z_2 that are defined as follows:

$$Z_1 \sim \begin{cases} N(0.5;1) & \text{if } X_0^* = 1, \\ N(-0.5;1) & \text{if } X_1^* = 1 \\ N(1.5;1) & \text{if } X_2^* = 1 \end{cases}$$

and

$$Z_2 = \begin{cases} 1 & \text{if } Z_1 \geq 0.5, \\ 2 & \text{otherwise.} \end{cases}$$

The dependent variable, Y, is then generated as a Bernoulli distributed random variable with $P(Y=1) = \frac{1}{1+exp(-\beta_1 X_1 - \beta_2 X_2 - \beta_{Z_1} Z_1 - \beta_{Z_2} Z_2)}$, with the true values $\beta_1 = \beta_2 = 0.5$ and $\beta_{Z_1} = \beta_{Z_2} = 1$. The naive estimates are obtained by estimating $\hat{\beta}_1$ to $\hat{\beta}_{Z_2}$ by a Logit model based on the observed variables. Model I contains a comparably high amount of misclassification. In order to see how the results change with only a little misclassification, we also perform a simulation for the misclassification of the immigration variable given in Table 3.8, i.e.

$$\Pi_{II} = \begin{pmatrix} 0.9759 & 0 & 0.0001 \\ 0.0199 & 0.9628 & 0.0316 \\ 0.0042 & 0.0372 & 0.9683 \end{pmatrix}.$$

Finally, we are interested whether the performance of the estimators depends on the size of the true coefficients. We therefore estimate a third model with a moderate amount of misclassification given by

$$\Pi_{III} = \begin{pmatrix} 0.8 & 0.1 & 0.1 \\ 0.1 & 0.8 & 0.1 \\ 0.1 & 0.1 & 0.8 \end{pmatrix}$$

and change the true values of the parameters of X_1 and X_2 to $\beta_1 = 2$ and $\beta_2 = 0.2$. The specification of the additional confounder, Z are the same in all models. The results for the three models are given in Table B.3.2 where we only display the results for the quadratic extrapolation function for the MC-SIMEX because they performed best. We display simulation mean and standard errors of the estimates for $\hat{\beta}_1$ and $\hat{\beta}_2$ together with the corresponding Means Squared Error (MSE). Moreover, we report the standard error based on the asymptotic variance estimation introduced by Küchenhoff et al. (2007) .

Obviously, there is a trade off between bias and variance when comparing the two estimators: While the bias of the naive estimator is comparatively large in our simulations, the simulation standard errors are clearly smaller than for the MC-SIMEX. The bias reduction of the MC-SIMEX comes at the cost of a large variance due to the simulation and extrapolation procedure. In order to analyze the role of the amount of misclassification, we can compare the estimates for $\hat{\beta}_1$ and $\hat{\beta}_2$, where the latter is less misclassified in Model I.[1] The bias and the variance of the MC-SIMEX estimates are larger for $\hat{\beta}_1$ than for $\hat{\beta}_2$, i.e. larger for higher misclassification. For the naive estimator, we also find a smaller bias for β_2 but a larger variance in this case. The advantage of the MC-SIMEX compared to the naive estimator becomes especially clear for the larger sample size: while the MSE is almost the same for the naive estimation and the MC-SIMEX with 5,000 observations, the MSE of the latter is only about 22% of the MSE of the naive estimator for $\hat{\beta}_1$ and about 35% for $\hat{\beta}_2$ for 20,000 observations. Model II is the model with the smallest amount of misclassification. In this case, the bias of the naive estimates is about the same size as the one of the MC-SIMEX, therefore, the naive estimator outperforms the MC-SIMEX in terms of the MSE due to the higher variance of the latter. Finally, the simulation results of Model III show that the MC-SIMEX is especially suited for larger coefficients, since the

[1] The main diagonal element of Π for X_1 is 0.4281 which means that the probability of correct classification of X_1 is about 42.8%, for X_2 we have a 77.5% probability of no misclassification.

advantage of the bias reduction matters considerably in these cases. For $\hat{\beta}_1$, the MSE of the MC-SIMEX is only 18% of the MSE of the naive estimator even though the variance is about twice as large. For the small coefficient $\hat{\beta}_2$, the naive estimator is much better in terms of the MSE (both based on $n = 20,000$).

Even though this Monte Carlo study cannot claim to be an extensive analysis of the properties of the MC-SIMEX estimator, it shows that this method can be an attractive solution for misclassified discrete variables. It outperforms the naive estimator in terms of the MSE as long as the sample size is large enough. In small samples, the large variance beats the gain in bias reduction and the MC-SIMEX is therefore not reasonable. Moreover, the MC-SIMEX should not be used in presence of only small misclassification probabilities (as for example the nation variable in our application) because in this case there is not much room for bias reduction compared to the naive estimator and the large variance then weakens the MC-SIMEX. The performance of the MC-SIMEX also depends on the size of the coefficient of interest: if it is very small, the advantage of bias reduction of the MC-SIMEX does not translate into a lower MSE since the variance is the main factor driving the MSE in this case. Overall, we can conclude that the MC-SIMEX is suited as an alternative estimation approach for the misclassification in the education variable given our simulation results and the large sample size in our application. However, more research is needed to investigate the properties of the MC-SIMEX further and to develop guidelines for its application.

Table B.3.2: Monte Carlo simulation for the MC-SIMEX estimator compared with the naive estimator; 1,000 repetitions
^{a}: Monte Carlo simulation standard error; ^{b}: $SE = \frac{1}{1000}\sum_i^{1000} SE_{KLL}$, where SE_{KLL} is the square root of the asymptotic variance estimator proposed by Küchenhoff et al. (2007).

Model I:			Π_I and $\beta_1 = \beta_2 = 0.5$				
	Naive estimator			MC-SIMEX			
	Mean	SE	MSE	Mean	SE^a	MSE	SE^b
$n = 5,000$							
$\hat{\beta}_1$	.1695	.1160	.1227	.4238	.2913	.0906	.2433
$\hat{\beta}_2$	.2693	.1418	.0733	.5465	.2775	.0792	.2347
$n = 20,000$							
$\hat{\beta}_1$	.1707	.0562	.1116	.4336	.1418	.0245	.1215
$\hat{\beta}_2$	.2624	.0720	.0616	.5388	.1414	.0215	.1173
Model II:			Π_{II} and $\beta_1 = \beta_2 = 0.5$				
	Naive estimator			MC-SIMEX			
	Mean	SE	MSE	Mean	SE^a	MSE	SE^b
$n = 5,000$							
$\hat{\beta}_1$	.4890	.1114	.0125	.5178	.1304	.0173	.2354
$\hat{\beta}_2$	.4974	.1379	.0190	.5071	.1767	.0313	.2330
$n = 20,000$							
$\hat{\beta}_1$	.4887	.0559	.0032	.5172	.0660	.0046	.1175
$\hat{\beta}_2$	.4979	.0683	.0047	.5081	.0880	.0078	.1163
Model III:			Π_{III} and $\beta_1 = 2$ and $\beta_2 = 0.2$				
	Naive estimator			MC-SIMEX			
	Mean	SE	MSE	Mean	SE^a	MSE	SE^b
$n = 5,000$							
$\hat{\beta}_1$	1.1926	.1451	.6729	2.3294	.2975	.1970	.2466
$\hat{\beta}_2$	.3204	.1215	.0293	.4987	.2325	.1433	.2382
$n = 20,000$							
$\hat{\beta}_1$	1.1817	.0712	.6747	2.3072	.1448	.1153	.1231
$\hat{\beta}_2$	.0620	.0620	.0174	.4918	.1183	.0991	.1189

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Erklärung

Ich versichere hiermit, dass ich die vorliegende Arbeit mit dem Thema

Three Essays on Empirical Labor Economics

ohne unzulässige Hilfe Dritter und ohne Benutzung anderer als der angegebenen Hilfsmittel angefertigt habe. Die aus anderen Quellen direkt oder indirekt übernommenen Daten und Konzepte sind unter Angabe der Quelle gekennzeichnet. Weitere Personen, insbesondere Promotionsberater, waren an der inhaltlich materiellen Erstellung dieser Arbeit nicht beteiligt.[2] Die Arbeit wurde bisher weder im In- noch im Ausland in gleicher oder ähnlicher Form einer anderen Prüfungsbehörde vorgelegt.

Konstanz, den 25. Mai 2010

(Laura Wichert)

[2]Siehe hierzu die Abgrenzung zu Kapiteln 1 und 3 auf der folgenden Seite.

Abgrenzung

Kapitel 1 entstammt einer gemeinsamen Arbeit mit Herrn Prof. Dr. Winfried Pohlmeier (Universität Konstanz). Meine individuelle Leistung bei der Erstellung dieser Arbeit beträgt 70%.

Ich versichere hiermit, dass ich Kapitel 2 der vorliegenden Arbeit ohne Hilfe Dritter und ohne Benutzung anderer als der angegebenen Hilfsmittel angefertigt habe.

Kapitel 3 entstammt einer gemeinsamen Arbeit mit Herrn Dr. Ralf Wilke (University of Nottingham). Meine individuelle Leistung bei der Erstellung dieser Arbeit beträgt 50%.