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HETEROGENEITY OR TRUE STATE DEPENDENCE IN POVERTY: THE TALE TOLD BY TWINS

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The purpose of this study is to distinguish between two different reasons that poverty could persist on an individual level. This study takes advantage of the similarity within pairs of identical twins to separate family-specific heterogeneity from true state dependence, where the experience of poverty leads to a higher risk of future poverty. The results, based on a four-variate probit model, show the importance of true state dependence in poverty. When using a poverty measure based on disposable income, family-specific heterogeneity explains between 21 and 25 percent of poverty persistence in the Swedish sample of twins.

JEL Codes: I32, C35, D31

Keywords: poverty, heterogeneity, state dependence, twins, multivariate probit

1. INTRODUCTION

A state of poverty is often referred to as a situation in which there is a lack of resources to achieve a reasonable standard of living. An individual living in such a situation usually is more likely to continue in this state in the following years. In the work against poverty and social exclusion, it is important to know who is at risk of becoming poor and what characteristics make poverty persistent at an individual level. In designing an efficient system against poverty, it is important to know to what extent poverty persists due to heterogeneity and to what extent it persists due to true state dependence.

In this case, true state dependence refers to a situation in which *the experience* of poverty causes a subsequently higher risk of continuing to be poor. The individual can, for example, lose motivation or develop health problems, thus making poverty more probable in the future. Heterogeneity also could be the explanation for the persistence of poverty. In this case, it could be characteristics that are specific to the individual, such as a low level of education, that increase the risk of poverty. These characteristics could have their origin in the environment in which

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the individual grew up. If the characteristics that are important for the risk of poverty persist, the risk of poverty also will persist.

If true state dependence is relatively more important than heterogeneity, an effective policy could focus on preventing people from becoming poor, since, once poor, they are likely to remain so no matter what their initial characteristics were. On the other hand, if heterogeneity explains the persistence in poverty, it is important to focus on changing the characteristics that keep the individual at a high risk of being poor.

The purpose of this study is to distinguish between true state dependence and family-specific heterogeneity. This is done using a dataset of identical twins. The study takes advantage of the similarity of identical twins, as their innate abilities are the same and their social backgrounds are very similar. The foundation of this study is the well-established method of using sibling correlation to investigate the importance of shared background factors for a certain outcome (Solon, 1999).[1] The assumption is that, if shared factors are important, the siblings will show a strong resemblance in the outcome. Corcoran *et al.* (1988) used this method to determine the importance of family background for welfare program participation. This study extends the approach to a new area by distinguishing true state dependence from family-specific heterogeneity.

The method used in this study relies on the assumption that *the experience* of poverty for one twin does not affect the probability of poverty for the sibling twin the following year. If this assumption is valid, and if the data show that one twin is more likely to be poor if the other twin was poor, then one can conclude that the outcome is due to the similarity between the twins. This information can be used to distinguish between family-specific heterogeneity and true state dependence.

Previous studies investigating true state dependence and heterogeneity as explanations for poverty persistence have, to my knowledge, never taken advantage of information on twins or siblings. An early study that identifies the difficulties of empirically separating heterogeneity from true state dependence is Heckman and Borjas (1980). Two different methods have since then been widely used. It has been common to rely on either strong assumptions of the distribution of unobserved heterogeneity or finding suitable exogenous instruments (Gregg, 2001).

Without information on twins, Stewart and Swaffield (1999) estimate a bivariate probit model consisting of two equations. The first equation models the probability of low pay in a base year. The second equation is a transition equation representing the probability of low pay in the following year for those who were low-paid in the base year. The equations are estimated simultaneously to address the potential problem that those who are low-paid in the base year are not necessarily a random sample of the total population. To assume exogeneity of low pay in the base year used in the transition equation could lead to biased estimates. Stewart and Swaffield (1999) identify the state dependence effect by using the estimates for the coefficients in the transition equation.[2] Cappellari and Jenkins

[1]See Björklund *et al.* (2005) for a Swedish study where various sibling types, including twins are used.

[2]The main idea is the same as in Cappellari and Jenkins (2004), and is explained in detail in Section 2 in this study.

(2004) estimate a similar model but include both the transition out of and the transition into low income. They also include a third equation that takes into account that survey data can be affected by non-random attrition.[3] In other words, individuals can leave the panel or fail to answer all important questions. If some individuals, for example poor individuals in the base year, are more likely to leave the panel, the estimates could be biased if this non-random attrition is not taken into account. Both the studies mentioned use survey data to investigate low pay or low income transitions.

The main contribution of this study is its use of a method based on twins to distinguish between family-specific heterogeneity and true state dependence in poverty. Using information for twins is a new and innovative way to study persistence in a state. The measures presented for family specific heterogeneity and true state dependence are appealing since the sibling twin provides a reference case with very similar unobserved characteristics. Another advantage with the study is that administrative data is used instead of survey data, which considerably reduces the rate of attrition.[4] The results reveal that, even though heterogeneity plays its role, true state dependence is relatively more important for the persistence of poverty for the sample of twins used here.

The remainder of this paper is structured as follows. Section 2 explains the model. Section 3 provides information on the data and discusses measures of poverty. Section 4 presents the results from the empirical investigation. Section 5 contains concluding remarks.

2. Model

In this section, the model is described. First, the theory of the new method of using twins is explained. Then the model, based on a multivariate probit model, is described. Finally, the measures for family-specific heterogeneity and true state dependence are defined based on the regression model.

2.1. *Theoretical Foundation*

Figure 1 gives an overview of poverty transitions for individuals. Individuals are observed as either poor ($P = 1$) or not ($P = 0$) in period $t - 1$ and t.[5]

If individuals who are poor in $t - 1$ are compared with those who were not poor in $t - 1$, we expect that the average probability of being observed as poor in t will differ between the groups. If poverty persists on an individual level, the group that was poor in $t - 1$ will have a higher average probability of being poor in t compared with the group that was not poor in t. Individuals in the two groups are expected to differ both because of their initial characteristics and because of their

[3]Panel attrition refers to a case where individuals leave the panel, and accordingly cannot completely contribute to the estimates.

[4]In this study, individuals can leave the panel through migration abroad or death. These reasons are, however, not very common.

[5]Note that poverty here is defined as a binary variable although there are degrees of poverty. The situations for specific poor individuals could vary greatly even though the number of poor would be the same. However, one reason for using a discrete variable in research is that a binary variable is often used when policies are constructed and later evaluated.

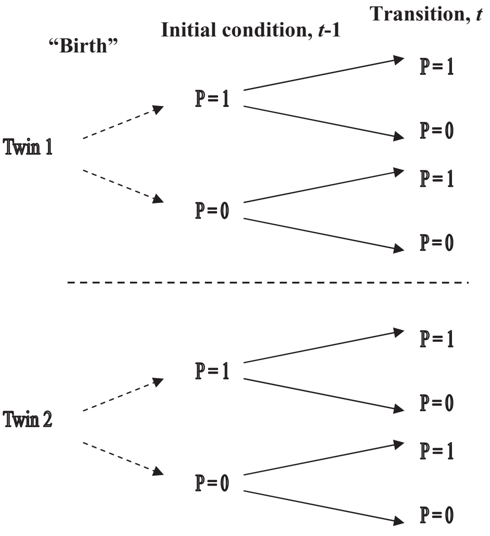

Figure 1. Overview of Poverty Transitions

experience of poverty in $t-1$. Thus, the measures do not tell us what part of the poverty persistence is caused by heterogeneity and what part is due to true state dependence.

The main idea in this study is to compare the average probability of being observed as poor depending on whether the twin sibling was observed as poor in the previous year or not. The important assumption for the analysis is that one twin's experience of poverty, *in itself*, does not affect the probability of the sibling twin being poor the following year. This assumption is reasonable if true state dependence comes from problems related to health or the labor market.[6] This assumption is hereafter called the Twin-State Independence Assumption. A sensitivity analysis of the assumption is performed using propensity score matching.[7] Instead of comparing two groups on the basis of their own base-year poverty status, the new method compares individuals depending on the status of their twin sibling. Thus, the first group includes twins who have a twin sibling who was poor the previous year, and the second group includes those whose sibling twin was not poor. If the group of twins with a twin who was poor the previous year has a higher average probability of being poor, this probably is due to the fact that the sibling twins have some important characteristics in common that increase the risk of poverty for both of them. True state dependence cannot explain a higher probability for the first group since the groups are not compared with respect to *their own* poverty status the previous year.

[6]If true state dependence is based on psychological motives, such as a loss of motivation, it is possible that the states for twins are dependent at least to some extent. See Section 4 for a further discussion concerning this issue.

[7]The author is very grateful to an anonymous referee for suggesting propensity score matching to evaluate the Twin-State Independence Assumption.

This method of distinguishing between true state dependence and heterogeneity gives a lower bound for the persistence of poverty caused by heterogeneity. The reason is that even identical twins are different, and these differences cannot be captured with this method. Identical twins are identical with respect to innate abilities and with respect to many acquired characteristics based on growing up in the same environment. There are, however, experiences that differ between the twins. One of these could be the experience of poverty. Since all acquired characteristics that differ between the twins, except from the experience of poverty, should be labeled heterogeneity, the method only identifies a lower bound for the heterogeneity. It is important for the understanding of the method to be aware that *family-specific* heterogeneity in this study refers to differences between the twins and the rest of the population, not to differences between the sibling twins.

2.2. *Econometric Model*

To distinguish between true state dependence and family-specific heterogeneity, this paper extends the models for low pay/income transition used in Stewart and Swaffield (1999) and Cappellari and Jenkins (2004) to include twin sibling homogeneity, as a way of revealing heterogeneity toward the rest of the population. As in the articles mentioned above, the first part of the model refers to the risk for poverty in a base period, $t-1$. This addresses the potential problem that the poverty status is not exogenously determined. The latent poverty propensity, P^*_{sit-1}, is assumed to be determined by:

$$P^*_{1it-1} = \boldsymbol{\beta}_1'\mathbf{x}_{1it-1} + \omega_i + \mu_{1i} + \delta_{1it-1} \tag{1}$$

$$P^*_{2it-1} = \boldsymbol{\beta}_2'\mathbf{x}_{2it-1} + \omega_i + \mu_{2i} + \delta_{2it-1} \tag{2}$$

$$P_{sit-1} = I(P^*_{sit-1} > 0)$$

$$s = 1, 2, i = 1, \ldots, N, \text{and } t = 2, \ldots, T$$

Subindex $s = 1$ indicates the first group of twins, and $s = 2$ indicates the second group of twins consisting of the sibling twin of $s = 1$. Subindex i refers to the pair of twins $i = 1, \ldots, N$ and $t = 2, \ldots, T$ refers to different periods.[8] Individuals are only observed to be either poor, $P_{sit-1} = 1$, or not, $P_{sit-1} = 0$. $I(P^*_{sit-1} > 0)$ is an indicator function which takes the value 1 if the inequality is satisfied, and zero otherwise. Individual characteristics that are assumed to influence the poverty status are included in $\mathbf{x}_{sit-1}$, and $\boldsymbol{\beta}_s$ is a vector of the parameters to be estimated.[9] u_{sit-1} is an error term which includes ω_i, an effect common for the twin siblings, μ_{si}, an individual-specific effect, and δ_{sit-1}, an orthogonal white noise error. The twin-

[8]At this point, it can be assumed that the data consist of two periods, as indicated in Figure 1. The case where more observations are present for each individual will be discussed briefly later.

[9]In the estimation, there is no reason to believe that $\boldsymbol{\beta}_1$ should differ systematically from $\boldsymbol{\beta}_2$. Likelihood-ratio tests are used to test the assumption of equality of the parameters. The conclusion of the tests is that it is possible to constrain $\boldsymbol{\beta}_1$ to be equal to $\boldsymbol{\beta}_2$.

specific effect, ω_i, captures unobserved heterogeneity that is shared by the twins, while the individual-specific effect, μ_{si}, represents unobserved heterogeneity that is specific for the twin, i.e. not shared with his/her twin sibling. The error term is assumed to follow a standard normal distribution, $u_{sit-1} \sim N(0,1)$.

Given the poverty status in period $t-1$, the next step is to model the transition equations, i.e. the transition to the next period, t, in Figure 1. The transition equations model the probability of remaining in poverty for those who were poor in the previous year and the probability of entering into poverty for those who were not poor the previous year.

(3) $$P^*_{1it} = [P_{1it-1}\boldsymbol{\gamma}'_{11} + (1-P_{1it-1})\boldsymbol{\gamma}'_{12}]\mathbf{z}_{1it-1} + \tau_i + \eta_{1i} + \zeta_{1it}$$

(4) $$P^*_{2it} = [P_{2it-1}\boldsymbol{\gamma}'_{21} + (1-P_{2it-1})\boldsymbol{\gamma}'_{22}]\mathbf{z}_{2it-1} + \tau_i + \eta_{2i} + \zeta_{2it}$$

$$P_{sit} = I(P^*_{sit} > 0)$$

$$s = 1, 2, i = 1, \dots, N \text{ and } t = 2, \dots, T$$

The included parameters, i.e. those attached to the explanatory variables, $\mathbf{z}_{sit-1}$, in equations (3) and (4), are allowed to vary in magnitude depending on the poverty status in the previous period.[10] This setup follows Cappellari and Jenkins (2004), except in two respects. First, there is a trivial extension of the notation for each twin. Second, Cappellari and Jenkins also model a panel retention equation, i.e. whether the individual remains in the panel, which is not necessary in the present study because of its use of administrative data. The error term, v_{sit}, consists of three parts, τ_i, a twin-specific effect, η_{si} an individual-specific effect, and ζ_{sit}, an orthogonal white noise error. The error term again is assumed to be $v_{sit-1} \sim N(0,1)$.

In general, many of the variables included in $\mathbf{x}_{sit-1}$ also are used in $\mathbf{z}_{sit-1}$. The estimation could be identified without excluded variables if a non-linear functional form is present. However, to avoid relying on the assumption of non-linearity, it is appropriate to include instruments in the first period equations (1) and (2), which can be excluded from the equations (3) and (4) for the transition. That is, variables should be included that affect the probability of the poverty status in the base year but do not affect the probability of poverty status in the transition equation, given information for the status of poverty in the base year. In Stewart and Swaffield (1999) and Cappellari and Jenkins (2004), these instruments are variables relating to the parents' socioeconomic group when the respondent was 14 years old. Similar variables are used in this study.

The joint distribution of the error terms, u_{1it-1}, u_{2it-1}, v_{1it}, v_{2it}, is assumed to have a correlation matrix. The correlation between the error terms for the different equations are labeled ρ_{21}, ρ_{31}, ρ_{32}, ρ_{41}, ρ_{42}, ρ_{43}, where the subindices indicate between which two equations the correlation refers. In the case where none of the error terms is correlated between the equations, it would be possible to estimate the

[10]As for $\boldsymbol{\beta}_s$, there are no reasons to expect $\boldsymbol{\gamma}'_{s1}$ and $\boldsymbol{\gamma}'_{s2}$ to differ systematically for the different sample of twins, i.e. $s = 1, 2$. Accordingly, $\boldsymbol{\gamma}'_{11}$ can be constrained to be equal to $\boldsymbol{\gamma}'_{21}$ and $\boldsymbol{\gamma}'_{12}$ can be constrained to be equal to $\boldsymbol{\gamma}'_{22}$.

four equations by four separate probit models. In this study, however, the equations are estimated simultaneously, and the correlations between the error terms of the equations are parameters to estimate.[11] This gives an opportunity to actually test whether or not the correlations are different from zero.

The log-likelihood function for each pair of twins, $i = 1, \ldots, N$, and $t = 1, 2$, is

$$\log L_i = \log \Phi_4(\mu_i; \Omega) \tag{5}$$

where $\Phi_4(\mu_i; \Omega)$ is a standard four-variate normal cdf, with

$$\mu_i = \{K_{i1}\boldsymbol{\beta}_1'\mathbf{x}_{i1t-1}, K_{i2}\boldsymbol{\beta}_2'\mathbf{x}_{i2t-1}, K_{i3}[P_{i1t-1}\boldsymbol{\gamma}_{11}' + (1 - P_{i1t-1})\boldsymbol{\gamma}_{12}']\mathbf{z}_{i1t-1},$$
$$K_{i4}[P_{i2t-1}\boldsymbol{\gamma}_{21}' + (1 - P_{i2t-1})\boldsymbol{\gamma}_{22}']\mathbf{z}_{i2t-1}\}$$

where $K_{i1} = 2P_{i1t-1} - 1$, $K_{i2} = 2P_{i2t-1} - 1$, $K_{i3} = 2P_{i1t-1} - 1$ and $K_{i4} = 2P_{i2t-1} - 1$.

The matrix, Ω is symmetric;

$$\Omega = \begin{pmatrix} 1 & K_{i2}K_{i1}\rho_{21} & K_{i3}K_{i1}\rho_{31} & K_{i4}K_{i1}\rho_{41} \\ K_{i2}K_{i1}\rho_{21} & 1 & K_{i3}K_{i2}\rho_{32} & K_{i4}K_{i2}\rho_{42} \\ K_{i3}K_{i1}\rho_{31} & K_{i3}K_{i2}\rho_{32} & 1 & K_{i4}K_{i3}\rho_{43} \\ K_{i4}K_{i1}\rho_{41} & K_{i4}K_{i2}\rho_{42} & K_{i4}K_{i3}\rho_{43} & 1 \end{pmatrix}.$$

As in Cappellari and Jenkins (2004), the multivariate standard normal distribution function is evaluated using a simulation method based on the GHK simulator.[12] (See Cappellari and Jenkins, 2003, for a detailed description of the method.)

With observations for more than two periods, it would be possible to estimate a pooled model for all periods. Doing so, however, would use a large amount of the observations for both the initial condition and the transition equation. Having more than two periods would extend the tree in Figure 1 to the right for poverty status in $t + 1$, $t + 2$, etc. As the new figure would indicate, each additional observation would have a longer history of transitions back to the initial condition. Accordingly, to pool the observations would involve basing the likelihood on the wrong set of information. Even if only a few more periods were added, taking the correct set of information into account would complicate the model considerably. If a panel of data is present, an alternative to pooling all the observations is to model two periods at a time. This would mean several different regressions and several different measures of state dependence. However, if the number of individuals in the dataset is small, each regression would be based on few observations.

A second alternative is to pool observations, but to avoid using the same observations for both the initial condition equation and the transition equation.

[11]In this application there is no reason to expect ρ_{41} to be different to ρ_{32}. In the estimations ρ_{41} is constrained to be equal to ρ_{32}. For the same reason, ρ_{31} is constrained to be equal to ρ_{42}.

[12]To estimate the model, I used the Stata program, mvprobit, written by Cappellari and Jenkins (2003). Stata users can obtain the program by typing "findit mvprobit" at the Stata prompt. GHK = Geweke–Hajivassiliou–Keane.

For example, in a panel of four years, $t-1$ would be used as base year for the transition in t, and $t+1$ would be the base year for the transition in $t+2$. This is the method used in this study. The standard errors for the estimates are corrected for repeated observations from the same twins over the years. Before focusing on the data and estimation, it is important to know how to use the model to estimate measures of state dependence and heterogeneity.

2.3. *Distinguishing True State Dependence and Heterogeneity*

The first step toward distinguishing between true state dependence and heterogeneity in the persistence of poverty is to define transition probabilities, such as those used in other studies (e.g. Cappellari and Jenkins, 2004). From the model, it is possible to calculate the probability of being poor at t, conditional on being poor in the previous year. This is the poverty persistence rate, i.e. the extent to which individuals remain in poverty.

$$\Pr(P_{sit}=1 \mid P_{sit-1}=1)=\frac{\Phi_2(\boldsymbol{\gamma}'_{s1}\mathbf{z}_{sit-1},\boldsymbol{\beta}'_s\mathbf{x}_{sit-1};\rho)}{\Phi(\boldsymbol{\beta}'_s\mathbf{x}_{sit-1})} \tag{6}$$

where $\rho=\rho_{31}$ for $s=1$ and $\rho=\rho_{42}$ for $s=2$. ρ_{31} refers, as explained above, to the correlation of the error terms for the equations for the first set of twins. If the poverty persistence rate is estimated for the sibling twins, the counterpart for $s=2$, ρ_{42}, is used. $\Phi(.)$and $\Phi_2(.)$are the cumulative distribution functions of univariate and bivariate standard normal distributions. The poverty entry rate is the probability of being poor at t, conditional on not being poor during the previous year.

$$\Pr(P_{sit}=1 \mid P_{sit-1}=0)=\frac{\Phi_2(\boldsymbol{\gamma}'_{s2}\mathbf{z}_{sit-1},-\boldsymbol{\beta}'_s\mathbf{x}_{sit-1};\rho)}{\Phi(-\boldsymbol{\beta}'_s\mathbf{x}_{sit-1})} \tag{7}$$

where $\rho=-\rho_{31}$ for $s=1$ and $\rho=-\rho_{42}$ for $s=2$. With these different measures of probabilities of poverty, it is possible to calculate measures of state dependence and heterogeneity. Cappellari and Jenkins (2004) estimate aggregate state dependence, *ASD*, as

$$ASD_s=\left(\frac{\sum\limits_{i\in(P_{sit-1}=1)}\Pr(P_{sit}=1 \mid P_{sit-1}=1)}{\sum\limits_i P_{sit-1}}\right)-\left(\frac{\sum\limits_{i\in(P_{sit-1}=0)}\Pr(P_{sit}=1 \mid P_{sit-1}=0)}{\sum\limits_i(1-P_{sit-1})}\right).$$

ASD is the difference in the average probability of being poor for those who were poor in the previous year and the average probability of being poor for those who were not poor the previous year.[13] *ASD* measures state dependence without taking into consideration that the poor and the non-poor the previous year could be very different.

[13]Note that $\Sigma_i\, P_{sit-1}$ is just the number of individuals poor the previous year, since $P_{sit-1}=1$ for those, and $P_{sit-1}=0$ for the non-poor. In the same way $\Sigma_i\,(1-P_{sit-1})$ is the number of individuals who were not poor. Thus, each term in ASD_s is just an average for each subgroup.

Another measure that Cappellari and Jenkins (2004) use is what they call genuine state dependence, *GSD*. *GSD* is an average, over all individuals, of the difference between the predicted probability of being poor conditional on being poor, and the predicted probability of being poor conditional on not being poor during the previous period.

$$GSD_s = (1/N)\sum_{i=1}^{N} \Pr^c(P_{sit} = 1 \mid P_{sit-1} = 1) - \Pr^c(P_{sit} = 1 \mid P_{sit-1} = 0).$$

This measure controls for heterogeneity since individual-specific probabilities are averaged. Depending on the actual poverty status in $t-1$, either the first probability or the second probability in the equation represents a counterfactual probability. The individual-specific probabilities differ due to differences between the estimated parameters ($\boldsymbol{\gamma}'_{s1}$ and $\boldsymbol{\gamma}'_{s2}$ in equations (3) and (4)) depending on the poverty status during the previous year.

Cappellari and Jenkins (2004) state that the measure controls for both observed and unobserved heterogeneity. While it is easy to see how the observed heterogeneity is taken into account for those explanatory variables included, it is not obvious how the inclusion of ρ_{31} (or ρ_{42}) in the individual-specific probabilities takes account of all unobserved heterogeneity. Note that the identification strategy is based on conditioning on one's own poverty status, and the instruments that explain the initial condition, but do not influence the transition, are crucial. Another identification strategy is available due to the information on the twin siblings, and an intuitively appealing measure can be calculated using information for twin siblings.

Equations for twin siblings allow one to devise probability expressions that can be used to construct a measure to identify the part of poverty persistence that is due to family-specific heterogeneity. The probability of the first twin being poor at t, conditional on the second twin being poor the previous year, can be calculated as

$$\Pr(P_{1it} = 1 \mid P_{2it-1} = 1) = \frac{\Phi_2(\boldsymbol{\gamma}'_1\mathbf{z}_{1it-1}, \boldsymbol{\beta}'_2\mathbf{x}_{2it-1}; \rho_{32})}{\Phi(\boldsymbol{\beta}'_2\mathbf{x}_{2it-1})} \tag{8}$$

where $\boldsymbol{\gamma}'_1$ refers to $\boldsymbol{\gamma}'_{11}$ and $\boldsymbol{\gamma}'_{12}$ estimated in equation (3).[14] The appropriate $\boldsymbol{\gamma}'$ is used depending on whether or not the first twin was poor the previous year. At this stage it is important to clarify that it is *not* necessary to simultaneously condition on the poverty status of the first twin. This is perfectly in line with the option to specify unconditional mean functions based on univariate probabilities. Hence, the expression above is different from calculating the corresponding probability based on a bivariate probit model where P_{1it} and P_{2it-1} are the only dependent variables. In that case the parameters could be estimated with bias due to omitting the initial condition equation for P_{1it-1}. Since equation (8) is based on the four-variate probit model, the parameters are estimated without such bias and it is perfectly fine to

[14]The probability of the *second* twin being poor at t, conditional on the *first* twin being poor the previous year is calculated with ρ_{41}. The changes in variables and coefficients are obvious.

specify unconditional or conditional probabilities based on, for example, the status of the twin sibling. Note that if we would condition on the previous poverty status of both twins, the heterogeneity identified due to the twin sibling would be very small. Remember that shared characteristics have influenced both twins in a similar way. The aim of the analysis is to capture the complete effect of family specific heterogeneity, not the possible "additional" heterogeneity that could be identified with information on the twin sibling, once the individual specific heterogeneity has been removed.

The probability of the first twin being poor at t, conditional on the second twin not being poor the previous year, is calculated as

$$\Pr(P_{1it}=1\mid P_{2it-1}=0)=\frac{\Phi_2(\boldsymbol{\gamma}_1'\mathbf{z}_{1it-1},-\boldsymbol{\beta}_2'\mathbf{x}_{2it-1};-\rho_{32})}{\Phi(-\boldsymbol{\beta}_2'\mathbf{x}_{2it-1})} \tag{9}$$

If the probability of being poor is higher for the first twin conditional on whether the second twin was poor the previous year, it can only be due to homogeneity within the pairs of twins, as long as the Twin-State Independence Assumption is valid. Once again, that assumption is that the experience of poverty for one twin does not *in itself* affect the probability of poverty the following year for the twin sibling. Given that assumption, the conclusion is that the twin pair has common characteristics and/or shared experiences that increase the risk of poverty. State dependence cannot be a reason that one twin's probability of poverty is higher in the second year, as it was the other twin who experienced poverty the previous year.

For the first sample of twins the new measure is calculated according to:

$$Twin_1=\left(\frac{\sum_{i\in(P_{2it-1}=1)}\Pr(P_{1it}=1\mid P_{2it-1}=1)}{\sum_i P_{2it-1}}\right)-\left(\frac{\sum_{i\in(P_{2it-1}=0)}\Pr(P_{1it}=1\mid P_{2it-1}=0)}{\sum_i(1-P_{2it-1})}\right).$$

The first term in $Twin_1$ is the average probability of the first twin being poor, conditional on the second twin being poor during the previous year. The second term is the average probability of poverty for the first twin if the second twin was not identified as poor. Finally, the difference between the averages among the respective subgroups is calculated. At this point, it is important to note that it is the averages among two different *groups* that are compared. The method is certainly different from, and should not be confused with, how unobserved heterogeneity is taken into account in other twin-based methods. In studies dealing with ability bias in estimates of the return to schooling, differences between twins are used to control for unobserved heterogeneity. Here, instead of differencing away heterogeneity, $Twin_1$ uses the similarity among pairs of twins to identify the family-specific heterogeneity in poverty persistence, i.e. it measures family-specific heterogeneity.

The reason that $Twin_1$ identifies family specific heterogeneity is that it is not possible to have state dependence between the twins under the Twin-State Independence Assumption. However, common traits, characteristics, or innate abilities may have influenced the risk of poverty for both the twins, hence $Twin_1$ captures the selection mechanism into poverty. Note that if twin siblings live in the same area it is possible that a shock on the local labor market will affect them both. If the shock happens to drive both twins into poverty, this suggests that both twins are sensitive to labor market shocks, and this is certainly something that should be labeled heterogeneity. If the twins are acting on the same local labor market it is, accordingly, not a violation of the Twin-State Independence Assumption. On the contrary, it is an advantage that heterogeneity, such as being more prone to poverty due to shocks on the local labor market, can be identified.

If a person's risk of poverty is determined in part by the person's background, it is expected that the probability of poverty is higher for those twins who have a twin sibling who was poor the previous year. Accordingly, it is expected that $Twin_1$ will be positive.

As described earlier, the persistence in poverty is explained by true state dependence and heterogeneity. In this study, the persistence in poverty is estimated using ASD, and the part that may be due to family-specific heterogeneity is estimated by means of $Twin_1$.

$$ASD_1 = TSD_1 + Twin_1 \tag{10}$$

If family-specific heterogeneity did not matter at all, there would be no difference between the averages in $Twin_1$. Accordingly, the measure of $Twin_1$ would be zero, and TSD_1 would be the explanation for state dependence.[15] If family-specific heterogeneity would explain almost all of the persistence in poverty, this measure would tend to approach the estimate of ASD_1, as measured above. As a consequence, TSD_1 would be very small. Accordingly, with the extra information on twins, it is possible to distinguish family-specific heterogeneity from true state dependence. The main measure of interest in this study is the share of ASD that comes from heterogeneity. This share is simply $Twin_1/ASD_1$. It also is possible to compare the results with estimates from methods used in the previous literature. Here, ASD and GSD are calculated and the share $(ASD - GSD)/ASD$ is compared with the share of heterogeneity in the ASD measure that can be calculated with the twin information.

3. Data

The data used for this study is a combination of survey data and administrative data covering the total Swedish population. The included individuals are twins born between 1949 and 1958. The information is found in the Swedish Twin

[15]In this study, no attempt is made to find the reasons for true state dependence. Using data from the Seattle–Denver Income Maintenance Experiments (SIME/DIME), Plant (1984) leads to a conclusion that the important reason for persistent welfare participation is correlation over time in earnings, rather than a welfare trap. Both these reasons could, in principle, be present to explain *TSD*. These explanations related to earnings are apart from the reason related to health problems mentioned in the introduction. Note, however, that if earnings are correlated over time due to family-specific heterogeneity, this reason would in fact be captured by *ASD*. However, if earnings are correlated over time due to, for example, the situation in the labor market for the individual, this would be a part of the explanation of *TSD*.

Registry. Unfortunately the Swedish Twin Registry does not include information on whether the twins are monozygotic or dizygotic for individuals born after 1958. Dizygotic twins are no more alike genetically than ordinary siblings, while monozygotic twins are genetically identical. Since this distinction is potentially important for our purposes, individuals born after 1958 are not included in this study. The focus is on the monozygotic sample, but results are also presented for the measures of true state dependence and heterogeneity for the dizygotic sample. The reason for including the dizygotic sample is to see whether the potential extra homogeneity is important.[16] The population is born exclusively in Sweden, which makes it dubious to generalize results to immigrants.[17]

Information concerning, for example, disposable income, unemployment, and education from 1994 until 1999 are attached to the population of twins. This information is based on different registers for the total Swedish population and also included in the longitudinal database, LOUISE.[18] Biological parents are connected to the twins through the "Several Generations Registry."[19] Data for the years 1960 and 1970 are also included. These data come from a nationwide census called "Population and Housing Census."[20] Information from 1994 until 1999 is also included for spouses. The data were linked and matched by Statistics Sweden. All the data, except the twin information, also come from Statistics Sweden.

One problem with empirical investigations of poverty is that it is necessary to find a measure that captures a definition of poverty. This can become rather complex. It is, for example, possible to define a measure of poverty in either absolute or relative terms, where poverty also depends on a relative position in society. Further, it is not obvious that the measure should be based on financial resources, since these are not necessarily a guarantee for a rich life.[21]

The analysis in this study is performed using a poverty measure based on whether the individual had a disposable income below 60 percent of the median of the sample. An equivalence scale, based on norms defined by the National Board of Health and Welfare in Sweden, is used for the measure. Further, the disposable incomes of the members of the family are added together. Then the sum of the disposable incomes is multiplied by the individual's consumption weight and divided by the sum of the consumption weights for the family.[22] An individual is

[16]It is not necessarily the case that monozygotic twins are more homogenous, even though the genes are more alike. Psychological reasons could, for example, create a larger need for monozygotic twins to diverge in decisions and lifestyle to underline that they are in fact different individuals.

[17]Data on immigrants can be included through spouses. However, there are relatively few cases on which to rely. In addition, no couples where both are immigrants would be included. In this study, no attempts are made to say anything about poverty among immigrants. See Hansen and Löfström (2003) for a study on immigrants' welfare participation in Sweden.

[18]The database is described (in Swedish) in Statistics Sweden (2002).

[19]In Swedish, "Flergenerationsregistret."

[20]In Swedish, "Folk- och Bostadsräkningen, FoB."

[21]There is substantial literature on different poverty measures. Chapter 4 in "Social Rapport 2001," published by The National Board of Health and Welfare in Sweden (Bennet, 2001), includes a deeper discussion of different measures of poverty in the Swedish context. However, this study is limited to measures that can be defined from administrative data.

[22]The consumption weights are based on norms defined by the National Board of Health and Welfare in Sweden. If the family only consists of one adult, the weight is 1.16. For two or more adults, each adult is weighted 0.96. Children, 0–3, 4–10, and 11–17 years old add, respectively, 0.56, 0.66, and 0.76.

identified as poor if he/she does not reach 60 percent of the median consumption-weighted disposable income for the sample.[23] In the sample, a little more the 5 percent of the observations are identified as situations of poverty.

The data analyzed include 1749 monozygotic pairs of twins, and 2620 dizygotic pairs of twins of the same sex, born between 1949 and 1958.[24] Information for the parents is included for 1960 and 1970. The twins were, accordingly, between 2 and 11 years old in 1960, and between 12 and 21 years old in 1970.

Where one of the twins was self-employed, the observations are excluded. In such a case, the twin has a different control over his/her yearly income than employees usually have. In addition, only pairs where both twins were alive at least until year 2000 are included in the analysis.

With these restrictions, 874 observations of poverty, using the measure based on disposable income, are identified for the monozygotic twins for the period 1995–99. Note that these numbers are added for both the twins and their twin siblings. The numbers are also added for the period 1995–99, and in the case of poverty persistence, fewer twins have experienced poverty than the numbers indicate. Descriptive statistics for the first set of monozygotic twins can be found in Table 1.

4. Results

The most important result in this study is that family-specific heterogeneity is estimated to be the reason for 21–25 percent of poverty persistence, when the poverty measure based on disposable income is used. Before presenting a detailed discussion, this section will present the results and will discuss briefly both the parameters of characteristics that are assumed to affect poverty transitions and the correlation of error terms between the equations. Even though the focus is on a sample of monozygotic twins, estimations are also made for dizygotic twins of the same sex.

Results for the four-variate probit model, for the monozygotic twin sample, can be found in Table A1 in the Appendix. The results are based on estimates where the years 1996 and 1998 are used as transition years, with 1995 and 1997 as the years for the initial condition.[25] Note that in the estimation, $\boldsymbol{\beta}_1$ are constrained to be equal to $\boldsymbol{\beta}_2$, i.e. the coefficients in equations (1) and (2) are assumed to be the same. In the same way, $\boldsymbol{\gamma}_{11}$ and $\boldsymbol{\gamma}_{12}$ are constrained to be equal to $\boldsymbol{\gamma}_{21}$ and $\boldsymbol{\gamma}_{22}$ for equations (3) and (4), respectively. This can be done since there are no reasons to

[23]With this poverty line, exit or entry into poverty could be identified for the individual, even though the economic situation has almost not changed at all. Jenkins (2000) suggests a method to avoid threshold effects due to arbitrarily defined poverty lines. The idea is to define an exit only if the disposable income reaches 10 percent above the poverty line, and to define entry only if disposable income does not reach 90 percent of the poverty line. This method is not applied here since the main focus is poverty persistence, and introducing this idea would make the results less transparent.

[24]Dizygotic pairs of twins that are not of the same sex are not included in the study. The reason is that the results from pairs of dizygotic twins will be compared to results from pairs of monozygotic twins and adding this difference would make it less relevant to compare the estimates.

[25]The data also permit estimates using 1997 and 1999 as years for transition, and 1996 and 1998 as the base year. These estimates, as well as estimates for the dizygotic twins, are available on request from the author.

TABLE 1

Summary Statistics

Monozygotic sample, 6491 observations Variable	Twin 1 Mean or %	 Std. dev.
Disposable consumption-weighted income less than 60% of median (1 = yes)	5.30	
Region (1 = Stockholm, Malmö or Gothenburg)	46.05	
Education (1 = upper secondary school)	47.65	
Education (1 = post secondary school and post graduate education)	33.10	
Married (1 = married)	59.78	
Number of children 0–3 years	0.0739	0.3047
Number of children 4–6 years	0.1246	0.3653
Number of children 7–10 years	0.2770	0.5321
Number of children 11–15 years	0.4623	0.6677
Number of children 16–17 years	0.1725	0.3895
Months unemployed (i.e. days unemployed during year/30)	1.0254	2.9783
Partner not identified (1 = cohabiting partner not identified)	32.43	
Education of partner (1 = upper secondary school)	47.17	
Education of partner (1 = post secondary school and post graduate education)	33.93	
Months of unemployment for partner (i.e. days during year/30)	0.6526	2.3791
Age	43.9111	3.0796
Age of partner	44.0337	5.7289
Female (1 = female)	55.42	
Mother not in the labor market 1960	87.18	
Mother not in the labor market 1970	42.00	
Education of mother, 1970 (1 = upper secondary school)	15.24	
Education of mother, 1970 (1 = post secondary school and post graduate)	5.45	
Education of father, 1970 (1 = upper secondary school)	25.13	
Education of father, 1970 (1 = post secondary school and post graduate)	7.06	

Notes: The reference case for educational level is compulsory school. Descriptive statistics for the second sample of twins are of course very similar to the results shown in the table. These results are, accordingly, not included in the table.

expect a systematic difference between the parameters for the different groups of twins. Likelihood-ratio tests do, also, not reject the hypothesis of equality of the parameters.

As indicated in the description of the model, the explanatory variables included are lagged one period in all the equations. However, variables concerning the unemployment of the individual and his/her spouse are an exception. It is possible, for example, that the individual enters unemployment and poverty simultaneously due to some unobserved event. Accordingly, the variables concerning unemployment are lagged two steps to reduce the risk that equations (1) and (2) include potentially endogenous variables.

The overview of the results indicates that many parameters are not significantly different from zero. With respect to the transition equations, this result has been found in previous literature (Stewart and Swaffield, 1999; Cappellari and Jenkins, 2004). The model allows different estimates of the parameters depending on the poverty status in previous years. The estimation of the parameters for some of the dummy variables has to rely on very few observations of poverty during the previous year. This could explain the difficulty of obtaining significant coefficients in the estimates for the transition out of poverty.

TABLE 2
Measures of State Dependence and Heterogeneity

Poverty Measured as Income Less Than 60 Percent of Median Disposable Income				
Panel A: Sample of Monozygotic Twins				
Measure	1996, 1998		1997, 1999	
	Twin 1	Twin 2	Twin 1	Twin 2
ASD	0.6370	0.6454	0.6527	0.6777
GSD	0.6090	0.6090	0.5619	0.5784
Difference (ASD–GSD)	0.0280	0.0364	0.0908	0.0993
Share, in percent, of ASD due to heterogeneity	4.4 (3.7–5.1)	5.6 (4.5–6.8)	13.9 (12.3–15.5)	14.7 (12.9–16.4)
Twin	0.1348 (0.132–0.138)	0.1634 (0.160–0.167)	0.1421 (0.136–0.148)	0.1558 (0.151–0.161)
Share, in percent, of ASD due to heterogeneity	21.2 (20.5–21.8)	25.3 (24.1–26.5)	21.8 (20.5–23.1)	23.0 (22.0–24.0)
Panel B: Sample of Dizygotic Twins				
	Twin 1	Twin 2	Twin 1	Twin 2
ASD	0.6571	0.6739	0.6521	0.6638
GSD	0.5594	0.5611	0.5628	0.5732
Difference (ASD–GSD)	0.0976	0.1129	0.0893	0.0906
Share, in percent, of ASD due to heterogeneity	14.9	16.7	13.7	13.6
Twin	0.0789	0.0841	0.0927	0.0958
Share, in percent, of ASD due to heterogeneity	12.0	12.5	14.2	14.4

Notes: 1996, 1998 refers to measures based on estimation with transition equation 1996 and 1998 and year 1995 and 1997 as initial condition equations. 1997, 1999 is based on a model with 1997 and 1999 as transition equations. Bootstrap-technique was used to estimate 95% confidence intervals for the most important measures. 100 replications were used, and the results are in the parenthesis.

Not surprisingly, higher education reduces the risk of being poor in the base year. The coefficient is significantly different from zero at the 1 percent significance level using a two-tailed test.[26] The correlations of the error terms for the equations are included in Table A2 in the Appendix. The correlations of the error terms between the twins are significantly different from zero in all cases. The signs of the correlations of the error terms are positive, which indicates a positive correlation of unobservables between the twin siblings.

The estimates for state dependence and heterogeneity for both the monozygotic and the dizygotic twins are included in Table 2.

Estimates are included for transition equations using both years 1996 and 1998 and years 1997 and 1999. The measure for the overall state dependence, *ASD*, is estimated to be about 0.64–0.68 when poverty is measured based on disposable income. Accordingly, an individual who experienced poverty during the preceding year has a substantially higher risk of staying in poverty than an individual who was not poor the previous year has of entering poverty. The estimates of genuine state dependence, *GSD*, are about 0.03–0.09 lower. The estimates for the family

[26]All the subsequently mentioned tests are two-tailed tests unless otherwise explicitly stated.

specific heterogeneity, estimated using the twin method (as in $Twin_1$), are about 0.13–0.16. In other words, the risk of being poor is about 0.13–0.16 higher if the twin sibling was observed to be poor the previous year than if he/she was not observed as poor. By using equation (10), it follows that 21–25 percent of the aggregate state dependence is due to family-specific heterogeneity. The *GSD* measure indicates that 4–15 percent of the poverty persistence is due to heterogeneity.

For the dizygotic twins, *ASD* is estimated to be 0.65–0.67, while *GSD* is 0.56–0.57. The difference between the measures is about 0.09–0.11. This indicates that about 14–17 percent of the persistence of poverty is due to heterogeneity according to the method previously used in the literature. The twin method attaches about 0.08–0.10 as due to family-specific heterogeneity, which suggests that 12–14 percent of the poverty persistence is due to this type of heterogeneity. The twin method ascribes a smaller amount of the causes of the persistence of poverty to family-specific heterogeneity when dizygotic twins are used instead of monozygotic twins. Since dizygotic twins are genetically no more alike than ordinary siblings, the measure reflects the greater difference in innate abilities between dizygotic twins than between monozygotic twins.

The data for this study also includes information on social assistance and it is possible to apply the method with this alternative measure of poverty. Social assistance is the last resort of public assistance when the other systems, such as unemployment benefits, are not enough or not applicable. To get social assistance in Sweden, the individual is required to be trying to support him/herself as far as he/she is able. Usually savings have to be used before social assistance is granted. Further, social assistance is not granted if the individual has a family member, such as a cohabiting partner, who can assist. To receive social assistance, the individual has to apply for it. This means that it is possible that individuals who are entitled to receive assistance do not apply for it, which creates a disadvantage in using social assistance as a measure, since poor individuals who do not apply for social assistance will not be counted. On the other hand, an advantage with this measure is that it is based on the information available to the local social welfare worker concerning the need for social assistance.[27] Using receipt of social assistance as the measure of poverty, a little less than 5 percent of the observations are identified as poor.

Applying this alternative poverty measure and the twin method to the monozygotic sample, about 23–30 percent of the poverty persistence is due to heterogeneity. Using the *GSD* measure, 12–16 percent of the poverty persistence of the monozygotic sample is due to heterogeneity. These results are included in Table A3 in the Appendix.

4.1. *Sensitivity Analysis*

The twin method relies on an assumption that the experience of one twin does not, in itself, increase the probability for the sibling twin to experience poverty the

[27]Note, however, that there could be cases where one single, and possibly short, spell of receiving social assistance overlaps two different years. For example, this could be the case if the need for social assistance starts in December. If this were to be a common case, the measure for aggregate state dependence would give too pessimistic a picture.

following year. While it is difficult to formulate a test to evaluate the assumption, it is nevertheless possible to conduct sensitivity analysis. This parallel analysis is made with propensity score matching. The idea in propensity score matching is to find a suitable control group to evaluate the causal effect of a treatment. In this application it is, for example, of interest to study the event (treatment) of having a twin sibling in poverty and its consequences on the probability of being in poverty the next year. Of course, those who have a twin sibling in poverty in the first year is not a random sample of the population, and to merely compare this group with a control group consisting of those with a twin sibling not being in poverty would not be appropriate to capture the causal effect. A first step would be to match the treated group to a more appropriate control group, i.e. a group who not had a poor twin sibling, but had similar characteristics as the group of twins with poor twin siblings. With a large set of pretreatment characteristics such matching is made feasible by constructing a propensity score that summarizes these characteristics.

To achieve an unbiased estimate of the treatment effect on the treated it is necessary that two hypothesis are fulfilled. The balancing hypothesis states that observations with the same propensity score must have the same distribution of observables irrespective of treatment status. That is, given propensity score, the exposure to treatment is random and treated and controls should on average be identical. The hypothesis of unconfoundedness states that conditioning on the variables used to construct the propensity score, selection into treatment is independent of the potential outcome of the treatment. Hence, whether the causal effect of the treatment is estimated depends on the richness and quality of the control variables used to perform the matching. A bias would persist if unobservable confounding factors are left out in the construction of the propensity score. The balancing hypothesis is testable, while the hypothesis of unconfoundedness is, in principle, not.[28] In the ideal situation we would like to interpret the treatment effect as a causal effect, and a positive effect would then be a violation of the Twin-State Independence Assumption. It is, however, expected that a positive treatment effect could be due to the fact that the twins could share unobserved characteristics that are important for the risk of poverty. This explanation is of course, a violation of the hypothesis of unconfoundedness. If the treatment effect is zero, the Twin-State Independence Assumption is fulfilled. If the treatment effect is estimated to be positive, it is nevertheless possible that unobservable confounding factors are the explanation for the effect. In fact, the unobserved factors that contribute to a positive measure of $Twin_1$ are the same that would violate the hypothesis of unconfoundedness, and hence contribute to a positive, but misleading, treatment effect.

Ideally we would like to know the relative importance of these explanations. It is difficult to estimate the magnitude, or more precisely to formally test the Twin-State Independence Assumption, but viewing matching as a parallel method, could provide an important path to evaluate the assumption. There is a growing and highly interesting literature on how to indirectly evaluate the hypothesis of

[28]See Imbens and Wooldridge (2009) for an extensive survey of the program evaluation literature.

unconfoundedness. Rosenbaum (1987) is an early reference that suggests using two control groups. The idea is also used in de Luna and Johansson (2006). Notice, however, that rejecting a hypothesis of unconfoundedness is not sufficient to validate the Twin-State Independence Assumption. In fact, only if a potential treatment effect is completely due to unconfoundedness is the Twin-State Independence Assumption fulfilled. It is possible that the methods to evaluate the hypothesis of unconfoundedness can be adjusted appropriately to test the Twin-State Independence Assumption, but this issue is not analyzed further in this paper. In the absence of a formal test, the results in this study should be analyzed keeping in mind the possibility that the assumption is not fulfilled.

In particular when it comes to social assistance, a number of questions could be raised concerning the independence of receiving social assistance for twin siblings. For example, it could be the case that one sibling twin opens the other twin's eyes to the possibility of getting assistance. It also could be that receipt of social assistance is accompanied by some degree of embarrassment which is partly taken away by the fact that the first twin sibling is already receiving assistance. If this were the case, the Twin-State Independence Assumption would not be fulfilled. That is, *the experience* of poverty for the sibling twin would *increase* the probability for poverty for the other twin. The reasons suggested above for a causal dependence of the poverty situations of twin siblings would imply an *over*estimated effect of family specific heterogeneity in the twin method. It is of course possible that the dependence could *decrease* the probability, and hence this would result in an *under*estimation of the family specific heterogeneity. The theoretical arguments for this option seem, however, to be weaker.

In Table A4 the results from the models of propensity score matching outlined above are included.[29] A baseline model consisting of dummy variables for gender, region, education, and marital status are used together with the variables age and its square and the variables capturing children in the household. The propensity scores are constructed by estimating the probability of poverty in $t - 1$ for the second twin sibling using characteristics for these variables, measured in $t - 1$, for the first twin. The poverty status for the second twin is then used as the treatment that could affect the first twin's poverty status in t. The reverse analysis is of course also implemented. If the balancing hypothesis is not fulfilled for variables with coefficients insignificantly different from zero, these are dropped. Additional control variables for the spouse and the parents are added sequentially if the balancing hypothesis still is not fulfilled.

In Panel A in Table A4 results are included when the poverty measure is based on disposable income. For the monozygotic sample, ATTtwin is estimated to be about 0.14–0.15. As an exercise ATTtwin is also estimated with only gender as a matching variable and, interestingly, the results hardly increase (0.145 and 0.154). This is remarkably similar to the twin measure capturing family-specific heterogeneity calculated from the multivariate probit model. The similarity also extends to the sample of dizygotic twins. Under the assumption of unconfoundedness this would mean a rejection of the Twin-State Independence Assumption, but as

[29]The propensity score matching was done in Stata, with the package SJ5-3 st0026_2 (Estimation of average treatment effects), written by Becker and Ichino (2002).

explained earlier it is reasonable to expect that unobserved variables, in fact, are omitted when the propensity score is estimated. If the same analysis is conducted when social assistance is used as poverty measure, ATTtwin is about 0.15 for the sample of monozygotic twins and about 0.09 for the sample of dizygotic twins. These measures are very similar to the measures of family specific heterogeneity estimated from the multivariate probit model.

It is important to note that the treatment effect is found to be substantially higher for monozygotic twins compared to the dizygotic twins. Assuming that the possible causal effect from poverty status is equal for monozygotic twins and dizygotic twins, the difference would follow from a failure to fulfill the assumption of unconfoundedness. Hence, the additional similarity that the genes contribute seems to matter. Dizygotic twins also share genes, apart from many unobserved experiences, and it seems reasonable to conclude that both measures are biased due to a failure to fulfill the assumption of unconfoundedness. The Twin-State Dependence Assumptions would require that unconfounded variables completely explain the estimated treatment effects. As this sensitivity analysis cannot provide such far-reaching conclusions, the results from the twin-method should be interpreted with care.

4.2. *Comparative Analysis*

The results underline the importance of true state dependence in poverty. This conclusion applies regardless of whether or not the twin method is used. For example, Biewen (2009), using a German dataset, estimates that the probability of being poor if the individual was already poor the previous year is about 45 percent higher than for individuals who were not poor previously. He estimates a joint dynamic model of poverty, employment status, and household composition. Observed and unobserved heterogeneity are estimated to be the reason for about half of the persistence of poverty. Cappellari (2002) also found that about half of the observed state dependence is due to genuine state dependence when studying low pay dynamics with Italian data. Using British data, Cappellari and Jenkins (2004) estimate *ASD* to be 0.526 and *GSD* to be 0.310 when using a poverty line set to 60 percent of median income.[30] Accordingly, about 41 percent of the poverty persistency is estimated to be due to heterogeneity.

In this study, when the poverty measure based on disposable income is used on the sample of monozygotic twins, the twin method attaches 21–25 percent of the poverty persistence as due to family-specific heterogeneity. In contrast, the *GSD* measure indicates that only 4–15 percent is due to heterogeneity. The corresponding result, when poverty is measured with reception of social assistance, is 22–30 percent due to family-specific heterogeneity. Using the *GSD* measure indicates that 11–16 percent is due to heterogeneity.

Even though it is difficult to compare different studies, these results indicate that heterogeneity seems to be relatively less important for the persistence in poverty in Sweden. However, it is important to remember that fewer individuals are identified as poor in the Swedish data compared to the British data used in

[30]They use the McClements equivalence scale, and post-tax and post-transfers income.

Cappellari and Jenkins (2004). Cappellari and Jenkins (2002) tested a number of different poverty lines and found that, for the lowest poverty threshold line, "*GSD* was estimated to be even larger than *ASD* (albeit only slightly)." They suggest that heterogeneity would vary less among individuals below and above the poverty line when it was set very low.

The results in this study suggest that heterogeneity could be underestimated when using the method applied by Cappellari and Jenkins (2004) to distinguish between true state dependence and heterogeneity. A possible reason for the low estimates for heterogeneity, when their method is used for the monozygotic sample, is that it is a small sample with few cases of poverty. The dizygotic sample seems to produce higher estimates for heterogeneity when Cappellari and Jenkins' (2004) method is used. It is possible that the twin method is less sensitive to a small sample size.

Another possible explanation for the rather low estimates for heterogeneity with the method used by Cappellari and Jenkins (2004) could be weak instruments, in particular if these are "almost valid." Finding suitable instruments is difficult, in general, and often the instruments are only weakly correlated to the endogenous variable. Using such instruments would lead to a very low precision in the estimates. Things would be even worse if the instruments are "almost valid," i.e. the covariance with the errors is small, but not zero. In such case the bias could be substantial (Murray, 2006). The instruments used in the model for 1996–98 for poverty based on disposable income do pass the likelihood-ratio tests, i.e. they contribute significantly in the initial condition equation (p-value: 0.015), but can be excluded in the transition equation (p-value: 0.123). Note, however, that the exclusion restriction of the instruments from the transition equation is not far from being rejected at the 10 percent level. This could indicate that the model, in fact, is identified with weak and "almost valid" instruments that could lead to biased estimates and explain the exceptionally high results for *GSD*.[31] The twin method could be much less sensitive to such specification error, since the identification is based on the difference of the average probability among two subgroups. This is also the case for *ASD*, which also seems rather robust.

A third interpretation is of course that the difference between the results found using the method by Cappellari and Jenkins (2004) compared to the twin method are due to an overestimated effect of family specific heterogeneity due to a failure to fulfill the Twin-State Independence Assumption.

As long as the Twin-State Independence Assumption is valid, individual specific heterogeneity appears more important when the twin method is used than when Cappellari and Jenkins' (2004) method is used. Nevertheless, both the twin method and the Cappellari and Jenkins (2004) method indicate that true state dependence is relatively more important than family-specific heterogeneity in explaining poverty persistence.

It is worth taking note of the difference between using monozygotic and dizygotic twins in the twin method. Not surprisingly, the importance of heterogeneity in explaining poverty persistence is estimated to be less for the dizygotic twins

[31]For 1997–99 the corresponding p-values are 0.006 for including the instruments in the initial condition equation, and 0.108 to include the instruments in the transition equation.

than for the monozygotic twins. The monozygotic twins are more homogenous and, accordingly, more family-specific heterogeneity is identified. When estimating the return to education, using data on Swedish twins, Isacsson (2004) also concludes that the information about zygosity seems to be important.

5. Concluding Remarks

This study focuses on the persistence of poverty in Sweden. The purpose is to distinguish between two different reasons why individuals who are found to be poor one year are more likely to continue to be poor the following year. One suggested reason for poverty persistence is that individuals with certain characteristics are more likely always to be poor, as these characteristics hardly change. In this case, the reason for continuing poverty would be heterogeneity. Another reason for poverty persistence is true state dependence, i.e. that the experience of poverty, in itself, causes a higher risk of remaining in poverty in the coming years. Distinguishing between these two reasons is important for designing an effective policy to handle poverty. By using monozygotic twins this study provides a new way to distinguish true state dependence and heterogeneity as reasons for persistence in a state for individuals. The method exploits the fact that monozygotic twins have very similar backgrounds and also are genetically the same. The similarity between the twins is used to identify the part of poverty persistence that is due to family-specific heterogeneity. The method is applicable to other situations where it is interesting to separate true state dependence and heterogeneity. The method assumes that *the experience* of the state for one twin does not affect the probability of the state for the sibling twin in the following year.

Using disposable income as an indicator of poverty, the probability of remaining poor is estimated to be 0.64–0.68 higher than the probability of becoming poor when a state of poverty was not experienced the previous year. This higher risk is likely to be due to both heterogeneity and true state dependence. The risk of poverty is estimated to be about 0.13–0.16 higher if the monozygotic sibling twin experienced poverty in the previous year than if he/she did not. If the Twin-State Independence Assumption is fulfilled, state dependence does not explain a higher risk, and the latter result is interpreted to be family-specific heterogeneity. Accordingly, about 21–25 percent of the poverty persistence is caused by this type of heterogeneity.

The results can be compared with Biewen (2009) who finds, for a German dataset, that heterogeneity explains half of the poverty persistence in the sample. Cappellari and Jenkins (2004) explain 41 percent of the persistence in poverty by heterogeneity. Thus, this study finds less effect of heterogeneity than do other studies. However, the twin method only can identify *family*-specific heterogeneity. The acquired experiences that differ between the twins, and which also can affect the risk of poverty, are not captured in the measure. Accordingly, the twin method identifies only that part of poverty persistence that is due to family-specific heterogeneity. Whether family-specific or individual-specific heterogeneity is measured, this study agrees with other studies as to the importance of true state dependence.

From a methodological point of view it is important to remember that the twin method relies on the assumption that the experience of poverty for one twin sibling does not in itself affect the status of his twin sibling. In the absence of such effect the result is interpreted as due to family specific heterogeneity. The analysis is similar in character to the methodology of matching. The difference is that the focus is reversed. For the method of matching the assumption is that in the absence of unconfounded variables (i.e. unobserved heterogeneity) the result can be interpreted as due to a causal effect. The recent development of indirect tests of the assumption of unconfoundedness strengthens the method. It is clear that the twin method also would benefit from the development of formal tests of the main assumption. It is certainly an interesting area for future research.

Another concern about the estimates is the limited sample of twins used, with regard to both age and the lack of immigrants. It is possible that the persistence of poverty differs for younger individuals and immigrants. In the same way, it is possible that the relative importance of family-specific heterogeneity and true state dependence could differ. The twin method also relies on the possibility of generalizing the results to the overall population. Growing up with a sibling twin is certainly not the same as growing up as an only child. However, it is not necessarily the case that these differences would affect poverty persistence, or true state dependence.

It would be interesting to see estimates for twin samples covering younger individuals and immigrants. It would also be interesting to repeat the study for different countries with different welfare systems. It is possible that heterogeneity plays a different role in a country where there is a smaller public sector. A comparative study on poverty dynamics is Valletta (2006), where Canada, Germany, Great Britain, and the United States are analyzed. The focus is, however, on governmental policies and not on the relative importance of heterogeneity and true state dependence.

Another area for future research is to investigate the reasons for true state dependence. Knowing that true state dependence is important encourages policies that seek to prevent people from entering into poverty. Knowing *why* true state dependence occurs would also help in designing a system that reduces the persistence of poverty.

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Supporting Information

Additional Supporting Information may be found in the online version of this article:

Table A1: Estimates from Four-Variate Probit Models
Table A2: Correlations of Error Terms
Table A3: Measures of State Dependence and Heterogeneity
Table A4: Sensitivity Analysis using Matching Methodology

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