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Berlin, March 2010

SOEPpapers on Multidisciplinary Panel Data Research
at DIW Berlin

ISSN: 1864-6689 (online)

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Perceived Job Insecurity and Well-Being Revisited: Towards Conceptual Clarity

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March 2010

Abstract

This paper analyzes the impact of job insecurity perceptions on individual well-being. In contrast to previous studies, we explicitly take into account perceptions about both the likelihood and the potential costs of job loss and demonstrate that most contributions to the literature suffer from simultaneity bias. When accounting for simultaneity, we find the true unbiased effect of perceived job insecurity to be more than twice the size of naive estimates. Accordingly, perceived job insecurity ranks as one of the most important factors in employees' well-being and can be even more harmful than actual job loss with subsequent unemployment.

Keywords: job security, life satisfaction, unemployment

JEL classifications: D84, J63, Z13

1 Introduction

Perceived job insecurity has been a recurring theme in sociology, organizational psychology and other fields of the social sciences. While economists are accustomed to focusing on objective labor market outcomes, such as wages or objective unemployment risk, the analysis of entirely subjective concepts such as perceived job insecurity can provide valuable insights. After all, one can argue that it is individuals' perceptions of reality rather than objective features of reality that determine individual behavior.

In economics, relatively few authors have taken this route of analysis, although having said that, the perceived threat of job loss and unemployment is a cornerstone in efficiency wage theory (see, e.g., Shapiro and Stiglitz 1984). One of the earliest empirical contributions in the field is Blanchflower (1991)[1] who finds a significant negative impact of perceived job insecurity on individual wages in the UK during the 1980s. In his seminal analysis, perceived job insecurity is operationalized by subjective individual assessments of the likelihood of job loss. However, it is important to bear in mind that in a wage- setting process, perceived job loss risks are probably only one aspect. Perceptions about the associated costs of losing a job, that depend, for instance, on forgone pay, chances of reemployment, social stigmas or other non-pecuniary effects arguably also alter a worker's bargaining position.

An early study that describes the phenomenon of perceived job insecurity in more detail is Dominitz and Manski (1997). Utilizing data from the *Survey of Economic Expectations*, the authors operationalize perceived job insecurity by subjective probabilities associated with job loss and find considerable heterogeneity with respect to gender, race, and educational attainment. A related study based on repeated cross-sections from the *General Social Survey* is Schmidt (1999), who also operationalizes perceived job insecurity by subjective job loss probabilities, however measured not continuously as in Dominitz and Manski (1997), but on a four-point scale and provides evidence for a significant upwards trend in perceived job insecurity between 1977 and 1996 from the *General Social Survey*.[2] Furthermore, Schmidt (1999) and in a later study, Manski and Straub (2000), employ an alternative subjective job insecurity measure relating to the perceived probability that individuals attach to their chances of finding a different job that is similar

[1]See also Blanchflower and Shadforth (2009) and Campbell, Carruth, Dickerson and Green (2007) for extended and updated analyses.

[2]Other early economic studies operationalizing perceived job insecurity in a similar way include Bender and Sloane (1999) on the impact of perceived job insecurity and union membership.

in terms of pay and fringe benefits. Thus, in some sense, this measure at least partly captures the expected individual costs associated with job loss.

Following authors such as Greenhalgh and Rosenblatt (1984), Manski and Straub (2000), Green, Felstead and Burchell (2000), and Nickell, Jones and Quintini (2002), perceived job insecurity can be decomposed into at least two components, one describing the perceived probability that the job will actually be lost and one describing the individual costs associated with job loss. However, despite such repeated efforts to define perceived job insecurity in a more systematic way, dozens of recent studies in economics as well as in other fields of the social sciences have continued to use the concept fairly arbitrarily.[3] A strand of the literature were this is most relevant and which we will consider in more detail in this paper looks at the impact of perceived job insecurity on individual well-being.

Most contributions on the subject can be found in the organizational and social psychology literature, which dates back at least to Cobb and Kasl (1977), who postulate that anticipation of unemployment is as harmful for individuals' well-being, operationalized by a variety of physiological and psychological indicators, as unemployment itself. Numerous studies have since related perceived job insecurity to individual psychological and physical health as well as psychological well-being (see, e.g., Ferrie et al. 2004, De Witte 1999 and Sverke and Hellgren 2002 for surveys of the literature). While unobserved individual heterogeneity is generally ignored in the psychological literature on the subject, which makes causal inference difficult, studies also vary starkly with respect to the operationalization of perceived job insecurity. Johnson, Messe and Crano (1984), for instance, utilize information on subjective fears of job loss, thereby implicitly taking into account the subjective probability of the job loss event and the associated expected costs. Other authors only use information on individual assessments of the probability of becoming unemployed (e.g., De Witte 1999) or of losing their job in the near future (e.g., Mohr 2000).

Building on this large body of empirical studies in the field of psychology, a small literature on the subject is emerging in economics, however, accounting for unobserved individual heterogeneity plaguing the aforementioned earlier contributions.

A recent study by Luechinger, Stutzer and Meier (2010) indirectly identifies the impact of perceived job insecurity on individual well-being by comparing the

[3]Recent examples of studies ignoring the subjective cost component of perceived job insecurity, only partly due to data constraints, include Elman and O'Rand (2002), Scheve and Slaughter (2004), Benito (2006), Fullerton and Wallace (2007), and Campbell et al. (2007).

effects of state-level unemployment for employees in the private sector with public sector employees who are more shielded from dismissals. While regional unemployment arguably generates negative externalities affecting individuals' well-being, the different size of the effect for private and public employees suggests that part of the negative well-being effects can be explained by individuals' different perceptions of economic security. Another recent study is Clark, Knabe and Rätzel (2009) who revisit the social norm hypothesis as put forward by authors such as Clark (2003) and Stutzer and Lalive (2004) and find that aggregate unemployment has a less negative or even positive well-being effect for employed respondents with directly measured high perceived job insecurity and for unemployed respondents with poor subjective employment prospects. A related study by Knabe and Rätzel (2009) evaluates the role of perceived job insecurity in individual well-being in comparison to the effects of past unemployment experience. While earlier studies (e.g., Clark et al. 2001) highlight the importance of past unemployment experience for individuals' well-being even after becoming reemployed, the authors argue that this effect operates through individual perceptions; thus according to Knabe and Rätzel (2009), it is not past unemployment per se that makes people unhappy but related perceptions about their job security.

While the aforementioned studies have greatly advanced our understanding of the relevance of perceived job insecurity for individuals' well-being, it is regrettable that they often lack a clear conceptualization of job insecurity perceptions. In what follows, we will show that in the analysis of individual well-being the correct operationalization of perceived job insecurity is essential to avoid omitted variable and simultaneity bias. Section 2 introduces the concept of perceived job insecurity in a slightly more formal way and discusses its measurement and required data. Section 3 implements perceived job insecurity in a model of individual well-being and discusses potential simultaneity bias. Section 4 applies a new operationalization of perceived job security to individual data from a large household panel survey and assesses the size of the endogeneity bias empirically. Section 5 concludes.

2 The Concept of Perceived Job Insecurity

Following authors such as Manski and Straub (2000), Green et al. (2000) and Nickell et al. (2002), perceived job insecurity essentially consists of two elements: the perceived probability of job loss and the subjective costs associated with job loss.

Accordingly, we denote perceived job security of individual i at time t most generally as follows:

$$F_{it} = f\left(p_{it}, (U_{it} - U'_{it})\right) \tag{1}$$

with p denoting the subjective probability of job loss and $(U_{it} - U'_{it})$ the expected difference between utility with and without the present job with $\frac{\partial F_{it}}{\partial p_{it}} \geq 0$ and $\frac{\partial F_{it}}{\partial (U_{it} - U'_{it})} \geq 0$ and $p_{it} \in [0, 1]$.

Accordingly, the only assumptions we have made sofar are that perceived job insecurity increases with the expected risk of job loss and the associated costs. We further may assume that $(U_{it} - U'_{it}) \in [0, \infty]$, i.e. an individual's utility in the present job U_{it} is at least as high as or higher than expected utility outside the present job U'_{it}. This seems plausible because if this assumption did not hold, one would have to ask why an individual actually were in his or her present job in the first place. However, it is also conceivable, at least temporarily, that $(U_{it} - U'_{it}) < 0$.

The size of the job loss cost component $(U_{it} - U'_{it})$ depends on expected pecuniary as well as non-pecuniary effects of job loss. Pecuniary effects occur due to the difference between current job earnings and unemployment compensation (see e.g., Nickell, Jones and Quintini, 2002) or through reduced earnings in a new job. Other expected pecuniary effects may stem from, for example, foregone premiums and pensions, loss of fringe benefits, or the costs of moving or transport to a potential new workplace.

Of course we would also expect substantial non-pecuniary effects. Numerous studies have established that in terms of individual well-being, the non-pecuniary effects of unemployment are in fact larger than the associated loss of income (see, e.g., Winkelmann and Winkelmann 1998). As argued by social psychologists such as Jahoda (1981, 1988), these non-pecuniary effects of unemployment are due to the associated loss of social contact outside the family, loss of purpose, status, and identity and perhaps most controversially due to the loss of imposed time structure. If the individual expects to experience some spell of unemployment after job loss, it seems likely that some if not all of the associated non-pecuniary effects are anticipated. After all, even if the individual does not expect to remain unemployed after job loss we can speculate that she may expect to be deprived of at least some of the latent functions of the current job.

A further assumption that seems logical is that if one of the perceived job security components is zero, perceived job insecurity would also be zero no matter what value the other component takes on, that is, the two terms enter the function in a multiplicative way. Thus, if the expected probability of job loss is zero, the expected costs of job loss should not matter. At the same time, regardless of the expected probability of job loss, if the utility levels inside and outside the present job are identical there is no insecurity. Under this condition we can substantiate perceived job security such that:

$$F_{it} = f\left(p_{it}, (U_{it} - U'_{it})\right) \begin{cases} 0 & \text{if } p_{it} = 0 \text{ or } U_{it} = U'_{it} \\ \mathbb{R}^{+} & \text{if } p_{it} \neq 0 \text{ and } U_{it} > U'_{it} \end{cases} \tag{2}$$

At present there exist several individual-level surveys that provide the required information for operationalizing perceived job insecurity. In the *Socio-Economic Panel* (SOEP),[4] which we will utilize in what follows, respondents are asked to answer the following question:

> "What is your attitude towards the following areas – are you concerned about them? - Your job security: very concerned, somewhat concerned, not concerned."[5]

Similar information can be obtained, for instance, from the *British Household Panel Survey* (BHPS), the *Household, Income and Labour Dynamics in Australia Survey* (HILDA)[6] and the *Russian Longitudinal Panel Survey* (RLMS)[7]. If Equation 2 is a good approximation of reality, we would expect individuals to simultaneously evaluate their subjective risk of job loss p_{it} as well as their associated subjective costs of job loss $(U_{it} - U'_{it})$ when revealing their concerns. We will look into this in more detail by utilizing a number of other items from the SOEP.

Starting from 1999 respondents have been asked biennially to state their expected p_{it}:

> "How likely is it that one or more of the following occupational changes will take place in your life within the next two years? - lose your job?"

with answers lying on an equidistant eleven point scale ranging from 0 "definitely not" to 100 "definitely." Figure 1 plots the distribution of p within the groups of respondents that are "not concerned," "somewhat concerned," and "very concerned" about their job security.

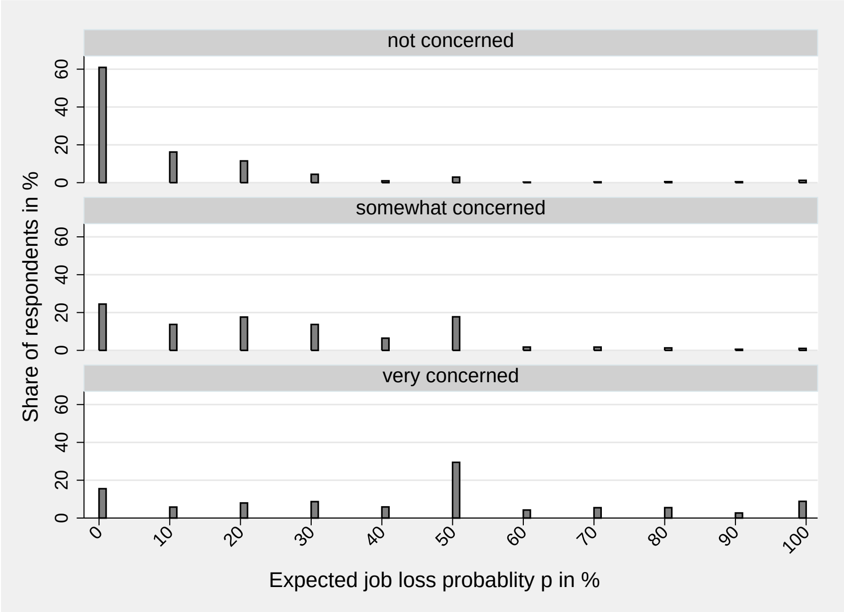
[4]For a detailed description of the data used in this study see Appendix A.

[5]The original German questionnaire asks: "Wie ist das mit den folgenden Gebieten - machen Sie sich da Sorgen? - Um die Sicherheit Ihres Arbeitsplatzes? Große Sorgen, Einige Sorgen, Keine Sorgen."

[6]In the BHPS and HILDA, the question is phrased somewhat differently: "[...] how satisfied or dissatisfied you are with [...] - Your job security."

[7]See Linz and Semykina (2008) for an application.

Figure 1: Perceived job insecurity and expected job loss probabilities



Note: Author's calculations, based on unbalanced SOEP sample of 13,598 individuals.

What becomes clear is that perceived job insecurity is only loosely related to the expected probability of job loss. About 60 percent of respondents who state being "not concerned" about their job security have an expected job loss probability of zero percent, which is reassuring. Furthermore, as one would expect, average expected job loss probability is higher among the group of "somewhat concerned" and further increases for the group of "very concerned." However, Figure 1 also points to remarkable inconsistencies, since within the group of the "very concerned" and the group of "somewhat concerned" the share of respondents with an expected job loss probability of zero is 15 and 25 percent, respectively. Thus, a significant proportion of respondents are concerned about job security but do not expect at all to lose their job within the next two years.

One possible reason for such apparently inconsistent responses may be the design of the questionnaire, which requires respondents to round off their expected job loss probabilities to zero or to full two digit percentage points (starting with 10 percentage points). According to Equation 2, high perceived job insecurity would, however, be fully in line with any p_{it} larger than zero, no matter how small, if $(U_{it} - U'_{it})$ is large. Another plausible explanation for such responses may bet that perceptions of job insecurity stretch far into the future and, thus, do not necessarily relate to immediately expected job loss risks. We test for this hypothesis by relating expected job loss risk to two, four and six-year lagged perceived job insecurity since, arguably, one can expect respondents who are very or somewhat concerned about their job security today to expect positive job loss risks at some point in the future. However, the same inconsistencies were found with our six-year lagged observations, suggesting, if anything at all, an even longer time horizon of perceived job insecurity. Thus, the aforementioned assumption of multiplicativity that led to Equation 2 does not appear to be borne out by the data, and we cannot rule out that some individuals simply do not take their expected job loss risk fully into account when evaluating their job insecurity. Hence, there appears to be some economically unjustified component of perceived job insecurity.

Accordingly, to account for the previously discussed inconsistencies and to allow for a most general functional form of perceived job insecurity, we chose to approximate Equation 1 by a polynomial in which p_{it} and $(U_{it} - U'_{it})$ enter multiplicatively as well as additively. Thus, as long $(U_{it} - U'_{it}) > 0$ our approximated function explicitly allows for $F_{it} > 0$ even if $p_{it} = 0$.

However, in our data, we do not observe the true values of F_{it} but as stated earlier only observe perceived job insecurity on a three-point scale. Accordingly, we can evaluate the predictive power of perceived job loss risk p_{it} for perceived job insecurity by estimating an ordered probit model (see, e.g., Cameron and Trivedi 2005, Ch. 15).

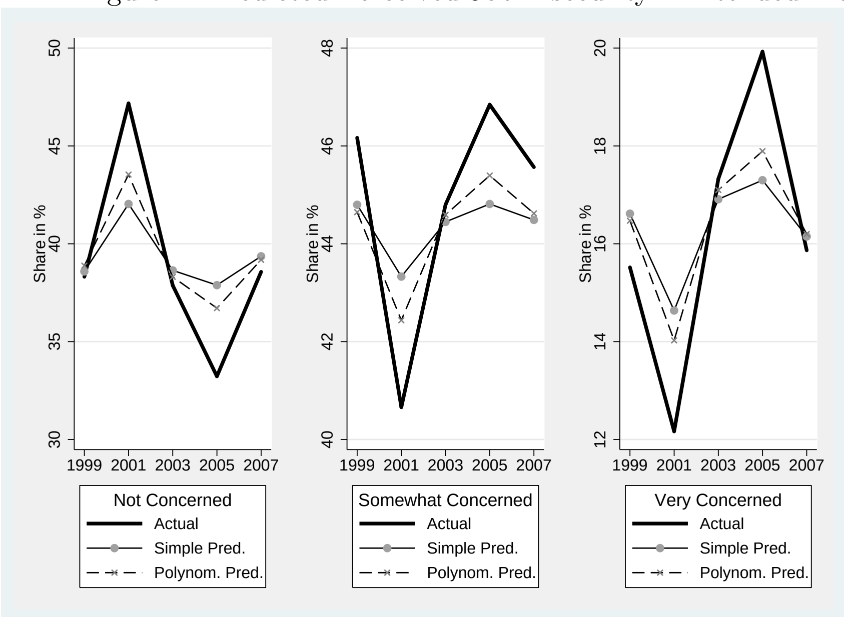
Figure 2 depicts the actual shares of respondents who are “not concerned”, “somewhat concerned” and “very concerned” about their job security and corresponding average predicted shares from a descriptive ordered probit model with subjective job loss risk p_{it} included as the only explanatory variable, but for more generality captured non-parametrically by a full set of dummy variables (see Column I of Table 1). As one may have expected, there is much room for improvement upon the precision of our prediction of F_{it}.

According to our conceptualization, a model predicting F_{it} would ideally include measures of the second component of Equation 1, namely $(U_{it} - U'_{it})$. The first variable in this expression U_{it} relates to the utility level in the current job and could in principle be easily operationalized by information on current individual well-being. However, therein lies a problem, as numerous studies mentioned earlier have already established that individual well-being in itself is a function of perceived job insecurity (see, e.g., Ferrie et al. 2004, De Witte 1999, Sverke and Hellgren 2002, Clark et al. 2009, Knabe and Rätzel 2009). Thus, following our concept, perceived job insecurity and individual well-being are most likely simultaneously determined.

To improve on the overall predictive power of our descriptive model we therefore concentrate on the operationalization of the second term in $(U_{it} - U'_{it})$, that is, the expected out-of-job utility level. To capture this, we follow Schmidt (1999) and Manski and Straub (2000) and take into account information on the perceived chances of finding an equivalent job if the present one is lost. In the SOEP, individual interviews contain the following question: “If you lost your job today, would it be easy, difficult, or almost impossible for you to find a new position which is at least as good as your current one?.” Thus, we have additional information on the subjectively expected costs of job loss. Accordingly, our polynomial approximation of Equation 1 now contains a full set of dummy variables for p_{it}, a full set of dummy variables capturing subjectively expected costs of job loss, and a full set of interaction terms (see Column II of Table 1).

Figure 2 shows that after taking information on the expected costs of job loss and associated interaction terms into account our average prediction of perceived job security matches much more closely actual shares of “not concerned”, “somewhat concerned” and “very concerned” respondents. Clearly, one could improve the model further by controlling more thoroughly for observed as well as unobserved individual heterogeneity. However, for our descriptive analysis, this should suffice for demonstrating that there is indeed more to perceived job insecurity than expected job loss risk.

Figure 2: Predicted Perceived Job Insecurity - Extended Model



Note: Author’s calculations, based on unbalanced SOEP sample of 13,598 individuals.

Table 1: Descriptive Ordered Probit Model

	I	II
$p = 10\%$	0.3434	0.5973
	(0.0184)***	(0.0454)***
$p = 20\%$	0.6443	0.7803
	(0.0180)***	(0.2506)***
$p = 30\%$	0.9791	1.0617
	(0.0207)***	(0.3286)***
$p = 40\%$	1.2601	1.3624
	(0.0288)***	(0.0817)***
$p = 50\%$	1.4774	1.3513
	(0.0185)***	(0.0521)***
$p = 60\%$	1.6488	2.4507
	(0.0462)***	(0.7374)***
$p = 70\%$	1.7143	1.3044
	(0.0435)***	(0.1273)***
$p = 80\%$	1.7411	1.0783
	(0.0456)***	(0.1402)***
$p = 90\%$	1.5021	2.0523
	(0.0607)***	(0.1383)***
$p = 100\%$	1.7425	0.9642
	(0.0391)***	(0.1043)***
p not reported	0.7691	0.8754
	(0.0704)***	(0.1941)***
Chance of finding equivalent Job		
Difficult		0.6423
		(0.0264)***
Impossible		0.5197
		(0.0310)***
Not reported		0.3443
		(0.1094)***
Full set of interaction terms		F=274.74***
Threshold 1	0.2877	0.7590
	(0.0100)***	(0.0229)***
Threshold 2	1.7916	2.3132
	(0.0125)***	(0.0246)***
Observations	41658	41658
Log-Likelihood	-37106.834	-36054.801

Note: Standard errors in parentheses, ***, **, * statistically significant at 1%, 5%, 10% level.
Default categories: $p = 10\%$, Chance of finding equivalent job - easy. Sample of employed respondents.

3 Simultaneity

As mentioned earlier, numerous studies have proclaimed a causal link between perceived job insecurity and individual well-being (see, e.g., Ferrie et al. 2004, De Witte 1999, Sverke and Hellgren 2002, Clark et al. 2009, Knabe and Rätzel 2009).

However, if our conceptualization of perceived job security is correct we would expect perceived job insecurity and individual well-being to be simultaneously determined. Accordingly, parameter estimates that do not take simultaneity into account would be biased. We can derive this more formally and also form an expectation about the theoretical direction of the bias. Later we will present an application that tests for simultaneity and empirically quantifies the associated bias.

Let us start with the hypothesis that indeed perceived job insecurity and individual well-being are simultaneously determined. Accordingly we can write that:

$$\begin{aligned} F_{it} &= f\left(p_{it}, (U_{it} - U'_{it})\right) \\ &\approx \alpha + \beta_U U_{it} + \beta_{U'} U'_{it} + \beta_p p_{it} + \mu_{it} \end{aligned} \tag{3}$$

and

$$\begin{aligned} U_{it} &= z(F_{it}, X_{it}) \\ &\approx \gamma + \delta F_{it} + \theta X_{it} + \epsilon_{it} \end{aligned} \tag{4}$$

with F and U denoting perceived job insecurity and subjective well-being and X representing any socio-economic control variables for individual i at time t.

Applying a bit of algebra we can derive an expression for the size and direction of the simultaneity bias of the estimated parameter $\widehat{\delta}$ for δ in Equation 4:

$$\begin{aligned} bias &= \frac{Cov(F, \epsilon)}{Var(F)} \\ &= \frac{\beta_U}{1 - \beta_U \delta} \frac{Var(\epsilon)}{Var(F)} \end{aligned} \tag{5}$$

with $\beta_U \delta \neq 1$.

As suggested by, for example, Ferrie, Shipleya, Newman, Stansfeld and Marmot (2005), De Witte (1999), Sverke and Hellgren (2002), Clark et al. (2009) and Knabe and Rätzel (2009) and in concordance with common sense, we obtain that $\delta < 0$, that is, perceived job insecurity lowers individual well-being. Furthermore, according to our conceptualization of perceived job insecurity in Equation 1 we have $\beta_U > 0$. Thus, we can derive that $bias \geq 0$, that is, if perceived job insecurity and individual well-being are indeed simultaneously determined, the coefficient of perceived job insecurity will be upward-biased in any model assessing individual well-being and operationalizing perceived job insecurity by information on job loss concerns (as in, e.g., Johnson et al. 1984, Clark et al. 2009, Knabe and Rätzel 2009).

Needless to say, if instead perceived job insecurity is operationalized by expected job loss risk only (as in, e.g., Mohr 2000) coefficients would also probably be biased since expected job loss risk is only one component of perceived job insecurity, as demonstrated in Section 2. The direction of bias would, however, depend on the covariance between p_{it} and $(U_{it} - U'_{it})$; if it is positive then disregarding $(U_{it} - U'_{it})$ also yields upward-biased coefficients.

In other words, if our conceptualization of perceived job insecurity is indeed plausible then the effect of perceived job insecurity on individual well-being has been systematically underestimated in the previously discussed literature.

4 Application: The Size of the Bias

In the next section, we apply our concept of perceived job insecurity to concrete data from the SOEP and quantify the previously discussed potential endogeneity bias in a model of individual well-being. A detailed description of the data as well as summary statistics are provided in Appendix A. We want to estimate the relationship sketched out in Equation 4 accounting for individual observed and unobserved heterogeneity and take the potential simultaneity problem into account.

We specify following empirical model with fairly standard control variables (see, e.g., Frey and Stutzer 2002, Ferrer-i-Carbonell and Frijters 2004, Van Praag and Ferrer-i-Carbonell 2008):

$$
\begin{aligned}
U_{irt} &= \sum_{d\in D} \beta_d uemp_{it} \times d \\
&+ \beta_{semp}\ semp_{it} + \beta_{olf}\ olf_{it} \\
&+ \rho\ unemprate_{rt} \\
&+ \gamma AGE_{it} + \delta KIDS_{it} + \eta HEALTH_{it} + \vartheta\ ln(hhincome_{it}) \\
&+ \phi\ emp_{it} \times F_{it} + \tau_t + \mu_i + \epsilon_{irt} \qquad (6)
\end{aligned}
$$

with i denoting the individual, r federal state, and t time. U is individual well-being and *uemp*, *semp*, and olf are dummy variables that take the value one if the individual in time t is unemployed, self-employed, or out of the labor force. Being employed (*emp*) is the default category. Following authors such as Clark (2003), we also take into account the duration of unemployment to separate the effects of very recent unemployment ($d = D :< 2\ months$), recent unemployment ($d = D : 2 - 5\ months$), medium-term ($d = D : 5 - 11\ months$), long-term ($d = D : 12 - 35\ months$), and permanent ($d = D :> 35\ months$) unemployment.

Following the literature (e.g., Kassenboehmer and Haisken DeNew 2009) we also control for the federal-state level unemployment rate (*unemprate*).[8] AGE is a vector of dummy variables for respondents falling into the age intervals [25,35), [35,45), [45,55), and [55,64], with [18,25) being the default category.[9] The vector $KIDS$ contains the number of children in the household and the number of children squared, both, if applicable, interacted with gender. $HEALTH$ captures the "objective" health status of the individual and contains the number of annual doctor visits and the number of doctor visits squared. The variable *hhincome* denotes the equivalence scale post-government household income in real prices from 2001.[10]

Perceived job insecurity enters the model through the interaction term $emp \times F$, since our sample consists of employed, unemployed, and self-employed respondents as well as individuals out of the labor force, and perceived job inse-

[8] We do not, however, interact regional unemployment rates by labor force status since the analysis of social norm effects as in, e.g., Stutzer and Lalive (2004) is beyond the scope of the present analysis. Furthermore, note that combining aggregate level and micro-level data could give rise to contemporaneous correlation and result in biased standard errors of the regional unemployment variable (see Moulton, 1986). Unfortunately, applying sandwich-type formulas for clustered standard errors is not an option in the present analysis, since the number of clusters is too small (16 federal states).

[9] Note that in our fixed effects specification with year dummies continuous age controls would result in perfect collinearity. Age interval dummies are identified through switches between categories.

[10] Applying the equivalence scale is essential to separate the life satisfaction effects of children and household income. To calculate the equivalent scale household income, we simply divide household income by the squared sum of household members. The analysis is, however, robust to more elaborate methods. Furthermore, we do not include measures of relative income in our model as this is beyond the scope of the analysis.

curity at any given time is naturally only observed for employees. F consists of a dummy variable for individuals who are very concerned about their job security (F : *very concerned*) and a dummy variable for individuals who are somewhat concerned (F : *somewhat concerned*) with unconcerned individuals constituting the default category. The error term is decomposed into time-specific effects τ_t and individual fixed effects μ_i. The remaining error term ϵ_{it} is allowed to be heteroscedastic, and according to our reasoning in Section 3, is expected to be correlated with F due to simultaneity.

As is common in such analyses we cannot directly observe individual life satisfaction. In the individual questionnaires of the SOEP, individuals are asked to state their current life satisfaction: "How satisfied are you with your life, all things considered?" ranging from 0 "completely dissatisfied" to 10 "completely satisfied" on an equidistant eleven-point scale. Accordingly, the obvious choice would be to estimate Equation 6 by a latent model similar to the one employed in the descriptive analysis presented in Section 2. However, as demonstrated in Ferrer-i-Carbonell and Frijters (2004), disregarding unobserved individual heterogeneity would result in severely biased coefficients.

Instead, we follow authors such as Luechinger (2009), Stevenson and Wolfers (2008), Clark et al. (2009), and Knabe and Rätzel (2009) and utilize the "Probit-Adapted OLS" framework by Van Praag and Ferrer-i-Carbonell (2008), who suggest representing ordinal life satisfaction responses as normally distributed bounded responses on a cardinal scale. The approach has the main advantage that once the transformation has been carried out, responses are bounded and simple linear models can be employed. Thus, it is straightforward to control for unobserved heterogeneity by including individual fixed effects and also to undertake instrumental variable regression. While such transformation is more restrictive than, for example, the extended conditional logit methodology proposed by Ferrer-i-Carbonell and Frijters (2004), the authors also demonstrate that their extended conditional logit estimates are generally fairly similar even to the ones of simple linear models as long as unobserved individual heterogeneity is accounted for (See also Frey and Stutzer 2000). To check the robustness of our findings from probit-adapted OLS we also estimate all models by simple within-transformed OLS (see Appendix B).

To test and account for potential simultaneity bias outlined in Section 3 we need excluded instruments that have sufficient predictive power for reported perceived job insecurity F and are orthogonal to the error term ϵ_{it} in Equation 6.

Importantly, as already discussed in Section 2, we do not observe perceived job insecurity on a cardinal but only on an ordinal scale. Accordingly, we capture and subsequently instrument perceived job insecurity falling into the categories "not concerned", "somewhat concerned" and "very concerned" by a set of dummy variables with the category "not concerned" as the default. Thus, we have to instrument for two variables simultaneously.

Following the discussion in Section 2, variables that capture individuals' perceptions of job loss risk and their perceived chances of finding an equivalent job seem to be promising candidates as valid instruments. Accounting for unobserved individual heterogeneity by a fixed effects specification, in a "first stage" we regress our dummy variables for F on all included and excluded instruments and test for the predictive power of our excluded instruments.[11] Accordingly, our initial model includes all explanatory variables from Column II in Table 1 in Section 2. Perceived job loss risk captured by a set of 11 dummy variables representing perceived job loss probability ranging from p=10% to p=100%, with p=0% being the default category and one dummy capturing item non-response. Furthermore, we include dummy variables for individuals whose perceptions about their chances of finding an equivalent job fall in the category "almost impossible", "difficult", and a dummy variable for individuals who give no response to this question, "easy" constitutes the default category. In addition we include a full set of interaction terms between the dummy variables for p and chances of finding an equivalent job.

Including all variables and interaction terms our initial GMM model uses 46 orthogonality restrictions. This is problematic since several studies summarized in Chapter 8.6. of Wooldridge (2002) highlight the poor finite sample properties of GMM estimators with many overidentifying restriction. We therefore also estimate GMM models with a drastically reduced set of excluded instruments.

Table 2 reports instrument validity tests for the "first stage" polynomial model specification with 46 orthogonality restrictions and for the reduced one. First of all, as the Kleibergen-Paap LM statistic indicates, we can clearly reject under-identification for the reduced as well as for the polynomial specification.[12] In addition, we can clearly reject weak identification for the reduced specification, since the F statistic is far above the critical values reported in Stock and Yogo

[11] A non-linear "first stage" model is not required since Kelejian (1971) and Heckman (1978) show that a simple linear probability model is sufficient to obtain consistent estimates in the "second-stage regression."

[12] The Kleibergen-Paap rank LM test is a heteroscedasticity-robust variant of the Anderson canonical correlation test. See Paap (2006) for further details.

(2005). However, for the polynomial specification we cannot reject weak identification for the male sample casting doubt on the explanatory power of at least some of the 46 excluded instruments.[13] Thus, we prefer the model specifications with a reduced number of overidentifying restrictions.

We proceed by testing the orthogonality of our excluded instruments and the error term in the "second stage." As indicated by the Hansen J-Statistics reported in Table 2, we cannot reject orthogonality in any case. Accordingly, our excluded instruments are valid and we can test whether the potential endogeneity bias outlined in Section 3 indeed materializes.[14]

Table 2 presents C-tests of exogeneity of the included dummy variables for perceived job insecurity. As indicated by the high Hansen J-Statistics, we can confidently reject exogeneity for all samples. Hence, the previously discussed endogeneity bias is indeed relevant. Not accounting for the simultaneity of perceived job insecurity and individual well-being results in biased coefficients.

We can quantify the size of the bias by comparing a restricted but efficient fixed effects model that assumes exogeneity of F with a consistent model that allows for endogeneity by instrumenting for F. In the light of the discussed poor finite sample properties of GMM models with a large number of orthogonality conditions we do so by utilizing the GMM model with a reduced number of orthogonality conditions reported in the second half of Table 2.[15]

Table 3 presents respective coefficient estimates for the whole sample and for completeness by gender for the restricted efficient as well as the consistent model. Regarding our standard control variables, our coefficients are in line with earlier empirical studies although many coefficients are not identified with sufficient precision. This may not be surprising, however, as we control for fixed individual as well as time effects.

Regarding perceived job insecurity, which we are most interested in, we find a negative and statistically significant effect on individual well-being in all model specifications with some small differences between genders. However, most importantly, in line with our expectation sketched out in Section 3, we find the coefficients of perceived job insecurity to be significantly upward biased in the simple

[13] We employ heteroscedasticity robust GMM estimations. All estimations and corresponding tests are carried out using the Stata add-ons "ivreg2" and "xtivreg2" provided by Baum, Schaffer, Stillman (2003, 2007).

[14] At first glance it may seem problematic to use perceived job loss probabilities as excluded instruments since one clearly would expect them to affect individuals life satisfaction. However, once we condition on perceived job insecurity, subjective job loss probabilities carry no additional explanatory power. At the same time the sceptical reader may worry about unobserved characteristics that are correlated with the excluded instruments and which also determine individual life satisfaction, i.e. a violation of the orthogonality condition. However, individual fixed effects control for this problem, at least as long unobserved characteristics do not change over time.

[15] We also report results for GMM models with full polynomial specification of the "first stage" in Appendix B.

Table 2: Validity of Instruments and Exogeneity Tests

	All	Males	Females
Full Polynomial "First Stage"			
Excluded instruments: 11 dummies for $p = 10,...,p = 100$, $p = \textit{not reported}$, ($p = 0$ default) 3 dummies for chance of finding equivalent job: difficult, impossible, not-reported (easy default); interaction terms			
Underidentification			
Kleibergen-Paap rk LM statistic	$Chi^2 = 1318.36$	$Chi^2 = 646.27$	$Chi^2 = 648.80$
	$p = 0.00$	$p = 0.00$	$p = 0.00$
Weak Identification			
Kleibergen-Paap Wald rk F statistic	$F = 35.42$	$F = 17.89$	$F = 45.23$
Stock-Yogo critical value for 5% relative IV bias - 21.02			
Overidentifying Restrictions (Orthogonality)			
Hansen J-Statistic	$Chi^2 = 48.12$	$Chi^2 = 44.60$	$Chi^2 = 36.35$
	$p = 0.32$	$p = 0.40$	$p = 0.75$
Exogeneity C-Test	$Chi^2 = 88.52$	$Chi^2 = 86.91$	$Chi^2 = 18.32$
	$p = 0.00$	$p = 0.00$	$p = 0.00$
Simplified "First Stage"			
Excluded instruments: 2 dummies for $p <= 20$, $p >= 80$ 2 dummies for chance of finding equivalent job: impossible, not-reported			
Underidentification			
Kleibergen-Paap rk LM statistic	$Chi^2 = 564.06$	$Chi^2 = 259.43$	$Chi^2 = 314.27$
	$p = 0.00$	$p = 0.00$	$p = 0.00$
Weak Identification			
Kleibergen-Paap Wald rk F statistic	$F = 158.76$	$F = 73.10$	$F = 88.37$
Stock-Yogo critical value for 5% relative IV bias - 11.04			
Overidentifying Restrictions (Orthogonality)			
Hansen J-Statistic	$Chi^2 = 2.68$	$Chi^2 = 2.95$	$Chi^2 = 2.39$
	$p = 0.26$	$p = 0.23$	$p = 0.30$
Exogeneity C-Test	$Chi^2 = 91.84$	$Chi^2 = 85.10$	$Chi^2 = 20.37$
	$p = 0.00$	$p = 0.00$	$p = 0.00$

restricted model that ignores simultaneity between perceptions of job insecurity and individual well-being. We can illustrate the size of the bias by calculating the compensating income differential as is commonly done in the literature (e.g., Winkelmann and Winkelmann 1998, Kassenböhmer and Haisken DeNew 2009). Thus, we can ask by how much individuals' income had to be raised to compensate them for the negative well-being effects of perceived job insecurity.

Using the point estimates from the biased model reported in Column I of Table 3, the compensating income differential of becoming somewhat concerned relative to being not concerned about job security is 1.4 log points ($\Delta \ln(\textit{hhincome}) = 0.1091/0.0781$) while for the very concerned it is 3.3 log points ($\Delta \ln(\textit{hhincome}) = 0.2603/0.0781$). When relying instead on the unbiased point estimates from Column II of Table 3, we find the compensating income differential to be 3.9 ($\Delta \ln(hhincome) = 0.2911/0.075$) and 8.5 ($\Delta \ln(hhincome) = 0.6367/0.075$) log points for somewhat and very concerned respondents, respectively.

Similarly, when using the point estimates from the naively estimated model for the male sub-sample (see Column III in Table 3) we find the compensating income differential to be 1.6 log points for somewhat concerned and 3.6 log points for very concerned males. When accounting for simultaneity, the compensating income differential is 4.4 and 10 log points respectively (see Column IV in Table 3). When looking at the model for the female sub-sample, our naively estimated coefficients imply a compensating income differential of 1.2 log points for somewhat concerned and 3 log points for very concerned female respondents. The endogeneity consistent GMM model implies a compensating income differential of 2.9 log points for somewhat concerned and 6.6 log points for very concerned females (see Columns V and VI in Table 3).

Thus, while there is some variation in the magnitude of the negative well-being effects of perceived job insecurity across gender, with males being most adversely affected, we generally find the true unbiased effect of perceived job insecurity to be more than twice the size of the naively estimated effects. Accordingly and in line with our theoretical prediction in Section 3, ignoring simultaneity between perceived job insecurity and individual well-being as is commonly done in the literature (e.g., Ferrie et al. 2004, De Witte 1999, Sverke and Hellgren 2002; Clark et al. 2009, Knabe and Rätzel, 2009) drastically underestimates the negative impact of job insecurity perceptions.

It is informative to put the size of the effects of perceived job insecurity in perspective by comparing compensating income differentials of other individual characteristics. For instance, using the regression results for the pooled sample from Column II in Table 3, the positive well-being effect of having a steady partner can only compensate for less than a quarter of the negative well-being effect of being very concerned about job security. Also, our estimates indicate that the negative well-being effect of being very concerned about job security, ceteris paribus, is more than eighteen times higher than the positive well-being effect women experience after their first child is born. Furthermore, being very concerned about job security has similar well-being effects to having fairly bad health as approximated by an equivalent number of 177 doctor visits per year. Accordingly, we can establish that perceived job insecurity is indeed one of the major determinants of employees' well-being.

In addition, perceived job insecurity also has implications for evaluating the well-being costs of unemployment and other labor force statuses. According to Table 3, recent and medium-term unemployment appears to significantly lower individual well-being compared to employed individuals in all model specifications. However, for correct interpretation it is essential to also consider the coefficients on all employment interaction terms when comparing individual well-being between different labor force statuses. In our model, being employed *emp* is the default category; accordingly we can substitute $emp = 1 - uemp - semp - olf$ in Equation 6. It now becomes clear that when comparing individual well-being of, for instance, those in recent unemployment with those in employment, one has to calculate

$$U^{uemp}_{D:<2\ months} - U^{emp} = \beta_{D:<2\ months} - \phi F, \tag{7}$$

that is, one has to take perceived job insecurity of those in employment into account.

On this basis we can calculate the compensating income differential, that is, the hypothetical income increase that holds individuals well-being constant once they become unemployed. Using the point estimates from the pooled regression (Column II in Table 3), we calculate a compensating income differential of 7 log points $\Delta \ln(hhincome) = (0.5247)/0.075)$ for recently unemployed individuals who were not concerned about their job security during employment. For the recent unemployed who were somewhat concerned about their job security when employed, the compensation income differential is 3.1 log points ($\Delta \ln(hhincome) = (0.5247 - 0.2911)/0.075$).

This clearly confirms earlier findings of, for example, Winkelmann and Winkelmann (1998) and points to a very large non-pecuniary component in the well-being effect of unemployment (see, e.g., Jahoda 1981, 1986 for explanations).

However, our estimates also indicate that for recently unemployed individuals who were very concerned about their job security when employed, this compensating income differential actually becomes negative ($\Delta \ln(hhincome) = (0.5247 - 0.6367)/0.075 = -1.5$ log points). Hence, this group of respondents actually becomes better off when their feared job loss eventually materializes.

Thus, for respondents who are very concerned about their job security, the negative well-being effects of job loss concerns are even larger than the well-being loss associated with recent unemployment. Accordingly, we can confirm a hypothesis put forward in the psychological literature (e.g., Cobb and Kasl 1977) and postulate that the fear of job loss may indeed be more damaging for individual well-being than actual job loss and unemployment.

Table 3: Regression Results - Probit-Adapted Linear Fixed Effects Model

	All		Male		Female	
	I - FE	II - FE GMM	III - FE	IV - FE GMM	V - FE	VI - FE GMM
$Age: 25-34$	-0.0146	-0.0194	-0.037	-0.0523	-0.0047	-0.0064
	[0.0205]	[0.0208]	[0.0310]	[0.0316]*	[0.0275]	[0.0276]
$Age: 35-44$	-0.0269	-0.0286	-0.064	-0.0769	-0.0038	-0.0031
	[0.0277]	[0.0281]	[0.0409]	[0.0420]*	[0.0378]	[0.0380]
$Age: 45-54$	-0.0528	-0.0492	-0.1163	-0.12	-0.0083	-0.0051
	[0.0340]	[0.0343]	[0.0496]**	[0.0508]**	[0.0468]	[0.0469]
$Age: 55-64$	-0.0673	-0.0748	-0.1059	-0.1239	-0.0448	-0.049
	[0.0415]	[0.0418]*	[0.0601]*	[0.0613]**	[0.0573]	[0.0576]
$Number\ Children \times Male$	0.0318	0.0285	0.029	0.0245		
	[0.0184]*	[0.0185]	[0.0186]	[0.0190]		
$Number\ Children^2 \times Male$	-0.0099	-0.0088	-0.0095	-0.0079		
	[0.0058]*	[0.0059]	[0.0058]	[0.0060]		
$Number\ Children \times Female$	0.0401	0.0414			0.0381	0.038
	[0.0176]**	[0.0177]**			[0.0178]**	[0.0179]**
$Number\ Children^2 \times Female$	-0.0078	-0.0077			-0.0073	-0.0071
	[0.0051]	[0.0051]			[0.0051]	[0.0051]
$Steady\ Partner \times Male$	0.1391	0.1438	0.1397	0.1457		
	[0.0247]***	[0.0249]***	[0.0250]***	[0.0254]***		
$SteadyPartner \times Female$	0.1697	0.1706			0.1665	0.1666
	[0.0228]***	[0.0229]***			[0.0229]***	[0.0230]***
$ISCED: UNI$	0.0171	0.002	-0.0741	-0.1158	0.0904	0.0888
	[0.0369]	[0.0372]	[0.0535]	[0.0545]**	[0.0512]*	[0.0514]*
$ISCED: HigherSecondary$	-0.0321	-0.0338	-0.092	-0.1013	0.0176	0.0189
	[0.0181]*	[0.0182]*	[0.0260]***	[0.0264]***	[0.0252]	[0.0253]
$ISCED: notreported$	-0.0152	-0.019	-0.0061	-0.0094	-0.0233	-0.028
	[0.0371]	[0.0373]	[0.0549]	[0.0550]	[0.0504]	[0.0506]
$Number\ of\ doctor\ visits$	-0.0036	-0.0036	-0.0042	-0.0041	-0.0031	-0.0031
	[0.0003]***	[0.0003]***	[0.0004]***	[0.0004]***	[0.0004]***	[0.0004]***
$ln(EquivalentIncome)$	0.0781	0.075	0.0829	0.0809	0.0749	0.0721
	[0.0112]***	[0.0113]***	[0.0178]***	[0.0180]***	[0.0145]***	[0.0145]***
$uemp * D :< 2\ months$	-0.3612	-0.5247	-0.4786	-0.71	-0.2532	-0.3543
	[0.0254]***	[0.0377]***	[0.0360]***	[0.0567]***	[0.0358]***	[0.0504]***
$uemp * D : 2-5\ months$	-0.4625	-0.634	-0.588	-0.8248	-0.3131	-0.4208
	[0.0448]***	[0.0541]***	[0.0567]***	[0.0731]***	[0.0717]***	[0.0824]***
$uemp * D : 6-12\ months$	-0.4218	-0.5982	-0.4959	-0.7489	-0.3495	-0.455
	[0.0412]***	[0.0507]***	[0.0535]***	[0.0716]***	[0.0641]***	[0.0735]***
$uemp * D : 12-35\ months$	-0.4633	-0.6465	-0.5667	-0.8287	-0.3672	-0.4796
	[0.0255]***	[0.0384]***	[0.0358]***	[0.0573]***	[0.0365]***	[0.0520]***
$uemp * D :\geq 36\ months$	-0.4203	-0.6135	-0.555	-0.8307	-0.2949	-0.4145
	[0.0364]***	[0.0470]***	[0.0507]***	[0.0689]***	[0.0525]***	[0.0649]***
$outlf$	-0.1572	-0.3063	-0.2296	-0.4442	-0.1092	-0.2026
	[0.0136]***	[0.0294]***	[0.0226]***	[0.0463]***	[0.0175]***	[0.0382]***
$semp$	0.0341	0.0235	0.0224	0.0038	0.0409	0.0346
	[0.0247]	[0.0248]	[0.0340]	[0.0340]	[0.0358]	[0.0361]
$regional\ unemployment$	-0.0048	-0.0032	-0.004	-0.0008	-0.0053	-0.0046
	[0.0031]	[0.0032]	[0.0046]	[0.0047]	[0.0043]	[0.0043]
$F: somewhat\ concerned$	-0.1091	-0.2911	-0.1305	-0.3564	-0.0879	-0.2061
	[0.0102]***	[0.0618]***	[0.0137]***	[0.0930]***	[0.0153]***	[0.0818]**
$F: very\ concerned$	-0.2603	-0.6367	-0.2984	-0.8168	-0.2248	-0.4775
	[0.0152]***	[0.0452]***	[0.0205]***	[0.0629]***	[0.0226]***	[0.0655]***
Observations	68622	68622	32623	32623	35999	35999
R^2	0.95	0.97	0.94	0.97	0.96	0.97

Note: Standard errors in parentheses. ***, **, * - statistically significant at 1, 5, 10%.
All specifications contain a full set of year dummies and are within transformed.
Default categories: $Age: 18-24$, $ISCED: lower\ secondary\ or\ less$, emp, $F: not\ concerned$

5 Conclusion

The present paper assesses the importance of job insecurity perceptions as a determinant of individual well-being. In Contrast to previous studies, our concept of perceived job insecurity explicitly takes into account individual perceptions about the likelihood of job loss as well as perceptions about the associated costs of job loss. We demonstrate that both job loss risk and cost perceptions constitute essential components of individual perceived job insecurity. Consequently, we theoretically demonstrate that through the associated cost component of job loss, any model assessing the impact of perceived job insecurity on individual well-being potentially suffers from simultaneity bias resulting in upward-biased coefficients. To the present date, the economics literature as well as other fields of the social sciences have ignored this problem and have thereby systematically underestimated the impact of job insecurity perceptions.

To illustrate the size of the simultaneity bias, we apply our concept of perceived job insecurity to a model of individual well-being using a large household panel survey and circumventing endogeneity by instrumenting. In our application, we find the true unbiased effects of perceived job insecurity to be more than twice the size of estimates that ignore simultaneity. Thus, simultaneity bias is not only a theoretical concern but is also very relevant empirically.

In comparison to other determinants, our results suggest that perceived job insecurity ranks as one of the most important factors for employees' well-being. Furthermore, our estimates indicate that while recent experience of unemployment is associated with substantial well-being losses, this is only true in comparison to employed individuals who are not or only somewhat concerned about their job security. For individuals who are very concerned about their job security, we have the paradoxical situation that when the event of job loss they fear eventually materializes, their well-being actually increases. Thus, for some individuals, the fear of job loss is more harmful to their well-being than actual job loss with subsequent unemployment.

Why does this matter? First of all, from a subjectivist viewpoint, our findings about the well-being effects of perceived job insecurity are interesting and relevant in their own right, as they concern welfare (see, e.g., Frey and Stutzer 2002b for a discussion). Second, our findings of the well-being implications of perceived job insecurity can contribute to a better understanding of individual job search activities. Do individuals who experience substantial well-being losses from perceived job insecurity expand their job search activities while in employment? How are job search activities affected by the aforementioned paradoxical situation that individuals who were very concerned about their job security are actually better off once they become unemployed? These are important questions for future research.

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A Data and Descriptive Statistics

Our individual-level data is from the 2008 release of the Socio-Economic Panel (SOEP). The SOEP is a representative longitudinal survey of private households in Germany that has been continuously running since 1984.[16]

[16] Recent studies on the basis of the SOEP include Kassenboehmer and DeNew (2009) and Luechinger et al. (2010). A detailed description of the SOEP is provided in Wagner, Frick and Schupp (2007). The data was extracted using the Add-On package PanelWhiz for Stata. PanelWhiz (http://www.PanelWhiz.eu) was written

We utilize all samples and make no exclusions with respect to foreigner status or former East and West Germany. As our analysis draws on information about subjective job loss risk which is only available on an biannual basis starting in 1999 we can only utilize data for the years 1999, 2001, 2003, 2005 and 2007. Our sample consists of male and female respondents in prime age (18-64 years). We do not select observations based on labor market status but rather include dummy variables and interaction terms for respondents in employment, self-employment, unemployment or out-of labor force. However, we do exclude a specific type of public officials from the analysis, namely "Beamte" that generally cannot be laid off.

We further only select individuals for which we have more than one wave of observation. In addition we had to exclude respondents with missing life satisfaction information, our dependent variable and missing information on perceived job insecurity, our main variable of interest. Other than that we make no exclusion with respect to item non-response and supplement the analysis with dummy variables for item non-response and recode missing values to zero. Furthermore, due to our fixed effects specification we only include respondents with a least two completed interviews over the sample period. This yields an unbalanced sample of 68622 observations for 18974 individuals.

Table 4 reports respective descriptive statistics for all included variables. Where relevant, e.g., perceived job insecurity, descriptive statistics are only reported for the sub-sample of employed respondents.

by Dr. John P. Haisken DeNew (john@PanelWhiz.eu). See Haisken-DeNew and Hahn (2006)for details. The PanelWhiz generated do-file to retrieve the data in the present paper is available from the authors upon request. Any data or computational errors in the paper are our own.

Table 4: Descriptive Statistics

Variable	Full Sample				Male				Female			
	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max
U	6.943	1.77	0.00	10.00	6.897	1.77	0.00	10.00	6.984	1.76	0.00	10.00
$Probit-adpatedU$	0.000	0.98	-3.01	2.26	0.000	0.98	-2.90	2.26	0.000	0.98	-3.01	2.15
$uemp$	0.071	0.26	0.00	1.00	0.079	0.27	0.00	1.00	0.065	0.25	0.00	1.00
$uemp \times D :< 2\ months$	0.024	0.15	0.00	1.00	0.025	0.16	0.00	1.00	0.022	0.15	0.00	1.00
$uemp \times D : 2-5\ months$	0.005	0.07	0.00	1.00	0.007	0.08	0.00	1.00	0.004	0.07	0.00	1.00
$uemp \times D : 6-11\ months$	0.007	0.09	0.00	1.00	0.009	0.09	0.00	1.00	0.006	0.08	0.00	1.00
$uemp \times D : 12-35\ months$	0.022	0.15	0.00	1.00	0.025	0.16	0.00	1.00	0.020	0.14	0.00	1.00
$uemp \times D :\geq 36\ months$	0.012	0.11	0.00	1.00	0.013	0.12	0.00	1.00	0.011	0.11	0.00	1.00
$outlf$	0.322	0.47	0.00	1.00	0.216	0.41	0.00	1.00	0.417	0.49	0.00	1.00
$semp$	0.066	0.25	0.00	1.00	0.088	0.28	0.00	1.00	0.046	0.21	0.00	1.00
$Age : 25-34$	0.198	0.40	0.00	1.00	0.194	0.40	0.00	1.00	0.201	0.40	0.00	1.00
$Age : 35-44$	0.267	0.44	0.00	1.00	0.267	0.44	0.00	1.00	0.267	0.44	0.00	1.00
$Age : 45-54$	0.224	0.42	0.00	1.00	0.221	0.41	0.00	1.00	0.227	0.42	0.00	1.00
$Age : 55-64$	0.188	0.39	0.00	1.00	0.192	0.39	0.00	1.00	0.184	0.39	0.00	1.00
$Number\ Children \times Male$	0.312	0.74	0.00	10.00	0.656	0.97	0.00	10.00	0.000	0.00	0.00	0.00
$Number\ Children^2 \times Male$	0.651	2.29	0.00	100.00	1.369	3.17	0.00	100.00	0.000	0.00	0.00	0.00
$Number\ Children \times Female$	0.366	0.79	0.00	10.00	0.000	0.00	0.00	0.00	0.699	0.98	0.00	10.00
$Number\ Children^2 \times Female$	0.759	2.46	0.00	100.00	0.000	0.00	0.00	0.00	1.446	3.25	0.00	100.00
$Steady\ Partner \times Male$	0.335	0.47	0.00	1.00	0.704	0.46	0.00	1.00	0.000	0.00	0.00	0.00
$SteadyPartner \times Female$	0.386	0.49	0.00	1.00	0.000	0.00	0.00	0.00	0.735	0.44	0.00	1.00
$ISCED : UNI$	0.168	0.37	0.00	1.00	0.186	0.39	0.00	1.00	0.151	0.36	0.00	1.00
$ISCED : HigherSecondary$	0.639	0.48	0.00	1.00	0.641	0.48	0.00	1.00	0.638	0.48	0.00	1.00
$ISCED : notreported$	0.023	0.15	0.00	1.00	0.023	0.15	0.00	1.00	0.023	0.15	0.00	1.00
$Number\ of\ doctor\ visits$	9.202	15.80	0.00	365.00	7.806	15.22	0.00	365.00	10.467	16.20	0.00	365.00
$ln(EquivalentIncome)$	9.806	0.55	1.77	14.07	9.846	0.52	4.48	13.47	9.770	0.58	1.77	14.07
Observations	68629				32627				36002			
$F : somewhat\ concerned$	0.45	0.50	0.00	1.00	0.46	0.50	0.00	1.00	0.43	0.50	0.00	1.00
$F : very\ concerned$	0.16	0.37	0.00	1.00	0.17	0.37	0.00	1.00	0.16	0.36	0.00	1.00
Observations		68622				32623				35999		

B Robustness Check

According to Ferrer-i-Carbonell and Frijters (2004) applying OLS or extended conditional logit methods that maintain non-linearity yields similar estimates as long as unobserved individual heterogeneity is appropriately accounted for. Accordingly, we re-estimate all specifications relying on simple linear fixed effects models to benchmark our findings from probit-adapted OLS which had not been discussed in Ferrer-i-Carbonell and Frijters (2004).

Table 5 presents the respective coefficients. Again, our earlier finding of a substantial simultaneity bias is confirmed. When looking at the pooled model of males and females the unbiased estimates of perceived job insecurity correspond to a compensating income differential of 2.5 log points for somewhat concerned individuals and 8 log points for very concerned individuals. Thus, they are fairly similar to the estimates from our earlier probit-adapted linear fixed effects model.

When calculating the compensating income differential of becoming unemployed we find it to be 6.38 log points for recent unemployed that were not concerned about their job security when in employment, 3.9 log points for the somewhat concerned and -1.6 log points for the very concerned. Accordingly, our estimates from simple fixed effects OLS are again close to the ones from the probit-adapted OLS model.

Summarizing, after controlling for unobserved individual heterogeneity our results derived through probit-adapted OLS as suggested by Van Praag and Ferrer-i-Carbonell (2008) are robust to applying simple OLS which also suggests that using extended conditional logit methods, which, however, do not easily lend themselves to GMM methods, yields fairly similar results (see Ferrer-i-Carbonell and Frijters, 2004).

As a further robustness check we re-estimate our GMM models using the polynomial "first stage" specification with 46 excluded instruments. Again, we find naively estimated effects of job loss concerns to be downward biased in comparison to the GMM results that account for simul-

Table 5: Regression Results - Simple Linear Fixed Effects Model

	All		Male		Female	
	I - FE	II - FE GMM	III - FE	IV - FE GMM	V - FE	VI - FE GMM
$Age: 25-34$	-0.0283	-0.0416	-0.0416	-0.1015	-0.015	-0.0209
	[0.0363]	[0.0369]	[0.0369]	[0.0566]*	[0.0484]	[0.0488]
$Age: 35-44$	-0.0559	-0.0648	-0.0648	-0.1592	-0.0152	-0.0159
	[0.0497]	[0.0504]	[0.0504]	[0.0758]**	[0.0676]	[0.0680]
$Age: 45-54$	-0.111	-0.1092	-0.1092	-0.2479	-0.0312	-0.025
	[0.0616]*	[0.0624]*	[0.0624]*	[0.0924]***	[0.0849]	[0.0852]
$Age: 55-64$	-0.1437	-0.1575	-0.1575	-0.2648	-0.0959	-0.0991
	[0.0757]*	[0.0763]**	[0.0763]**	[0.1119]**	[0.1047]	[0.1052]
$Number\ Children \times Male$	0.0767	0.0682	0.0682	0.0608		
	[0.0348]**	[0.0352]*	[0.0352]*	[0.0361]*		
$Number\ Children^2 \times Male$	-0.0192	-0.0169	-0.0169	-0.0153		
	[0.0114]*	[0.0116]	[0.0116]	[0.0117]		
$Number\ Children \times Female$	0.0796	0.0838	0.0838		0.0745	0.0758
	[0.0313]**	[0.0315]***	[0.0315]***		[0.0319]**	[0.0320]**
$Number\ Children^2 \times Female$	-0.0153	-0.0154	-0.0154		-0.0142	-0.014
	[0.0090]*	[0.0090]*	[0.0090]*		[0.0090]	[0.0090]
$Steady\ Partner \times Male$	0.2506	0.2592	0.2592	0.2602		
	[0.0457]***	[0.0461]***	[0.0461]***	[0.0472]***		
$SteadyPartner \times Female$	0.3151	0.317	0.317		0.3104	0.311
	[0.0425]***	[0.0428]***	[0.0428]***		[0.0427]***	[0.0429]***
$ISCED: UNI$	-0.0011	-0.0287	-0.0287	-0.2417	0.1314	0.1272
	[0.0638]	[0.0646]	[0.0646]	[0.0943]**	[0.0894]	[0.0899]
$ISCED: HigherSecondary$	-0.0423	-0.0455	-0.0455	-0.1606	0.0394	0.0419
	[0.0320]	[0.0322]	[0.0322]	[0.0468]***	[0.0447]	[0.0448]
$ISCED: notreported$	-0.0068	-0.0099	-0.0099	0.0173	-0.0286	-0.0347
	[0.0669]	[0.0672]	[0.0672]	[0.0991]	[0.0914]	[0.0917]
$Number\ of\ doctor\ visits$	-0.0073	-0.0072	-0.0072	-0.0083	-0.0063	-0.0062
	[0.0006]***	[0.0006]***	[0.0006]***	[0.0008]***	[0.0008]***	[0.0008]***
$ln(EquivalentIncome)$	0.155	0.1494	0.1494	0.1615	0.1482	0.1427
	[0.0207]***	[0.0208]***	[0.0208]***	[0.0339]***	[0.0262]***	[0.0263]***
$uemp * D: < 2\ months$	-0.6986	-0.9537	-0.9537	-1.2848	-0.4993	-0.6553
	[0.0496]***	[0.0715]***	[0.0715]***	[0.1075]***	[0.0692]***	[0.0953]***
$uemp * D: 2-5\ months$	-0.9139	-1.1778	-1.1778	-1.5516	-0.594	-0.7571
	[0.0897]***	[0.1059]***	[0.1059]***	[0.1447]***	[0.1385]***	[0.1577]***
$uemp * D: 6-12\ months$	-0.832	-1.1101	-1.1101	-1.3707	-0.7008	-0.8659
	[0.0811]***	[0.0978]***	[0.0978]***	[0.1368]***	[0.1269]***	[0.1435]***
$uemp * D: 12-35\ months$	-0.9114	-1.2041	-1.2041	-1.5519	-0.7098	-0.8876
	[0.0509]***	[0.0733]***	[0.0733]***	[0.1091]***	[0.0719]***	[0.0993]***
$uemp * D: \geq 36\ months$	-0.8862	-1.1969	-1.1969	-1.5888	-0.6518	-0.8436
	[0.0759]***	[0.0936]***	[0.0936]***	[0.1368]***	[0.1085]***	[0.1294]***
$outlf$	-0.2998	-0.53	-0.53	-0.7867	-0.2062	-0.3485
	[0.0246]***	[0.0542]***	[0.0542]***	[0.0857]***	[0.0311]***	[0.0703]***
$semp$	0.0625	0.045	0.045	0.0015	0.0774	0.0703
	[0.0460]	[0.0459]	[0.0459]	[0.0639]	[0.0653]	[0.0658]
$regional\ unemployment$	-0.0045	-0.0015	-0.0015	0.0061	-0.008	-0.0067
	[0.0059]	[0.0060]	[0.0060]	[0.0090]	[0.0080]	[0.0080]
$F: somewhat\ concerned$	-0.1612	-0.3729	-0.3729	-0.4554	-0.1365	-0.2633
	[0.0180]***	[0.1164]***	[0.1164]***	[0.1753]***	[0.0273]***	[0.1541]*
$F: very\ concerned$	-0.4695	-1.19	-1.19	-1.502	-0.4137	-0.9175
	[0.0282]***	[0.0846]***	[0.0846]***	[0.1175]***	[0.0421]***	[0.1229]***
Observations	68622	68622	68622	32623	35999	35999
R^2	0.95	0.97	0.94	0.97	0.96	0.97

Note: Standard errors in parentheses. ***, **, * - statistically significant at 1, 5, 10%.
All specifications contain a full set of year dummies and are within transformed.
Default categories: $Age: 18-24$, $ISCED: Lower\ Secondary\ or\ less$, emp, $F: not\ concerned$

taneity. We calculate a compensating income differential of 3.3 log points for respondents who report to be somewhat concerned about their job security and 7.6 log points for very concerned individuals (see Table 6).

Thus, based on these estimates we can conclude that the size of the simultaneity bias is only slightly smaller when applying this alternative model specification instead of the preferred one reported in Table 3.

Table 6: Regression Results - Probit Adapted Linear Fixed Effects GMM Model - Full Polynomial in "First Stage"

	All I - FE GMM	Male II - FE GMM	Female III - FE GMM
$Age: 25-34$	-0.0182	-0.0546	-0.0004
	[0.0206]	[0.0313]*	[0.0275]
$Age: 35-44$	-0.0278	-0.0827	0.0033
	[0.0279]	[0.0414]**	[0.0378]
$Age: 45-54$	-0.0481	-0.1292	-0.0008
	[0.0341]	[0.0502]**	[0.0468]
$Age: 55-64$	-0.0711	-0.1312	-0.0451
	[0.0416]*	[0.0608]**	[0.0573]
$Number\ Children \times Male$	0.0284	0.0231	
	[0.0185]	[0.0189]	
$Number\ Children^2 \times Male$	-0.0089	-0.0081	
	[0.0058]	[0.0059]	
$Number\ Children \times Female$	0.0408		0.0379
	[0.0176]**		[0.0177]**
$Number\ Children^2 \times Female$	-0.0077		-0.0074
	[0.0051]		[0.0051]
$Steady\ Partner \times Male$	0.1409	0.1444	
	[0.0248]***	[0.0252]***	
$SteadyPartner \times Female$	0.1736		0.1629
	[0.0227]***		[0.0220]***
$ISCED: UNI$	0.0074	-0.1089	0.0904
	[0.0371]	[0.0543]**	[0.0511]*
$ISCED: HigherSecondary$	-0.0333	-0.1015	0.0147
	[0.0181]*	[0.0263]***	[0.0244]
$ISCED: notreported$	-0.0185	-0.004	-0.0321
	[0.0372]	[0.0550]	[0.0504]
$Number\ of\ doctor\ visits$	-0.0036	-0.0042	-0.0032
	[0.0003]***	[0.0004]***	[0.0004]***
$ln(EquivalentIncome)$	0.0754	0.0812	0.0736
	[0.0113]***	[0.0178]***	[0.0144]***
$uemp * D :< 2\ months$	-0.4902	-0.6456	-0.3544
	[0.0316]***	[0.0468]***	[0.0435]***
$uemp * D : 2-5\ months$	-0.5995	-0.7579	-0.4252
	[0.0492]***	[0.0646]***	[0.0772]***
$uemp * D : 6-12\ months$	-0.5633	-0.6812	-0.4562
	[0.0460]***	[0.0631]***	[0.0689]***
$uemp * D : 12-35\ months$	-0.6092	-0.7632	-0.4764
	[0.0323]***	[0.0475]***	[0.0450]***
$uemp * D :\geq 36\ months$	-0.5727	-0.7587	-0.4086
	[0.0418]***	[0.0604]***	[0.0592]***
$outlf$	-0.2754	-0.3845	-0.2053
	[0.0221]***	[0.0354]***	[0.0295]***
$semp$	0.0241	0.0046	0.0318
	[0.0247]	[0.0337]	[0.0360]
$regional\ unemployment$	-0.0035	-0.0017	-0.0051
	[0.0031]	[0.0046]	[0.0043]
$F: somewhat\ concerned$	-0.25	-0.2445	-0.2621
	[0.0388]***	[0.0565]***	[0.0523]***
$F: very\ concerned$	-0.5709	-0.7608	-0.3807
	[0.0383]***	[0.0535]***	[0.0544]***
Observations	68622	32623	35999
R^2	0.96	0.97	0.97

Note: Standard errors in parentheses. ***, **, * - statistically significant at 1, 5, 10%.
All specifications contain a full set of year dummies and are within transformed.
Default categories: $Age: 18-24$, $ISCED: Lower\ Secondary\ or\ less$, emp, $F: not\ concerned$