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

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

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## **Abstract**

Using the German PASS panel survey, I analyze the relationship between employment and self-efficacy. Estimating a dynamic model which takes into account reverse causality and selection on unobservables, I show that employment positively affects self-efficacy and vice versa. Hence, changes in the personal trait self-efficacy may be a source of state dependence in labor market dynamics. The result also suggests that reverse causality should be taken into account when estimating the effect of self-efficacy on labor market outcomes.

*Keywords: state dependence, personal traits*

*New JEL-Classification: J60*

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# 1 Introduction

There is a large number of empirical studies which 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). Repeated spells of non-employment may particularly emerge because employment episodes after non-employment are often low-paid and unstable (Arulampalam et al., 2001; Stewart, 2007). 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 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.<sup>1</sup>

An individual's belief in own productivity is related to the personal trait self-efficacy which is widely known in the psychologic 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 psychologic 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

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<sup>1</sup>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.

(PASS) to examine whether there is an effect of non-employment on self-efficacy and whether the loss of self-efficacy due to non-employment leads to state dependence in employment dynamics. 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 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. Relating to this, self-efficacy is an exception compared to most other personal traits discussed in the literature like locus of control or self-esteem. Those traits 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 Almlund et al., 2011, section 8 for a survey). 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.

Other studies focus on training programs designed for improving characteristics like motivation or discipline. Bloom et al. (2009) investigate the effect of a program for adolescents who dropped out of school. The program increased the probability of obtaining a degree and of obtaining a full-time job. It also improved the level of self-efficacy. 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 speaks in favor of 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. 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 should concentrate more on improving personal traits like self-efficacy (besides classical skills like language or computer skills).<sup>2</sup> If non-employment has additionally a negative effect on self-efficacy, such training programs would be specifically important for long-term unemployed workers as the loss of self-efficacy should get more serious with the duration of unemployment.

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

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<sup>2</sup>Active labor market programs often are designed for improving language skills, computer skills or specific vocational skills like technical and manufacturing skills (Kluve, 2010).

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 in four consecutive waves.

This allows me to follow an empirical strategy similar to the one of 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 funds 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 modelling the probability of having a certain level of self-efficacy and the probability of being employed as a joint dynamic process. That is, I model the probability of having a high, middle or low level of self-efficacy (where self-efficacy is treated as an ordinal variable) and the probability of being employed jointly in one likelihood function. I control for random effects, allowing for correlation between unobserved variables which affect self-efficacy and employment, 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 four waves of PASS (*Panel Labour Market and Social Security*), covering the years 2006-2010. The panel study is a new 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. Here, low income households are oversampled. The

recipient sample is a sample of (former) benefit recipients with 6804 interviewed households in the first wave (9386 individuals). 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).

The data is analyzed on the individual level. In this study I do not investigate labor market dynamics of women since there is a large share of women on the German labor market with a low labor supply and the effect of non-employment on self-efficacy might be very heterogenous for females. 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. 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 because they are likely to be out of the labor force. An individual enters the unbalanced dataset if it is observed in the first two 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. The resulting dataset consists of 4758 men.<sup>3</sup>

I define a worker as employed if he works more than 1 hour in a week. The items regarding self-efficacy are the following:<sup>4</sup>

- 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.

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<sup>3</sup>Considering the comparatively high number of about 10000 male 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 we will assume that attrition is unrelated to the error term, given the lagged dependent variables and further control variables.

<sup>4</sup>English translations can be found in the English versions of the questionnaires. For more information on the data documentation see Trappmann et al. (2010).

- 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”. For each wave, I apply a factor analysis separately for women and men. The results clearly indicate that there is one underlying factor behind those items. Figure 5.1 shows the factor scores corresponding to wave 1.

- Figure 1 about here -

Self-efficacy is treated as an ordinal variable. The definition of self-efficacy applied here assigns the value 1 to an individual if its factor score lies below the lowest decile of the distribution of the factor scores. This corresponds to a low level of self-efficacy. Value 2 which corresponds to a middle level of self-efficacy is assigned if the observation has a factor score which lies between the first and the ninth decile. An individual has a high level of self-efficacy if its factor score lies above the highest decile of the distribution. In the econometric analysis, I also experimented with further definitions. Instead of using factor scores, I also considered definitions applying sum indices. However, the results did not differ qualitatively (see section 4).

Table 1 shows descriptive statistics of the pooled regression sample. The sample consists of 2152 individuals and 4758 observations. By construction, about 20 percent have either a low level or high level of self-efficacy and about 80 percent have a middle level of self-efficacy. Only about 58 percent in the sample of men are employed and about 42 percent in the sample of women. Note that all individuals of the recipient sample were members of households receiving basic income support in July 2006.

- Table 1 about here -

Table 2 shows a descriptive transition matrix for men concerning the transitions



between the different levels of self-efficacy between the periods  $t - 1$  and  $t$  with respect to all transitions between wave 1 and wave 4. The upper part of the table shows transitions for those individuals who were not employed in period  $t - 1$  and the lower part transitions for those who were employed in  $t - 1$ .

- Table 2 about here -

I first discuss the transitions for those who were not employed in  $t - 1$ . Persistence in the low level of self-efficacy is relatively high. About 51 percent stay in the lowest decile of the distribution of self-efficacy in two consecutive waves. About 47 percent move up to the middle part of the distribution. Persistence in the middle level of self-efficacy is considerably stronger (about 83 percent stay in this category between period  $t - 1$  and period  $t$ ). About 39 percent of those who had a high level of self-efficacy in  $t - 1$  also had a high level in  $t$  while about 75 percent change to the middle level.

Concerning the transitions of those men who were employed in period  $t - 1$ , the probability of staying in the low level of self-efficacy is considerably lower than for those who were not employed in period  $t - 1$  (38.2 percent versus 50.5 percent) and the downward mobility from the middle level of self-efficacy to the lower level is slightly higher (4.1 percent versus 10.2 percent). Also, the probability of staying in the high level of self-efficacy is slightly larger when being employed in  $t - 1$  (42 versus 39.3 percent). What is more, overall probabilities to have a low level of self-efficacy are lower for those who were employed in period  $t - 1$  (5.5 percent versus 15.9 percent). This pattern may be explained by a positive effect of employment in  $t - 1$  on the probability of having a middle or high level of self-efficacy or by other characteristics not represented in the descriptive statistics which are correlated with both, the probability of being employed and the probability of having a middle or high level of self-efficacy.

### 3 Empirical specification

I model the probability of individual  $i$  in period  $t$  of having level  $j$  of self-efficacy ( $j = 1, 2, 3$ ) jointly with its probability of being employed in period  $t$ :

$$S_{it}^* = \alpha_1 S_{it-1} + \alpha_2 e_{it-1} + \alpha_3 X_{it} + \eta_i + \epsilon_{it} \quad (1)$$

$$e_{it}^* = \beta_1 S_{it-1} + \beta_2 e_{it-1} + \beta_3 Z_{it} + \alpha_5 \bar{Z}_i + \tau_i + \omega_{it}, \quad (2)$$

where  $S_{it}^*$  is a latent variable underlying the probability of having level  $j$  of self-efficacy and  $e_{it}^*$  is a latent variable for the probability of being employed.  $S_{it-1}$  is a vector of dummy variables representing the lagged level of self-efficacy and  $e_{it-1}$  represents the employment state in  $t - 1$ .  $X_{it}$  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.<sup>5</sup>

I use a dynamic ordered logit specification for self-efficacy to allow for a nonlinear relationship between self-efficacy and the explanatory variables. Particularly, in the dynamic ordered logit model it is straightforward to allow for a nonlinear effect of the past level of self-efficacy on the current level of self-efficacy (and on the probability of employment) (Wooldridge, 2005). For identification of the ordered logit specification,  $X_{it}$  does not contain a constant.

Problems regarding endogeneity stemming from reverse causality between  $S_{it}^*$  and  $e_{it}^*$  are avoided by modeling the impact of the lagged employment state on self-efficacy. A further bias might result from correlation of  $\eta_i$  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

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<sup>5</sup> $X_{it}$  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<sup>2</sup>, 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.  $\bar{Z}_i$  is a vector of individual-specific means of the time-varying variables in  $Z_{it}$ .  $\eta_i$  and  $\tau_i$  are time-constant individual-specific unobserved effects.  $\epsilon_{it}$  and  $\omega_{it}$  are time-varying unobserved effects. We assume that there is no autocorrelation in the error terms.<sup>6</sup>

probability of being employed and the probability of having a certain level of 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 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 modelled 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  $\eta_i$  and  $\tau_i$ . 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).<sup>7</sup>

$$S_{it}^* = \alpha_1 S_{it-1} + \alpha_2 e_{it-1} + \alpha_3 X_{it} + \alpha_4 S_{i1} + \nu_i + \epsilon_{it} \quad (3)$$

$$e_{it}^* = \beta_1 S_{it-1} + \beta_2 e_{it-1} + \beta_3 Z_{it} + \beta_4 \bar{Z}_i + \beta_5 e_{i1} + \zeta_i + \omega_{it}, \quad (4)$$

where  $\nu_i$  as well as  $\zeta_i$  are random effects which are uncorrelated with the lagged dependent variables. An alternative method to deal with the initial conditions problem is suggested by Heckman (1981). This method approximates the probabilities of the initial states by modelling:

$$S_{i1}^* = \gamma X_{i1} + \lambda \eta_i + \phi_i \quad (5)$$

$$e_{i1}^* = \delta Z_{i1} + \iota \tau_i + \kappa_i, \quad (6)$$

where  $\phi_i$  and  $\kappa_i$  are error terms.

The attractiveness of the Wooldridge-method compared to the Heckman-

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<sup>7</sup>Apart from age — which is exogenous —  $X_{it}$  does not contain time-varying variables.

method lies in the simple implementation in statistic software packages. In most empirical 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) do Monte-Carlo-Simulations and also show that both estimators mainly yield similar results. However, their simulations suggest that for small  $N$  and small  $T$  coefficients of state dependence may vary. Particularly, in very short panels, the estimators may be biased. However, Akay (2012) comes to more positive conclusions and states that the Heckman-model is unbiased even when  $T$  is small. Following the results of Rabe-Hesketh and Skrondal (2013), the Wooldridge-method also performs well for small  $T$ .<sup>8</sup>

I estimate the probability of an individual of being in level  $j = 1, \dots, 3$  of self-efficacy with an ordered response specification. An individual has level  $j$  of self-efficacy if the latent variable  $S_{it}^*$  lies between two thresholds:

$$S_{it} = j \Leftrightarrow \mu_{j-1} \leq S_{it}^* \leq \mu_j, \quad (7)$$

where  $\mu_0 = -\infty$ ,  $\mu_1$  and  $\mu_2$  are constants to be estimated and  $\mu_3 = \infty$ . I assume a logistic distribution for  $\epsilon_{it}, \omega_{it}, \phi_i, \kappa_i$ . The time-constant random effects are assumed to follow a bivariate normal distribution. Random effects are integrated out using Maximum Simulated Likelihood (Train, 2003).<sup>9</sup> The individual contribution to the likelihood function for the Heckman-method can be found in the Appendix.

The model is identified by its functional form. Another source of identification is given by exclusion restrictions.  $X_{it}$  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

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<sup>8</sup>Wooldridge (2005) originally proposed to include  $Z_{i2}, \dots, Z_{iT}$  instead of  $\bar{Z}_i = \frac{1}{T-1} \sum Z_{i2}, \dots, Z_{iT}$ . However, Rabe-Hesketh and Skrondal (2013) show in their simulation that the specification using  $\bar{Z}_i$  performs well (for small and large  $T$ ). Akay (2012) uses a restricted version of the Wooldridge-estimator which leads to problems with small  $T$ .

<sup>9</sup>To draw Halton Draws from a bivariate normal distribution I use a Stata-Ado-File by Cappellari and Jenkins (2006). All models are estimated using Mata 11.1. See also Haan and Uhlenborff (2006) for an implementation of MSL in Stata.

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 the concept of self-efficacy is very much focussed on own actions and own abilities for achieving results.

As coefficients of nonlinear models cannot be interpreted with respect to economic significance, I calculate average partial effects by applying parametric bootstrap methods. Individual predictions are calculated by integrating over the estimated distribution of the random effects (Skrondal and Rabe-Hesketh, 2009). In order to provide test statistics I draw 1000 times parameter values from the estimated sampling distribution and calculate partial effects.

Heckman et al. (2006) estimate a structural model where employment is a function of personality, cognitive ability and control variables. In this model, personality should ideally be measured using at the same time different concepts of personality like self-efficacy, self-control or time preferences. The PASS-survey, however, provides yearly information on self-efficacy but not on other personal traits and cognitive ability. In equation (4), other aspects of personality than self-efficacy as well as cognitive ability will be captured by the time-constant unobserved effects. Note that by jointly modelling equation (3) and equation (4) those unobserved variables are allowed to be correlated with self-efficacy. Correlation of self-efficacy and other aspects of personality is highly plausible. For instance, Judge et al. (2002) show that self-efficacy is highly related to other concepts of personality, most importantly to neuroticism, locus of control and self-esteem (Almlund et al., 2011, section 5.D.1.).

## 4 Econometric results

Table 3 shows results of regressions ignoring time-constant unobserved heterogeneity for men. Model 1 is an ordered logit model for the probability of having level  $j = 1, 2, 3$  of self-efficacy. Model 2 is a binomial logit for the probability of being employed.

- Table 3 about here -

Model 1 confirms the descriptive results of Table 2. There is a high persistence in self-efficacy. Individuals having a low level of self-efficacy in  $t - 1$  more often have a lower self-efficacy in period  $t$  compared to individuals with a middle level of self-efficacy. In contrast, individuals with a high level of self-efficacy in  $t - 1$  have a higher probability of having a high level of self-efficacy in period  $t$ . Employment in  $t - 1$  is positively associated with a high level of self-efficacy. The coefficient is significant at the 1 percent level. 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.

Model 2 again shows a significant correlation between self-efficacy and employment. Conditioning on observed variables, a low level of self-efficacy in  $t - 1$  is negatively associated with the probability of employment. Moreover, there seems to be considerable state dependence in employment.

I now turn to the results of the model which takes time-constant unobserved heterogeneity into account. Table 4 shows the coefficients of the model outlined in section 3. Here, the probability of having level  $j = 1, 2, 3$  of self-efficacy and the probability of employment are modeled as a joint dynamic process and unobserved characteristics affecting self-efficacy and employment are allowed to be correlated.

- Table 4 about here -

The lower part of the table shows the coefficients of the variance-covariance matrix. The coefficients for the variances of the unobserved effects ( $\sigma_1$  and  $\sigma_2$ ) are highly significant. The correlation coefficient  $\rho_{12}$  of unobserved effects affecting self-efficacy and employment is positive and significant which indicates that time-constant unobserved variables having a positive effect on self-efficacy also have a positive effect on employment which may lead to an upward bias of the coefficient of employment in  $t - 1$  on the probability of having a high level of self-efficacy. The coefficients of the initial states “Low self-efficacy, t=1”, “High self-efficacy, t=1” are significant in the equation for self-efficacy which shows that it has been important to control for the problem of initial conditions. Looking at the equation for the probability of employment, the coefficient of the initial state of employment is different from zero.

The coefficients of the lagged endogenous variables in model 3 are smaller than those of the models not taking unobserved heterogeneity into account. This indicates that a large part of the effects derived by the models 1 and 2 are due to correlation of these variables with time-constant unobserved heterogeneity. The coefficients of employment in  $t - 1$  on the probability of having level  $j = 1, 2, 3$  of self-efficacy, however, is still positive and significant. Furthermore, the coefficient of having a low level of self-efficacy is significantly different from the one of having a high level of self-efficacy. Coefficients still indicate that there is persistence in self-efficacy and employment. For instance, the coefficient of “High self-efficacy, t-1” is positive and highly significant in the equation for self-efficacy. Also, the coefficient of the lagged employment state is positive and significant in the employment equation.

- Table 5 about here -

Partial effects are presented in Table 5. I show that there is genuine state dependence in self-efficacy. This may come from a positive effect of self-efficacy on

life outcomes which in turn have a positive effect on self-efficacy in future. Having a high level of self-efficacy in  $t - 1$  leads to a probability of having a high level of self-efficacy in  $t$  which is about 7 percentage points higher than the probability of those who had a low level of self-efficacy in  $t - 1$ . The partial effect of employment in  $t - 1$  on the probability of being employed in  $t$  confirms the result found in many studies that there is genuine state dependence in employment (e.g. Mühleisen and Zimmermann, 1994). Moreover, estimated partial effects confirm that being employed positively affects the probability of having a high level of self-efficacy and *vice versa*.

## 5 Conclusions

In this study, I use German PASS-data to analyze jointly dynamics in employment and dynamics in self-efficacy. 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. I use dynamic discrete choice models that allow for the correlation of unobserved variables affecting both variables and for a reverse relationship. In particular, I am interested in whether or not changes in self-efficacy are a source of state dependence in employment dynamics. 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.

Applying models which control for unobserved heterogeneity, a reverse relationship between self-efficacy and employment is obtained. That is, being employed positively affects the probability of having a high level of self-efficacy. Furthermore, having a high level of self-efficacy positively affects the probability of employment. Hence, changes in self-efficacy are responsible for state dependence in labor market dynamics. Future research should investigate if self-efficacy is important for other outcomes like wages or health outcomes.



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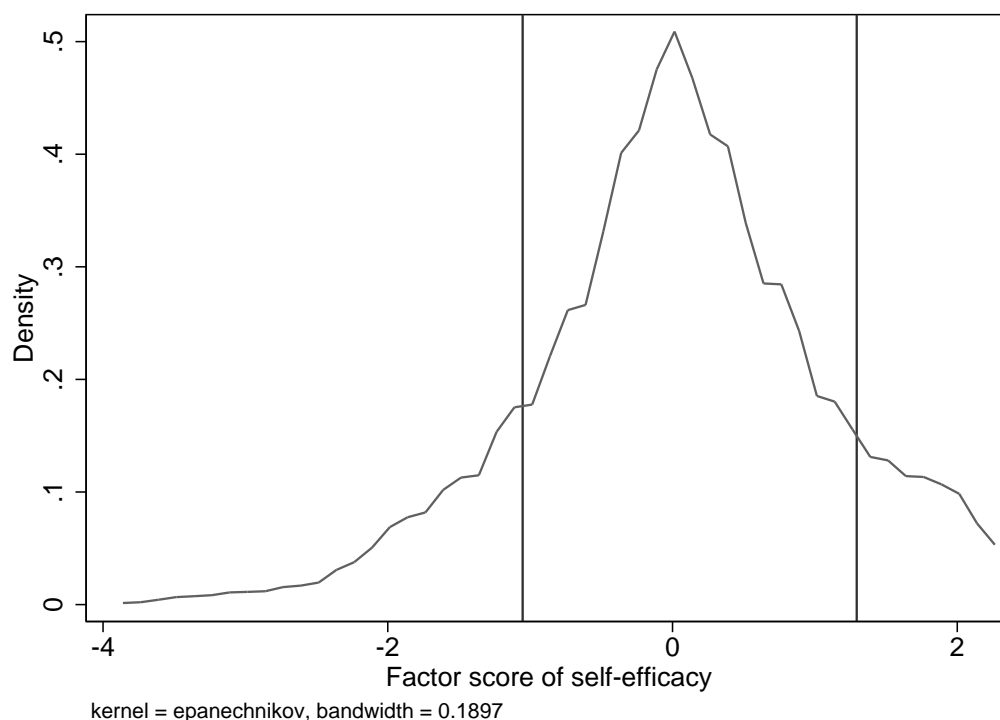


Figure 1: Distributions of the factor scores of self-efficacy. The left vertical lines indicate the thresholds between the low and the middle level of self-efficacy. The right vertical lines indicate the thresholds between the middle and the high level of self-efficacy.

Table 1: Descriptive statistics (mean values of variables)

	Men
Low level of self-efficacy	0.10
Middle level of self-efficacy	0.80
High level of self-efficacy	0.11
Employed	0.58
First generation migrant (dummy)	0.12
Second generation migrant (dummy)	0.05
Vocational training (dummy)	0.63
University degree (dummy)	0.23
Age	43.07
Age <sup>2</sup>	1934.85
Unemployment rate	8.80
Eastern Germany (dummy)	0.28
Wave 3 (dummy)	0.33
Wave 4 (dummy)	0.22
Individual mean: Unemployment rate	9.23
Individual mean: Eastern Germany	0.28
General population sample (dummy)	0.57
Father has at least vocational training (dummy)	0.72
Number of individuals	2152
Number of observations in pooled regression sample	4758

*Source:* PASS, waves 1-4; unweighted

Table 2: Transition matrix

	Low Self-Efficacy, $t$	Middle Self-Efficacy, $t$	High Self-Efficacy, $t$	Total
	Not employed in $t - 1$			
Low Self-Eff., $t - 1$	50.5	46.8	2.7	100.0
Middle Self-Eff., $t - 1$	10.2	83.0	6.8	100.0
High Self-Eff., $t - 1$	5.2	55.5	39.3	100.0
Total	15.9	75.1	9.0	100.0
	Employed in $t - 1$			
Low Self-Eff., $t - 1$	38.2	61.1	0.7	100.0
Middle Self-Eff., $t - 1$	4.1	87.7	8.2	100.0
High Self-Eff., $t - 1$	0.9	57.1	42.0	100.0
Total	5.5	82.9	11.6	100.0

*Source:* PASS (2006-2010); pooled unweighted sample; Transitions between periods  $t - 1$  and  $t$ ; values indicate percentages

Table 3: Dynamic discrete choice model without random effects

	Model 1		Model 2	
	Self-Efficacy		Employment	
Low self-efficacy, t-1 (dummy)	-1.304***	(0.0673)	-0.183**	(0.0923)
High self-efficacy, t-1 (dummy)	1.223***	(0.0632)	0.0422	(0.0881)
Employed, t-1 (dummy)	0.198***	(0.0626)	2.855***	(0.0798)
First generation migrant (dummy)	-0.0189	(0.0856)	0.00805	(0.119)
Second generation migrant (dummy)	0.00501	(0.118)	0.224	(0.167)
Vocational training (dummy)	0.339***	(0.0814)	0.409***	(0.111)
University degree (dummy)	0.303***	(0.0964)	0.361***	(0.131)
Age	-0.00285	(0.0255)	0.0559	(0.0357)
Age <sup>2</sup>	0.000002	(0.0003)	-0.001**	(0.0004)
Father has at least vocational training (dummy)	0.0175	(0.0616)		
Wave 3	0.120**	(0.0597)	0.436***	(0.0900)
Wave 4(2010)	0.0870	(0.0683)	0.263***	(0.0963)
General population sample	0.161**	(0.0632)	0.797***	(0.0840)
Unemployment rate			-0.249***	(0.0766)
Eastern Germany (dummy)			2.326**	(1.082)
Individual mean: Unemployment rate			0.240***	(0.0771)
Individual mean: Eastern Germany			-2.380**	(1.097)
Constant			-2.856***	(0.735)
Observations	5508		5508	
<i>AIC</i>	10639.4		4765.1	
Log Likelihood	-5304.68		-2365.57	
Wald-Test-Chi <sup>2</sup>	1386.05		2839.96	
Prob > Chi <sup>2</sup>	0.00		0.00	

Standard errors in parantheses

\* $p < 0.10$ . \*\* $p < 0.05$ . \*\*\* $p < 0.01$ .

Table 4: Dynamic discrete choice model with random effects

	Model 3			
	Self-Efficacy		Employment	
Low self-efficacy, t-1 (dummy)	-0.173	(0.117)	-0.239	(0.133)
High self-efficacy, t-1 (dummy)	0.197*	(0.109)	0.0927	(0.008)
Employed, t-1 (dummy)	0.168*	(0.0907)	1.375***	(0.187)
First generation migrant (dummy)	-0.0160	(0.128)	-0.0593	(0.248)
Second generation migrant (dummy)	-0.0853	(0.181)	0.320	(0.341)
Vocational training (dummy)	0.506***	(0.124)	0.835***	(0.238)
University degree (dummy)	0.485***	(0.148)	0.702**	(0.279)
Age	-0.0168	(0.0381)	0.0972	(0.0730)
Age <sup>2</sup>	0.000133	(0.000458)	-0.00169*	(0.000884)
Father has at least vocational training (dummy)	0.0686	(0.0942)		
Wave 3	0.0733	(0.0667)	0.571***	(0.120)
Wave 4	0.0727	(0.0775)	0.391***	(0.135)
General population sample	0.254***	(0.0966)	1.649***	(0.218)
Low self-efficacy, t=1 (dummy)	-1.457***	(0.143)		
High self-efficacy, t=1 (dummy)	1.296***	(0.132)		
Unemployment rate			-0.407***	(0.111)
Eastern Germany (dummy)			3.074**	(1.454)
Individual mean: Unemployment rate			0.410***	(0.118)
Individual mean: Eastern Germany			-3.333**	(1.509)
Employed, t=1 (dummy)			2.765***	(0.367)
Constant			-4.707***	(1.517)
$\mu_1$	-2.630**	(1.076)		
$\mu_2$	4.100***	(1.094)		
Variance self-efficacy equation: $\sigma_1$	2.171***	(0.452)		
Variance employment equation: $\sigma_2$	7.002***	(1.308)		
$\rho_{12}$	0.215***	(0.061)		
Observations	5508			
<i>AIC</i>	15024.7			
Log Likelihood	-7474.34			
Wald-Test- $\chi^2$	734.55			
Prob > $\chi^2$	0.00			

Standard errors in parantheses

\* $p < 0.10$ . \*\* $p < 0.05$ . \*\*\* $p < 0.01$ .



Table 5: Average partial effects

	Men			
	Low self-efficacy, t	Middle self-efficacy, t	High self-efficacy, t	Employment, t
Low Self-Eff., $t - 1$ (ref.)	-	-	-	-
Middle Self-Eff., $t - 1$	-0.025 (0.032)	0.018 (0.032)	0.035** (0.025)	0.022 (0.016)
High Self-Eff., $t - 1$	-0.119* (0.058)	0.047 (0.058)	0.071** (0.033)	0.037** (0.029)
Employment, $t - 1$	-0.021** (0.009)	0.006 (0.009)	0.015* (0.007)	0.141*** (0.007)

Simulations based on parametric bootstrap using coefficients of the Wooldridge-estimator presented in Table 4 (model 3); standard errors in parantheses