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Re-Employment Expectations and the Eye of Providence

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Abstract

Using a nationally representative panel dataset, this study investigates the extent and impact of systematic misconceptions of the currently unemployed concerning their statistical re-employment probability, affecting their labor market behavior in a sub-optimal way. Specifically, people with unemployment experience of 3 to 5 years significantly underestimate their objective re-employment probabilities as determined by the econometrician's all-seeing 'Eye of Providence'. Simply having information concerning the individuals' previous unemployment experience is sufficient to make more accurate predictions than the individuals themselves. People who underestimate their re-employment probability are less likely to search actively for a job and indeed more likely to exit the labor force. If re-employed, they are more likely to accept lower wages, work fewer hours, work part-time and experience lower levels of job satisfaction. This information can be used by employment agency case workers to counsel clients better and prevent client adverse behavior and outcomes.

JEL classification: J64, J01, D84.
Keywords: Job Insecurity, Re-employment Expectations, Prediction Errors.

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I. Introduction

One of the main goals of labor economics is to understand and predict individual choices, for example with respect to labor force participation, occupation, consumption, saving and education. Choices in the labor market are often intertemporal and usually made under uncertainty so that analyzing subjective expectations is crucial in understanding the heterogeneity in revealed preferences that is otherwise unexplained. As such, incorporating expectations into empirical economic models is likely to help us understand otherwise unexplained observed behavior.

Drawing conclusions about decision processes from revealed preference data may be difficult if the decision maker is not rational and may only have partial information about all possible outcomes. In that case, data on self-reported expectations may be useful to understand revealed choices and to validate assumptions about expectations (Manski, 2004).

One of the main uncertainties in the labor market context is job security and employability and it is the expectation about these that influences labor market choices. Perception of job security is usually defined in the literature as the expected probability of an employee to loose a job whereas perceptions of employability refer to the subjective probability of obtaining employment within a certain time frame once unemployed. Interestingly, the research in this area is rather scarce, although the psychological literature suggests that the observed rise in perceived job insecurity in recent years has detrimental effects on health (physical and mental), employees' job attitudes and consequently job satisfaction (Sverke et al. 2002; Cheng and Chan 2008). Most previous research in this area has analyzed how an employee forms unemployment expectations: the source of information forming the basis of the expectation. Some have investigated whether the unemployment expectations convey useful information by analyzing whether they are actually related to unemployment experience. Few researchers have connected unemployment expectations with other labor market outcomes, aside from the realization of the expectation itself.

Only a handful of studies have looked at the re-employment expectations for the unemployed, although several studies have shown that unemployment is one of the life events that is associated the strongest with decreases in well-being as measured by subjective self-evaluated life satisfaction questions in surveys (Kassenboehmer and Haisken-DeNew, 2009). Very little is known about the formation of re-employment probabilities and the divergence in subjective and objective re-employment probabilities for the unemployed. Any discrepancy in these two would likely have significant implications for the well-being of the unemployed, their search behavior, their reservation wages and might alter these in a sub-optimal manner. Misconceptions, i.e. overconfidence, concerning re-employment probabilities might result in suboptimal job search effort or unrealistic reservation wages.

To our knowledge, there is no comparable study that explicitly looks at re-employment expectations such as ours. Using data from the German Socio-Economic Panel (SOEP), the longest running household panel in the EU, this paper closes this research gap by investigating whether the unemployed are able to predict their re-employment probabilities accurately or whether there is a divergence between subjective and objective re-employment probabilities, leading to a variety of sub-optimal labour market outcomes. More specifically, this paper investigates the following research questions: (1) What are the determinants of re-employment expectations? (2) What informational content is found in subjective re-employment expectations? (3) What are the determinants of prediction errors? What are the characteristics of the people who make prediction errors and how large are the prediction errors? (4) What critical information about the individuals is needed so that they can make better predictions? (5) Do these prediction errors lead to adverse behavioral changes? Because this rich data set identifies the respondents' stated *subjective* expectations *and* allows identifying the model-driven *objective* probabilities through the econometrician's all-seeing 'Eye of Providence', this analysis offers a unique contribution to the literature.

Unknown to the respondents themselves, our 'Eye of Providence' finds that people with previous unemployment experience of 3 to 5 years significantly underestimate their actual re-employment probabilities. In fact, our model performs better on average at predicting re-employment than the individuals themselves. The only information needed about the individuals to make significantly better predictions on average is their previous career total unemployment experience. This information would typically be available to all employment agency case workers. Underestimation is also found to be related to subsequent behavioral changes. People who underestimate their re-employment probability are more likely to exit the labor force and less likely to search actively for a job. If re-employed, they are more likely to accept lower wages, work fewer hours, work part-time and experience lower levels of job satisfaction. This information can be used in employment agencies to inform clients directly and prevent adverse behavior.

II. Related Literature and Background

Since the early 1990's questions regarding respondents expectations about certain life events have been added to surveys (Manski, 2004). Using these new variables, economic research has, for example, analyzed the divergence between subjective life expectancy and actual mortality such as in Hurd and McGarry (2002) or Smith et al. (2001).

In past labor economics research, subjective expectations and their divergence from actual realizations have mainly been analyzed in the context of income expectations such as the studies by Jappelli and Pistaferri (2010), Dominitz and Manski (1997b), Kaufmann and Pistaferri (2009) or Jappelli and Pistaferri (2000).

Another strand of the literature has investigated the subjective perceptions of job insecurity where job insecurity is measured by questions for the employed regarding their subjective job loss expectations and sometimes also by questions on expectations of re-employment in case of a hypothetical lay-off. Most of these papers have analyzed whether unemployment expectations for the employed are related to certain observable characteristics of the individual, to job characteristics or whether they largely convey unobserved information.

Previous research found that job insecurity (as measured by unemployment expectations questions and sometimes additional re-employment expectations of the employed for a hypothetical layoff) is related to past unemployment experience (also Campbell et al., 2007; Green et al., 2001) and type of employment contract (Green, 2003; Green et al., 2001). Campbell et al. (2007) also find that unemployment experience of a close friend and other objective indicators of insecure jobs are related to perceived job insecurity. Also unemployment in the external labor market was found to influence individual's unemployment expectations (Green et al., 2000; Linz and Semykina, 2008). Perceptions of job security were found to be higher for women (Green, 2009), for individual's with higher levels of education (Dominitz and Manski, 1997a; Green, 2009; Linz and Semykina, 2008; Manski and Straub, 2000), higher supervisory responsibilities (Linz and Semykina, 2008), more tenure (Bender and Sloane, 1999) and older individuals (Green, 2009; Linz and Semykina, 2008).

There are significantly fewer papers that have compared unemployment expectations with actual realizations to assess whether subjective unemployment expectations convey useful information. All of these papers found that subjective unemployment expectations are strong predictors of unemployment experiences in the near future, even when other job and individual characteristics are accounted for, such as Green (2011), Green et al. (2001), Stephens (2004), Campbell et al. (2007) and Dominitz and Manski (1997a).

Only a handful of studies have analyzed perceived employability of the unemployed. Dickerson and Green (2012) mainly look at unemployment expectations but also at re-employment expectations, although in lesser detail. They show that the re-employment expectations are related to finding a job, both for Germany (using the German Socio-Economic Panel (SOEP)) and Australia (using the Household, Income and Labour Dynamics in Australia (HILDA) Survey). Green (2011) analyzed how subjective re-employment probabilities for the unemployed modify the impacts of unemployment on life satisfaction and health for example.

Apart from these findings, little is known about the formation and validity of re-employment expectations. This paper will build on the analysis by Dickerson and Green (2012) in several ways. First, contrary to Dickerson and Green (2012), we use a variable in the SOEP that specifically asks the unemployed and not the employed about their re-employment expectation. Dickerson and Green (2012) use a variable that asks the employed about their concern of re-employment in the hypothetical event of a lay-off. They then restrict the sample to individuals who indeed lost their jobs. Hence they have to restrict their sample to individuals with a short time in unemployment and who could be observed in employment prior to the unemployment spell. Furthermore, this variable they use for the analysis with the German data only has categorical outcomes (easy, difficult, almost impossible), although they show using the Australian data that numeric cardinal scales perform better at predicting subsequent re-employment than verbal ordinal scales. These limitations prevent them from exploring re-employment probabilities in more detail.

Second, this paper investigates how re-employment expectations are formed and third who makes prediction errors. This will allow us to draw some important policy conclusions about which people need to be informed about their potential misconception in order to prevent those individuals from basing their labor market decisions and behavior on these misconceptions.

Another important contribution of this paper will be to investigate the extent to which researchers can make better predictions than the individuals themselves based on objective information readily available about the individuals. We also show that efforts to prevent these misconceptions may be important, as they impact negatively on individuals' actual behavior in the labor market and on work satisfaction.

To our knowledge, there is no other comparable study that explicitly examines re-employment expectations in this manner and can make sufficiently comprehensive policy conclusions.

III. Data

The analysis is based on the German Socio-Economic Panel (SOEP)[1], a longitudinal representative panel dataset of private households in Germany starting in 1984. The SOEP re-interviews the same private households annually and thereby approximately 11,000 households and 20,000 people are sampled every year. Data from the SOEP is used as it is ideal for analyzing objective and subjective re-employment probabilities because there is information on both. The SOEP collects information on objective characteristics such as education, health and labor force status as well as subjective information like opinions on several domains or life satisfaction. Haisken-DeNew and Frick (2005) and Wagner et al. (2007) describe the SOEP in detail.

The focus in this project is on the question concerning subjective expectation about re-employment of the unemployed: 'How likely is it that you start paid work within the next two years?' The responses range on an 11-point scale from 0 percent to 100 percent.

The years 1999-2009 in two year intervals are used since the subjective re-employment probability is only asked in these waves. For any period, the two subsequent years will

[1] We use version 28 of the SOEP, DOI: 10.5684/soep.v28. The data used in this paper were extracted using the Add-On package PanelWhiz v4.0 (Oct 2012) for Stata. PanelWhiz was written by Dr. John P. Haisken-DeNew (john@panelwhiz.eu). The PanelWhiz generated DO file to retrieve the HILDA data used here and any Panelwhiz Plugins are available upon request. Any data or computational errors in this paper are our own. Haisken-DeNew and Hahn (2010) describe PanelWhiz in detail.

be used to estimate the 'objective' probability that someone will be employed within the next two years after his initial unemployment status. This analysis only focuses on individuals who are observed to be unemployed, actively looking for work (they reported that they would be able to immediately take up a suitable position or actively sought work within the last 4 weeks - the official International Labour Organization (ILO) definition of unemployed and still in labor force)[2], between 16 and 64 years of age and not self-employed. Of these 3308 person-year observations, we drop 596 observations because they exit the labor market in t+1 or t+2. We apply this restriction because the estimates should not be biased due to anticipated behavioral changes.[3] We lose another 628 observations because we do not observe the employment status of the person in time t+1 and t+2. We loose another 419 observations due to missings in the control variables. This leaves us with 1665 person-year observations.

Standard Control Variables.— We account for a number of factors that have been found to be important determinants of subjective and objective re-employment prospects. More specifically, we control for similar variables as in Dickerson and Green (2012): (1) socio-demographic characteristics such as gender, age (and its squared) and education; (2) previous unemployment experience (total length of unemployment in years over the respondent's career); and (3) characteristics of the last job such as whether the person was previously working in the private sector, whether the person was temporary employed and information on the size of the company (indicator for 20 or more persons at the previous workplace).

[2] ILO definition of 'unemployed' can be found at http://stats.oecd.org/glossary/detail.asp?ID=2791.

[3] We also re-do the analysis with the people who exit the labor force as a sensitivity test and refer to this in more detail in the relevant results sections. The results are not sensitive to this.

We additionally account for other characteristics of the previous job that are likely to influence subjective and objective re-employment prospects such as last labor income, type of last occupation[4], industry[5] and socio-economic status of the previous job[6] .

We also account for the total number of years of work experience of the respondent (full-time and part-time separately) as well as the local unemployment rate which varies between federal states and over time. We also control for a range of other demographic characteristics that are likely to influence subjective and objective re-employment prospects such as marital status, home ownership and whether the respondent has children.

Personality Control Variables.— Finally, we also control for individuals' so called 'Big 5' personality traits (which measure five different personality dimensions) and locus of control which should capture some of the otherwise unobserved heterogeneity in subjective and objective re-employment prospects. It has been shown for example that personality traits related to neuroticism are predictive of labor market outcomes (Almlund et al., 2011). People with an internal locus of control or with higher self-esteem for example are found to search more for a job (Caliendo et al., 2014). Similarly, conscientiousness, is found to be related to performance and wages (Almlund et al., 2011).

The 2005 and 2009 waves contain questions on the respondent's personality based on the Five Factor Model developed by McCrae and Costa (1985) and Costa and McCrae (1992). The Five Factor Model measures five basic psychological dimensions: openness to experience, conscientiousness, extraversion, agreeableness, and neuroticism. A short 15 item version is implemented in the SOEP based on the 25 item measure by John et al. (1991) (Gerlitz and Schupp, 2005). Each of the five components of the Five Factor Model

[4]Last occupation is based on the International Standard Classification of Occupations (ISCO-88, International Labour Organization (ILO), 2014) and grouped into 7 categories: (1) Legislators, senior officials, managers and professionals; (2) Technicians, associate professionals; (3) Clerks, service and shop and market sales workers, skilled agricultural and fishery workers, craft workers and related trade workers; (4) Plant and machine operators and assemblers; (5) Elementary occupations (base category).

[5]Last industry is based on the Statistical Classification of Economic Activities in the European Community (European Commission, 2014) and grouped into 14 categories: (1) Agriculture, forestry and fishing and mining and quarrying; (2) Manufacturing, electricity, gas, steam and air conditioning supply and water supply, sewerage, waste management and remediation activities (base category); (3) Construction; (4) Wholesale and retail trade, repair of motor vehicles and motorcycles; (5) Accommodation and food service activities; (6) Transportation and storage; (7) Information and communication; (8) Financial and insurance activities and real estate activities; (9) Professional, scientific and technical activities; (10) Public administration and defense and compulsory social security; (11) Education; (12) Human health and social work activities; (13) Arts, entertainment and recreation; (14) Other activities.

[6]The Standard International Socio Economic Index of Occupational Status (ISEI) measures the socio-economic status of a person. It was developed based on information about income, education, and occupation (7 categories of profession based on the ISCO88 code) by Ganzeboom et al. (1992).

is represented by three items. Gerlitz and Schupp (2005) show the internal consistency and validity of the short version. We confirm the five component structure by conducting a principal component analysis for the years 2005 and 2009, restricting the principal component analysis to finding 5 components.[7] Each of the components indeed represents one of the five personality factors with the three relevant items loading highly on the relevant factor. We follow Gerlitz and Schupp (2005) and predict the first five components for the years 2005 and 2009. We then average over 2005 and 2009 if information in both waves is available to reduce measurement error as in Cobb-Clark et al. (2014) and Cobb-Clark et al. (2013). The final variables are standardized over 2005 and 2009 to have mean 0 and standard deviation 1.

Locus of control is a psychological concept capturing individuals beliefs about the extent to which future outcomes are determined by his or her own actions as opposed to external factors. Those with an external locus of control generally believe that what happens to them in life is outside their own control (and mainly due to fate, luck, other people, etc.), while those with an internal locus of control believe that their own actions determine to a large extent what happens to them in life (Rotter, 1966; Gatz and Karel, 1993). Questions on locus of control were asked in 1994-1996, 1999, 2005 and 2010. However, the locus of control items are not consistent over time. We therefore use the 2005 and 2010 locus of control questions only that fall into the analysis period and which are consistent over time.[8] After rescaling the variables so that they are increasing in internal control tendencies, principal component analysis is conducted for the years 2005 and 2010. We then average over 2005 and 2010, if information in both waves is available to reduce measurement error (as in Cobb-Clark et al., 2014 and Cobb-Clark et al., 2013). Cobb-Clark and Schurer (2013) show that locus of control is stable over time and not affected by a series of life events. The final variables are standardized over 2005 and 2010 to have mean 0 and standard deviation 1.

[7]We reverse the scores of the 7-point Likert scale for some items as in Heineck and Anger (2010) so that a higher score corresponds to the relevant personality type.

[8]For more information on the specific locus of control questions in the SOEP, compare Heineck and Anger (2010).

IV. Empirical Application

This empirical application aims to identify the determinants of re-employment expectations; the value-added over and above objective indicators that additional subjective information might offer; the characteristics of the people making prediction errors or accurate predictions and the extent to which people, on the basis of incorrect predictions, make suboptimal behavioral responses. These could take the form of reduced job search effort, exiting the workforce, accepting inappropriately lower paid jobs, or few work hours and therefore experiencing reduced job satisfaction.

Examining wholistically the issue of subjective and objective unemployment probabilities, this section outlines the estimation strategy and results for: (A) the determinants of expectation formation, (B) the interplay between subjective and objective re-employment probabilities, (C) reconciling prediction and realization, and (D) quantifying adverse behavioral responses to incorrect subjective predictions, potentially taking the form of reduced job search effort, exiting the workforce, accepting inappropriately lower paid jobs, or few work hours and therefore experiencing reduced job satisfaction.

Although information on how re-employment expectations are formed is important to understand observed behavior of the unemployed in the labor market, there is a lack of research in this area. The only comparable study by Dickerson and Green (2012) shows that subjective re-employment expectations are predictors of future labor market outcomes, without quantifying this effect or looking at subsequent behavioral responses. Understanding however who makes prediction errors and how to improve individual's expectations is important to prevent a group of people of inappropriately accepting jobs with lower wages, fewer work hours or to exit the labor market completely. This has important welfare implications as an involuntary job loss has been shown to decrease individual life satisfaction levels significantly (Kassenboehmer and Haisken-DeNew, 2009) and unemployment rates in general are positively related to inequality and poverty. Apart from these social costs, there are also economic costs to the government as an unnecessary reduction of the workforce diminishes tax revenues and may increase welfare reliance, therefore potentially increasing government borrowing.

If people indeed underestimate their re-employment probabilities and this induces sub-optimal behavior in the labor market, policy measures need to be developed to increase participation rates.

The combined results from sections (A) to (C) will not only inform on the predictive power of subjective re-employment expectations, but also shed light on the group of people that make prediction errors and for whom these errors may be so severe such that this could influence labor market behavior. Section (C) also provides information on what information is needed of an individual, such that job agencies can help individuals to make better, more accurate, predictions. Section (D) shows that policy measures to prevent prediction errors may help to reduce adverse effects of prediction erros.

A. Re-Employment Expectation Formation

Estimation.— In a first step, the analysis examines how re-employment expectations are formed:

$$\begin{aligned} SubProb_{it} &= \alpha + X'_{it}\beta + \varepsilon_{it} \\ \varepsilon_{it} &= \mu_i + \nu_{it} \end{aligned} \tag{1}$$

where the dependent variable is the subjective self-reported re-employment probability for the unemployed, X'_{it} represents a vector of control variables (consisting of socio-demographic characteristics, labor market history, external labor market characteristics, previous job characteristics and personality traits as explained in the previous section), ε_{it} is a composite error term that consists of an individual-specific random effect μ_i and an idiosyncratic error ν_{it}. Standard OLS models are estimated as well as correlated random effects (CRE) models, in which μ_i is allowed to be correlated with the explanatory variables of the form $\mu_i = \overline{x_i}\eta + \vartheta_{it}$ (Mundlak, 1978) in order to control for unobserved heterogeneity. This first step provides information on what objective information individuals form their re-employment expectation.

Results.— We estimate 3 specifications as shown in Table 1: (1) an OLS model, (2) an OLS model with random effects and (3) a correlated random effects model. Several socio-demographic variables are found to be related to a perceived higher re-employment probability if unemployed. The strongest relationship is found for gender: Men on average expect a 6 percentage points (%-points) higher probability of re-employment than women. This relationship holds even if we control for fixed unobserved heterogeneity in column (3). The positive association between home ownership and the perceived re-employment probability as well as the positive relationship between education and the perceived re-employment probability disappears once we move to the random effects model. Similarly, the negative association between marriage and the perceived re-employment probability disappears once we control for the individual-specific averages of the control variables, suggesting that these variables are correlated with some fixed unobserved characteristic. We also find a significant relationship between age and the perceived re-employment probability which is inversely u-shaped (maximum of approximately 30 and negative effects starting at around age 55).

[**Insert Table 1 here**]

The labor market history variable that is associated the strongest with the perceived re-employment probability is the previous unemployment experience. People with an unemployment experience accumulated over their life time of about 5 or more years expect a 9.6 %-points lower re-employment probability than individuals without previous unemployment experience (column 3). Full-time work experience is positively related to the re-employment probability, but insignificant in the correlated random effects specification as standard errors are high. Having 10 or more years of tenure is associated with lower expected re-employment probabilities of around 8.3 %-points (significant, column 1) to 0.9 %-points (insignificant, column 3).

Although a higher unemployment rate in general is found to be associated with lower re-employment expectations, this result seems to be driven by unobservables as the coefficient becomes small and insignificant in the correlated random effects specification.

Interestingly, many of the characteristics of the previous workplace do not seem to influence the expected re-employment probability. Agricultural/craft workers (machine operators) are significantly more optimistic than those in elementary occupations as they have a 8 %-points (16 %-points) higher re-employment expectation.

Personality traits are strongly and significantly correlated with re-employment expectations. A 1 standard deviation increase in openess to experiences is associated with a 2 %-points higher re-employment expectation; a 1 standard deviation increase in agreeability with a 1.5 %-points lower re-employment probability and a 1 standard deviation increase in locus of control with a 1.7 %-points higher re-employment probability.

Robustness Check.— The results in general hold when those who exit the labor force are included in the regressions. If anything, the relationship between previous unemployment experience and re-employment expectations becomes stronger and even significant at the 99%-level in the correlated random effects specification. Interestingly, conscientiousness displays a significant effect once those who drop out of the labor force are included, whereas the coefficient of openness to experience is reduced in magnitude and is rendered insignificant in the correlated random effects specification. This reflects the fact that those who drop out of the labor force have generally lower levels of conscientiousness and openness to experience and also lower expectations than those who remain in the labor force.

Summary.— The analysis demonstrates that unemployed females, unemployed with many years of unemployment experience, as well as people who are less open, more agreeable and have low levels of locus of control, are more pessimistic. Also people in elementary occupations are more pessimistic in their re-employment prospects than in other occupations (craft workers or machine operators).

B. *Re-Employment Expectations and Realizations*

Estimation.— In a second step, we will investigate whether an individuals' subjective re-employment expectation is related to the actual realization of re-employment. Therefore the following logit model is estimated where the dependent variable is a binary indicator that equals 1 if the individual is observed to be employed in $t+1$ and/or $t+2$:

$$Pr(employed_{t+1,t+2} = 1|X) = \Delta(\alpha_1 + W_{it}'\delta + X_{it}'\beta + \varepsilon_{it}) \tag{2}$$

where $W_{it}^{'}$ represents a vector of five dummy variables for the subjective re-employment probability (10-20%, 30-40%, 50-60%, 70-80%, 90-100%). Including control variables $X_{it}^{'}$

allows one to make statements about whether the subjective re-employment probabilities reported by the respondents offer any additional information over and above the observed characteristics of the individual. In other words, one can answer the question whether individuals know more about their re-employment than what researchers can observe.

In a further step, the analysis will investigate whether individuals on average are better at predicting their re-employment or whether we as researchers can make better predictions based on the observables (excluding the self-reported subjective re-employment probabilities). We will therefore compare prediction-realization tables for the subjective predicted self-reported information and for the model based predicted probabilities (prediction of the dependent variable in equation (2)). Prediction-realization tables compare the prediction from a model with the actual realization.

As the percentage of total predictions can be misleading if one of the outcomes is particularly likely (Veall and Zimmermann, 1992), we will adopt a method suggested by Veall and Zimmermann (1992) who show that to measure performance, McFaddens σ_n (McFadden et al., 1977), performs best:

$$\sigma = p_{11} + p_{22} - p_{.1}^2 - p_{.2}^2 \tag{3}$$

$$\sigma_n = \sigma/(1 - p_{.1}^2 - p_{.2}^2) \tag{4}$$

where p_{ij} are the entries of the prediction-realization table with expectation j and realization i. The number $p_{.i}$ represents the fraction of times alternative i is predicted. As the realization is binary (employed/unemployed), we employ several alternative cut-off values to transform the subjective re-employment probability and the model based predicted probability from equation (2), which are on a scale from 0 to 100%, into a binary variable and calculate σ_n for all alternative prediction-realization tables.

We then determine the minimum amount of information that is needed about an individual to be able to make a more accurate prediction about the individuals future prospects than the individual is able to make himself. This will be done by calculating σ_n for the predictions from equation (2) which result from all the different possible combinations of control variables and finding the combination that produces a σ_n that is (significantly) larger than the σ_n for the prediction-realization table based on the self-reported expectation.

Results.— Table 2 shows the results of the labor force status model where the dependent variable is a binary variable that equals 1 if the respondent is employed in t+1 and/or t+2 and 0 otherwise.

The first column merely controls for the self-reported re-employment expectations. The higher the expectation, the higher the actual re-employment probability. People with a personal expectation of 70 - 80% for example, have a 23 %-points higher re-employment probability than people who do not expect to be re-employed in the near future.

Column (2) controls for the same or very similar variables as in Dickerson and Green (2012). This reduces the size of the effects and only an expected re-employment probability of 70 - 80% and 90 - 100% (compared to a re-employment expectation of 0%) remains significantly associated with actual re-employment in the future.

We move to column (3) where we control for a more extensive set of information about the individual's characteristics as described in Section 3. Now an expected re-employment probability of 70 to 80% is no longer significant and the coefficient for a 90 to 100% re-employment expectation is reduced, although not significantly. Controlling also for individuals' 'Big 5' personality traits and locus of control in specification (4) reduces the size of the coefficient furthermore. The coefficient becomes very small and insignificant in column (5) when we estimate the correlated random effects model where the individual specific means of the control variables are included to reduce unobserved heterogeneity in the estimates.

[Insert Table 2 here]

These results indicate, the additional information that the subjective perceptions hold are fairly limited. Once a basic set of controls is added, there is only additional information for the 90 to 100% re-employment expectation. Furthermore, this correlation is completely absorbed in the unobserved fixed effects correlated with the time varying control variables in the CRE specification.

The measures-of-fit statistics at the end of the table also indicate that the model fit could be increased due to the inclusion of further controls as well as random effects and correlated random effects (McKelvey and Zavoina's R2 increases from 0.146 to 0.557 for example).

Figure 1 graphs the actual re-employment probability (on the vertical axis) against the ordinal response categories of the self-reported probability (blue line), and the predictions of specifications (2) to (5) of the labor force status model (excluding the self-reported expectations in the prediction). The dashed line is the 45° line and denotes perfect prediction. The black line is our preferred prediction from the correlated random effects model and it can be seen that is is very close to the 45° line. The prediction from the other specifications seem to perform reasonably well for re-employment probabilities of 30% and above, but are less accurate at the lower end of the distribution. Especially moving from specification (3) to specification (4) where we also control for personality traits, improves the fit at the low end of the distribution.

[Insert Figure 1 here]

The blue line lies above the 45° line for self-reported probabilities of 50% and below, indicating that there are some people who consistently seem to underestimate their re-employment probability. The bottom part of Figure 1 shows the self-reported probability and the prediction from specification (5) from the top part of the graphic but including confidence intervals. This shows that at the bottom of the distribution our prediction is often significantly better than the perception of the individuals themselves (where the confidence intervals do not overlap). In any case, the 45° line lies within the confidence interval of our prediction based on specification (5) from Table 2, suggesting that our model on average is able to make better predictions than individuals themselves.

We test this formally as presented in Table 3 by comparing prediction-realization tables for subjective self-reported expectations with the different predictions of our specifications in Table 2. This allows calculating McFaddens σ_n (McFadden et al., 1977) which indicates the performance of the prediction. In order to do so, the ordered response categories of the self-reported expectations as well as the predictions from our labor force model (excluding the self-reported expectations as regressors) have to be recoded to a binary 0/1-variable to compare the prediction with the actual realization in t+1 and t+2 which is also a binary variable (employed vs. unemployed). We choose a cutoff value of 60% to do so, so that values of 60 and above are assumed to be expectations for future employment whereas values below 60 are assumed to be expectations of unemployment.[9]

[Insert Table 3 here]

The numbers in the first two rows in Table 3 show the fraction of correct predictions for each combination of realization i (0=unemployed, 1=employed) and expectation j (0=unemployed, 1=employed). The row below that shows the performance measure σ_n (row labeled 'McFaddens' σ_n') with the 95% confidence interval in square brackets.

Table 3 shows that even σ_n for the predictions from the baseline model (2) is higher – although not significantly higher – than σ_n for the self-reported expectations (last two columns). Once we include personality traits in the model for the prediction, as in specification (4) of Table 2, the performance measure is significantly higher, indicating that our model on average can predict the individuals' future labor market outcomes better than the individual's themselves. McFaddens' σ_n is especially high for the prediction from the correlated random effects model of specification (5) in Table 2 (0.58 compared to 0.30).

The results remain the same when we consider another performance measure as a sensitivity check in the last two rows, δ_n, which was shown to perform second to McFaddens σ_n (Veall and Zimmermann, 1992).[10]

As a next step, we rerun the correlated random effects labor force model with every possible combination of control variables and calculate σ_n for all estimation results to find the minimum amount of information needed about the individual to make a better prediction on average than the individuals themselves. The top part of Table 4 shows that there is only one variable needed to make a significantly better prediction than the individuals themselves and that is previous unemployment experience (Panel A).

[9] Sensitivity tests around this cutoff value were conducted where σ_n for all possible prediction-realization tables for all different cutoff values for the predictions were calculated as shown in Appendix Table A2 (for the self-reported probability) and A3 (for the prediction based on the correlated random effects model). Appendix Table A4 and A5 report an adjusted σ_n, where σ_n is multiplied by n^2/N^2 – the squared proportion of used observations in the prediction-realization-table compared to the total number of observations – in order to adjust for the fact that dependent on the cutoff value not all observations are used. The tables show that adjusted σ_n is maximized at our chosen cutoff value of 60.

[10] $\delta_n = (p_{11}p_{22} - p_{12}p_{21})/[(p_{11} + p_{12})(p_{21} + p_{22})]$ as in Veall and Zimmermann (1992).

Panel B shows all combinations of two variables (excluding the previous unemployment experience) to achieve a prediction that is as good as the prediction based on the self-reported expectation information. A significantly better prediction cannot be achieved with two variables without the unemployment experience. If previous unemployment experience is not known, ideally one would have information on age and the last occupation to make a prediction as accurately as the individual. The bottom panel (Panel C) shows that at least 7 variables are needed to make a significantly better prediction than the individuals themselves if the unemployment experience is unknown.

Robustness Check.— Because the question on re-employment used as the dependent variable does not mention the quality of the next employment, it is unclear how people interpret the question. It could be that some people state their expected re-employment probability with respect to a job of equal quality as the previous one. We investigated whether the results changed in this section when re-employment is defined as finding a job with equal (within 2 standard deviations) ISEI status as the previous one. This does not change the results qualitatively.[11]

The results in Table 3 are based on in-sample predictions, but are similar when out-of sample predictions are conducted. We selected at random two thirds of the original sample for the estimation of the coefficients of the labor force model and the other one third for the out-of-sample prediction and the calculation of the performance measures σ_n. This exercise was performed 100 times based on 100 random samples for which an average performance measure for each prediction from specifications (1) to (5) could be calculated. The results are robust to out-of sample predictions. While the performance measure σ_n is slightly reduced in our preferred specification 5 (from 0.58 to 0.48), the confidence interval indicates that it remains that we as researchers can make significantly better predictions than the individuals themselves.

We also test the sensitivity of the results to a sample where the people who drop out of the labor force are included. The coefficients for having high re-employment expectations as opposed to zero re-employment expectations in Table 3 increase in size as one would expect when we include people with low expectations who will not be re-employed. As we have restricted our analysis to people who would be able to start working immediately

[11]Furthermore, the results are also stable to the exclusion of individuals who were never observed in employment in the dataset.

and who are actively looking for a job, it seems likely that the negative relationship between expectations and exiting the labor force is observed due to people exiting the labor force because they have low expectations and not because they already know that they want to drop out, otherwise they would not be in our sample of people actively looking for work. This underlines the importance of restricting the analysis to people who do not exit the labor force as we do not want behavioral responses to influence our predictions because they should only reflect the objective chance a person has on the labor market. The relationship between the subjective re-employment expectations and actual re-employment realizations remain relatively small and insignificant in our preferred Mundlak (CRE) specification for this larger sample of individuals. The performance measure σ_n for this specifications is again significantly higher than σ_n for the self-reported prediction, indicating that we as researchers make better predictions.

[**Insert Table 4 here**]

Summary.— Our results indicate that the additional contribution of the subjective re-employment probabilities in comparison to objective information observed by job agencies for example is limited: Only those who are very certain that they will be able to regain employment within the next two years know more than their objective characteristics might suggest to an econometrician. We have established that especially among those who have low re-employment expectations, underestimation is quite common and that on average we are able to make more accurate predictions about the individuals' re-employment if we simply knew the individuals' past unemployment experience. In order to develop policy recommendations, one has to identify the group of people who are more likely to making (severe) errors than others so that specific policies can be targeted to these people. This will be done in the next section.

C. Re-Employment Prediction Errors

Estimation.— We estimate an ordered logit model where the dependent variable y_j has 3 categories (m=underestimation; exact estimation and overestimation) and X_{it} is a set of control variables as described in Section III:

$$Pr(y_j = m) = Pr(\kappa_{m-1} < \alpha_1 + X'_{it}\beta + \varepsilon_{it} \leq \kappa_m) \tag{5}$$

where κ_m's are the 3 parameter estimates of the cut-point thresholds, transforming the continuous latent variable into the 3 categories.

This will provide insight about the group of people that potentially need to be informed about their re-employment prospects to counteract adverse effects of this misconception on their behavior.

Underestimation means that someone did not think he would be re-employed within the next two years (expectation of 50% or below), but was actually re-employed within the next two years; overestimation means that the person thought he would be re-employed (expectation of 60% or above) whereas he actually was not and exact estimation occurs if someone thought he would get a job and did get a job or did not expect to get a job and indeed was still unemployed two years later.

As this analysis cannot tell us anything about the actual size of the prediction error, we next move on to investigate who is susceptible to making especially big errors, regardless of the absolute size of the subjective re-employment expectation. This is done by calculating the difference between the subjective self-reported re-employment expectation and the objective re-employment expectation based on the prediction of the labor force model in Table 2 specification (5) (excluding the subjective expectations). As was shown in Figure 1 and the previous analysis, this prediction performs very well in predicting re-employment. Hence we assume that this prediction is equal to the underlying true re-employment probability.[12]

We investigate the determinants of the prediction error along the entire prediction error distribution as we suspect there could be differential effects dependent on whether you are at the top of the distribution and overestimated the re-employment probability or at the bottom and underestimated re-employment chances.

We apply the unconditional quantile regression method recently developed by Firpo et al. (2009) in order to estimate marginal effects at various quantiles of the overall prediction

[12] As a sensitivity test, we also use as the dependent variable the difference between the actual re-employment observation (0 or 100%) and the self-reported expectations. The results do not change qualitatively.

error distribution. This allows us to interpret the marginal effects with respect to the prediction error distribution $F(\textit{prediction error})$ and not the distribution of prediction errors conditional on prediction error determinants X as in the classic conditional quantile regression developed by Koenker and Bassett (1978) : $F(\textit{prediction error}|X) = F(\epsilon)$.[13]

The method by Firpo et al. (2009) estimates OLS on a transformed dependent variable. This transformation is called 'recentered influence function' and reweighs the dependent variable so that the mean of the reweighed variable corresponds to the quantile of interest.[14]

We estimate following unconditional quantile regression at each quantile τ where RIF is the recentered influence function described above[15] :

$$E[\text{RIF}(\textit{prediction error}_{it}; q_\tau)|X_{it}] \quad = \quad X'_{it}\beta^\tau + \epsilon^\tau_{it}. \tag{8}$$

Results.— The results of an ordered logit model where the dependent variable y_j has 3 categories (i=underestimation, exact estimation and overestimation) are presented in Table 5. Four variables can be identified that are related to making prediction errors. The first one is gender. It was shown in Section 4 that men were very positive with respect to their re-employment chances. Table 5 now shows that they seemed to be overly optimistic as being male is related to a 2.8 %-points higher probability of overestimating the re-employment probability compared to women.

Married people have a 6.7 %-points higher probability of underestimating their re-employment probability. Interestingly, people with an unemployment experience of 3

[13]This distinction is important as someone's conditional prediction error quantile may change as covariates change (Froehlich and Melly, 2010). Furthermore, someone who is in the 50th percentile of the prediction error distribution conditional on their IQ and other characteristics might be in the 75th percentile of the overall prediction error distribution (Borah and Basu, 2013).

[14]We use the program code from Firpo, Fortin and Lemieux (2009) provided at at http://faculty.arts.ubc.ca/nfortin/datahead.html.

[15]RIF at each quantile τ of the distribution of Y:

$$RIF(Y; q_\tau) = q_\tau + \text{IF}(Y; q_\tau). \tag{6}$$

with

$$\text{IF}(Y; q_\tau) = (\tau - \mathbf{1}\{Y \leq q_\tau\})/f_Y(q_\tau), \tag{7}$$

where q_τ is the value of the cumulative distribution of Y at the τth quantile and $f_Y(\cdot)$ is the marginal density function of Y.

to 5 years have a 8.8 %-points higher probability of underestimating compared to people with no unemployment experience.

Managers, professionals, technicians, clerks and service and shop workers are all more likely to underestimate their re-employment probabilities (ranging from 4 to 8 %-points).

People who are more agreeable are also more likely to underestimate their re-employment probability (a 1 std. dev. increase in agreeability increases the probability to underestimate by 2.2 %-points).

[Insert Table 5 here]

Table 6 provides more information on the determinants of the size of the prediction error at various points of the prediction error distribution, regardless of the absolute size of the subjective re-employment expectation. The prediction error was calculated by subtracting the subjective re-employment expectation from the model based predicted re-employment probability (from Table 2 specification (5), excluding the subjective expectations as predictors). Hence, the higher the prediction error, the more the person overestimates the re-employment probability. The more negative the prediction error, the more the person underestimate the re-employment probability. The 50%-decile corresponds approximately to a prediction error of 0 (correct estimation) as Figure 2 shows which graphs the prediction error distribution.

[Insert Figure 2 here]

Although being male is significantly positively related to a higher prediction error, Table 6 shows that this only plays a role for those who severely underestimate (hence being male reduces a severe underestimation). Being married and home ownership contribute to underestimating the re-employment probability along the entire prediction error distribution. Being married has an especially strong and negative effect at the bottom of the distribution, for those who severely underestimate their re-employment probability (-11 %-points)

Big contributors to underestimation along the entire distribution are having previously worked as a manager/professional, technician or associate profession, clerk or service or shop worker (8 %-points to 35 %-points increase in prediction error).

Locus of control plays a significant role for those who overestimate their re-employment probability. The more internal, the less likely to make a big overestimation error. Agreeability on the other hand seems responsible for a big underestimation of the re-employment probability.

We saw in Table 1 that especially unemployment experience of 3 years or more was significantly negatively associated with the subjective re-employment perceptions. Table 6 reveals that those with an unemployment experience of 3 to 5 years significantly underestimate their re-employment probability as already suspected in Table 5. Those with unemployment experience of 5 or more years on the other hand are more likely to overestimate their re-employment probability even though their reported subjective re-employment expectations are already the lowest among all respondents as was shown in Table 1.

[**Insert Table 6 here**]

Furthermore, if the local unemployment rate is high, this significantly increases the probability to severely underestimate the re-employment probability.

Summary.— This analysis identified which respondents are more likely to make prediction errors, hence who should be targeted by policy to prevent adverse behavior because they are in danger to underestimate their re-employment probability (subjective expectation of 50% or below but regained employment): Females[16], married people[17], certain occupations (especially managers/professionals[18], technicians[19] and clerks[20]), people with high levels of agreeability and people with unemployment experience of 3 to 5 years[21]. To prevent severe underestimation (prediction error in the bottom 25 percentile of the prediction error distribution where a more negative values means higher underestimation) regardless

[16] 47% of the unemployed are female.
[17] 53% of the unemployed are married.
[18] 7% of the unemployed are managers/professionals.
[19] 13% of the unemployed are tchnicians.
[20] 9% of the unemployed are clerks.
[21] 18% of the unemployed have previous unemployment experience of 3 to 5 years.

of the absolute size of the subjective re-employment expectation, one should additionally target people with any previous short-term unemployment experience below one year[22], those living in a high unemployment region, those with low ISEI status and those with high levels of agreeability.

Because it was shown in section (A) that especially those with high unemployment experience report very low re-employment probabilities, in section (B) that the only information needed to make a better prediction on average than the individuals themselves is the previous unemployment experience and now in section (C) that those with unemployment experience of 3 to 5 years are more likely to make a prediction error, it is important to target this group of people especially and inform them about their true re-employment probabilities.

In fact, almost 60% of those who have previous unemployment experience of 3 to 5 years underestimate[23] their re-employment probability. Almost 80% of those who have previous unemployment experience of 3 to 5 years and underestimate report a re-employment probability of 50% or lower. This underestimation results in social and economic costs as shown in this section. Targeting those with a previous unemployment experience of 3 to 5 years may be particularly efficient, not only because these are the ones who make large prediction errors, but also because a significant percentage of the sample - 18% - have an unemployment experience of 3 to 5 years, hence suggesting the largest impact for policy measures tailored to this specific group.

D. Behavioral Responses to Prediction Errors

Having established that prediction errors are indeed being systematically made and having identified the characteristics of the people who make prediction errors, the remaining question is whether these prediction errors have any behavioral consequences in actually changing any real outcomes. If so, it is important to inform people of their potential prediction errors in order to prevent them from making behavioral changes to their disadvantage.

[22] 22% of the unemployed have some previous unemployment below 1 year.

[23] Underestimation is defined as reporting a re-employment expectation below the re-employment expectation predicted from our labor force model in Table 2.

Estimation.— We investigate several types of behavioral responses that might occur among those who regain employment in $t+1$ or $t+2$: (1) accepting inappropriately low earnings as measured by gross labor income per month, (2) potentially having a lower probability to work full-time, (3) potentially working fewer hours and (4) having lower job satisfaction levels. The other two behavioral responses that are investigated are (5) exiting the labor force in $t+1$ or $t+2$ and (6) expending insufficient job search effort in t. People who underestimate their re-employment probability might be more likely to drop out of the labor force and might not actively search for work if they think that they have little chance of becoming re-employed.

We estimate the following equation:

$$\begin{gathered} BehavioralResponse_{it} = \alpha + \delta w_{it} + X_{it}'\beta + \varepsilon_{it} \\ \varepsilon_{it} = \mu_i + \nu_{it} \end{gathered} \tag{9}$$

where the dependent variable is one of the five behavioral response variables, X_{it}' represents a vector of control variables (consisting of socio-demographic characteristics, labor market history, external labor market characteristics, previous job characteristics and personality traits as explained in Section III), ε_{it} is a composite error term that consists of an individual-specific random effect μ_i and an idiosyncratic error ν_{it}. Correlated random effects models are estimated in which μ_i is allowed to be correlated with the explanatory variables of the form $\mu_i = \overline{x_i}\eta + \vartheta_{it}$ (Mundlak, 1978) in order to control for unobserved heterogeneity.

We estimate several versions of this model where the variable w_{it} is either the subjective re-employment probability (on a scale from 0 to 100%), a dummy variable for underestimation[24], or the prediction error itself. This will first inform us whether the subjective expectations are related to future behavioral responses, but also whether a prediction error increases the likelihood of a behavioral response.

In the case of the income, work hours and work satisfaction variable, equation (9) is estimated by OLS, otherwise by logit regression. As we are now investigating behavioral

[24] Underestimation is defined as 1 if a person reports a subjective re-employment expectation below our prediction of the re-employment probability based on Table 2 column (5) excluding the subjective re-employment probabilities. We also tested the sensitivity of the results to a definition of underestimation where the variable takes the value 1 if a person reported a subjective re-employment expectation of 50% or below but regained employment in t+1 or t+2. This did not change the results significantly.

responses, we also include the people in the analysis that will later drop out of the labor force in t+1 and t+2. These people had been excluded in the previous analysis because the results for the objective re-employment probability should not have been biased due to behavioral responses (the sample was restricted to individuals actively looking for work and able to start work immediately), increasing the sample size to 2680 observations. For the behavioral responses that relate to being re-employed in t+1 and t+2, we restrict the sample to those individuals who are re-employed in t+1 or t+2. This leaves us with 1154 observations.

Results.— Panel A of Table 7 shows the relationship between the subjective re-employment probability and the various behavioral responses (the same set of control variables are included as in Table 6). We see that the subjective re-employment probability is indeed related to all behavioral responses. If the subjective re-employment probability increases from 40% to 60% for example (by 20 %-points), this is related to a higher income of €60 (=3.0×20) per month, 2.2 %-points (=0.11×20 which is 3.4% of the average probability of gaining full-time employment) higher probability of being full-time employed, 0.6 more work hours per week (=0.03×20) and 0.1 point (=0.005×20) higher level of work satisfaction among those who regain employment in t+1 or t+2. A 20 %-point higher subjective re-employment probability is also related to a 1.8 %-point (=0.09×20 which is 8%) lower probability of exiting the labor force.

[**Insert Table 7 here**]

Panel B shows the relationship between an underestimation of the re-employment probability and the same behavioral responses. Among those who regain employment, having underestimated the re-employment probability is related to a monthly income that is €111 smaller, a 7 %-points (=11%) lower probability of being full-time employed and an average of 2.0 work hours lower per week. Work satisfaction is 0.1 points lower for those who underestimated and regained employment. Underestimation is also associated with a 7 %-point (=31%) higher probability to drop out of the labor force and negatively related to job search effort, although not significantly.

Panel C puts the size of the prediction error (positive prediction error=underestimation; negative prediction error=overestimation) in relation to the behavioral responses. If the prediction error is 20 %-points compared to 0 %-points, this is associated among those who regain employment with an income that is €62 (=3.1×20) smaller, a decreased likelihood of full-time employment that is 2.2 %-points (=0.11×20 which is 3.4%) smaller and 0.4 less work hours a week (=0.02×20). Work satisfaction is 0.1 points (=0.007×20) lower. This would also increase the likelihood of dropping out of the labor force by 2.4 %-points (=0.12×20 which equals 11%) and the probability of actively looking for a job by 1.2 %-points (=0.06×20).

Summary.— Those currently unemployed who underestimate their objective re-employment probability, accept lower quality jobs, especially with respect to income (€111 lower) and work hours (11% lower probability of being full-time employed). Furthermore, their probability to exit the labor force is 31% higher and there are significant negative implications for job satisfaction. Furthermore, this will induce additional social costs as it is well-known that non-employment is related to inequality and poverty, leading to diminished tax revenues for the government and increased welfare reliance, potentially increasing government expenditure.

V. Discussion and Conclusion

This paper is the first to investigate wholistically subjective re-employment expectations such that policy conclusions can be drawn. The only comparable study by Dickerson and Green (2012) shows that subjective re-employment expectations have some predictive power in explaining future labor market outcomes. Contrary to Dickerson and Green (2012), we demonstrate the limited informational content of subjective re-employment expectations over and above objective information collected by the job agencies.

We show that a substantial number of the currently unemployed consistently underestimate their re-employment probability and that our econometrician's model performs better on average at predicting re-employment than the individuals stated expectations. The only information needed about the individuals to make a significantly better prediction on average is their previous total years of unemployment experience.

We find an especially large scarring effect of past unemployment as people with high unemployment experience report the lowest subjective re-employment expectations, such that almost 60% of those who have previous unemployment experience of 3 to 5 years underestimate their re-employment probability. Almost 80% of those who have previous unemployment experience of 3 to 5 years and underestimate report a re-employment probability of 50% or lower.

In addition to previous unemployment experience, being married, previously being employed in certain occupations (especially managers/professionals, technicians and clerks) and people with certain personality traits such as having high levels of agreeability are all characteristics associated with underestimation which identify people who should be targeted by policy to prevent adverse behavior. They should be interviewed by unemployment office case workers early in their unemployment and asked about their expectations. Based on this subjective information, potentially corrective objective information can be offered to the clients.

People who underestimate accept lower quality jobs, especially with respect to income (€111 lower montly earnings) and work hours (11% lower probability of being full-time employed as opposed to part-time). Furthermore, the probability to exit the labor force is 31% higher for those who underestimate. Individuals will also be less likely to actively search for a job and job satisfaction will be lower.

Because of this, underestimation is likely to be related to increased income inequality, diminished tax revenues for the government and increased welfare reliance, potentially increasing net government expenditure.

This analysis lends itself to some important policy conclusions as it can inform policy makers which group of people is at risk of making prediction errors and should therefore be informed about their true re-employment probabilities. Especially people with high previous unemployment experience (3 to 5 years) should be informed about their actual re-employment chances as they are more likely to make prediction errors, have in general low re-employment expectations, and constitute a significant share of the unemployed (18%).

The model driven 'Eye of Providence' provides empirically based objective information that can be used by employment agencies the world over (in Germany, the *Arbeitsagentur*) to improve their clients' re-employment prospects. The characteristics of those likely to under-estimate their re-employment probabilities, such as previous unemployment experience, are typically already available to the employment agency case workers without any need of additional data collection. Case workers should ask individuals about their subjective re-employment expectations and inform them of any discrepancies due to underestimation. By providing employment agency clients with objective re-employment probabilities, suboptimal behavior in the labor market such as accepting low quality jobs or exiting the labor force may be prevented. Not only would this information be welfare improving for the unemployed, but also it would improve the employment offices' performance statistics.

Table 1: Model Based Subjective Re-employment Probability

	(1) OLS	(2) OLS RE	(3) CRE
Socio-demographics			
Male	5.6338***	5.4330***	6.1357***
	(1.6316)	(1.7632)	(1.8606)
Age	1.5668***	1.6028***	0.5268
	(0.4891)	(0.5045)	(1.3237)
Age squared/1000	-35.9267***	-37.3191***	-27.6023*
	(5.9412)	(6.1696)	(14.5585)
Years of Education	2.2760***	2.2055***	3.5189
	(0.3861)	(0.4111)	(2.1446)
Is Married	-3.4111**	-3.0333*	-2.8998
	(1.5223)	(1.6363)	(4.4300)
Children	-0.4046	-1.1005	-2.4444
	(1.4536)	(1.5036)	(2.8762)
Home Owner	2.6572*	2.7081*	2.6934
	(1.4339)	(1.5306)	(4.8698)
Labor Market History			
Part Time Exp	0.4100	0.5190*	1.6591
	(0.2689)	(0.2845)	(1.8323)
Full Time Exp	0.4001**	0.4622***	0.7419
	(0.1683)	(0.1787)	(0.9245)
Unempl. Exp. 0.1-1.0 yrs	-3.0677	-2.7303	-5.9568
	(2.6726)	(2.6194)	(3.9644)
Unempl. Exp. 1.1-3.0 yrs	-4.4230*	-4.8699*	-5.6998
	(2.6597)	(2.6131)	(4.0970)
Unempl. Exp. 3.1-5.0 yrs	-11.3137***	-10.8191***	-7.4552
	(2.8971)	(2.8513)	(4.6080)
Unempl. Exp. 5+ yrs	-17.2286***	-16.0914***	-9.5700*
	(3.0589)	(3.0690)	(5.4381)
Tenure last Job 3-9 Years?	-1.6829	-1.8041	-0.8072
	(1.9832)	(2.0499)	(4.0980)
Tenure last Job 10 or more Years?	-8.2960***	-8.2443***	-0.9281
	(2.5241)	(2.6466)	(6.0913)
External Labor Market			
Unempl Rate	-1.0507***	-1.0381***	-0.2414
	(0.1561)	(0.1645)	(0.5962)
Previous Job Characteristics			
Was working in the Privat Sector	3.0150	1.7958	-3.0578
	(2.4453)	(2.5450)	(4.6137)
Was temporary employed	-0.9288	-0.7797	1.7356
	(1.7386)	(1.7874)	(3.1846)
More than 20 at last Workplace	0.2628	0.9221	3.5422
	(1.4942)	(1.5300)	(2.7908)

Table 1 (continued): Model Based Subjective Re-employment Probability

	(1) OLS	(2) OLS RE	(3) CRE
Log Last Income (Gross)	1.2069	1.2450	0.7043
	(0.9398)	(0.9371)	(1.2854)
Last ISEI Status	-0.0320	-0.0563	-0.0492
	(0.1342)	(0.1377)	(0.2682)
Occupation[1]			
Agricult. Workers/Craft Workers	2.3530	3.8924	8.0913*
	(2.5194)	(2.6480)	(4.6778)
Machine Operators	3.7092	5.1069	16.3052**
	(3.1606)	(3.3415)	(6.6911)
Industry[2]			
Construction	5.9597**	5.8438**	-0.1471
	(2.5117)	(2.6184)	(5.8626)
Information and Communication	-9.8796*	-6.7998	-2.7845
	(5.3982)	(5.6937)	(11.5971)
Never obs. in empl.	3.8760	3.8916	0.3695
	(8.3760)	(8.4583)	(13.0024)
Personality Traits			
Extraversion	-0.4546	-0.4472	-0.4550
	(0.7349)	(0.7935)	(0.8015)
Conscientiousness	0.6155	0.7231	0.4749
	(0.7923)	(0.8639)	(0.8728)
Neuroticism	0.7210	0.7095	0.8316
	(0.7100)	(0.7664)	(0.7752)
Openess	2.3267***	2.0456**	1.9995**
	(0.7880)	(0.8495)	(0.8642)
Agreeability	-1.6923**	-1.6271**	-1.5120*
	(0.7424)	(0.8070)	(0.8217)
Locus of Control	2.1690***	1.9566**	1.7187**
	(0.7143)	(0.7725)	(0.7945)
R2	0.375	0.373	0.388
Number of Observations	1665	1665	1665

Note: Year dummies are also included. $^{*}p < 0.10,^{**}p < 0.05,^{***}p < 0.01$. [1] Only sign. coef. listed. Full set of occ. dummies included in regressions: Managers/Professionals; Techn./Assoc. Profess.; Clerks, Service/Shop Workers; Agricult. Workers/Craft Workers; Machine Operators; Elementary Occupations (base category). [2] Only sign. coef. listed. Other ind. dummies included in regressions: Agric./Forest./Fish./Mining/Quarring; Manufactur. (base category), Wholesale/Retail Trade/Repair of Motor Vehic. and Motors; Accomm. and Food Service Activities; Transport. and Storage; Information and Communic.; Financ. and Insurance Activities/Real Estate Activities; Professional/Scientific and Tech. Activities; Public Admin. and Defence/Compuls. Social Sec.; Edu.; Human Health and Social Work Activities; Arts/Entertainment and Recreation; other.

Table 2: Labor Force Status Model

	(1) Logit	(2) Logit	(3) Logit	(4) Logit	(5) Logit CRE
Expectations					
Subjective Probability 10 - 20%	-0.0165	-0.0590	-0.0565	-0.0581	-0.0832
	(0.0600)	(0.0584)	(0.0587)	(0.0592)	(0.0733)
Subjective Probability 30 - 40%	0.0527	-0.0171	-0.0250	-0.0278	-0.0101
	(0.0562)	(0.0583)	(0.0583)	(0.0593)	(0.0733)
Subjective Probability 50 - 60%	0.1115**	-0.0001	-0.0044	-0.0144	-0.0120
	(0.0471)	(0.0512)	(0.0515)	(0.0523)	(0.0684)
Subjective Probability 70 - 80%	0.2309***	0.0881*	0.0649	0.0566	0.0545
	(0.0417)	(0.0529)	(0.0540)	(0.0552)	(0.0759)
Subjective Probability 90 - 100%	0.3691***	0.1811***	0.1555***	0.1442**	0.0400
	(0.0399)	(0.0543)	(0.0558)	(0.0571)	(0.0797)
Variables as in Dickersen and Green (2012)					
Male	–	-0.0264	0.0021	0.0110	0.0053
		(0.0228)	(0.0277)	(0.0295)	(0.0280)
Age	–	0.0000	0.0057	0.0065	0.0563***
		(0.0075)	(0.0083)	(0.0083)	(0.0205)
Age squared/1000	–	-0.0604	-0.1617	-0.1746*	0.0072
		(0.0932)	(0.1000)	(0.1012)	(0.2299)
Years of Education	–	0.0185***	0.0146**	0.0117*	-0.0083
		(0.0060)	(0.0068)	(0.0066)	(0.0345)
Was working in the Privat Sector	–	0.0303	0.0908**	0.0912**	0.0509
		(0.0354)	(0.0435)	(0.0422)	(0.0774)
Was temporary employed	–	0.0086	0.0162	0.0198	-0.1601***
		(0.0269)	(0.0297)	(0.0297)	(0.0501)
More than 20 at last Workplace	–	-0.0079	-0.0044	0.0025	0.1152**
		(0.0251)	(0.0252)	(0.0251)	(0.0450)
Nerver obs. in empl.	–	-0.0805	0.0100	-0.0192	0.1457
		(0.0491)	(0.1447)	(0.1481)	(0.1585)
Unemployment Experience	–	-0.0271***	–	–	–
		(0.0041)			
Other Socio-demographics					
Is Married	–	–	0.0645**	0.0603**	-0.0014
			(0.0272)	(0.0275)	(0.0736)
Children	–	–	-0.0549**	-0.0605**	-0.0068
			(0.0260)	(0.0259)	(0.0466)
Home Owner	–	–	0.0791***	0.0806***	0.0816
			(0.0254)	(0.0254)	(0.0796)
Other Labor Market History					
Part Time Exp	–	–	0.0012	0.0003	-0.1041***
			(0.0048)	(0.0046)	(0.0278)
Full Time Exp	–	–	0.0003	0.0003	-0.0952***
			(0.0030)	(0.0030)	(0.0151)
Unempl. Exp. 0.1-1.0 yrs	–	–	-0.0033	-0.0063	0.0501
			(0.0499)	(0.0497)	(0.0692)
Unempl. Exp. 1.1-3.0 yrs	–	–	-0.0806*	-0.0779*	0.1588**
			(0.0473)	(0.0466)	(0.0663)
Unempl. Exp. 3.1-5.0 yrs	–	–	-0.0954*	-0.0872*	0.2460***
			(0.0524)	(0.0518)	(0.0541)
Unempl. Exp. 5+ yrs	–	–	-0.2532***	-0.2361***	0.1624***
			(0.0600)	(0.0599)	(0.0602)
Tenure last Job 3-9 Years?	–	–	0.0318	0.0324	0.0884
			(0.0357)	(0.0357)	(0.0665)

Table 2 (continued): Labor Force Status Model

	(1) Logit	(2) Logit	(3) Logit	(4) Logit	(5) Logit CRE
Tenure last Job 10 or more Years?	–	–	-0.0812*	-0.0672	0.1824**
			(0.0492)	(0.0475)	(0.0733)
External Labor Market					
Unempl Rate	–	–	-0.0058**	-0.0071**	-0.0264***
			(0.0028)	(0.0028)	(0.0097)
Previous Job Characteristics					
Log Last Income (Gross)	–	–	0.0130	0.0081	0.0087
			(0.0163)	(0.0162)	(0.0195)
Last ISEI Status	–	–	-0.0049*	-0.0049**	-0.0130***
			(0.0025)	(0.0025)	(0.0043)
Occupation[1]					
Managers/Professionals	–	–	0.2624***	0.2656***	0.3497***
			(0.0706)	(0.0703)	(0.0634)
Techn./Assoc. Profess.	–	–	0.1815***	0.1741**	0.3496***
			(0.0671)	(0.0679)	(0.0605)
Clerks	–	–	0.2397***	0.2260***	0.3098***
			(0.0534)	(0.0562)	(0.0682)
Service/Shop Workers	–	–	0.1237**	0.1226**	0.1423
			(0.0508)	(0.0512)	(0.1045)
Industry[2]					
Construction	–	–	-0.0034	0.0022	0.2203***
			(0.0452)	(0.0448)	(0.0697)
Wholesale/Retail;Motor Vehicles	–	–	-0.0807*	-0.0827*	-0.0383
			(0.0474)	(0.0473)	(0.0893)
Arts, Entertainment and Recreation	–	–	-0.0904	-0.0795	0.2303**
			(0.0839)	(0.0828)	(0.0900)
Personality					
Extraversion	–	–	–	0.0073	0.0121
				(0.0123)	(0.0119)
Conscientiousness	–	–	–	0.0063	0.0058
				(0.0126)	(0.0130)
Neuroticism	–	–	–	-0.0060	-0.0171
				(0.0119)	(0.0115)
Openess	–	–	–	0.0039	-0.0086
				(0.0133)	(0.0127)
Agreeability	–	–	–	0.0159	0.0134
				(0.0128)	(0.0120)
Locus of Control	–	–	–	0.0418***	0.0223*
				(0.0124)	(0.0117)
McKelvey and Zavoina's R2	0.146	0.231	0.283	0.303	0.557
McFadden's R2	0.088	0.140	0.170	0.180	
McFadden's Adj R2	0.078	0.122	0.123	0.128	
AIC	2043.044	1945.695	1943.256	1931.514	1647.892
BIC	2097.22	2048.63	2219.553	2240.316	2200.485
Log likelihood	-1011.522	-953.8477	-920.6282	-908.7568	-721.946
Number of Observations	1665	1665	1665	1665	1665
Number of Cluster	1180	1180	1180	1180	

Note: Marginal Effects. Year dummies are also included. Standard errors are clustered by person-number. $^{*}p < 0.10,^{**} p < 0.05,^{***} p < 0.01$. [1] [2] See notes Table 1.

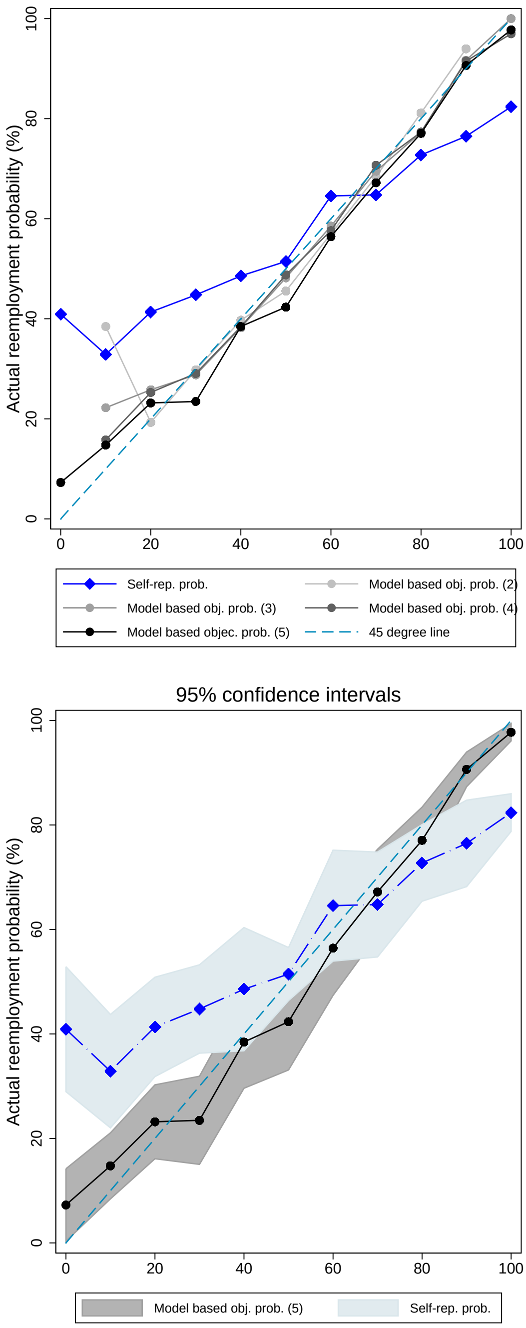

Figure 1: Perceived, Predicted and Actual Re-employment Probability

Table 3: Prediction-Realization Tables

		Predictions									
		(2) Model Based Obj. DG		(3) Model Based Obj. w/o Pers.		(4) Model Based Obj.		(5) Model Based Obj. (CRE)		**Self-Rep.**	
		0	1	0	1	0	1	0	1	**0**	**1**
Realization	0	0.2318	0.1520	0.2553	0.1285	0.2625	0.1213	0.2967	0.0871	0.2649	0.1189
	1	0.1628	0.4535	0.1646	0.4517	0.1694	0.4468	0.1171	0.4991	0.2288	0.3874
McFadden's σ_n		0.3413		0.3983		0.4076		0.5791		**0.3044**	
		[0.2955,0.3871]		[0.3567,0.4400]		[0.3670,0.4482]		[0.5367,0.6215]		[0.2598,0.3490]	
Veall and Zimmermann's δ_n		0.3399		0.3980		0.4090		0.5830		**0.3188**	
		[0.2862,0.3936]		[0.3479,0.4482]		[0.3661,0.4520]		[0.5449,0.6212]		[0.2804,0.3572]	

Table 4: Minimum Information needed

Variables	Sigma	Std. Err.	Lower Bound	Upper Bound
(A) One Variable - sigma sign. higher				
Unempl. Exp.	.4538564	.0188137	.4169815	.4907312
(B) Two Variables without unemployment experience- sigma as high as				
Age, ISCO Occ. Code	0.26059	0.02518	0.21124	0.30994
Age, ISEI Status	0.24858	0.02384	0.20185	0.29530
Age, Tenure	0.24766	0.02544	0.19779	0.29753
Age, Locus of Control	0.24605	0.02448	0.19806	0.29404
Age, Unemp. rate	0.23982	0.03009	0.18084	0.29881
Age, Income	0.23688	0.02451	0.18883	0.28493
Age, Industry	0.23338	0.02707	0.18032	0.28644
Age, Temporary employed	0.22619	0.03557	0.15647	0.29591
Age, Full-time experience	0.22619	0.02989	0.16761	0.28478
Age, Size of company	0.20550	0.03010	0.14650	0.26450
Age, Private sector	0.20424	0.03270	0.14013	0.26835
Age, Education	0.20396	0.02852	0.14806	0.25986
(C) Seven Variables without unemployment experience- sigma sign higher				
Age, Unemp. rate, Part-time exp., Full-time exp., Home owner, ISCO , Ind.	0.41417	0.02515	0.36487	0.46347
Age, Unemp. rate , Part-time exp., Full-time exp., ISCO , Loc. of. c., Ind.	0.41323	0.02487	0.36449	0.46198
Age, Unemp. rate , Part-time exp., Full-time exp., Tenure, ISCO , Ind.	0.41069	0.01937	0.37272	0.44867
Age, Unemp. rate, Edu. , Part-time exp., Full-time exp. , Home owner, Ind.	0.41045	0.01811	0.37495	0.44596
Age, Unemp. rate , Edu. , Part-time exp., Full-time exp., Tenure, Home owner	0.40601	0.02609	0.35486	0.45716
Age, Unemp. rate, Private sector, Part-time exp., Full-time exp., ISCO , Ind.	0.40356	0.02414	0.35624	0.45087
Age, Unemp. rate , Edu., Temp. empl. , Part-time exp., Full-time exp. , Home owner	0.40271	0.02165	0.36027	0.44515
Age, Unemp. rate, Married , Home owner, Child., ISCO , LOC	0.40251	0.02191	0.35955	0.44547
Age, Unemp. rate , Part-time exp., Full-time exp., ISCO , Conscient., Ind.	0.40093	0.02393	0.35401	0.44785
Age, Unemp. rate , Edu. , Part-time exp., Full-time exp. , Home owner, Income	0.40045	0.02278	0.35579	0.44511
Age, Unemp. rate , Part-time exp., Full-time exp.,ISCO , Neuroticism, Ind.	0.39829	0.02302	0.35316	0.44343
Age, Unemp. rate Full-time exp. , Home owner, ISCO , Agree., Ind.	0.39497	0.02145	0.35291	0.43702

Table 5: Under-, Exact and Overestimation

	Coef.	Marginal Effects (ME)		
	(1) ordered logit	(2) underestimation	(3) exact estimation	(4) overestimation
Socio-demographics				
Male	0.2750*	-0.0465*	0.0190*	0.0275*
	(0.1436)	(0.0244)	(0.0103)	(0.0144)
Age	0.0257	-0.0043	0.0017	0.0026
	(0.0405)	(0.0068)	(0.0027)	(0.0041)
Age squared/1000	-0.5756	0.0966	-0.0383	-0.0583
	(0.4900)	(0.0824)	(0.0330)	(0.0498)
Yrs in Education	0.0508	-0.0085	0.0034	0.0051
	(0.0345)	(0.0058)	(0.0023)	(0.0035)
Is Married	-0.3984***	0.0667***	-0.0263***	-0.0404***
	(0.1390)	(0.0231)	(0.0096)	(0.0143)
Children	0.0709	-0.0119	0.0047	0.0072
	(0.1301)	(0.0217)	(0.0084)	(0.0133)
Home Owner	-0.1987	0.0340	-0.0145	-0.0195*
	(0.1225)	(0.0213)	(0.0097)	(0.0118)
Labor Market History				
Part Time Exp	-0.0065	0.0011	-0.0004	-0.0007
	(0.0245)	(0.0041)	(0.0016)	(0.0025)
Full Time Exp	0.0083	-0.0014	0.0006	0.0008
	(0.0148)	(0.0025)	(0.0010)	(0.0015)
Unempl. Exp. 0.1-1.0 yrs	-0.2307	0.0399	-0.0175	-0.0224
	(0.1734)	(0.0309)	(0.0149)	(0.0161)
Unempl. Exp. 1.1-3.0 yrs	-0.2218	0.0381	-0.0164	-0.0217
	(0.1898)	(0.0334)	(0.0157)	(0.0179)
Unempl. Exp. 3.1-5.0 yrs	-0.4857**	0.0877**	-0.0438*	-0.0439**
	(0.2186)	(0.0423)	(0.0252)	(0.0175)
Unempl. Exp. 5+ yrs	-0.0822	0.0139	-0.0057	-0.0082
	(0.2390)	(0.0409)	(0.0175)	(0.0235)
Tenure last Job 3-9 Years?	-0.2363	0.0413	-0.0188	-0.0225
	(0.1734)	(0.0315)	(0.0161)	(0.0155)
Tenure last Job 10 or more Years?	-0.0830	0.0142	-0.0060	-0.0082
	(0.2336)	(0.0406)	(0.0181)	(0.0225)
External Labor Market				
Unempl Rate	-0.0210	0.0035	-0.0014	-0.0021*
	(0.0129)	(0.0022)	(0.0009)	(0.0013)
Previous Job Characteristics				
Was working in the Privat Sector	-0.1595	0.0264	-0.0099	-0.0165
	(0.1820)	(0.0296)	(0.0105)	(0.0193)
Was temporary employed	-0.2283	0.0390	-0.0165	-0.0225
	(0.1474)	(0.0256)	(0.0116)	(0.0142)
More than 20 at last Workplace	-0.0035	0.0006	-0.0002	-0.0004
	(0.1255)	(0.0211)	(0.0084)	(0.0127)

Table 5 (continued): Under-, Exact and Overestimation

	Coef.	Marginal Effects (ME)		
	(1) ordered logit	(2) underestimation	(3) exact estimation	(4) overestimation
Log Last Income (Gross)	-0.0101	0.0017	-0.0007	-0.0010
	(0.0697)	(0.0117)	(0.0046)	(0.0071)
Last ISEI Status	0.0171	-0.0029	0.0011	0.0017
	(0.0106)	(0.0018)	(0.0007)	(0.0011)
Occupation[1]				
Managers/Professionals	-1.0940**	0.2195*	-0.1397	-0.0797***
	(0.5337)	(0.1188)	(0.0922)	(0.0274)
Techn./Assoc. Profess.	-0.7139*	0.1340*	-0.0738	-0.0602**
	(0.3737)	(0.0764)	(0.0508)	(0.0261)
Clerks	-0.5761*	0.1074	-0.0583	-0.0492**
	(0.3380)	(0.0686)	(0.0448)	(0.0242)
Service/Shop Workers	-0.5080*	0.0937	-0.0496	-0.0441**
	(0.2975)	(0.0594)	(0.0378)	(0.0220)
Industry[2]				
Wholesale/Retail/Vehicles	0.3785	-0.0591*	0.0167***	0.0424
	(0.2304)	(0.0332)	(0.0058)	(0.0285)
Never obs. in empl.	-0.0672	0.0114	-0.0047	-0.0067
	(0.6200)	(0.1061)	(0.0452)	(0.0610)
Personality Traits				
Extraversion	-0.0455	0.0076	-0.0030	-0.0046
	(0.0573)	(0.0096)	(0.0038)	(0.0058)
Conscientiousness	-0.0184	0.0031	-0.0012	-0.0019
	(0.0641)	(0.0108)	(0.0043)	(0.0065)
Neuroticism	0.0791	-0.0133	0.0053	0.0080
	(0.0570)	(0.0096)	(0.0039)	(0.0058)
Openess	0.0387	-0.0065	0.0026	0.0039
	(0.0696)	(0.0117)	(0.0047)	(0.0070)
Agreeability	-0.1313**	0.0220**	-0.0087*	-0.0133**
	(0.0654)	(0.0110)	(0.0045)	(0.0066)
Locus of Control	-0.0579	0.0097	-0.0039	-0.0059
	(0.0636)	(0.0107)	(0.0042)	(0.0065)
McKelvey and Zavoina's R2	0.083	0.083	0.083	0.083
Number of Observations	1665	1665	1665	1665
Number of Cluster	1180	1180	1180	1180

Note: Year dummies are also included. Standard errors are clustered by person-number. $^{*}p < 0.10, ^{**}p < 0.05, ^{***}p < 0.01$. [1] [2] See notes Table 1.

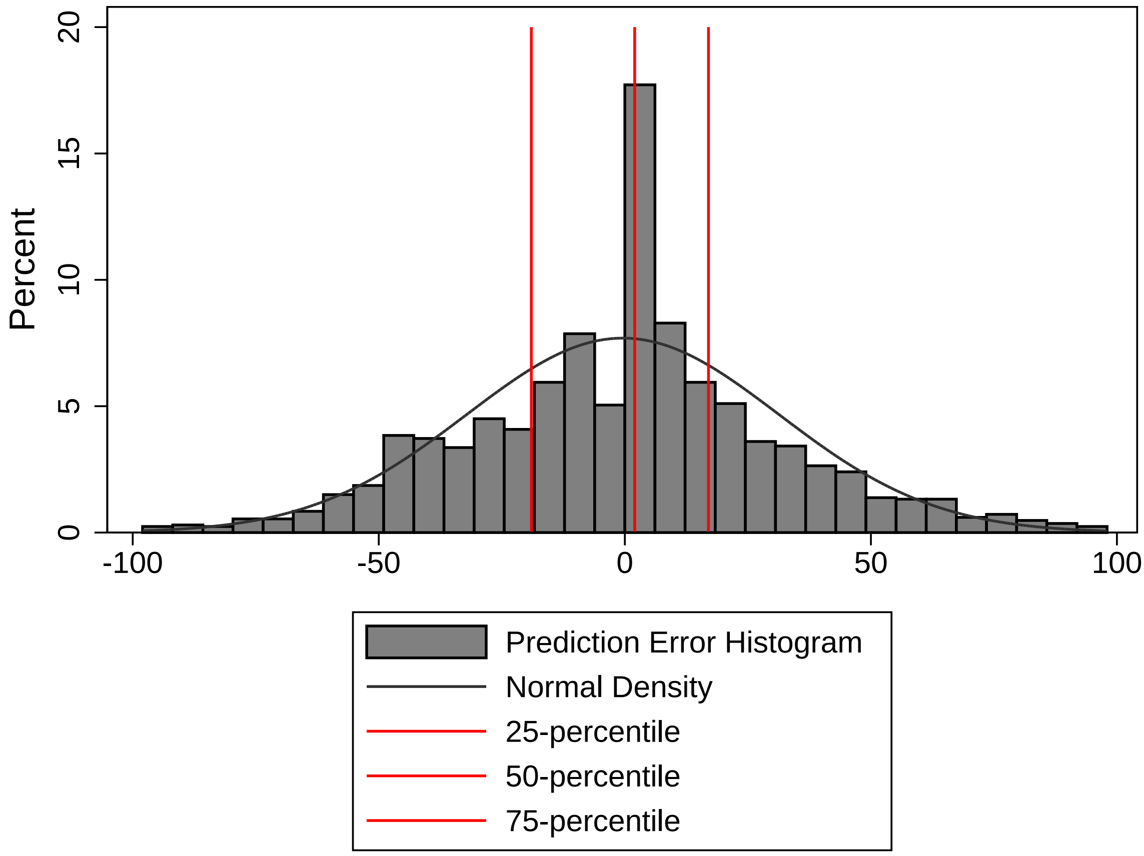

Figure 2: Prediction Error Distribution

Table 6: Determinants of Size of Prediction Error

	OLS	Q25	Q50	Q75
Socio-demographics				
Male	3.6449*	7.6373**	1.9392	2.4778
	(2.0529)	(3.0711)	(1.7555)	(2.6051)
Age	0.5779	0.2399	0.0719	0.7771
	(0.5982)	(0.9574)	(0.5342)	(0.7788)
Age squared/1000	-10.1901	-10.8923	-3.9606	-6.2394
	(7.5468)	(11.7421)	(6.4328)	(9.5111)
Yrs in Education	0.5013	0.7775	0.3066	-0.3001
	(0.4780)	(0.7520)	(0.4172)	(0.6170)
Is Married	-8.8875***	-11.3341***	-5.4352***	-7.0755***
	(1.9620)	(2.8623)	(1.6192)	(2.5628)
Children	5.8450***	3.8428	5.2607***	5.8788**
	(1.8541)	(2.7715)	(1.5622)	(2.4192)
Home Owner	-6.4880***	-4.7325*	-4.8348***	-8.8122***
	(1.7937)	(2.8531)	(1.5203)	(2.2206)
Labor Market History				
Part Time Exp	0.3628	0.0894	0.1307	0.1911
	(0.3643)	(0.5780)	(0.2830)	(0.4366)
Full Time Exp	0.3446	0.3471	0.3136*	0.0576
	(0.2135)	(0.3322)	(0.1815)	(0.2901)
Unempl. Exp. 0.1-1.0yrs	-1.9866	-10.9506**	-1.7580	-1.4351
	(2.8963)	(4.8344)	(2.8229)	(3.8007)
Unempl. Exp. 1.1-3.0yrs	2.6153	-6.0809	1.7849	4.6356
	(3.0800)	(4.7607)	(2.8169)	(4.0363)
Unempl. Exp. 3.1-5.0yrs	-0.8277	-9.5238*	1.0668	1.8485
	(3.3644)	(5.2978)	(3.1032)	(4.5316)
Unempl. Exp. 5+yrs	9.2427**	1.4815	7.1844**	15.3001***
	(3.9319)	(5.5358)	(3.2559)	(5.1052)
Tenure last Job 3-9 Years?	-4.4769**	-1.5953	-4.7601**	-4.8376
	(2.2577)	(3.9205)	(2.0883)	(3.0049)
Tenure last Job 10 or more Years?	0.8360	5.4845	0.5388	0.7199
	(3.2446)	(4.8659)	(2.6251)	(4.0704)
External Labor Market				
Unempl Rate	-0.1041	-0.5717**	-0.0788	0.3798
	(0.1811)	(0.2803)	(0.1588)	(0.2503)
Previous Job Characteristics				
Was working in the Privat Sector	-3.0553	-6.5536*	-0.8486	-5.1156
	(2.4478)	(3.9574)	(2.0874)	(3.1678)
Was temporary employed	-2.7951	-4.8397	-3.9562**	-4.0384
	(2.1055)	(3.1154)	(1.7190)	(2.6302)

Table 6 (continued): Determinants of Size of Prediction Error

	OLS	Q25	Q50	Q75
More than 20 at last Workplace	-1.3442	-0.4132	0.0118	-2.3049
	(1.8347)	(2.9502)	(1.5724)	(2.3680)
Log Last Income (Gross)	-0.9446	-0.7354	-0.8679*	-0.8373
	(0.5881)	(0.9540)	(0.5164)	(0.7804)
Last ISEI Status	0.4948***	0.4560**	0.2691**	0.5508***
	(0.1430)	(0.2314)	(0.1215)	(0.1707)
Occupation[1]				
Managers/Professionals	-32.4576***	-26.5685**	-18.2366***	-34.2737***
	(7.7467)	(12.5618)	(6.3494)	(8.8746)
Techn./Assoc. Profess.	-18.1119***	-13.8200	-7.3877	-21.0547***
	(5.7714)	(8.8763)	(4.6060)	(6.7320)
Clerks	-20.9577***	-17.3294**	-9.8712**	-22.4651***
	(5.3923)	(7.7015)	(4.1804)	(5.9770)
Service/Shop Workers	-8.0068*	-5.6206	-0.7640	-10.6984*
	(4.5275)	(6.9694)	(3.7203)	(5.5003)
Industry[2]				
Agricult. Workers/Craft Workers	-4.7272	-3.2109	2.7794	-4.6587
	(3.3835)	(4.9295)	(2.7318)	(4.4047)
Never obs. in empl.	3.5911	35.7712**	11.8410	-1.6548
	(11.6884)	(16.5668)	(8.7558)	(14.5514)
Personality Traits				
Extraversion	-0.5997	0.4431	-0.5865	0.0511
	(0.9237)	(1.4347)	(0.7809)	(1.1769)
Conscientiousness	-0.8411	-1.2692	0.0333	-0.2221
	(0.9858)	(1.5551)	(0.8513)	(1.3031)
Neuroticism	1.2297	1.8230	0.9658	0.7228
	(0.8345)	(1.3388)	(0.7628)	(1.1479)
Openess	0.9417	1.4635	0.5904	-0.1250
	(1.0120)	(1.5721)	(0.8473)	(1.2669)
Agreeability	-2.6555***	-3.3753**	-2.3474***	-1.6604
	(0.9028)	(1.4268)	(0.7973)	(1.2153)
LOC	-2.4504***	-1.8792	-1.3761*	-4.4900***
	(0.8756)	(1.4360)	(0.7790)	(1.1462)
R2	0.129	0.079	0.091	0.107
Number of Observations	1665	1665	1665	1665

Note: OLS and Unconditional Quantile Regressions. Marginal Effects. Year dummies are also included. $^{*}p < 0.10, ^{**}p < 0.05, ^{***}p < 0.01$. [1] [2] See notes Table 1.

Table 7: Behavioral Reponse

	UE in t, Empl in t+1/t+2				UE in t (incl. future dropouts)	
	(1) Income	(2) FT Empl.	(3) Work Hours	(4) Work Sat	(5) Dropping OLF	(6) Job Search
Panel A						
Subj Re-Empl Prob	2.9712***	0.0011**	0.0315***	0.0053*	-0.0009***	0.0006*
	(0.9225)	(0.0005)	(0.0115)	(0.0032)	(0.0003)	(0.0003)
R2	0.405		0.330	0.123		
McKelvey and Zavoina's R2		0.491			0.180	0.218
Number of Observations	1154	1154	1154	1154	2680	2680
Panel B						
Underestimation	-110.8203**	-0.0670**	-1.9670***	-0.1246	0.0651***	-0.0255
	(46.8127)	(0.0286)	(0.5833)	(0.1609)	(0.0184)	(0.0187)
R2	0.402		0.331	0.121		
McKelvey and Zavoina's R2		0.491			0.183	0.216
Number of Observations	1154	1154	1154	1154	2680	2680
Panel C						
Prediction Error	-3.0636***	-0.0011*	-0.0239*	-0.0072**	0.0012***	-0.0006*
	(0.9853)	(0.0006)	(0.0125)	(0.0034)	(0.0003)	(0.0003)
R2	0.404		0.327	0.124		
McKelvey and Zavoina's R2		0.492			0.182	0.217
Number of Observations	1154	1154	1154	1154	2680	2680

Note: Marginal Effects. Same control variables as in Table 6. Standard errors are clustered by person-number. $^{*}p < 0.10,^{**} p < 0.05,^{***} p < 0.01$.

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A Appendix

Table A.1: Summary Statistics

Variable	Mean	Std. Dev.	Min.	Max.
Employed in t+1 or t+2	0.62	0.49	0	1
Male	0.53	0.5	0	1
Age	40.39	11.15	17	63
Age squared/1000	1.76	0.89	0.29	3.97
Yrs in Education	11.42	2.1	7	18
Is Married	0.53	0.5	0	1
Children	0.43	0.49	0	1
Home Owner	0.32	0.47	0	1
Part Time Exp	1.32	3.33	0	30.7
Full Time Exp	13.52	10.69	0	43.8
Unemployment Experience	3.5	3.33	0	21.5
Tenure last Job 3-9 Years?	0.14	0.35	0	1
Tenure last Job 10 or more Years?	0.09	0.28	0	1
Unempl Rate	13.28	4.77	4.8	20.5
Was working in the Privat Sector	0.67	0.47	0	1
Was temporary employed	0.34	0.48	0	1
More than 20 at last Workplace	0.49	0.5	0	1
Log Last Income (Gross)	5.8	2.9	0	9.69
Last ISEI Status	29.88	19.17	0	90
Managers/Professionals	0.07	0.26	0	1
Techn./Assoc. Profess.	0.13	0.34	0	1
Clerks	0.09	0.28	0	1
Service/Shop Workers	0.08	0.27	0	1
Agricult. Workers/Craft Workers	0.23	0.42	0	1
Machine Operators	0.09	0.28	0	1
Agriculture, Forestry and Fishing/Mining, Quarring	0.04	0.19	0	1
Construction	0.14	0.34	0	1
Wholesale a. Retail Trade; Repair of Motor Vehicles	0.13	0.33	0	1
Accommodation and Food Service Activities	0.03	0.16	0	1
Transportation and Storage	0.03	0.16	0	1
Information and Communication	0.02	0.12	0	1
Financial a. Insurance Activities/Real Est. Act.	0.01	0.11	0	1
Professional, Scientific and Technical Act.	0.05	0.23	0	1
N		1665		

Table A.1 (continued): Summary Statistics

Variable	**Mean**	**Std. Dev.**	**Min.**	**Max.**
Public Admin. a. Defence; Compulsory Social Sec.	0.05	0.22	0	1
Education	0.05	0.21	0	1
Human Health and Social Work Activities	0.07	0.25	0	1
Arts, Entertainment and Recreation	0.02	0.15	0	1
Other	0.04	0.2	0	1
nerver obs. in empl.	0.19	0.39	0	1
Extraversion	-0.02	0.96	-3.58	2.43
Conscientiousness	0.08	0.95	-3.59	1.8
Neuroticism	0.1	0.94	-2.58	2.9
Openess	-0.14	0.93	-4.12	3.09
Agreeability	-0.02	0.99	-4.15	2.31
Locus of Control	-0.42	0.98	-3.1	2.48
N		1665		

Table A.2: Realisation-Prediction Sigma by 0/1-Coding Variation, Self-Reported Subjective Probability

x \ y	>0	≥ 10	≥ 20	≥ 30	≥ 40	≥ 50	≥ 60	≥ 70	≥ 80	≥ 90	≥ 100
= 0	**-3.946** (0.586) [39; 600] [27; 999]	**-3.946** (0.590) [39; 600] [27; 999]	**-3.568** (0.469) [39; 551] [27; 975]	**-3.098** (0.423) [39; 490] [27; 932]	**-2.528** (0.475) [39; 416] [27; 872]	**-2.250** (0.392) [39; 380] [27; 838]	**-0.838** (0.228) [39; 198] [27; 645]	**-0.621** (0.183) [39; 170] [27; 594]	**-0.380** (0.157) [39; 139] [27; 537]	**-0.081** (0.136) [39; 100] [27; 433]	**0.100** (0.111) [39; 76] [27; 355]
< 10		**-3.946** (0.577) [39; 600] [27; 999]	**-3.568** (0.622) [39; 551] [27; 975]	**-3.098** (0.423) [39; 490] [27; 932]	**-2.528** (0.446) [39; 416] [27; 872]	**-2.250** (0.453) [39; 380] [27; 838]	**-0.838** (0.248) [39; 198] [27; 645]	**-0.621** (0.177) [39; 170] [27; 594]	**-0.380** (0.173) [39; 139] [27; 537]	**-0.081** (0.133) [39; 100] [27; 433]	**0.100** (0.120) [39; 76] [27; 355]
< 20			**-1.363** (0.192) [88; 551] [51; 975]	**-1.136** (0.168) [88; 490] [51; 932]	**-0.861** (0.170) [88; 416] [51; 872]	**-0.727** (0.127) [88; 380] [51; 838]	**-0.043** (0.085) [88; 198] [51; 645]	**0.060** (0.075) [88; 170] [51; 594]	**0.176** (0.071) [88; 139] [51; 537]	**0.315** (0.065) [88; 100] [51; 433]	**0.396** (0.049) [88; 76] [51; 355]
< 30				**-0.407** (0.090) [149; 490] [94; 932]	**-0.247** (0.072) [149; 416] [94; 872]	**-0.170** (0.066) [149; 380] [94; 838]	**0.226** (0.047) [149; 198] [94; 645]	**0.284** (0.037) [149; 170] [94; 594]	**0.348** (0.041) [149; 139] [94; 537]	**0.419** (0.033) [149; 100] [94; 433]	**0.453** (0.041) [149; 76] [94; 355]
< 40					**0.023** (0.038) [223; 416] [154; 872]	**0.073** (0.033) [223; 380] [154; 838]	**0.324** (0.032) [223; 198] [154; 645]	**0.358** (0.030) [223; 170] [154; 594]	**0.395** (0.029) [223; 139] [154; 537]	**0.425** (0.028) [223; 100] [154; 433]	**0.428** (0.026) [223; 76] [154; 355]
< 50						**0.131** (0.037) [259; 380] [188; 838]	**0.339** (0.024) [259; 198] [188; 645]	**0.365** (0.021) [259; 170] [188; 594]	**0.392** (0.025) [259; 139] [188; 537]	**0.408** (0.026) [259; 100] [188; 433]	**0.398** (0.031) [259; 76] [188; 355]
< 60							**0.304** (0.025) [441; 198] [381; 645]	**0.304** (0.026) [441; 170] [381; 594]	**0.299** (0.027) [441; 139] [381; 537]	**0.256** (0.034) [441; 100] [381; 433]	**0.192** (0.041) [441; 76] [381; 355]
< 70								**0.272** (0.023) [469; 170] [432; 594]	**0.261** (0.035) [469; 139] [432; 537]	**0.206** (0.032) [469; 100] [432; 433]	**0.129** (0.042) [469; 76] [432; 355]
< 80									**0.218** (0.029) [500; 139] [489; 537]	**0.150** (0.029) [500; 100] [489; 433]	**0.059** (0.052) [500; 76] [489; 355]
< 90										**0.044** (0.039) [539; 100] [593; 433]	**-0.072** (0.055) [539; 76] [593; 355]
< 100											**-0.169** (0.048) [563; 76] [671; 355]

Notes: In each cell: Sigma, (standard error), [n_{11};n_{21}] [n_{21};n_{22}]

Table A.3: Realisation-Prediction Sigma by 0/1-Coding Variation, Model Based Objective Probability (Mundlak)

x \ y	>0	≥ 10	≥ 20	≥ 30	≥ 40	≥ 50	≥ 60	≥ 70	≥ 80	≥ 90	≥ 100
= 0	**-318.192** (86.451) [1; 638] [0; 1026]	**-264.672** (71.492) [1; 531] [0; 1012]	**-210.149** (56.214) [1; 422] [0; 991]	**-166.629** (48.090) [1; 335] [0; 960]	**-130.611** (39.431) [1; 263] [0; 926]	**-99.593** (29.184) [1; 201] [0; 881]	**-71.574** (21.582) [1; 145] [0; 831]	**-46.556** (13.697) [1; 95] [0; 751]	**-28.041** (7.988) [1; 58] [0; 643]	**-9.521** (3.611) [1; 21] [0; 474]	**1.000** (0.000) [1; 0] [0; 25]
< 10		**-1.410** (0.192) [108; 531] [14; 1012]	**-0.941** (0.155) [108; 422] [14; 991]	**-0.565** (0.137) [108; 335] [14; 960]	**-0.252** (0.136) [108; 263] [14; 926]	**0.019** (0.086) [108; 201] [14; 881]	**0.267** (0.088) [108; 145] [14; 831]	**0.489** (0.068) [108; 95] [14; 751]	**0.654** (0.041) [108; 58] [14; 643]	**0.821** (0.032) [108; 21] [14; 474]	**0.663** (0.128) [108; 0] [14; 25]
< 20			**-0.068** (0.075) [217; 422] [35; 991]	**0.123** (0.056) [217; 335] [35; 960]	**0.283** (0.063) [217; 263] [35; 926]	**0.423** (0.040) [217; 201] [35; 881]	**0.551** (0.033) [217; 145] [35; 831]	**0.665** (0.030) [217; 95] [35; 751]	**0.749** (0.028) [217; 58] [35; 643]	**0.832** (0.021) [217; 21] [35; 474]	**0.231** (0.235) [217; 0] [35; 25]
< 30				**0.303** (0.036) [304; 335] [66; 960]	**0.417** (0.035) [304; 263] [66; 926]	**0.516** (0.023) [304; 201] [66; 881]	**0.607** (0.022) [304; 145] [66; 831]	**0.687** (0.024) [304; 95] [66; 751]	**0.744** (0.021) [304; 58] [66; 643]	**0.795** (0.021) [304; 21] [66; 474]	**-0.409** (0.263) [304; 0] [66; 25]
< 40					**0.466** (0.029) [376; 263] [100; 926]	**0.545** (0.030) [376; 201] [100; 881]	**0.617** (0.020) [376; 145] [100; 831]	**0.680** (0.021) [376; 95] [100; 751]	**0.721** (0.023) [376; 58] [100; 643]	**0.751** (0.020) [376; 21] [100; 474]	**-1.105** (0.586) [376; 0] [100; 25]
< 50						**0.543** (0.022) [438; 201] [145; 881]	**0.603** (0.017) [438; 145] [145; 831]	**0.652** (0.023) [438; 95] [145; 751]	**0.681** (0.020) [438; 58] [145; 643]	**0.690** (0.025) [438; 21] [145; 474]	**-2.024** (0.518) [438; 0] [145; 25]
< 60							**0.579** (0.021) [494; 145] [195; 831]	**0.618** (0.018) [494; 95] [195; 751]	**0.636** (0.023) [494; 58] [195; 643]	**0.625** (0.027) [494; 21] [195; 474]	**-3.042** (0.770) [494; 0] [195; 25]
< 70								**0.555** (0.020) [544; 95] [275; 751]	**0.559** (0.023) [544; 58] [275; 643]	**0.520** (0.026) [544; 21] [275; 474]	**-4.668** (1.842) [544; 0] [275; 25]
< 80									**0.457** (0.025) [581; 58] [383; 643]	**0.382** (0.031) [581; 21] [383; 474]	**-6.859** (1.248) [581; 0] [383; 25]
< 90										**0.176** (0.038) [618; 21] [552; 474]	**-10.276** (2.606) [618; 0] [552; 25]
< 100											**-19.325** (5.001) [639; 0] [1001; 25]

Notes: In each cell: Sigma, (standard error), [n_{11};n_{21}] [n_{21};n_{22}]

Table A.4: Realisation-Prediction Adj.Sigma by 0/1-Coding Variation, Self-Reported Subjective Probability

x \ y	>0	≥ 10	≥ 20	≥ 30	≥ 40	≥ 50	≥ 60	≥ 70	≥ 80	≥ 90	≥ 100
= 0	**-3.946** (0.722) [39; 600] [27; 999]	**-3.946** (0.588) [39; 600] [27; 999]	**-3.903** (0.540) [39; 551] [27; 975]	**-3.879** (0.602) [39; 490] [27; 932]	**-3.823** (0.712) [39; 416] [27; 872]	**-3.784** (0.819) [39; 380] [27; 838]	**-2.812** (0.738) [39; 198] [27; 645]	**-2.500** (0.788) [39; 170] [27; 594]	**-1.915** (0.942) [39; 139] [27; 537]	**-0.628** (0.900) [39; 100] [27; 433]	**0.009** (0.285) [39; 76] [27; 355]
< 10		**-3.946** (0.530) [39; 600] [27; 999]	**-3.903** (0.575) [39; 551] [27; 975]	**-3.879** (0.632) [39; 490] [27; 932]	**-3.823** (0.614) [39; 416] [27; 872]	**-3.784** (0.670) [39; 380] [27; 838]	**-2.812** (0.832) [39; 198] [27; 645]	**-2.500** (0.891) [39; 170] [27; 594]	**-1.915** (1.027) [39; 139] [27; 537]	**-0.628** (0.896) [39; 100] [27; 433]	**0.009** (0.379) [39; 76] [27; 355]
< 20			**-1.363** (0.197) [88; 551] [51; 975]	**-1.293** (0.202) [88; 490] [51; 932]	**-1.172** (0.218) [88; 416] [51; 872]	**-1.095** (0.186) [88; 380] [51; 838]	**-0.125** (0.211) [88; 198] [51; 645]	**0.018** (0.103) [88; 170] [51; 594]	**0.042** (0.074) [88; 139] [51; 537]	**0.051** (0.010) [88; 100] [51; 433]	**0.046** (0.007) [88; 76] [51; 355]
< 30				**-0.407** (0.083) [149; 490] [94; 932]	**-0.293** (0.101) [149; 416] [94; 872]	**-0.221** (0.103) [149; 380] [94; 838]	**0.096** (0.023) [149; 198] [94; 645]	**0.104** (0.016) [149; 170] [94; 594]	**0.106** (0.014) [149; 139] [94; 537]	**0.091** (0.009) [149; 100] [94; 433]	**0.074** (0.008) [149; 76] [94; 355]
< 40					**0.023** (0.045) [223; 416] [154; 872]	**0.067** (0.038) [223; 380] [154; 838]	**0.174** (0.020) [223; 198] [154; 645]	**0.168** (0.015) [223; 170] [154; 594]	**0.158** (0.012) [223; 139] [154; 537]	**0.127** (0.011) [223; 100] [154; 433]	**0.101** (0.008) [223; 76] [154; 355]
< 50						**0.131** (0.035) [259; 380] [188; 838]	**0.204** (0.019) [259; 198] [188; 645]	**0.193** (0.018) [259; 170] [188; 594]	**0.178** (0.012) [259; 139] [188; 537]	**0.141** (0.011) [259; 100] [188; 433]	**0.111** (0.012) [259; 76] [188; 355]
< 60							**0.304** (0.024) [441; 198] [381; 645]	**0.276** (0.022) [441; 170] [381; 594]	**0.242** (0.024) [441; 139] [381; 537]	**0.170** (0.023) [441; 100] [381; 433]	**0.109** (0.020) [441; 76] [381; 355]
< 70								**0.272** (0.020) [469; 170] [432; 594]	**0.234** (0.022) [469; 139] [432; 537]	**0.153** (0.025) [469; 100] [432; 433]	**0.082** (0.024) [469; 76] [432; 355]
< 80									**0.218** (0.033) [500; 139] [489; 537]	**0.125** (0.027) [500; 100] [489; 433]	**0.043** (0.029) [500; 76] [489; 355]
< 90										**0.044** (0.034) [539; 100] [593; 433]	**-0.081** (0.048) [539; 76] [593; 355]
< 100											**-0.169** (0.052) [563; 76] [671; 355]

Notes: In each cell: Sigma, (standard error), [n_{11};n_{21}] [n_{21};n_{22}]

Table A.5: Realisation-Prediction Adj.Sigma by 0/1-Coding Variation, Model Based Objective Probability (Mundlak)

x \ y	>0	≥ 10	≥ 20	≥ 30	≥ 40	≥ 50	≥ 60	≥ 70	≥ 80	≥ 90	≥ 100
= 0	**-318.192** (87.817) [1; 638] [0; 1026]	**-307.781** (78.444) [1; 531] [0; 1012]	**-291.379** (91.728) [1; 422] [0; 991]	**-275.024** (84.718) [1; 335] [0; 960]	**-255.690** (73.657) [1; 263] [0; 926]	**-235.396** (71.683) [1; 201] [0; 881]	**-207.872** (57.415) [1; 145] [0; 831]	**-179.903** (54.958) [1; 95] [0; 751]	**-157.744** (51.918) [1; 58] [0; 643]	**-107.290** (39.734) [1; 21] [0; 474]	**0.000** (0.000) [1; 0] [0; 25]
< 10		**-1.410** (0.202) [108; 531] [14; 1012]	**-1.107** (0.194) [108; 422] [14; 991]	**-0.780** (0.228) [108; 335] [14; 960]	**-0.406** (0.182) [108; 263] [14; 926]	**0.010** (0.185) [108; 201] [14; 881]	**0.116** (0.029) [108; 145] [14; 831]	**0.165** (0.022) [108; 95] [14; 751]	**0.160** (0.014) [108; 58] [14; 643]	**0.113** (0.009) [108; 21] [14; 474]	**0.005** (0.001) [108; 0] [14; 25]
< 20			**-0.068** (0.078) [217; 422] [35; 991]	**0.106** (0.051) [217; 335] [35; 960]	**0.212** (0.042) [217; 263] [35; 926]	**0.271** (0.031) [217; 201] [35; 881]	**0.300** (0.019) [217; 145] [35; 831]	**0.289** (0.017) [217; 95] [35; 751]	**0.245** (0.013) [217; 58] [35; 643]	**0.168** (0.009) [217; 21] [35; 474]	**0.006** (5.169) [217; 0] [35; 25]
< 30				**0.303** (0.047) [304; 335] [66; 960]	**0.366** (0.026) [304; 263] [66; 926]	**0.392** (0.025) [304; 201] [66; 881]	**0.397** (0.018) [304; 145] [66; 831]	**0.367** (0.019) [304; 95] [66; 751]	**0.308** (0.014) [304; 58] [66; 643]	**0.214** (0.010) [304; 21] [66; 474]	**-7.270** (5.082) [304; 0] [66; 25]
< 40					**0.466** (0.022) [376; 263] [100; 926]	**0.477** (0.020) [376; 201] [100; 881]	**0.469** (0.021) [376; 145] [100; 831]	**0.429** (0.016) [376; 95] [100; 751]	**0.360** (0.015) [376; 58] [100; 643]	**0.255** (0.011) [376; 21] [100; 474]	**-12.205** (5.503) [376; 0] [100; 25]
< 50						**0.543** (0.023) [438; 201] [145; 881]	**0.528** (0.018) [438; 145] [145; 831]	**0.481** (0.017) [438; 95] [145; 751]	**0.405** (0.017) [438; 58] [145; 643]	**0.289** (0.012) [438; 21] [145; 474]	**-15.181** (4.922) [438; 0] [145; 25]
< 60							**0.579** (0.023) [494; 145] [195; 831]	**0.525** (0.017) [494; 95] [195; 751]	**0.443** (0.018) [494; 58] [195; 643]	**0.316** (0.016) [494; 21] [195; 474]	**-16.539** (6.019) [494; 0] [195; 25]
< 70								**0.555** (0.020) [544; 95] [275; 751]	**0.466** (0.022) [544; 58] [275; 643]	**0.324** (0.021) [544; 21] [275; 474]	**-18.166** (5.024) [544; 0] [275; 25]
< 80									**0.457** (0.025) [581; 58] [383; 643]	**0.294** (0.021) [581; 21] [383; 474]	**-19.439** (4.585) [581; 0] [383; 25]
< 90										**0.176** (0.042) [618; 21] [552; 474]	**-19.949** (5.638) [618; 0] [552; 25]
< 100											**-19.325** (5.139) [639; 0] [1001; 25]

Notes: In each cell: Sigma, (standard error), [n_{11};n_{21}] [n_{21};n_{22}]