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Change in self-efficacy as a source of state dependence in labor market dynamics?

Alexander Mosthaf

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Johannes Gutenberg University Mainz
Gutenberg School of Management and Economics
Jakob-Welder-Weg 9
55128 Mainz
Germany
wiwi.uni-mainz.de

Contact Details:

Alexander Mosthaf
University of Mainz
Chair of Applied Statistics and Econometrics
Jakob-Welder-Weg 4
55128 Mainz

mosthaf@uni-mainz.de

Change in self-efficacy as a source of state dependence in labor market dynamics?

Alexander Mosthaf (University of Mainz)

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Abstract

Personal traits are often treated as time-constant, partly because of the lack of longitudinal data on personal traits. Using the first eight waves of the German PASS panel survey containing yearly information on self-efficacy, the paper analyzes the stability of self-efficacy and the relationship between employment dynamics and self-efficacy. Descriptive evidence shows that the within variation in self-efficacy is rather small. Models not controlling for unobserved heterogeneity point to a positive effect of self-efficacy on the employment probability and vice versa. However, dynamic discrete choice models which take unobserved heterogeneity and reverse causality into account reveal that the impact of employment status on self-efficacy is close to zero.

Keywords: state dependence, personal traits

New JEL-Classification: J60

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1 Introduction

A large number of empirical studies show the importance of state dependence in dynamics between employment and non-employment (e. g. Mühleisen and Zimmermann, 1994; Hyslop, 1999; Arulampalam et al., 2000). Typical explanations for observed state dependence are loss of human capital (Pissarides, 1992), signalling effects (Vishwanath, 1989) or transaction costs (Hyslop, 1999). Launov and Wälde (2013) provide an additional explanation for state dependence in non-employment and argue that state dependence may appear because of uncertainty of unemployed workers with respect to their search productivity when being not employed. The longer an individual stays in non-employment, the lower is his belief of having a high search productivity which results in decreasing search effort over the spell of non-employment, leading to negative duration dependence and lower re-employment wages.[1]

An individual's belief in own productivity is related to the personal trait self-efficacy which is widely known in the psychological literature. Self-efficacy is the belief of an individual that it is able to achieve desired outcomes (Almlund et al., 2011, section 5.D.1.). According to the theory of Bandura (1977, p. 191) this belief determines "(...) *whether coping behavior will be initiated, how much effort will be expanded, and how long it will be sustained in the face of obstacles and aversive experiences*". Hence, according to this psychological theory, unemployed workers with a low level of self-efficacy should put less effort in job search than individuals with a high level of self-efficacy. The theory also predicts a negative effect of non-employment on self-efficacy as individuals use information on past outcomes in order to assess self-efficacy (Bandura, 1977).

In this study I use the German Panel Study Labour Market and Social Security (PASS) to examine whether there is an effect of the employment state on self-efficacy and whether a change in self-efficacy affects employment probabilities. The

[1] In their search model a low probability of having a high level of search productivity leads to a decreasing subjective job offer arrival rate. As marginal costs of job search must comply with marginal utility of job search, search effort will decrease with unemployment duration.

presence of both effects would lead to state dependence in employment dynamics. I distinguish between three employment states: employment, non-employment, and welfare receipt. Besides adding to the literature on state dependence in employment dynamics, I also contribute to another strand of the literature which investigates the stability of personal traits and the degree to which personal traits change in response to events in life. While there is a growing literature investigating the role of personal traits like locus of control and the Big-Five and labor market outcomes (e. g. Caliendo et al., 2015; Heckman et al., 2006; Heineck and Anger, 2010), this is, to my knowledge, the first study investigating the role of self-efficacy for labor market behavior.

As mentioned above, the theory of self-efficacy predicts that this personal trait is affected by recent life outcomes. Indeed, psychologists have shown in several studies that self-efficacy may change in reaction to specific events. Zlomuzica et al. (2015), Brown et al. (2012), and Brown et al. (2016) perform experiments where groups receive either high or low self-efficacy inductions (through persuasive verbal feedback). The authors show that these inductions significantly affect problem solving capacity, attentional bias associated with remembering averse stimuli, emotional learning and other outcomes. Other studies using non-experimental evidence descriptively point to possible changes in self-efficacy. For instance, McAvay et al. (1996) show that health and demographic factors are correlated with self-efficacy. Additionally, Bloom et al. (2009) investigate the effect of a program for adolescents who dropped out of school and find that the program is associated with a higher level of self-efficacy. Yet, I am not aware of studies using field data and dealing with endogeneity to examine the stability of self-efficacy. This study adds to the literature on the stability of self-efficacy by using a large representative panel survey using yearly observations of self-efficacy and taking the endogeneity of labor market dynamics into account.

Several personal traits discussed in the literature like locus of control or self-esteem are regarded as being fairly stable over the life cycle. Personal traits in general are formed by biology, parental investment and education. Therefore, personality is mainly alterable during childhood. Yet, there are also some studies that show changes of personal traits during adolescence and adulthood (see Borghans et al., 2008 and Almlund et al., 2011, section 8 for surveys). For instance, Gottschalk (2005) shows that there is a positive impact of job quality on locus of control. Using data on a randomized experiment, he studies the effect of a subsidy to work on locus of control. Individuals who received the subsidy had higher wages than workers from the control group. Workers of the treatment group had a significantly higher locus of control three years after treatment.[2]

Other studies focus on training programs designed for improving characteristics like motivation or discipline. Martins (2010) analyzes a program in Portugal which was aimed at improving self-esteem, motivation etc. of pupils with poor performance in school. The program significantly reduced the retention rate of those students who participated in the program, a result which favors the possibility of changing personal traits by policy interventions.

Cobb-Clark and Schurer (2013) study the stability of locus of control. They investigate data from the Australian HILDA-dataset (using information on locus of control in the years 2003, 2004 and 2007) and find that locus of control is not affected by labor market events and by several demographic and health events of individuals. In a related study Cobb-Clark and Schurer (2012) use the same dataset and conclude that the Big-Five personality traits (extraversion, agreeableness, conscientiousness, emotional stability, and openness to experience) are stable during adulthood. Anger et al. (2017) mainly confirm this result using the German SOEP and information on the Big-Five in the years 2005, 2009 and 2013. They analyze how personal traits change after episodes of unemployment caused by plant closures. While all other personal traits remain stable, openness to experience increases for high-

[2] Locus of control is strongly related to self-efficacy (Judge et al., 2002; Cobb-Clark, 2015). It is the belief that individuals in general are responsible for their achievements (rather than external factors like luck) and that there is a causal relationship between an individual's behavior and its achievements. In contrast to locus of control, self-efficacy is a belief which focusses on the own behavior (rather than the behavior of individuals in general) and describes the perceived own ability to achieve goals (Cobb-Clark, 2015).

educated workers if they find a job quickly after becoming unemployed. Roberts and DelVecchio (2000) provide a survey on psychological studies about the changeability of personal traits and infer that traits are quite stable over the life course but that the degree of stability is specific to the trait considered.

The existence of an effect of self-efficacy on the employment probability would suggest that active labor market programs for unemployed individuals should concentrate more on improving personal traits like self-efficacy (besides classical skills like language or computer skills) in particular if non-employment leads to a reduction of self-efficacy.[3]

The question whether there is an effect of non-employment on self-efficacy and vice versa is also interesting for applied empirical researchers. Reverse causality leads to biased coefficients if it is not controlled for. A second source of bias appears if there are unobserved characteristics like motivation which are correlated with the level of self-efficacy and the probability of being employed. A combination of both leads to a bias with unclear direction (see for instance Cobb-Clark and Schurer, 2013).

Most surveys like the Australian HILDA-dataset (mentioned above) and the German SOEP provide information on personal traits only for some cross-sections. For instance, the German SOEP provides information about locus of control in the waves 1999, 2005 and 2010 (Richter et al., 2013). In contrast, PASS — the survey dataset used in this study — has yearly information about self-efficacy and employment. This allows me to follow a similar strategy as Biewen (2009). He estimates state dependence in poverty dynamics and controls for feedback effects of employment and household composition on poverty by jointly modeling the three variables as dependent variables in one likelihood function and controlling for unobserved heterogeneity. He shows that not controlling for feedback effects may bias the estimates of state dependence in poverty. Similar strategies are applied by Alessie et al. (2004) who analyze ownership dynamics of stocks and mutual fonds

[3]Active labor market programs often are designed for improving language skills, computer skills or specific vocational skills like technical and manufactural skills (Kluve, 2010).

and by Haan and Myck (2009) who estimate joint dynamics of non-employment and health. In this paper, endogeneity produced by reversed causality and unobserved variable bias is handled by modeling self-efficacy and the probability of the labor market status as a joint dynamic process. That is, I model the density of self-efficacy and the probability of being employed, not-employed or receiving welfare jointly in one likelihood function. I control for random effects, allowing for correlation between unobserved variables which affect self-efficacy and the labor market status, and control for the problem of initial conditions (Heckman, 1981).

The paper proceeds as follows: section 2 presents the dataset. Section 3 discusses the empirical specification. Section 4 presents the econometric results and section 5 concludes.

2 Data and descriptive statistics

I use the first eight waves of PASS (*Panel Labour Market and Social Security*), covering the years 2006-2014. The panel study is a survey dataset covering topics related to labor market, welfare state and poverty research in Germany. The first wave comprises two samples. The sample of the general population consists of 9568 individuals in 5990 households.[4] The recipient sample is a sample of (former) benefit recipients. It was drawn randomly from all German households with at least one recipient of basic income support (unemployment-benefit-II) in July 2006 (Trappmann et al., 2010). In this study, I only use the sample for the general population to avoid endogenous selection.

The data is analyzed on the individual level. I restrict the analysis to men since labor supply of women is lower and it is empirically difficult to distinguish between voluntary and involuntary career breaks of women. Voluntary career breaks are

[4] Although low income households are moderately oversampled in PASS, studies using the sample should be representative for the general population. First, the sample includes individuals of all income levels in Germany. Second, a descriptive comparison with the German SOEP shows that the difference between both datasets with respect to main economic and demographic variables is quite low. In the econometric analysis, endogenous selection should be avoided by controlling for demographic variables like qualification.

unlikely to affect self-efficacy. In order to omit transitions from education to work and transitions from work to retirement, I restrict the sample to individuals older than 19 and younger than 59 years. Additionally, I drop all observations of individuals who during the observation period are in education, self-employed, on paternity leave, in early retirement, doing military or community service, or disabled. Furthermore, as the employment status should only be important for the individual's self-efficacy if it has an incentive to work I do not analyze persons who during the observation period never have worked or never received unemployment benefits. An individual enters the unbalanced dataset if it is observed at least in two consecutive waves of PASS. The individual leaves the sample in the first wave in which it is not observed or has a missing value in the dependent or in one of the explanatory variables. Finally, wave 5 is dropped from the dataset since it is the only wave which does not provide information on self-efficacy. This restriction leads to a gap of two years between the fifth and sixth period in the applied dataset, whereas the gap between other consecutive waves is only one year. In the empirical analysis, it was taken care of this issue by interacting the coefficients representing state dependence with a dummy variable for wave 6. The results did not change compared to the basic models.

The resulting dataset consists of 3966 observations from 1053 men.[5] I define a worker as employed if he works more than 1 hour in a week and if he does not receive welfare. An individual enters the state of "non-employment" if it is not working and does not receive welfare. Note that this includes individuals with and without receipt of unemployment benefit I. The respondent enters the state "welfare" if he receives

[5]Considering the comparatively high number of 9568 respondents in the first wave, the resulting sample size is disappointingly low. The major reason is the high attrition rate between wave 1 and wave 2 (Trappmann et al., 2015). The Wooldridge-estimator used in this analysis has some advantages in the case of attrition (Wooldridge, 2005, p. 44) because attrition is allowed to depend on the initial states of the dependent variables. This should be of relevance in the given context since attrition in PASS is related to the employment state (Trappmann et al., 2015). Throughout the paper I will assume that attrition is unrelated to the error term, given the lagged dependent variables, the initial values of the dependent variables, and the explanatory variables.

unemployment benefit II.[6] The items regarding self-efficacy are the following:[7]

- For each problem I have a solution.
- Also, if surprising events occur, I believe I can handle them well.
- I have no difficulties in realizing my goals.
- In unexpected situations I always know how to behave.
- I always succeed in resolving difficult problems if I make an effort.

Respondents may indicate values between 1 and 4, where 1 corresponds to "applies completely" and 4 corresponds to "applies not at all". A sum index which measures self-efficacy is constructed. As an alternative, I also applied a variable using factor scores from a factor analysis. The results do not vary qualitatively. Note that the factor analysis clearly indicates that there is one underlying factor between the five items. Figure 1 shows the sum index for the pooled dataset.

- Figure 1 about here -

Most observations have the value 15 in the sum index for self-efficacy (about 35 percent). This value corresponds to an individual who answers "tends to apply" to all 5 questions. Only 3 out of 3966 observations answer "does not apply at all" to all questions whereas about 4 percent always answer "applies completely". The left graph in figure 2 shows differences between the sum indices of self-efficacy between two consecutive waves. It is shown that the amount of changes in self-efficacy is quite low. For about 31 percent of all observations, the change in self-efficacy is 0. About 32 percent have a change of -1 or 1 and only about 10 percent have a change of

[6] In Germany, individuals receive unemployment benefit I for a duration of 12-24 months if they have been working in a job covered by social security for a minimum amount of 12 months before unemployment. If this does not apply, they may receive the means-tested unemployment benefit II (Eichhorst et al., 2010).

[7] English translations can be found in the English versions of the questionnaires. For more information on the data documentation see Trappmann et al. (2010).

more than 3 in absolute values. The standard deviation of the change in self-efficacy is about 2.01. A change of 2 in the sum index corresponds to a change of 1 in 2.5 items on average.

- Figure 2 about here -

The effects of self-efficacy identified by the econometric model in this paper come from deviations with respect to the initial conditions. These deviations are shown in the right part of figure 2. In comparison to the yearly differences, the amount of changes is larger. The share of observations with a value of 0 is now about 26 percent and the standard deviation grows from 2.01 to 2.22. In only about 23 percent of all observations, the change is larger than 1 standard deviation. Altogether, the amount of changes observed in self-efficacy is quite small. The numbers presented here seem to be comparable with the ones presented by Cobb-Clark and Schurer (2013) for locus of control.

- Table 1 about here -

Table 1 shows descriptive statistics of the pooled regression sample. The sample of men consists of 1053 individuals and 4412 observations. About 88 percent of the observations are employed, about 3.5 percent belong to the state "non-employment" while about 8 percent to the state welfare. The mean value of self-efficacy is about 15.47 under employed individuals, 14.68 under individuals who are not employed and 14.47 under individuals who receive welfare. Thus, descriptive statistics point to a positive relationship between self-efficacy and employment. The share of first generation migrants is considerably higher under welfare recipients (23 percent) than under employed individuals (8 percent). Furthermore, the share of individuals in the lowest age group with 20-34 years is relatively high (31 percent).

- Table 2 about here -

Table 2 shows a matrix for the transitions between the three employment states considered. Persistence is extremely high in employment and in welfare receipt. 97.2 percent of individuals employed in $t-1$ are also employed in period t. About 80 percent of the individuals who receive welfare in period $t-1$ stay in this employment state in period t. Only about 17 percent of the welfare recipients in period $t-1$ have a job in period t. In contrast, non-employment seems to be a transitory experience, with about 23 percent persistence and a transition rate of about 57 percent from non-employment to employment.

3 Empirical specification

I use a joint model for an individual's self-efficacy and its probability of being employed, not employed or of receiving welfare in period t:

$$\begin{aligned} s_{it} &= \alpha_1 s_{it-1} + \alpha_2 E_{it-1} + \alpha_3 X_{it} + \eta_i + \epsilon_{it} && (1) \\ e^*_{ijt} &= \beta_{j1} s_{it-1} + \beta_{j2} E_{it-1} + \beta_{j3} Z_{it} + \tau_{ij} + \omega_{ijt}, && (2) \end{aligned}$$

where s_{it} is the sum index for self-efficacy and e^*_{ijt} is a latent variable underlying the probability of being in employment state $j = 1, \ldots, 3$. Both dependent variables may depend on their lagged values s_{it-1} and E_{it-1}, where the latter is a vector of dummy variables indicating the employment state. X_{it} is a vector of observed explanatory variables for the probability of level j of self-efficacy and Z_{it} represents observed variables explaining the probability of employment.[8] η_i and τ_i are time-constant individual-specific unobserved effects. ϵ_{it} and ω_{it} are time-varying unobserved effects.

[8] X_{it} includes dummy variables indicating if the individual is a first or second generation migrant, dummy variables indicating if the individual has had vocational training or a university degree, age, age^2, a dummy variable indicating the father's education, time dummies and a dummy indicating if an individual belongs to the general population sample. z_{it} additionally includes the unemployment rate at the state (Bundesland) level and a dummy indicating if the individual lives in Eastern Germany. The father's education is not included in z_{it}. The exclusion restrictions are justified below.

I assume that there is no autocorrelation in the error terms.

Problems regarding endogeneity stemming from reverse causality between s_{it} and e^*_{ijt} are avoided by modeling the impact of the lagged employment state on self-efficacy. A further bias might result from correlation of η_i with e_{it-1} which appears if there are some time-constant unobserved variables which affect both, employment and self-efficacy. This is handled by simultaneously estimating the probability of being in employment state j and self-efficacy. Correlation of time-constant unobserved effects is explicitly modeled.

The coefficients representing the effects of the lagged variables may additionally be inconsistent because of a correlation between the initial values of self-efficacy and employment in s_{it-1} and E_{it-1} with unobserved heterogeneity. As I do not observe the states of self-efficacy and employment preceding the first period of observation, it is not possible to model the initial observations S_{i1} and e_{i1} as dependent variables and hence correlation with the random effects cannot be modeled with help of equations (1) and (2). Wooldridge (2005) proposes to control for the correlation of the random effects with the initial states by explicitly including s_{i1} and E_{i1} on the right side of the equations. The coefficients representing the effects of the initial states will then control for the correlation with η_i and τ_i. As proposed by Wooldridge (2005) I additionally include individual-specific means of the time-varying variables in Z_{it} to control for correlation of time-varying explanatory variables with the random effects (see also Mundlak, 1978; Chamberlain, 1984).[9,10]

$$
\begin{aligned}
s_{it} &= \alpha_1 s_{it-1} + \alpha_2 E_{it-1} + \alpha_3 X_{it} + \alpha_5 s_{i1} + \alpha_6 E_{i1} + \nu_i + \epsilon_{it} && (3) \\
e^*_{ijt} &= \beta_1 s_{it-1} + \beta_2 E_{it-1} + \beta_3 Z_{it} + \beta_4 \bar{Z}_i + \beta_5 s_{i1} + \beta_6 E_{i1} + \zeta_i + \omega_{it}, && (4)
\end{aligned}
$$

where ν_i as well as ζ_i are random effects which are uncorrelated with the lagged dependent variables. An alternative method to deal with the initial conditions

[9]Wooldridge (2005) originally proposed to include $Z_{i2}, \ldots, Z_{iT}$ instead of $\bar{Z}_i = \frac{1}{T-1}\sum Z_{i2}, \ldots, Z_{iT}$. However, Rabe-Hesketh and Skrondal (2013) show in their simulation that the specification using $\bar{Z}_i$ performs well.

[10]Apart from age — which is exogenous — X_{it} does not contain time-varying variables.

problem is suggested by Heckman (1981). The attractiveness of the Wooldridge-method compared to the Heckman-method lies in the simple implementation in statistic software packages. In an earlier version of this paper, I applied both estimators and showed that they led to the same conclusions. Results are available on request.[11]

I assume a linear relationship between self-efficacy and its explanatory variables. ϵ_{it} are assumed to follow a normal distribution. ω_{ijt} are assumed to follow a logistic distribution, leading to a multinomial logit specification for the probability of employment state j. The random effects $\boldsymbol{\nu}$ and $\boldsymbol{\zeta}$ follow a joint discrete distribution (Heckman and Singer, 1984). The number of mass points of the discrete distribution is a priori unknown. For each specification, I start with one mass point and then increase the number of mass points until the minimal Akaike Information Criterion is achieved. This approach implies relatively weak distributional assumptions on the time-constant unobserved variables.

The model is identified by its functional form, where the discrete distribution requires relative weak assumptions on the distribution of time-constant variables. As stated by Altonij et al. (2005), exclusion restrictions might be helpful for semi-parametric identification in limited dependent variable models. X_{it} contains dummy variables which indicate if the father of the individual obtained vocational training. Personal traits are affected by childhood conditions and the environment provided by the parents. I assume that given self-efficacy, the qualification of parents does not have an influence on the probability of employment. Heckman et al. (2006) also use parent's education as exclusion restriction when estimating the impact of personality on economic outcomes. Z_{it} contains the unemployment rate of the state (Bundesland) and a dummy for residence in Eastern Germany as variables which are not included in the equation for self-efficacy. My argument is that the level of self-efficacy of an individual should not be affected by the economic environment since

[11] In various studies, the estimators by Wooldridge (2005) and Heckman (1981) yield similar results (see for instance Stewart, 2007; Michaud and Tatsiramos, 2011; Arulampalam and Stewart, 2009; Rabe-Hesketh and Skrondal, 2013).

the concept of self-efficacy is very much focussed on own actions and own abilities for achieving results. Basan and Mosthaf (2017) applied Monte-Carlo simulations on a model similar to the one used in this paper and did not find differences between specifications with and without exclusion restrictions. Hence, we are confident that our results are robust with respect to the choice of exclusion restrictions.

Whereas the partial effects in the self-efficacy equation are given by the coefficients, the coefficients of the employment equations cannot be interpreted with respect to economic significance. Therefore, I calculate average partial effects by applying parametric bootstrap methods. In order to provide test statistics I draw 1000 times parameter values from the estimated sampling distribution and calculate partial effects.

4 Econometric results

Table 3 shows results of regressions ignoring time-constant unobserved heterogeneity for men (model 1 and model 2). Model 1 is an OLS model for the sum index of self-efficacy. Model 2 is a multinomial logit for the probability of being employed, not employed or of receiving welfare.

- Table 3 about here -

Model 1 shows that there is persistence in self-efficacy. Increasing the sum index of self-efficacy in $t-1$ by 1 leads to an increase of self-efficacy of 0.03 ceteris paribus. The effect is significant at the 1 percent level. Being not employed in period $t-1$ compared to being employed in period $t-1$ reduces self-efficacy significantly by about 0.07. Receiving welfare in period $t-1$ also reduces self-efficacy significantly by about 0.07. This result may reflect a positive impact of employment on self-efficacy or a correlation of serially correlated unobserved variables like motivation that are positively correlated with the level of self-efficacy and with the probability of employment. Note, however, that the effect is small, given that the standard deviation of self-efficacy is 2 and the range of self-efficacy is between 5 and 20.

Model 2 is a standard multinomial logit model for the probabilities of employment, non-employment and welfare-receipt in period t, where employment serves as the reference category for the dependent variable. I first discuss the coefficients for the probability of non-employment compared with the probability of employment. Conditioning on observed variables, increasing the sum index of self-efficacy in $t-1$ is negatively associated with the probability of non-employment compared with the probability of employment. However, this coefficient is not significant. Being not employed in period $t-1$ compared with being employed in period $t-1$ significantly increases the probability of non-employment compared with employment, indicating that there is state dependence in non-employment. This effect is significant at the 1 percent level. While the coefficient is somewhat smaller, the same is true for receiving welfare in $t-1$. First generation migrants are on average more likely to be not employed compared with being employed, although the effect is not significant. Having a university degree significantly decreases the probability of being not employed compared with the probability of being employed.

The effects of observed variables on the probability of welfare in period t compared with the probability of employment in period t are comparable with those on the probability of non-employment compared with employment. However, the effect of self-efficacy is now significant at the 5 percent level. Being a first generation migrant has a positive effect. The probability of receiving welfare compared with the probability of being employed is significantly larger in Eastern Germany.

As the coefficients of the multinomial logit model cannot be interpreted with respect to their size, table 4 shows average partial effects. Being not employed in $t-1$ compared with being employed in $t-1$ significantly decreases the probability of employment by 37 percentage points. Individuals receiving welfare in $t-1$ have a much lower probability (- 66 percentage points) of being employed than individuals being employed in $t-1$. Increasing the sum index of self-efficacy by 1 in $t-1$ significantly increases the probability of employment in period t by 0.4

percentage points. Note, however, that this model does not account for selection on unobservables, i. e. individuals having a high self-efficacy might have other unobserved characteristics like a high ability which increase the probability of employment. In contrast, self-efficacy has a negative association with the probability of welfare in t while the effect on the probability of non-employment is not significant.

I now turn to the results of the models which take time-constant unobserved heterogeneity into account. Table 5 shows the coefficients of the model outlined in section 3. Here, the sum index of self-efficacy and the probabilities of the three considered employment states are modeled as a joint dynamic process and unobserved characteristics affecting self-efficacy and employment, non-employment and welfare are allowed to be correlated. The model presented is a model with 7 mass points. The model with 8 mass points did not converge. Models with 5 and 6 mass points had only slightly higher AIC-values and the results between the different models did not change qualitatively.

- Table 5 about here -

The initial values of self-efficacy as well as receiving welfare in the initial period are strongly significant when looking at the equation of self-efficacy. This indicates that not controlling for the initial conditions problem would lead to an overestimation of the lagged endogenous variables. The dummy variable for the qualification status of the father does not have a significant effect. This variable is excluded from the employment equations. However, exclusion restrictions are not necessarily needed in this model since I include the lagged and not the current values of the endogenous variables. Moreover, identification stems from a semiparametric specification of time-constant heterogeneity. Furthermore, in a Monte-Carlo study on a similar model to the one used here, specifications without exclusion restrictions do not perform worse than specifications with exclusion restrictions (Basan and

Mosthaf, 2017).[12]

Looking at the equations for the probabilities of non-employment versus the probability of employment and the probabilities of welfare compared with the probability of employment, the initial values of the lagged endogenous variables are again significant (apart from the initial value of self-efficacy in the non-employment equation). Here, the unemployment rate, which is excluded from the self-efficacy equation, is significant in the non-employment equation and the Eastern Germany dummy, which is excluded from the self-efficacy equation, is significant in the welfare equation.

The coefficients for the equation of self-efficacy reveal that there is true state dependence in self-efficacy. Increasing self-efficacy in $t-1$ by 1 increases self-efficacy in t by 0.0863. This state dependence may be explained by positive effects of self-efficacy on life-outcomes like health in $t-1$, which in turn may positively affect self-efficacy in t. While the formerly significant effect of welfare in $t-1$ on self-efficacy has become insignificant, the effect of non-employment in $t-1$ is still significant. Being not employed in $t-1$ decreases the sum index of self-efficacy by 0.374. However, given that the sum index of self-efficacy ranges between 5 and 20 and that the standard deviation is about 2, this effect is quite small.

Table 6 shows average partial effects. These indicate that there is strong state dependence in employment dynamics. However, compared with the model not controlling for unobserved heterogeneity, the partial effects are reduced. For instance, the negative effect of receiving welfare in $t-1$ is reduced by from about 65 to 30.9 percentage points. Also the effects of self-efficacy on the probabilities of employment and receiving welfare are now insignificant. Note that it should not be concluded that self-efficacy does not have any effect on the probabilities of the employment state considered. The coefficients of the lagged dependent variables in this model are identified by the within deviations from the initial observed values. As shown in the descriptive statistics in section 2, within variation in self-efficacy is small.

[12]Results of the simulation study are available on request.

The between variation in the time-constant part of self-efficacy in this model is captured by the initial values of self-efficacy — which show a negative impact on the probability of welfare-receipt compared with the probability of employment. Furthermore, between variation in the time-constant part of self-efficacy is captured by the random effects. The correlation coefficients for the random effects show that unobserved characteristics which positively affect the probability of non-employment compared with the probability of employment also positively affect the probability of welfare compared with the probability of employment (correlation coefficient = 0.584). In contrast, these characteristics negatively affect self-efficacy (as the correlation coefficients for the non-employment and welfare equations with the self-efficacy equation are negative), meaning that the same unobserved effects enhance the probability of employment and the value of self-efficacy.

As a robustness check, this paper shows models where self-efficacy is not treated as a sum index but as a binary variable. In these models, individuals have a high level of self-efficacy if the sum index is 15 or larger. Remind that a sum index of 15 is achieved if an individual answers "tends to apply" to all 5 questions. About 73 percent in the sample have a sum index of 15 or a larger sum index. Table 7 shows models not including random effects and initial values of the dependent variables. The probability of having a high level of self-efficacy is estimated using a pooled logit model. The coefficients have similar signs as the coefficients of the former model in table 3. For instance, having a university degree has a positive effect on the probability of having a high self-efficacy and a negative effect on the probabilities of being not employed or receiving welfare compared with the probability of employment.

Table 8 shows partial effects. Being not employed is considerably associated with the probability of having a high level of self-efficacy. Individuals who are not employed rather than employed in $t-1$ have a probability of having a high level of self-efficacy which is about 5.5 percentage points lower. The effect of receiving welfare is even larger (-7.3 percentage points). Moreover, there is a significant positive association of self-efficacy and the probability of employment. Having a high level of self-efficacy increases the probability of employment significantly by about 1.3 percentage points. On the other hand, it decreases the probability of welfare receipt significantly by 1.1 percentage points. This effect is comparable in size with the effect of having a middle qualification (apprenticeship) compared with having a low qualification (no degree) which is 2.0 percentage points for the probability of employment and -1.1 percentage points for the probability of welfare.

The effects shown in table 8 seem to be larger in size than the effects in the tables 3 and 4. Hence, the association between self-efficacy and the labor market state seems to be more pronounced for the probability of having a sum index of self-efficacy lower than 15 than for the value of self-efficacy given that the sum index of self-efficacy is higher than 15 (i. e. there is a nonlinear relationship between self-efficacy and the probability of employment). Note that 73 percent of the sample have a value of self-efficacy of 15 or larger and hence the coefficients in the models using the sum index of self-efficacy are mainly identified by variation in this part from the distribution.

Table 9 shows the model where the probability of having a high level of self-efficacy is jointly estimated with the probabilities of the three employment states using one likelihood function. The specification with 4 mass points yields a lower AIC than the specification with 5 mass points and is therefore preferred. The models using 3, 4, and 5 mass points lead, however, to comparable results. The coefficients show that the results do not change much compared to the ones of table 6 where the sum index instead of the binary variable of self-efficacy was included. Still there is considerable state dependence in self-efficacy and in the labor market states. However, the effect of non-employment on self-efficacy is now not significant anymore, while it was small and significant in table 6. As in table 6, there is no effect of self-efficacy on the employment states.

Various robustness checks led to similar results. For instance, models with interaction effects between the lagged dependent variables and a dummy variable for wave 6 were included. In wave 6 the length of the gap to the previous observation is 2 years (instead of 1 year), since the question for self-efficacy is not asked in wave 5. Moreover, I applied models including the second lags of the dependent variables. In an earlier version of this paper, I used a model using an ordinal variable for self-efficacy, separating between a high, a middle and a low level of self-efficacy, and a binomial variable for employment versus non-employment. This model was estimated using the method by Wooldridge (2005) and by using the method by Heckman (1981). Both specifications confirm that there is state dependence in self-efficacy as well as in employment, but there is no effect of self-efficacy on employment and vice versa. Results are available on request.

5 Conclusions

This study uses German PASS-data to analyze the stability of self-efficacy and its causal relationship to employment dynamics. While most panel surveys only provide cross-section information on personal traits, PASS has yearly information on self-efficacy and on employment. This allows the application of panel data methods to control for possible endogeneity caused by reverse causality and by correlated unobserved variables which affect employment and self-efficacy. In particular, the study focusses on the question whether or not changes in self-efficacy are a source of state dependence in employment dynamics, distinguishing between employment, non-employment, and welfare receipt. While there is a growing literature on the effect of other personal traits (like locus of control and the Big-Five) on labor market outcomes this is, to my knowledge, the first study investigating the role of self-efficacy for labor market behavior.

Descriptive statistics reveal that the amount of change in self-efficacy within individuals is small. When applying models which do not control for unobserved heterogeneity, an effect of self-efficacy on the probability of employment and the reversed effect are obtained. Here, the size of the effect of having a high value of self-efficacy on the probability of employment is comparable with the effect of having an apprenticeship rather than not having any degree.

When taking time-constant individual effects into account which may affect both, self-efficacy and the labor market state, the effects mainly vanish. Hence, changes in self-efficacy are not a source of state dependence in employment dynamics. This analysis supports earlier studies which show that personal traits are not strongly affected by labor market events and are mainly stable over time (e.g. Cobb-Clark and Schurer, 2013). As a result, studies which aim at measuring the effect of self-efficacy on labor market outcomes using cross-sectional information should not suffer from problems caused by reversed causality.

The results of the main specification in this study controlling for time-constant individual effects also suggest that self-efficacy does not have an effect on the employment state. However, one should keep in mind that the effects of the dynamic nonlinear models in this study are identified by changes in self-efficacy in the observation period within the observed individuals and this paper has shown that the amount of change in self-efficacy within one individual is quite small. Models using variation between individuals point to a positive effect of self-efficacy on employment. Yet, it cannot be excluded that this effect catches up confounding variables.

The results in this study are not in favor of designing active labor market programs for improving self-efficacy, since the data points to the time-invariance of self-efficacy. However, although the results show that self-efficacy is usually stable over the life-cycle, it would be interesting to see whether training programs using self-efficacy inductions like those applied by Brown et al. (2012) may help unemployed individuals in the application process. In addition, the results cannot exclude that training programs which are aimed at improving other personal traits like self-esteem are effective (Martins, 2010).

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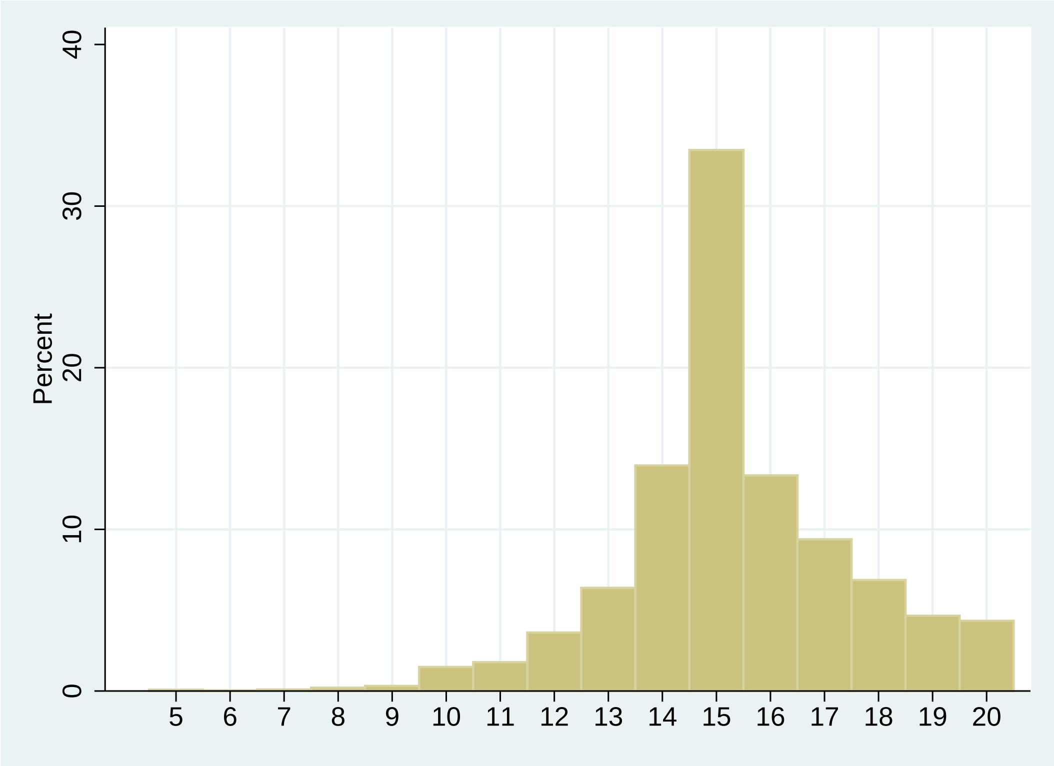

Figure 1: Sum index for self-efficacy. Source: PASS (Waves 1-8).

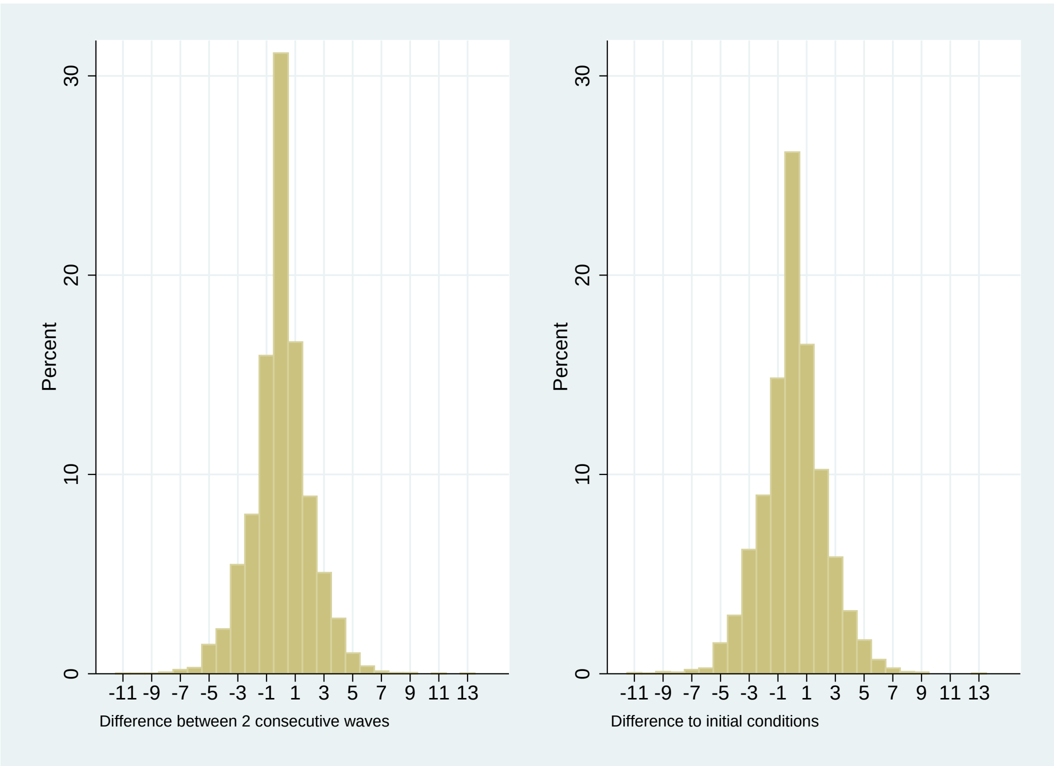

Figure 2: Change of the sum index for self-efficacy between two consecutive waves (left graph) and with respect to the initial observation (right graph). Source: PASS (Waves 1-8).

Table 1: Descriptive statistics

	Employment	Non-Employment	Welfare
	Variable means		
Self-efficacy (sum index)	15.47	14.68	14.47
No migration background (dummy)	0.87	0.86	0.73
First generation migrant (dummy)	0.08	0.11	0.23
Second generation migrant (dummy)	0.05	0.03	0.04
No qualification (dummy)	0.06	0.20	0.36
Vocational training (dummy)	0.67	0.60	0.59
University degree (dummy)	0.27	0.20	0.05
Age: 20-34 (dummy)	0.16	0.19	0.31
Age: 35-44 (dummy)	0.34	0.31	0.23
Age: 45-57 (dummy)	0.50	0.50	0.45
Unemployment rate	8.54	8.82	10.42
Eastern Germany (dummy)	0.19	0.17	0.32
Father has at least vocational training (dummy)	0.80	0.77	0.56
Wave 2006/2007 (dummy)	0.17	0.29	0.23
Wave 2008 (dummy)	0.19	0.18	0.26
Wave 2008/2009 (dummy)	0.15	0.13	0.18
Wave 2010 (dummy)	0.11	0.10	0.11
Wave 2012 (dummy)	0.14	0.12	0.10
Wave 2013 (dummy)	0.13	0.11	0.07
Wave 2014 (dummy)	0.10	0.08	0.05
Number of individuals	909	34	110
Number of observations	3943	135	334
Share of observations (%)	88.46	3.51	8.03

Source: PASS waves 1-8; unweighted; pooled sample

Table 2: Transition matrix between employment states

	Employment, t	Non-employment, t	Welfare, t	Total
Employment, no welfare, t-1	97.2	2.1	0.7	100.0
Non-employment, t-1	57.4	23.4	19.1	100.0
Welfare, t-1	16.9	3.3	79.8	100.0
Total	89.6	2.9	7.5	1.0
N	3553	116	297	3966

Source: PASS (2006-2014); pooled unweighted sample; Transitions between periods t - 1 and t; values indicate percentages

Table 3: Dynamic models without random effects

	Model 1		Model 2			
	Self-Efficacy, t		Non-employment, t		Welfare, t	
Self-efficacy, t-1 (sum index)	0.0345***	(0.00179)	-0.0684	(0.0443)	-0.100**	(0.0441)
Unemployment, t-1 (dummy)	-0.0684***	(0.0206)	2.839***	(0.249)	3.597***	(0.322)
Welfare, t-1 (dummy)	-0.0675***	(0.0150)	2.086***	(0.377)	6.186***	(0.274)
First generation migrant (dummy)	-0.0293**	(0.0134)	0.176	(0.322)	1.074***	(0.325)
Second generation migrant (dummy)	-0.0460***	(0.0173)	-0.681	(0.604)	-0.411	(0.547)
Vocational training (dummy)	0.0741***	(0.0143)	-0.436	(0.297)	-0.671**	(0.278)
University degree (dummy)	0.0818***	(0.0158)	-0.757**	(0.349)	-1.676***	(0.417)
Age: 35-44 (dummy)	-0.0433	(0.0293)	-0.453	(0.800)	0.0223	(0.798)
Age: 45-57 (dummy)	-0.0571	(0.0361)	-0.826	(0.997)	1.268	(1.099)
Father has at least vocational training (dummy)	0.0132	(0.00949)	—	—	—	—
Wave 2008/2009 (dummy)	0.0101	(0.0113)	0.0348	(0.312)	0.0850	(0.318)
Wave 2010 (dummy)	0.0242*	(0.0125)	0.0752	(0.339)	-0.382	(0.351)
Wave 2012 (dummy)	0.0192	(0.0141)	0.462	(0.382)	0.208	(0.433)
Wave 2013 (dummy)	0.0213*	(0.0124)	0.253	(0.333)	-0.469	(0.391)
Wave 2014 (dummy)	0.0279**	(0.0133)	0.283	(0.355)	-0.642	(0.422)
Individual mean over time: Age: 35-44	0.0281	(0.0324)	0.242	(0.894)	-0.899	(0.891)
Individual mean over time: Age: 45-57	0.0472	(0.0378)	0.882	(1.052)	-1.787	(1.152)
Unemployment rate	—	—	0.257	(0.168)	0.173	(0.159)
Eastern Germany (dummy)	—	—	-1.763	(3.832)	-6.606***	(2.245)
Individual mean: Eastern Germany	—	—	1.522	(3.836)	6.092***	(2.264)
Individual mean: Unemployment rate	—	—	-0.256	(0.168)	0.0218	(0.159)
Constant	0.861***	(0.0195)	-3.384***	(0.589)	-5.314***	(0.668)
Observations	3966		3966			
AIC	-165.9		1633.8			
Log Likelihood	100.97		-774.91			
Wald-Test-Chi^2			1590.52			
Prob > Chi^2	0.00		0.00			

Standard errors in parantheses
$^{*}p < 0.10$. $^{**}p < 0.05$. $^{***}p < 0.01$.
Model 1 is an OLS model for the sum index of self-efficacy.
Model 2 is a multinomial model for the probabilities of
being employed, not employed or receiving welfare. Being employed is the reference category.
The variable for self-efficacy is centered at its mean.

Table 4: Average partial effects

	Employment, t		Non-employment, t		Welfare, t	
Employment, $t-1$ (ref.)	-	-	-	-	-	-
Non-employment, $t-1$	-0.370***	(0.097)	0.211**	(0.092)	0.158**	(0.079)
Welfare, $t-1$	-0.655***	(0.010)	0.034	(0.033)	0.621***	(0.118)
Self-efficacy, $t-1$	0.004**	(0.002)	-0.002	(0.002)	-0.002**	(0.014)

Simulations based on parametric bootstrap using coefficients of the estimators presented in Table 3; standard errors in parentheses

Table 5: Dynamic model with random effects

	Model 3					
	Self-Efficacy, t		Non-employment, t		Welfare, t	
Self-efficacy, t-1	0.0863***	(0.0213)	0.0464	(0.0791)	0.0374	(0.0808)
Non-employment, t-1	-0.374**	(0.164)	1.551***	(0.422)	2.555***	(0.448)
Welfare, t-1	0.0453	(0.173)	0.431	(0.556)	4.716***	(0.348)
First generation migrant (dummy)	-0.246*	(0.130)	0.435	(0.379)	1.489***	(0.376)
Second generation migrant (dummy)	0.0646	(0.161)	-0.928	(0.660)	-0.969	(0.640)
Vocational training (dummy)	0.480***	(0.141)	-0.547	(0.373)	-0.677**	(0.334)
University degree (dummy)	0.521***	(0.154)	-1.006**	(0.453)	-1.933***	(0.501)
Age: 35-44 (dummy)	-0.0294	(0.186)	-0.702	(0.828)	-0.490	(0.856)
Age: 45-57 (dummy)	-0.0240	(0.229)	-1.206	(1.053)	0.801	(1.204)
Father has at least vocational training (dummy)	0.0478	(0.0829)	—	—	—	—
Wave 2008/2009 (dummy)	0.117*	(0.0699)	-0.0931	(0.340)	-0.0394	(0.341)
Wave 2010 (dummy)	0.0476	(0.0790)	-0.0534	(0.376)	-0.503	(0.396)
Wave 2012 (dummy)	0.0253	(0.0901)	0.341	(0.433)	0.0428	(0.498)
Wave 2013 (dummy)	0.0177	(0.0832)	0.228	(0.373)	-0.417	(0.432)
Wave 2014 (dummy)	-0.0177	(0.0893)	0.232	(0.408)	-0.794	(0.488)
Individual mean over time: Age: 35-44	-0.0734	(0.223)	0.408	(0.945)	-0.664	(0.961)
Individual mean over time: Age: 45-57	-0.0662	(0.252)	1.182	(1.125)	-1.503	(1.272)
Self-efficacy, t=1	0.380***	(0.0225)	-0.118	(0.0754)	-0.157**	(0.0788)
Non-employment, t=1	0.0684	(0.169)	1.473***	(0.494)	1.272***	(0.479)
Welfare, t=1	-0.547***	(0.210)	3.336***	(0.656)	3.153***	(0.474)
Unemployment rate	—	—	0.297*	(0.180)	0.219	(0.171)
Eastern Germany (dummy)	—	—	-3.159	(3.948)	-7.796***	(2.318)
Individual mean: Eastern Germany	—	—	3.000	(3.962)	7.544***	(2.344)
Individual mean: Unemployment rate	—	—	-0.282	(0.180)	-0.0134	(0.171)
σ	1.993***	(0.059)				
m_1 ($p_1 = 0.002$)	7.130***	(1.416)	-41.87	(3.88e+08)	-8.935***	(2.366)
m_2 ($p_2 = 0.174$)	0.289	(0.381)	-17.92	(645.5)	-6.372***	(0.992)
m_3 ($p_3 = 0.145$)	1.648***	(0.209)	-3.193***	(0.834)	-5.395***	(0.838)
m_4 ($p_4 = 0.009$)	-5.055***	(0.491)	-1.034	(1.122)	-3.059*	(1.315)
m_5 ($p_5 = 0.049$)	-2.713***	(0.382)	-2.827**	(1.019)	-4.699***	(1.014)
m_6 ($p_6 = 0.562$)	-0.842***	(0.204)	-3.923***	(0.820)	-5.859***	(0.815)
m_7 ($p_7 = 0.059$)	-0.379	(0.345)	-0.955	(0.915)	-3.287**	(1.068)
Correlation coefficient Self-Efficacy & Non-employment	-0.328					
Correlation coefficient Self-Efficacy & Welfare	-0.249					
Correlation coefficient Non-employment & Welfare	0.584					
Observations	3966					
AIC	16931.3					
Log Likelihood	-8371.67					
Wald-Test-Chi^2	785.45					
Prob > Chi^2	0.00					

Standard errors in parantheses
$^*p < 0.10$. $^{**}p < 0.05$. $^{***}p < 0.01$.
Source: PASS, Waves 1-8
The variable for self-efficacy is centered at its mean.

Table 6: Average partial effects

	Employment, t		Non-employment, t		Welfare, t	
Employment, $t-1$ (ref.)	-	-	-	-	-	-
Non-employment, $t-1$	-0.145**	(0.061)	0.059	(0.041)	0.086*	(0.053)
Welfare, $t-1$	-0.309***	(0.106)	-0.021	(0.020)	0.331***	(0.111)
Self-efficacy, $t-1$	-0.001	(0.003)	0.001	(0.003)	0.001	(0.002)

Simulations based on parametric bootstrap using coefficients of the Wooldridge-estimators presented in the Table 5; standard errors in parantheses

Table 7: Dynamic models without random effects

	Model 4		Model 5			
	High self-Efficacy, t		Non-employment, t		Welfare, t	
High self-efficacy, t-1	2.089***	(0.0820)	-0.276	(0.211)	-0.717***	(0.226)
Unemployment, t-1	-0.365*	(0.204)	2.859***	(0.248)	3.642***	(0.321)
Welfare, t-1	-0.447***	(0.148)	2.087***	(0.377)	6.185***	(0.276)
First generation migrant (dummy)	-0.177	(0.138)	0.192	(0.322)	1.108***	(0.327)
Second generation migrant (dummy)	-0.0285	(0.187)	-0.697	(0.604)	-0.423	(0.550)
Vocational training (dummy)	0.345**	(0.144)	-0.446	(0.296)	-0.658**	(0.279)
University degree (dummy)	0.519***	(0.163)	-0.754**	(0.349)	-1.665***	(0.420)
Age: 35-44 (dummy)	-0.181	(0.314)	-0.450	(0.798)	0.0546	(0.802)
Age: 45-57 (dummy)	-0.323	(0.387)	-0.825	(0.996)	1.332	(1.104)
Father has at least vocational training (dummy)	-0.0349	(0.102)				
Wave 2008/2009 (dummy)	0.0602	(0.119)	0.0427	(0.312)	0.0970	(0.318)
Wave 2010 (dummy)	0.222	(0.136)	0.0843	(0.339)	-0.370	(0.354)
Wave 2012 (dummy)	0.148	(0.154)	0.473	(0.383)	0.226	(0.436)
Wave 2013 (dummy)	0.103	(0.133)	0.260	(0.334)	-0.437	(0.391)
Wave 2014 (dummy)	0.155	(0.144)	0.291	(0.355)	-0.617	(0.424)
Individual mean over time: Age: 35-44	0.116	(0.347)	0.243	(0.892)	-0.892	(0.895)
Individual mean over time: Age: 45-57	0.332	(0.406)	0.881	(1.051)	-1.856	(1.158)
Unemployment rate			0.255	(0.168)	0.167	(0.159)
Eastern Germany (dummy)			-1.883	(3.965)	-6.710***	(2.271)
Individual mean: Eastern Germany			1.631	(3.969)	6.185***	(2.289)
Individual mean: Unemployment rate			-0.253	(0.168)	0.0315	(0.158)
Constant	-0.636***	(0.207)	-3.195***	(0.599)	-4.909***	(0.675)
Observations	3966		3966			
AIC	3841.8		1629.6			
Log Likelihood	-1902.91		-772.80			
Wald-Test-Chi^2	790.82		1594.74			
Prob > Chi^2	0.00		0.00			

Standard errors in parantheses
$^{*}p < 0.10$. $^{**}p < 0.05$. $^{***}p < 0.01$.
Source: PASS, Waves 1-8

Table 8: Average partial effects

	High self-efficacy, t		Employment, t		Non-employment, t		Welfare, t	
Employment, $t-1$ (ref.)	-	-	-	-	-	-	-	-
Non-employment, $t-1$	-0.055*	(0.035)	-0.324***	(0.038)	0.187***	(0.034)	0.137***	(0.024)
Welfare, $t-1$	-0.073**	(0.026)	-0.651***	(0.035)	0.021	(0.016)	0.630***	(0.036)
Self-efficacy, $t-1$	0.426***	(0.016)	0.013*	(0.008)	-0.003	(0.006)	-0.011**	(0.005)

Simulations based on parametric bootstrap using coefficients of the estimators presented in the Table 7; standard errors in parentheses

Table 9: Dynamic discrete choice model with random effects (Model 6)

	Model 6					
	High self-Efficacy, t		Non-employment, t		Welfare, t	
High self-efficacy, t-1	0.566***	(0.145)	0.266	(0.353)	-0.517	(0.388)
Unemployment, t-1	-0.184	(0.319)	1.513***	(0.483)	2.508***	(0.476)
Welfare, t-1	0.0377	(0.326)	0.0894	(0.580)	4.461***	(0.407)
First generation migrant (dummy)	-0.224	(0.340)	0.617	(0.561)	1.740***	(0.457)
Second generation migrant (dummy)	-0.295	(0.309)	-0.578	(0.676)	-0.705	(0.662)
Vocational training (dummy)	0.546**	(0.264)	-0.425	(0.386)	-0.611*	(0.354)
University degree (dummy)	0.957***	(0.300)	-1.033**	(0.444)	-1.976***	(0.521)
Age: 35-44 (dummy)	0.0318	(0.388)	-0.640	(0.837)	-0.503	(0.863)
Age: 45-57 (dummy)	-0.143	(0.482)	-1.118	(1.057)	0.754	(1.207)
Father has at least vocational training (dummy)	0.0179	(0.182)	—	—	—	—
Wave 2008/2009 (dummy)	0.162	(0.143)	-0.172	(0.337)	-0.0290	(0.348)
Wave 2010 (dummy)	0.424**	(0.166)	-0.159	(0.373)	-0.520	(0.430)
Wave 2012 (dummy)	0.409**	(0.191)	0.214	(0.425)	0.105	(0.509)
Wave 2013 (dummy)	0.295*	(0.172)	0.107	(0.368)	-0.456	(0.446)
Wave 2014 (dummy)	0.368**	(0.187)	0.107	(0.401)	-0.879*	(0.511)
Individual mean over time: Age: 35-44	-0.202	(0.465)	0.497	(0.950)	-0.421	(0.982)
Individual mean over time: Age: 45-57	0.188	(0.525)	1.140	(1.125)	-1.525	(1.275)
High self-efficacy, t=1	2.186***	(0.227)	-0.711*	(0.373)	-0.266	(0.431)
Non-employment, t=1	-0.103	(0.364)	1.518***	(0.510)	1.568***	(0.581)
Welfare, t=1	-0.903**	(0.401)	4.156***	(1.034)	3.846***	(1.193)
Unemployment rate	—	—	0.298*	(0.181)	0.244	(0.177)
Eastern Germany (dummy)	—	—	-3.499	(4.231)	-8.427***	(2.750)
Individual mean: Eastern Germany	—	—	3.614	(4.224)	8.404***	(2.763)
Individual mean: Unemployment rate	—	—	-0.302*	(0.179)	-0.0441	(0.175)
m_1 ($p_1 = 0.292$)	3.362**	(1.421)	-4.741***	(1.260)	-5.346***	(0.985)
m_2 ($p_2 = 0.112$)	-3.913***	(0.592)	-2.088**	(0.872)	-3.645***	(0.933)
m_3 ($p_3 = 0.136$)	-0.554	(0.663)	-0.546	(0.887)	-3.013***	(0.940)
m_4 ($p_4 = 0.460$)	-0.495	(0.518)	-4.108***	(1.049)	-5.746***	(0.973)
Correlation coefficient Self-Efficacy & Non-employment	-0.591					
Correlation coefficient Self-Efficacy & Welfare	-0.395					
Correlation coefficient Non-employment & Welfare	0.930					
Observations	3966					
AIC	5236.9					
Log Likelihood	-2537.44					
Wald-Test-Chi^2	298.09					
Prob > Chi^2	0.00					

Standard errors in parantheses
$^{*}p < 0.10$. $^{**}p < 0.05$. $^{***}p < 0.01$.
Source: PASS, Waves 1-8