State dependence and unobserved heterogeneity in a double hurdle model for remittances: evidence from immigrants to Germany[*]

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Summary

The increasing availability of panel datasets makes it possible to explore the persistence in remittance decisions as a result of intertemporal choices, possibly consistent with several motivations to remit. Building a dynamic model with longitudinal data poses the additional problem of dealing with permanent unobserved heterogeneity; the specific censored nature of international transfers has also to be accounted for. We propose a dynamic, random-effects double hurdle model: we extend the traditional setting to account for state dependence and unobserved heterogeneity. Empirical evidence, based on the GSOEP dataset, suggests that there is significant state dependence in remitting behaviour consistent with migrants' intertemporal allocation of savings; transaction costs are likely to affect the temporal steadiness of transfers.

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1 Introduction

International remittances have long been one of the most investigated issues in the migration research agenda. Transfers sent home by international migrants exceeded official development assistance and portfolio investment since the late 1990s and almost approached the magnitudes of FDI flows during the global financial crisis (Yang, 2011). In 2015, flows to developing countries reached $432 billion and represented a major source of income and foreign exchange revenue for a large number of poor countries[1] (World Bank, 2016).

Given their size, the resilience of remittance flows represents a crucial factor for the future of migrants' countries of origin and the way individual remittance behaviour over time contributes to aggregate trends is of noticeable interest for scholars in the field.

A number of different theoretical motivations for remittances, often simultaneously at work, have been suggested by the literature (Rapoport and Docquier, 2006; Brown and Jimenez-Soto, 2015) and can be broadly categorised as either altruistic or self-interested triggers. Several of these motives entail intertemporal planning that translate into persistent behaviour over time. Migrants who have to repay a loan because parents back home funded their education and/or migration costs are likely to adopt a multi-period strategy which lasts until the debt is paid off (Cox et al., 1998; Poirine, 1997). Individuals who want their relatives to take care of their assets (land, cattle, house etc.) in the home country might have to guarantee them a periodic amount of money to this purpose. Likewise, migrants willing to support their children education are likely to do recurrent payments in order to avoid the risk that a sizeable *lump–sum* transfer might be diverted to other purposes (eg. land purchase, house building). The altruistic attitude towards the family back home, if conceived as an individual (unobserved) time-invariant characteristic, may also be considered as a different source of persistence in remitting behaviour over time.

Nevertheless, relatively little attention has been placed on the intertemporal nature of remitting behaviour, given that the vast majority of migration and remittances surveys provide cross-sectional information and empirical evidence from panel data is still scarce (Dustmann and Mestres, 2010; Duval and Wolff, 2010; Holst et al., 2012). Among the few contributions based on longitudinal surveys, Bettin and Lucchetti (2016) focused on persistence but the issue was addressed within the decision to remit only.

The aim of the present paper is to propose a fully dynamic empirical model that accounts for the intertemporal nature of remittance decisions possibly due to the different motives mentioned above. To this purpose, we need to prop-

[1] According to the World Bank estimates, in 2015 remittances amounted to 37.6% of GDP in Tajikistan, 30.3% in Kyrgyzstan, 29.4% in Nepal.

erly identify and estimate *true* state dependence, that is the causal effect of past remittance decisions on their present value, separately from permanent individual unobserved heterogeneity, i.e. the propensity of the individual to make the same decision in all periods (Heckman, 1981a) that, for instance, may capture unobserved altruistic attitudes.

An additional complication that the literature has long taken into account (see eg Banerjee (1984) and Hoddinott (1994)) is that that a large non-random share of migrants do not remit money at all. The mainstream empirical approach is to account for the possible selection bias by modelling the decision process as two separate steps: first, the choice to remit or not (the extensive margin) and second, the choice on the amount remitted (the intensive margin). Recent contributions have further explored the censoring mechanism by allowing zero remitters to have a double nature: they may either be unwilling remitters or unable to remit because of a budget constraint (or high transaction costs) (Sinning, 2011; Bettin et al., 2012; Brown et al., 2014b; Batista and Umblijs, 2016).

We therefore propose a dynamic, random-effects double hurdle model for remittances. We extend the Maximum Likelihood estimator introduced by Jones (1989) in order to deal with state dependence and individual permanent unobserved heterogeneity. The estimation of dynamic models with short panel data poses the so-called "initial conditions" problem, arising from the correlation between the initial realisations of the dependent variables and the unobserved heterogeneity. We follow Heckman (1981b) and tackle this issue by specifying additional equations that approximate the distribution of the initial values conditional on the random effects. The choice of a random-effects strategy is mainly driven by distinctive features of remittance data: determinant individual characteristics in modelling remittance behaviour, such as the migrant's family composition, typically exhibit little time variation and the decision to send remittances, the outcome of the selection equation, is highly persistent. With these data, estimation approaches based on differencing or conditioning on sufficient statistics for the individual intercepts (such as fixed-effects estimators) may not allow for the identification of crucial determinants of the agent's behaviour and/or lead to a substantial information loss.

The analysis is based on micro-level longitudinal data from the German Socio-Economic Panel (SOEP), which covers a large sample of immigrants from 1997 onwards and provides information on their characteristics, including remitting behaviour, both at the individual level and at the household level. Our empirical analysis provides suggestive results on the dynamic nature of remitting behaviour. We find significant evidence of positive state dependence in the amounts remitted, which is consistent with the intertemporally planned strategy entailed by motivations such as investment, loan repayment, exchange, and consumption smoothing of the household back home. At the same time, transaction costs hamper the migrants' ability to remit, therefore affecting the steadiness of transfers over time.

The paper is structured as follows: the main empirical issues in modelling remittance decisions and the way they have been addressed in the literature so far are discussed in depth in Section 2. In Section 3 we illustrate the dynamic random-effects double hurdle model and survey the related econometric literature. Section 4 describes the GSOEP data and provides some descriptive evidence and the related empirical results are presented and discussed in Section 5. Section 6 concludes.

2 Empirical issues in modelling remittance behaviour

Empirical literature investigating the drivers of individual remittance decisions by means of microlevel data has largely developed in the last decade (Rapoport and Docquier, 2006; Brown and Jimenez-Soto, 2015). Different motivations to remit might contribute to explain migrants' strategies, including altruistic feelings (Funkhouser, 1995; Aggarwal and Horowitz, 2002; Yang and Choi, 2007; Yang, 2008), inheritance motives (Hoddinott, 1994; de la Briere et al., 2002), insurance contracts (Lucas and Stark, 1985; Rosenzweig, 1988), exchange motives (Bernheim et al., 1985; Cox, 1987) and loan repayments (Cox et al., 1998; Poirine, 1997).

In general, empirical modelling of remittance behaviour poses a first main issue that needs to be addressed, that is the treatment of zeros. The share of remitting migrants is often not high in dedicated surveys[2] that have been employed in the literature to investigate remittance behaviour and might become even lower when using data from standard household surveys on either receiving or sending countries. In fact, remittances in most cases cannot be treated as a continuous variable but can be more accurately approximated by a mixture distribution, as they often present a non-negligible frequency mass on the value zero.

The choice of the appropriate econometric model to deal with the large number of zero–remittances depends on the interpretation given to the individual's behaviour. Banerjee (1984) and Hoddinott (1992, 1994) were among the first to model the extensive (the choice of whether to remit or not) and the intensive margin (the decision on the amount remitted) separately and use the Heckman (1979) procedure to correct for the selection bias.

Subsequent studies made large use of the same empirical methodology (e.g.

[2] Amuedo-Dorantes and Pozo (2006) for example use the Encuesta sobre Migración en la Frontera Norte de México (EMIF) and show that approximately 53% of working immigrants in their sample does not remit.

Funkhouser, 1995; Cox et al., 1998; Aggarwal and Horowitz, 2002; Amuedo-Dorantes and Pozo, 2006; Bouyiour and Miftah, 2015) often relying also on the exclusion restrictions used in Hoddinott (1992) to correctly identify the two separate choices. However, in order to circumvent the identification problem, many scholars preferred the Tobit model (Tobin, 1958) that addresses the censored nature of the dependent variable in a single equation with a common set of regressors (Bouyiour and Miftah, 2015; Brown, 1997; de la Briere et al., 2002; Hoddinott, 1992). In this case, the observed zeros can only be caused by a budget constraint.

More recently, the double hurdle model (Jones, 1989) has been proposed in the empirical literature on remitting decisions as a further alternative to the Heckman (1979) selection model in order to take into account that both the above mechanism could be in place. Therefore, non-remitting migrants might not simply be individuals who are unwilling to send any money home whatever their income, but also individuals that are prevented from doing so by the presence of transfer costs and/or budget constraints. The double hurdle setting in fact allows for the existence of a positive minimum transfer below which the costs to be covered are not offset by the additional utility migrants derive from remitting. Sinning (2011), Brown et al. (2014b) and Batista and Umblijs (2016) used a double hurdle model in its restricted independent version (Cragg, 1971), while Bettin et al. (2012) developed an instrumental variable extension of the dependent double hurdle model, where the potential endogeneity of explanatory variables (migrants' income and consumption expenditure) is also taken into account.

The censored nature of the remittance variable is an issue affecting all datasets, irrespective of their time dimension. The vast majority of migration and remittances surveys are cross–sectional surveys and empirical analyses based on them provide a snapshot of one point in time (Brown et al., 2014a). In these cases, the data do not allow for an analysis of the individual behaviour through time, which instead requires the usage of panel datasets; with these, however, two additional issues arise: unobserved heterogeneity and, when accounting for the (possible) intertemporal nature of remittance choices, state dependence. If remittances were conceived as an alternative to consumption in the context of household's budget allocation, we might observe a smoothing process over time, according to the individual expectations on future income. This forward looking behaviour would imply a high level of persistence of remitting behaviour that directly depends on the stability of migrants' income over time, but also on (sudden) changes in other socioeconomic characteristics.

Evidence based on household panel surveys is still relatively scarce. Duval and Wolff (2010) adopted a static framework and estimated the probability to receive remittance for Albanian households using the Living Standard Measurement Study (LSMS) data for 2002-2004 and control for unobserved heterogeneity of recipient households via either a random-effects Probit model or a fixed-effects Logit model according to the different assumption on the correlation between covariates and individual effects.

A few other studies made use of the German Socio-Economic Panel (GSOEP) data which are available since 1984 and offer information on remittance behaviour of immigrant households living in Germany. Holst et al. (2011, 2012), for example, addressed both the censored nature of the amount remitted and unobserved heterogeneity at the individual level by means of a random-effects Tobit model, thus assuming that the explanatory variables were uncorrelated with the unobserved individual effects. Dustmann and Mestres (2010) investigate how return plans affect the decision on whether to remit and on the amount remitted, separately considered. Some dynamics was introduced in their model, but only by treating the intention to return as endogenous and using past realisations of either the probability to remit or the size of the transfer as the corresponding instruments.

The persistence in the decision to remit was instead the focus in Bettin and Lucchetti (2016), where different discrete choice dynamic models (random-effects Probit and fixed-effects Logit) were applied to GSOEP data and provided evidence in favour of an intertemporal strategy. True state dependence was found to be highly significant, meaning that the propensity to remit at time t depends on what the migrant actually did the year before, in $t-1$, even after controlling for persistence in observable and unobservable characteristics. The authors thus suggested a multi-period scheme as the best description of the allocation of remittances in time.

3 A random-effects double hurdle model

In this section, we discuss the specification and Maximum Likelihood estimation of a static and dynamic random-effects double hurdle model that extends the traditional setting for cross-section data put forward by Jones (1989) and Blundell et al. (1987). We also illustrate a simple specialisation that extends the sample selection model proposed by Heckman (1974) to embed unobserved heterogeneity and state dependence. In order to streamline the exposition, a general formulation for the pooled models is considered first; then, its extension to random-effects static and dynamic models is described.

In order to pursue the censored nature of the data, let us consider the latent variables

$$
\begin{aligned}
y^*_{it} &= \mu_{it}\left(\mathscr{F}_{it}, \alpha_i; \boldsymbol{\psi}\right) + \varepsilon_{it} && (1)\\
s^*_{it} &= \nu_{it}\left(\mathscr{F}_{it}, \eta_i; \boldsymbol{\psi}\right) + u_{it}, \quad \text{for } i = 1, \ldots, n \quad t = 1, \ldots, T && (2)
\end{aligned}
$$

where y_{it}^* is the (latent) desired remitted amount and s_{it}^* is the unobservable propensity to remit. Furthermore, $\mu(\cdot)$ and $\nu(\cdot)$ are index functions, assumed measurable with respect to the information set at time t available to individual i, $\mathscr{F}_{it}$;[3] α_i and η_i are individual time-invariant unobserved heterogeneity terms and the vector $\boldsymbol{\psi}$ contains the model parameters. Finally, ε_{it} and u_{it} are iid error terms.

The amounts remitted are subject to a double censoring mechanism: zero remittances may be observed because the migrant is either unwilling to send remittances or unable to remit because of a budget constraint and/or transaction costs. Let us define a binary variable d_{it} indicating whether positive remitted amounts are observed as

$$d_{it} = \mathbb{I}\left(s_{it}^* > 0 \wedge y_{it}^* > y_{\min}\right) \tag{3}$$

so that $y_{it} = y_{it}^* d_{it}$. Expression (3) clearly shows the double censoring nature of the amounts remitted: positive amounts are sent if migrants are willing, $s_{it}^* > 0$, and if the amount exceeds a minimum threshold $y_{\min}$, representing the corner solution. Note that $y_{\min}$ may be strictly greater than 0 (see Sections 4.1 and 5.3).[4]

Note that the common sample selection model arises as a special case of this setup when $y_{\min} \to -\infty$, so that $d_{it} = \mathbb{I}(s_{it}^* > 0)$, and positive amounts are observed depends only as a consequence of the decision to remit or not. The joint density of (y_{it}, d_{it}), for model (1)-(2) can be written as

$$f\left(y_{it}, d_{it} | \mathscr{F}_{it}, \alpha_i, \eta_i; \boldsymbol{\psi}\right) = g\left(y_{it}, d_{it} = 1 | \mathscr{F}_{it}, \alpha_i, \eta_i; \boldsymbol{\psi}\right)^{d_{it}} \Pr\left(d_{it} = 0 | \mathscr{F}_{it}, \eta_i; \boldsymbol{\psi}\right)^{1-d_{it}}. \tag{4}$$

A Maximum Likelihood estimator of $\boldsymbol{\psi}$ can be obtained by making suitable choices for $\mu(\cdot)$ and $\nu(\cdot)$, and distributional assumptions on α_i, η_i, ε_{it}, and u_{it}. For $i = 1, \ldots, n$:

- DD Conditional on $\mathscr{F}_{it}$, the terms ε_{it} and u_{it} are distributed as a bivariate normal with zero mean and variance-covariance matrix with elements $\mathrm{E}\left(\varepsilon_{it}\varepsilon_{il}\right) = \sigma_\varepsilon^2$, $\mathrm{E}\left(u_{it}u_{il}\right) = 1$, $\mathrm{E}\left(\varepsilon_{it}u_{il}\right) = \sigma_\varepsilon\rho$ if $t = l$, 0 otherwise, for $t, l = 2, \ldots, T$.
- IED Conditional on $\mathscr{F}_{it}$, α_i and η_i have degenerate distributions.
- IS The information set $\mathscr{F}_{it}$ includes a set of individual covariates $\boldsymbol{X}_i = [\boldsymbol{x}_{i1}, \ldots, \boldsymbol{x}_{iT}]$ in (1), the same set of covariates plus suitable exclusion restrictions $\boldsymbol{Z}_i = [\boldsymbol{z}_{i1}, \ldots, \boldsymbol{z}_{iT}]$ in (2).

[3] Formally, $\mathscr{F}_{it}$ should be defined as the σ-field generated by a given set of observable random variables. To make our argument more readable, we adopt a somewhat liberal approach and identify $\mathscr{F}_{it}$ with the set of those random variables.

[4] Without loss of generality, the following formulations are nonetheless derived for a threshold normalised to 0.

Assumption (DD) is the standard distributional assumption for the sample selection and double hurdle models, Assumption (IED) leads to pooled models, and Assumption (IS) excludes lags of the dependent variables from the set of covariates. Following (IS), we further specify the usual linear index functions as

$$\mu_{it} = \mathbf{x}_{it}'\boldsymbol{\beta}, \quad \nu_{it} = \mathbf{z}_{it}'\gamma$$

where $\boldsymbol{\beta}$ and γ are regression parameters and $\boldsymbol{x}_{it}$, $\boldsymbol{z}_{it}$ are vectors of explanatory variables, where $\boldsymbol{z}_{it}$ may contain additional exogenous variables with respect to $\boldsymbol{x}_{it}$.

Under Assumptions (DD)-(IS) and the linear index expressions, we can derive the joint density of $(y_{it}, d_{it} = 1)$. We follow Davidson and MacKinnon (2004) and write the joint density, omitting the relevant conditioning sets for brevity, as

$$g\left(y_{it}, d_{it} = 1\right) = \Pr\left(d_{it} = 1 | y_{it}\right) \times \frac{1}{\sigma_\varepsilon}\varphi\left[\frac{(y_{it} - \mu_{it})^2}{\sigma_\varepsilon^2}\right] \tag{5}$$

for $t = 1, \ldots, T$, where $\varphi(\cdot)$ is the standard normal density function. The probability of d_{it} conditional on y_{it} can easily be derived from the conditional distribution of $d_{it}^*|y_{it}^*$ under bivariate normality of ε_{it} and u_{it}, that is

$$\Pr\left(d_{it} = 1 | y_{it}\right) = \Phi\left(c_\omega \nu_{it} + s_\omega (y_{it} - \mu_{it})/\sigma_\varepsilon\right) \tag{6}$$

where $\Phi(\cdot)$ is the standard normal cdf, $c_\omega = \cosh(\omega)$, $s_\omega = \sinh(\omega)$, and $\omega = \operatorname{atanh}(\rho)$. The probability $\Pr\left(d_{it} = 0\right)$ can be written as $1 - P_{it}$, with

$$P_{it} = \Phi_2\left(-\mu_{it}/\sigma_\varepsilon, \nu_{it}, \rho\right) \tag{7}$$

where $\Phi_2(\cdot)$ is the bivariate standard normal distribution function. In the case of the sample selection model, the probability to send remittances specialises to $P_{it} = \Phi\left(\nu_{it}\right)$. Finally, we can specify the likelihood for individual i as

$$\mathscr{L}_i(\boldsymbol{\psi}) = \prod_{t=1}^{T}\left[\Phi\left(c_\omega \nu_{it} + s_\omega (y_{it} - \mu_{it})/\sigma_\varepsilon\right)\frac{1}{\sigma_\varepsilon}\phi\left(\frac{y_{it} - \mu_{it}}{\sigma_\varepsilon}\right)\right]^{d_{it}} \times (1 - P_{it})^{1-d_{it}}.$$

The empirical literature dealing with the estimation of the sample selection model has brought forward a great deal of alternatives to Maximum Likelihood estimation under normality. In particular, the proposed approaches aim at either replacing the normality assumption, by specifying flexible bivariate distributions with copulae, or removing it, therefore relying on semi-parametric estimators. [5] Nevertheless, the fully parametric specification and the bivariate normality assumption allows for a general formulations that lends itself to

[5] See Pigini (2015) for a survey on alternative strategies for the estimation of the Heckman sample selection model, Escanciano et al. (2014) for a novel semi-parametric estimation approach to general double index models, and Schwiebert (2015) for the specification of double hurdle models with bivariate copulae and flexible margins.

a straightforward extension to include unobserved heterogeneity and state dependence.

Individual unobserved effects may be introduced by suitably modifying Assumption (IED). The joint density of $\boldsymbol{y}_i, \boldsymbol{d}_i$, where $\boldsymbol{y}_i = [y_{i1}, \ldots, y_{iT}]$ and $\boldsymbol{d}_i = [d_{i1}, \ldots, d_{iT}]$, for model (1)-(2) can be written as

$$f\left(\boldsymbol{y}_i, \boldsymbol{d}_i | \mathscr{F}_{it}, \alpha_i, \eta_i; \boldsymbol{\psi}\right) = \int_{\mathbb{R}} \int_{\mathbb{R}} \prod_{t=1}^{T} f\left(y_{it}, d_{it} | \mathscr{F}_{it}, \alpha_i, \eta_i; \boldsymbol{\psi}\right) h(\alpha_i, \eta_i) \mathrm{d}\alpha_i \mathrm{d}\eta_i$$

where $f\left(y_{it}, d_{it} | \mathscr{F}_{it}, \alpha_i, \eta_i; \boldsymbol{\psi}\right)$ is defined in (4).

The Maximum Likelihood estimator of $\boldsymbol{\psi}$ can be derived under additional distribution assumptions on α_i and η_i. For $i = 1, \ldots, n$:

IED′ Conditional on $\mathscr{F}_{it}$, the terms α_i and η_i are jointly distributed as a bivariate normal with zero mean and variance-covariance matrix Σ, where

$$\Sigma = \begin{bmatrix} \sigma_\alpha^2 & \\ \sigma_\alpha \sigma_\eta \kappa & \sigma_\eta^2 \end{bmatrix}$$

IED″ $(\alpha_i, \eta_i) \perp\!\!\!\perp (\varepsilon_{it}, u_{it})$ for all i and t.

Assumption (IED′) is necessary to evaluate the double integral, by exploiting standard properties of the bivariate normal to derive the conditional distribution of η_i on α_i, that is $\eta_i | \alpha_i \sim N\left[\kappa \frac{\sigma_\eta}{\sigma_\alpha} \alpha_i \; ; \; \sigma_\eta^2 (1 - \kappa^2)\right]$. This means that the random effect of the selection equation can be written as $\eta_i = \kappa \frac{\sigma_\eta}{\sigma_\alpha} \alpha_i + \delta_i$ where $\delta_i \sim N\left[0 \; ; \sigma_\eta^2 (1 - \kappa^2)\right]$, and $\alpha_i \perp\!\!\!\perp \delta_i$, for $i = 1, \ldots, n$. Since the model has two random effects whose bivariate integral will have to be evaluated, specifying a bivariate normal distribution allows us to write the model as a function of two independent normally distributed random variables. Following Raymond et al. (2010), the marginalisation with respect to the random-effects can then easily be performed by two independent consecutive integrations. Furthermore, we respecify the linear index functions to include the individual unobserved effects:

$$\begin{aligned} \mu_{it} &= \mathbf{x}_{it}' \boldsymbol{\beta} + \alpha_i \\ \nu_{it} &= \mathbf{z}_{it}' \gamma + \kappa \frac{\sigma_\eta}{\sigma_\alpha} \alpha_i + \delta_i \end{aligned}$$

for $t = 1, \ldots, T$.

Under assumptions (DD), (IED′), (IED″) and (IS), and with the linear index expressions stated above, the joint density of $(y_{it}, d_{it} = 1)$ can be written using expressions (5)-(7); therefore, the likelihood function takes the form

$$\mathscr{L}_i(\boldsymbol{\psi}) = \int_{\mathbb{R}} \int_{\mathbb{R}} \prod_{t=1}^{T} \left[\Phi\left(c_\omega v_{it} + s_\omega (y_{it} - \mu_{it})/\sigma_\varepsilon\right) \frac{1}{\sigma_\varepsilon} \phi\left(\frac{y_{it} - \mu_{it}}{\sigma_\varepsilon}\right)\right]^{d_{it}} \times (1 - P_{it})^{1-d_{it}}$$
$$\mathrm{d}\Phi\left(\frac{\alpha_i}{\sigma_\alpha}\right) \mathrm{d}\Phi\left(\frac{\delta_i}{\sigma_\eta\sqrt{1-\kappa^2}}\right) \tag{8}$$

Independence of α_i and δ_i makes it possible to evaluate the double integral sequentially, which in turn becomes a simple application of the Gauss-Hermite quadrature technique (Butler and Moffitt, 1982).

The availability of the time dimension also makes it possible to address the dynamic nature of the dependent variables so as to investigate the possibility that the migrant's remitting behaviour follows an intertemporal strategy. In order to allow for state dependence in model (1)–(2), we modify Assumption (IS) to enlarge the information set of individual i at time t, $\mathscr{F}_{it}$, to lags of the dependent variables, $\boldsymbol{y}_i^{t-1} = [y_{i1}, \ldots, y_{it-1}]$ and $\boldsymbol{d}_i^{t-1} = [d_{i1}, \ldots, d_{it-1}]$, together with the set of explanatory variables in $\boldsymbol{X}_i$ and $\boldsymbol{Z}_i$. In this case, the recursive nature of the joint density of (y_{i1}, d_{i1}) requires that the process is initialised, giving rise to the so-called "initial conditions" problem. Therefore, accounting for a different conditioning set for the probability of the initial realisation (y_{i1}, d_{i1}), the joint density of $(\boldsymbol{y}_i, \boldsymbol{d}_i)$ is

$$f\left(\boldsymbol{y}_i, \boldsymbol{d}_i | \mathscr{F}_{it}, \alpha_i, \eta_i; \boldsymbol{\psi}\right) = \int_{\mathbb{R}} \int_{\mathbb{R}} f\left(y_{i1}, d_{i1} | \mathscr{F}_{i1} \alpha_i, \eta_i; \boldsymbol{\psi}\right) \times$$
$$\prod_{t=2}^{T} f\left(y_{it}, d_{it} | \mathscr{F}_{it}, \alpha_i, \eta_i; \boldsymbol{\psi}\right) h(\alpha_i, \eta_i) \mathrm{d}\alpha_i \mathrm{d}\eta_i$$

where $f\left(y_{it}, d_{it} | \mathscr{F}_{it}, \alpha_i, \eta_i; \boldsymbol{\psi}\right)$ for $t = 1, \ldots, T$ is defined in (4). While the definition of $\mathscr{F}_{it}$ stated above is very general, we express the information set as to contain only the first lags of the dependent variables.

IS′ For $i = 1, \ldots, n$ and $t = 2, \ldots, T$, the information set is $\mathscr{F}_{it} = [y_{it-1}, d_{it-1}, \boldsymbol{X}_i]$ in (1), $\mathscr{F}_{it} = [y_{it-1}, d_{it-1}, \boldsymbol{Z}_i]$ in (2).

Under Assumption (IS′), the specification of (1) - (2) become

$$y_{it}^* = \mu_{it} + \varepsilon_{it}, \quad \mu_{it} = \phi_{11} y_{it-1} + \phi_{12} s_{it-1} + \mathbf{x}_{it}' \boldsymbol{\beta} + \alpha_i \tag{9}$$
$$s_{it}^* = \nu_{it} + u_{it}, \quad \nu_{it} = \phi_{21} y_{it-1} + \phi_{22} s_{it-1} + \mathbf{z}_{it}' \gamma + \kappa \frac{\sigma_\eta}{\sigma_\alpha} \alpha_i + \delta_i \tag{10}$$

for $t = 2, \dots, T$, where $\phi_{11}, \phi_{12}, \phi_{21}, \phi_{22}$ are the state dependence parameters and the observed y_{it} and d_{it} follow the observational rule in (3).

Finally, we deal with the conditional distribution of (y_{i1}, d_{i1}) following Heckman (1981b), that is we specify two additional linearised reduced form equations with indices

$$\mu_{i1} = \mathbf{x}'_{i1}\boldsymbol{\pi} + \theta_1\alpha_i + \theta_2\delta_i \quad (11)$$

$$\nu_{i1} = \mathbf{z}'_{i1}\boldsymbol{\lambda} + \theta_3\alpha_i + \theta_4\delta_i \quad (12)$$

In the spirit of Heckman (1981b), the linear index functions are merely an approximation of the distribution of (y_{i1}, d_{i1}) conditional in α_i and η_i. Therefore, we allow for both the random effects to enter linearly each index, as is done in Alessie et al. (2004), multiplied by nuisance parameters. For the same reason, we leave the scale of ε_{i1} unrestricted, so that $\mathrm{E}(\varepsilon_{i1}^2) = \theta_5$.

With Assumptions (DD), (IED′), (IED″), (IS) and expressions (9)-(12), the joint density of $(y_{it}, d_{it} = 1)$ can be written using expressions (5)-(7) and the likelihood function for individual i can be written as in (8).

The double hurdle model here proposed extends the approach adopted by Raymond et al. (2010) for the sample selection model; in addition, we introduce a more general dynamic specification that allows lags of both dependent variables to enter both the primary and the selection equations. Differently from Raymond et al. (2010), we model initial conditions by specifying two approximating equations for the distribution of the initial realisations of the outcome variables conditional on the random-effects, whereas they parametrise the distribution of the random effects conditional on the initial realisations of the dependent variables as in Wooldridge (2005).

In our case, Heckman's strategy for dealing with initial conditions has some advantages over Wooldridge's approach, which in our opinion offset its greater computational complexity: first, the latter relies on the stronger assumption of strict exogeneity of covariates entering the conditioning set of α_i in the correlated random-effects approach, whereas Heckman's strategy only hinges on a sequential factorisation argument, by which $\mathscr{F}_{i,t} \supseteq \mathscr{F}_{i,t-1}$; as a consequence, the validity of the decomposition only requires the absence of unobserved effects from future $\mathbf{x}_{i,t+k}$ to y_{it}. Second, Heckman's estimator has been shown to exhibit superior finite sample properties with short T in simulation (Akay, 2012). In Section 5.3 we will compare the estimation results obtained via both these estimators, as the specification adopted in Wooldridge (2005) allows for a more flexible parametrization of unobserved heterogeneity.

A number of different solutions also exist to the closely related problem of estimating a random-effect version of the sample selection model. Vella and Verbeek (1999) adopt a two-step estimation approach where they first obtain estimates of the unobserved heterogeneity component based on a random-effects estimation of the selection equation following Heckman (1981b); this quantity is then used in the augmented primary equation to correct for the selection bias, estimated by OLS. However, they consider a model where the state dependence is included only in the selection equation. Recently, Semykina and Wooldridge (2013) proposed to perform the backward substitution for the lagged dependent variable in the main equation, so that the resulting equation of interest contains the lags of the explanatory variables and the initial realisation of the dependent variable.

Alternative estimation approaches to dynamic panel data sample selection models rely on differencing to remove the individual unobserved effects. Arellano et al. (1999) and Labeaga (1999) specified a sample selection model and double hurdle model, respectively, where the autoregressive specification is adopted only in the main equation. The two-step estimation strategy builds on Chamberlain (1984)'s specification of the conditional distribution of the unobserved effect for the selection equation. The estimation of the main equation parameters is carried out following Arellano and Bover (1995) and Bover and Arellano (1997). Similarly, Wooldridge (1995) developed a two-step fixed-effects estimator for testing and correcting for the presence of selection bias following the strategy of Chamberlain (1980). An extension was recently proposed by Semykina and Wooldridge (2010) to include endogenous explanatory variables along with a semi-parametric estimation strategy based on the two-step series estimator of Newey (2009). In the same line is the three-step semi-parametric series estimator of Gayle and Viauroux (2007) for the dynamic formulation of the sample selection models. Semi-parametric estimators of the static and dynamic sample selection model have also been developed by Kyriazidou (1997) and Kyriazidou (2001), where sample selectivity is eliminated by pair-wise comparison between similar observations, as in Powell (1987) and Ahn and Powell (1993): the parameters of the selection equation are estimated and then used to construct kernel weights to be used in the least squares/GMM estimation of the main equation's parameters.

While attractive, fixed-effects approaches based on removing the incidental parameters are not considered in this paper, since they would not allow us to identify determinant individual characteristics in modelling remittance behaviour, such as the migrants family composition, that typically exhibit little time variation. In addition, fixed-effects strategies require that migrants contribute to the likelihood only if their response configurations for the decision to remit exhibit some time variation; this would lead to substantial information loss when estimating the parameters for the selection mechanism, since the decision to send remittances is typically very persistent.

4 Data

Our empirical analysis is based on data from the German Socio-Economic Panel (SOEP) for the period between 1996 and 2012[6]. SOEP is a representative longitudinal survey that includes yearly information on a large sample of households residing in Germany. Individual questionnaires are administered to each household member above 18 years together with a household-level one, which is usually answered by the head of the household. This allows for a perfect matching between information on demographic and socioeconomic individual characteristics and details on household composition and budget decisions for every person in the sample. Immigrant households were included in the sample from the first wave of the survey in 1984 but the nationality groups initially covered were only those with the longer tradition of immigration to Germany: Turks, Italians, Greeks, Spaniards and Yugoslavians[7]. The immigrant subsample was then significantly increased to include also other nationalities from 1995 onwards.

A detailed picture of the socio-economic conditions of relatives in the home country is missing in the SOEP dataset. Available information simply concerns the family structure, i.e. what relatives are still living abroad. This shortcoming might explain why, despite its longitudinal nature and its wide usage in the literature on migrants' assimilation and performance in the labour market, the SOEP has not been employed in many empirical contributions on remittance behaviour.[8] The sample used in the empirical analysis is restricted to the

[6]The data used in this paper was extracted using the Add-On package PanelWhiz for Stata. PanelWhiz was written by Dr. John P. Haisken-DeNew. See Haisken-DeNew and Hahn (2010) for details. The PanelWhiz generated Stata script to retrieve the data used here is available from us upon request. Any data or computational errors in this paper are our own.

[7]Formal guest workers programmes were implemented in West Germany during the 1950s and 1960s. Foreign workers were recruited from Southern Europe first (bilateral agreements with Italy and Greece were signed in 1955 and 1960, respectively), but soon from Turkey and former Yugoslavia as well. Immigrants who entered the SOEP in the 1980s indicated Yugoslavia as their home country. Aggregate data have been calculated as mean values for the group of current countries that were once enclosed in the Federal Republic.

[8]Merkle and Zimmermann (1992) look at the way migrants' remittance and saving behaviour is influenced by return intentions. Holst et al. (2008, 2010, 2011) investigate the links between gender, transnational networks, legal status and the remittance patterns while Bollard et al. (2011) include SOEP data in their cross-country study and investigate how remittance patterns change according to migrants' different educational levels. Bauer and Sinning (2011) analyse immigrants' savings behaviour while Sinning (2011) focuses on the differences in remitting strategy between permanent and temporary migrants. Similarly to Merkle and Zimmermann (1992), Dustmann and Mestres (2010) look at the way return plans affect the amount remitted but they also exploit the longitudinal nature of the survey in a dynamic panel setting. Bettin and Lucchetti (2016) investigate the issue of time persistence in the decision to remit by means of discrete choice dynamic models.

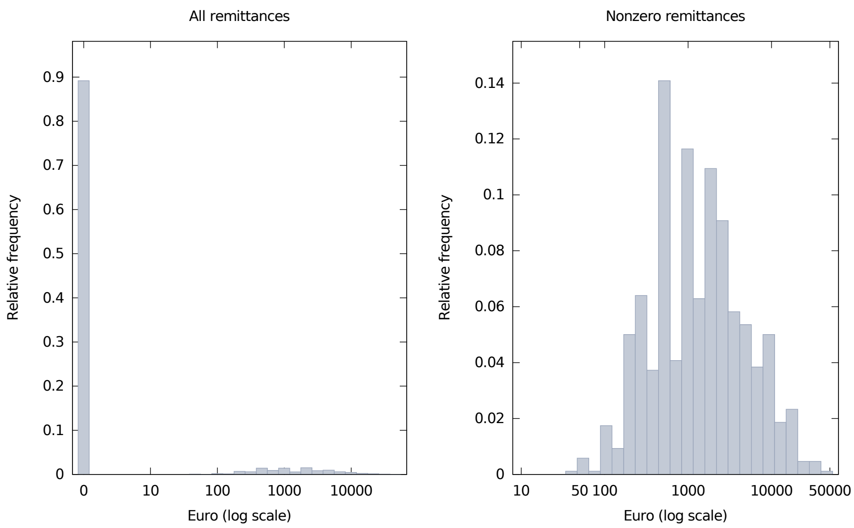
adult immigrant population. Immigrants are defined as foreign-born individuals who moved to Germany after 1948 and therefore include individuals who became German citizens after immigration while excluding second-generation immigrants (see also Bauer and Sinning (2011)).

All waves before 1996 were excluded due to the inconsistency in the questions on remittance behaviour before and after that date.

4.1 The amount remitted: definition and some descriptive figures

Information on remittances are collected in the individual questionnaire by asking the following question: "In the last year, that is, in [...], have you personally given money or financial support to relatives or other people outside this household? How much in the year as a whole? ". Specifically, individuals are asked about transfers to parents/parents–in–law, children/son–in–law/daughter–in–law, spouse/ divorced spouse, other relatives and non–relatives. In the definition of the amount remitted, our dependent variable in the main equation, we consider all remittances towards close and distant relatives and express them in natural logarithm[9]. In the selection equation, the dependent variable is equal to 1 when migrants send a positive amount R in year t and is equal to 0 when there are no transfers to any relative back home.

Figure 1: Distribution of amounts remitted

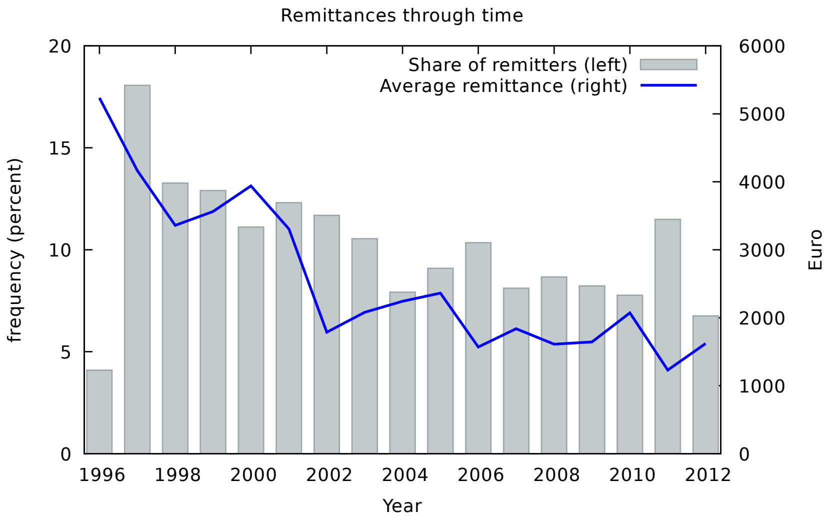


On average, 11% of migrants in our sample remit (Figure 1). However, it

[9] All financial variables (remittances, but also income) before 2002 have been expressed in Euro before taking natural logs.

is interesting to note that most non-zero remittances are relatively distant from zero. While of course the distribution displayed in the figure is a marginal, and not a conditional, one, it seems difficult to justify empirically the idea of non-remitting behaviour only as the observable outcome of a corner solution at 0 in the migrant's optimisation process.

Figure 2: Share of remitters and average amount remitted by year, 1996-2012



The share of remitting migrants decreases over time, especially in the last years covered in our sample (see Figure 2). This trend might be related to the consequences of the sovereign debt crisis that spread throughout Europe between 2010 and 2011, although we do not observe significant variations in migrants' income levels and employment outcomes over time. If we focus on the sample of remitters, the mean amount sent home is not constant over time; there seems to be a small but visible drop in the size of transfers before and after that date.[10]. As a matter of fact, the highest value is registered in 1996, 4276 Euros, while the lowest in 2011, 1269 Euros.

When looking at remitting behaviour by country of origin (Table 1), sizeable differences emerge. In general, the average share of remitters is higher among migrants from Asia and the Pacific region (33.63%) and from the Balkan region (21.13%). The lowest values (6-7%) are associated to Southern Europeans (Italians, Greeks, Spaniards, the traditional immigration groups in 1960s and 1970s) and other EU-15 or OECD citizens. It is worth noting, however, that these immigrant groups are the ones who send the larger amount of money, with a yearly

[10]Data prior to 2002 were converted from DM to Euros.

Table 1: Average share of remitters and amount remitted by country of origin

Country	Share of remitters (%)	Mean amount (Euros)	Std. Dev. (Euros)
Turkey	10.33	2581	3779
Ita-Gre-Spa	6.44	5129	7393
Ex Yugoslavia	21.13	2944	3507
Other EU - OECD	7.44	4360	9410
New EU members	13.67	1547	2464
Ex USSR	11.17	1304	2304
Africa	8.68	1991	2851
Latin America	12.18	2079	2318
Asia-Pacific	33.63	2585	2693

average remittance above 5100 Euros for individual from Southern Europe and around 4400 Euros for other EU-15 or OECD citizens. Migrants from the ex USSR countries send the lowest amounts (1300 Euros).

4.2 The explanatory variables

We include a common set of explanatory variables in both the main and the selection equation. This set includes those immigrants' personal characteristics usually considered in the literature as observable determinants of the decision to remit: gender (1 if male), age and time since migration[11], migrant household composition (number of adult members and number of children), educational level (years of education), migrants' individual yearly labour income and household net yearly income (both in natural logarithm), their squares and a time trend.[12] In order to capture migrants' attachment to the host country we also build a categorical variable by interacting the intention to stay in Germany (1 for staying, 0 for going back to the home country), with their German citizenship status (1 if acquired). Categories are ordered from the lowest (both zeros) to the highest level of attachment (both 1). The reference group in our estimates is represented by individuals with the lowest level of attachment.

We then consider some additional country-level variables in both equations to proxy for the socio-economic conditions of the origin household in the home country that could affect remittance behaviour but are not covered in the SOEP

[11] Both variables enter the two equations with their value at the first sampling year.

[12] The choice of a linear time trend was found to be a valid parsimonious alternative to the more common choice of including yearly fixed effects.

survey. The ratio between per capita GDP[13] in the home country[14] and in Germany (in logs) is included to proxy for the living conditions of those left behind. Its square is also added to control for possible non-linear effects. In addition, we also include a set of "pseudo-country" dummies[15] to control for time-invariant factors, such as distance, which might exert an influence on the strength of the relationship with the family at home and therefore affect the decision to remit.

In order to identify the two decision mechanisms correctly, we need to define some exclusion restrictions. Such variables will enter the selection equation, thus affecting the choice whether to remit or not, but are supposed to have no direct effect on the amount remitted. Most of the exclusion restrictions previously employed in the literature relate to either information on recipient households that we are not able to exploit here[16] or to factors which cannot be disregarded *a priori* as determinants of the amount remitted.[17]

Following Czaika and Spray (2013), we employ a dummy that takes value 1 if the individual is currently employed in the German labour market on the assumption that being employed (economically active) may affect the decision to remit, but not the size of individual remittances once we control for the migrant's individual and household income. In addition, we exploit the available information on the structure of the receiving household by including four dummy variables respectively for the presence of parents, children and partner in the home country. Finally, we consider a dummy that identifies mixed families by taking value 1 if migrant's partner has not a migration background and 0 otherwise. When both partners share a foreign origin their incentives to send remittances are likely to be higher compared to mixed households.[18].

[13]Data are drawn from the World Development Indicators database. GDP per capita is expressed in constant 2005 international dollars.

[14]During the interview, the home country was not chosen from a predefined list, but rather declared freely. For this reason, a non-negligible share of individuals list as their home country a territorial entity that is not recognised as a sovereign state per se or no longer exists as such. As a consequence, data for Benelux are calculated as means between those for Belgium and the Netherlands. For Kurdistan and Ex-Yugoslavia we make use of data for Iraq and Serbia, respectively.

[15]Countries of origin are grouped as follows: Turkey, Southern Europe (Italy, Greece, Spain), Ex Yugoslavia, other EU-OECD countries, new EU members, ex URSS, Africa, Latin America, Asia-Pacific.

[16]Hoddinott (1992), Gubert (2002), and Amuedo-Dorantes and Pozo (2006) all use proxies for the location of the recipient family that provide an indirect measure of the fixed transaction costs associated with remitting fund.

[17]Hoddinott (1992), and Aggarwal and Horowitz (2002) consider the years of absence from the home country, which are likely to have an impact also on the size of transfers as predicted by Poirine (1997).

[18]In order to test for the validity of these exclusion restrictions, we included them also in the main equation and they all proved not significant, without altering other results.

5 Estimation results

5.1 State dependence and unobserved heterogeneity in double hurdle models

In this section, we present the estimation results of our proposed random-effects double hurdle model for remittances. Results for the static and dynamic specifications are reported in Table 2.

As widely discussed before, the double hurdle model allows for a double form of censoring, which considers that zero remittances might derive from either a budget constraint (possibly including opportunity and transaction costs, usually unobservable) or the absence of any gain related to international transfers. Positive amounts of remittances are therefore observed according to (3) in Section 3. In other words, there is a minimum amount $y_{\min} > 0$ below which the overall cost migrants need to cover to remit money back home is not offset by the additional gains (in terms of utility or future expected income) they derive from the transfer. In our sample, around 1% of remitting migrants report transfers substantially smaller than 100 euros per year, that may be considered as the result of misreporting since they would hardly cover opportunity and transaction costs. In the estimated model, $y_{\min}$ is assigned a value below which we assume it is not worthwhile for the migrant to transfer money and, in our baseline specification, this threshold is set to 50 euros, equal to 5% of the median amount remitted.[19]

In order to properly describe migrants' behaviour two separate, but not independent, mechanisms are needed: one governing the choice as to whether to remit and another the decision on how much to transfer. This finding is suggested by the statistically significant correlations between the selection and the main equations κ and ρ, where κ is the correlation between the time-invariant unobserved heterogeneity components α and η, whereas ρ captures correlation between the idiosyncratic error terms in (9)-(10).

Although no substantial differences emerge between the static and the dynamic specification when looking at the effects of the control variables (discussed below in Section 5.2), the significant coefficients associated to both y_{t-1} and d_{t-1} in the main equation show that *true* state dependence cannot be disregarded when modelling individual remittance decisions. The signs of these coefficients offer a suggestive insight on the mechanisms generating persistence in the amount remitted. First, the sign associated with y_{t-1} in the main equation is consistent with the presence of intertemporal planning that translates into a positive persistence: motivations to remit such as investment, loan repayment, exchange, consumption smoothing of the household back home entail

[19]Sensitivity analysis to this choce is reported in section 5.3.

Table 2: Static and dynamic random effects Double Hurdle models for remittances

	Static			**Dynamic**		
	coeff	(stderr)		coeff	(stderr)	
Main eq.						
y_{t-1}				0.078	(0.030)	**
d_{t-1}				-0.240	(0.100)	**
sex	0.057	(0.057)		0.094	(0.074)	
education yrs	0.007	(0.012)		0.013	(0.017)	
yrs since mig	0.013	(0.003)	***	0.009	(0.004)	**
age at mig	0.082	(0.028)	***	0.117	(0.036)	***
stay&citiz$_1$: ref.						
stay&citiz$_2$	-0.189	(0.117)		-0.061	(0.139)	
stay&citiz$_3$	-0.047	(0.048)		-0.022	(0.055)	
stay&citiz$_4$	-0.266	(0.073)	***	-0.289	(0.090)	***
n_adults	-0.096	(0.028)	***	-0.065	(0.034)	*
n_children	-0.061	(0.024)	**	-0.082	(0.030)	***
individual income	0.055	(0.019)	***	0.043	(0.021)	**
household income	0.401	(0.063)	***	0.382	(0.077)	***
Per capita GDP diff.	0.172	(0.239)		0.271	(0.244)	
Per capita GDP diff.^{2}	0.028	(0.059)		0.045	(0.059)	
Wald test for state dependence $\chi^2(2)$				6.555		**
Selection eq.						
y_{t-1}				0.073	(0.047)	
d_{t-1}				0.103	(0.134)	
sex	0.146	(0.086)	*	0.197	(0.098)	**
education yrs	0.023	(0.017)		0.013	(0.018)	
yrs since mig	0.023	(0.004)	***	0.025	(0.005)	***
age at mig	0.070	(0.038)	*	-0.011	(0.043)	
stay&citiz$_1$: ref.						
stay&citiz$_2$	0.382	(0.131)	***	0.221	(0.200)	
stay&citiz$_3$	-0.264	(0.058)	***	-0.336	(0.071)	***
stay&citiz$_4$	0.095	(0.101)		0.101	(0.127)	
n_adults	-0.063	(0.033)	*	-0.046	(0.055)	
n_children	-0.100	(0.026)	***	-0.119	(0.037)	***
individual income	0.115	(0.037)	***	0.076	(0.045)	*
household income	0.181	(0.083)	**	0.065	(0.100)	
Per capita GDP diff.	-1.382	(0.289)	***	-1.467	(0.367)	***
Per capita GDP diff.^{2}	-0.330	(0.067)	***	-0.259	(0.082)	***
partner_hc	1.615	(0.455)	***	1.191	(0.326)	***
children_hc	3.618	(0.306)	***	3.785	(0.268)	***
parents_hc	2.914	(0.117)	***	3.172	(0.194)	***
employed	0.219	(0.088)	**	0.328	(0.109)	***
mixed family	-0.219	(0.089)	**	-0.240	(0.105)	**
Wald test for state dependence $\chi^2(2)$				25.489		***
Wald test for state dependence $\chi^2(4)$				34.463		***
κ	-0.213	(0.046)	***	-0.229	(0.045)	***
ρ	-0.486	(0.040)	***	-0.480	(0.048)	***
σ_α	0.743	(0.025)	***	0.735	(0.039)	***
σ_η	1.432	(0.072)	***	1.614	(0.131)	***
σ_ϵ	0.772	(0.017)	***	0.732	(0.020)	***
Log-lik		-12961.221			-9766.4	
N. obs.		5054			3555	

Models specifications include an intercept term, a time trend and country of origin fixed-effects as defined in section 4. Standard errors are panel and heteroskedasticity robust. Significance level: * 10%, ** 5%, *** 1%.

Table 3: Dynamic random effects Double Hurdle models for remittances: restrictions on ϕ_{21} and ϕ_{22} in (10)

	$\phi_{21} = 0$			$\phi_{22} = 0$		
	coeff	(stderr)	p-value	coeff	(stderr)	p-value
Main eq.						
y_{t-1}	0.088	(0.029)	***	0.072	(0.031)	**
d_{t-1}	-0.274	(0.097)	***	-0.216	(0.096)	**
sex	0.094	(0.074)		0.086	(0.075)	
age	0.012	(0.004)	***	0.012	(0.004)	***
education yrs	0.013	(0.017)		0.013	(0.017)	
yrs since migration	-0.003	(0.005)		-0.003	(0.005)	
stay&citiz$_1$: ref.						
stay&citiz$_2$	-0.064	(0.139)		-0.062	(0.138)	
stay&citiz$_3$	-0.021	(0.055)		-0.022	(0.055)	
stay&citiz$_4$	-0.296	(0.091)	***	-0.292	(0.091)	***
n_adults	-0.066	(0.034)	*	-0.066	(0.035)	*
n_children	-0.081	(0.030)	***	-0.083	(0.030)	***
individual income	0.043	(0.021)	**	0.044	(0.021)	**
household income	0.379	(0.077)	***	0.378	(0.077)	***
Per capita GDP diff.	0.276	(0.245)		0.272	(0.245)	
Per capita GDP diff.^{2}	0.045	(0.059)		0.044	(0.059)	
Wald test for state dependence $\chi^2(2)$	8.970		**	5.8932		*
Selection eq.						
y_{t-1}				0.105	(0.021)	***
d_{t-1}	0.301	(0.060)	***			
sex	0.150	(0.101)		0.150	(0.108)	
age	0.003	(0.005)		0.003	(0.006)	
education yrs	0.008	(0.017)		0.007	(0.017)	
yrs since migration	0.023	(0.006)	***	0.024	(0.007)	***
stay&citiz$_1$: ref.						
stay&citiz$_2$	0.218	(0.173)		0.214	(0.174)	
stay&citiz$_3$	-0.334	(0.073)	***	-0.336	(0.074)	***
stay&citiz$_4$	0.087	(0.119)		0.083	(0.124)	
n_adults	-0.024	(0.053)		-0.022	(0.055)	
n_children	-0.108	(0.039)	***	-0.108	(0.039)	***
individual income	0.084	(0.044)	*	0.081	(0.045)	*
household income	0.058	(0.106)		0.060	(0.108)	
Per capita GDP diff.	-1.473	(0.369)	***	-1.501	(0.389)	***
Per capita GDP diff.^{2}	-0.266	(0.086)	***	-0.271	(0.108)	***
partner_hc	1.147	(0.373)	***	1.141	(0.373)	***
children_hc	3.797	(0.246)	***	3.770	(0.251)	***
parents_hc	3.171	(0.193)	***	3.171	(0.191)	***
employed	0.310	(0.111)	***	0.317	(0.112)	***
Wald test for state dependence $\chi^2(3)$	33.096		***	33.756		***
κ	-0.194	(0.047)	***	-0.231	(0.057)	***
ρ	-0.490	(0.048)	***	-0.471	(0.049)	***
σ_α	0.727	(0.037)	***	0.740	(0.041)	***
σ_η	1.611	(0.122)	***	1.619	(0.121)	***
σ_ϵ	0.735	(0.020)	***	0.731	(0.020)	***
Log-lik		-9782.8			-9762.4	
N. obs.		3555			3555	

Models specifications include an intercept term, a time trend and country of origin fixed-effects as defined in section 4. Standard errors are panel and heteroskedasticity robust. Significance level: * 10%, ** 5%, *** 1%.

some kind of commitment to send steady amounts over time.

Second, the sign of d_{t-1} implies negative correlation between past decisions to remit and the present amount remitted, which may capture an additional, possibly simultaneous, mechanism: if able, migrants may choose to alternate the moments when remittances are sent so as to ensure that the transferred amount always exceeds transaction costs, thereby avoiding to send rather small amounts that may not offset the transfer fees. Notice that the above result is in line with the negative signs of the statistically significant correlations coefficients κ and ρ. A negative correlation between the decision to remit and the amount remitted suggests that migrants with a lower probability to remit, if they do so send higher amounts (see Bettin et al., 2012). This result also carries an interpretation in terms of budget constraints generated by transfer costs and, in this respect, the negative state dependence associated with d_{t-1} adds an intertemporal dimension to this same mechanism in a two-period setting.

In the selection equation, significance of the coefficients for the lagged variables occurs only jointly but not individually. The lack of statistical significance can also be ascribed to weak identification of the corresponding model parameters given the strong correlation between the decision to remit and the amount remitted. In order to improve the identification of at least one of the state dependence parameters in the selection equation, we estimate our model by imposing some parameter restrictions to the linear index in (10), either $\phi_{21} = 0$, that is excluding the lagged amounts in the selection equation, or $\phi_{22} = 0$, implying that y_{t-1} carries all the information on past remitting behaviour alone. Results are reported in Table 3. In both cases the remaining state dependence coefficient in the selection equation gains statistical significance and maintains a positive sign. Between the two specification, we focus on the second as our preferred one, where more information on the dynamics in the extensive margin is preserved (the log-likelihood is also markedly higher). Note that the implications suggested by the main equation estimation results remain unchanged. This evidence confirms and extends the findings by Bettin and Lucchetti (2016) and strongly supports the hypothesis of intertemporal planning of the remittance strategy by migrants, and consequently, the importance of using longitudinal data sets to shed light on the actual mechanism of remittance behaviour.

Finally, we find evidence of strong individual unobserved heterogeneity from the estimates of the standard deviations of the individual random effects in Table 2 and 3, and in both the main and selection equations, corresponding to σ_α and σ_η, respectively. Even in the absence of a proper "poolability" test, as the reported p-value refers to the rejection of a null hypothesis on the frontier of the parameter space, the values of the estimated coefficients and standard errors are such that random-effects models can safely be preferred to specifications based on pooled cross-sections where the presence of unobserved heterogeneity is neglected.[20]

5.2 The other determinants of remitting behaviour

Analysing the remaining determinants of remitting behaviour, the indications we get from either the static or the dynamic double hurdle model are substantially similar. The size of the transfer seems to depend on both family-related and individual variables. The larger the household in Germany (that is, the larger the number of adults and children), the lower the amount remitted. On the other hand, higher household and individual income are associated to larger remittances (Lucas and Stark, 1985; Hoddinott, 1994; Funkhouser, 1995; Dustmann and Mestres, 2010).

The age of the migrant at the entrance in the sample may capture unobservable characteristics, such as individual ability, or migrants' working experience that might be associated to a higher capacity to remit and hence to larger transfers. As far as the attachment to the host country is considered, migrants who have acquired German citizenship and declare their intention to stay in Germany send significantly smaller amounts than individuals without citizenship that plan to return. This confirms the evidence provided in Dustmann and Mestres (2010) from the GSOEP data according to which migrants with temporary migration plans remit more.

As for the selection equation, the length of stay in Germany (at the first sampling year) and individual income are associated to a higher probability to remit. The number of children in the migrant's household and her/his attachment to Germany have instead a negative effect on the extensive margin. Non-linearity characterises the effect of the GDP differential between the home country and Germany, which is negative both in its linear and its square term.

As is well known, the literature on selection models has long recognised the necessity of having some exclusion restrictions between the selection equation and the main equation to strengthen identification of the model, which otherwise would rely on non-linearity only. In our case, migrants' employment status and the dummies related to the household structure in the country of origin are all extremely significant and positively affect the probability to remit, while the chance of being a remitter gets significantly lower for migrants belonging to mixed families.

The time trend variable (not reported in the tables) enters both the main and the selection equation with a negative sign, suggesting, consistently with the preliminary descriptive evidence in Figure 2 that the size of the transfer decreases over time.

[20] Results from the pooled models are not reported for the sake of brevity but available upon request.

5.3 Robustness checks

In this section, we illustrate a few robustness exercises to check for the sensitivity of our results to the choice of the censoring mechanism and to the chosen estimation method.

In our baseline specification in Table 3, $y_{\min}$ is set to 50 euros. As this value is rather high compared to the minimum positive amount remitted in our sample, equal to 5, we first estimate a double hurdle model with a lower threshold, $y_{\min} = 30$. Then, we illustrate the results for the sample selection model (Heckman, 1974) where a single censoring mechanism is in place, that is positive remittances are observed only if migrants are willing to remit, $s^* > 0$ in (3), with no other hurdle placed by either a budget constraint nor transaction costs.

Table 4 displays the estimation results. The estimated state dependence coefficients, as well as the other determinants, maintain the sign and significance of the baseline model. Notice the slight change in the magnitude of the coefficients associated with d_{t-1} in the main equation between the baseline (second column of Table 3) and this double hurdle model. A similar difference emerges for the sample selection model, where the estimated ϕ_{12} in (9) is almost twice as large. Nevertheless, the insights entailed by the evidence presented in Section 5.1 still apply. Moreover, we argue that the double hurdle model is a preferable modelling strategy for remittances since it does allow for a double censoring mechanism, which may indeed be in place when observing positive amounts.

An additional robustness check we presented relates to the choice of estimator: we compare our baseline results with those obtained by estimating a dynamic double hurdle model where initial conditions are handled as in Wooldridge (2005). As discussed in Section 3, our preferred strategy follows Heckman (1981b) and we specify the two approximating equations (11) and (12) for the distribution of the initial realisations of y_{i0} and d_{i0}, conditional on the individual effects. Instead, Wooldridge (2005) proposed to parametrise the distribution of the random effects conditional on the initial realisations of the dependent variables.

An advantage of Wooldridge's approach is that is allows for a richer representation of the permanent unobserved heterogeneity by parametrising its conditional distribution via a correlated random effects-type correction (Mundlak, 1978), that includes the individual time averages of explanatory variables. Therefore, the following exercise also allows us to check whether there is still significant evidence of *true* state dependence after further controlling for individual unobserved effects. We specify the conditional distributions for α_i and η_i in (9) and (10) as follows:

Table 4: Dynamic random effects Double Hurdle and Sample Selection models for remittances: $\phi_{22} = 0$, $y_{\min} = 30$

	Double Hurdle - $y_{\min} = 30$			**Sample Selection**		
	coeff	(stderr)		coeff	(stderr)	
Main eq.						
y_{t-1}	0.073	(0.027)	***	0.075	(0.026)	***
d_{t-1}	-0.260	(0.101)	**	-0.528	(0.181)	***
sex	0.096	(0.073)		0.108	(0.070)	
education yrs	0.013	(0.016)		0.015	(0.016)	
yrs since mig	0.008	(0.004)	*	0.008	(0.004)	**
age at mig	0.111	(0.035)	***	0.109	(0.034)	***
stay&citiz$_1$: ref.						
stay&citiz$_2$	-0.056	(0.136)		-0.112	(0.139)	
stay&citiz$_3$	-0.018	(0.055)		-0.017	(0.054)	
stay&citiz$_4$	-0.283	(0.089)	***	-0.255	(0.088)	***
n_adults	-0.058	(0.033)	*	-0.062	(0.032)	*
n_children	-0.084	(0.029)	***	-0.084	(0.029)	***
individual income	0.039	(0.021)	*	0.040	(0.021)	*
household income	0.374	(0.076)	***	0.370	(0.075)	***
Per capita GDP diff.	0.244	(0.228)		0.218	(0.222)	
Per capita GDP diff.^{2}	0.042	(0.055)		0.036	(0.054)	
Wald test for state dependence $\chi^2(2)$	7.169		**	8.491		**
Selection eq.						
y_{t-1}	0.091	(0.018)	***	0.047	(0.009)	***
sex	0.176	(0.096)	*	0.173	(0.095)	*
education yrs	0.010	(0.018)		0.008	(0.018)	
yrs since mig	0.025	(0.005)	***	0.025	(0.005)	***
age at mig	-0.009	(0.042)		-0.008	(0.043)	
stay&citiz$_1$: ref.						
stay&citiz$_2$	0.192	(0.189)		0.228	(0.187)	
stay&citiz$_3$	-0.332	(0.070)	***	-0.331	(0.070)	***
stay&citiz$_4$	0.090	(0.127)		0.076	(0.127)	
n_adults	-0.050	(0.055)		-0.047	(0.055)	
n_children	-0.119	(0.036)	***	-0.121	(0.036)	***
individual income	0.077	(0.046)	*	0.076	(0.045)	*
household income	0.098	(0.101)		0.098	(0.100)	
Per capita GDP diff.	-1.363	(0.341)	***	-1.328	(0.330)	***
Per capita GDP diff.^{2}	-0.239	(0.079)	***	-0.232	(0.076)	***
partner_hc	1.202	(0.325)	***	1.205	(0.323)	***
children_hc	3.739	(0.261)	***	3.742	(0.261)	***
parents_hc	3.141	(0.186)	***	3.140	(0.185)	***
employed	0.342	(0.108)	***	0.344	(0.108)	***
mixed family	-0.240	(0.102)	**	-0.234	(0.102)	**
Wald test for state dependence $\chi^2(3)$	35.839		***	36.988		***
κ	-0.222	(0.044)	***	-0.213	(0.042)	***
ρ	-0.476	(0.048)	***	-0.483	(0.048)	***
σ_α	0.739	(0.036)	***	0.739	(0.033)	***
σ_η	1.598	(0.123)	***	1.596	(0.124)	***
σ_ϵ	0.732	(0.020)	***	0.733	(0.019)	***
Log-lik		-10094.424			-10741.290	
N. obs.		3555			3555	

Models specifications include an intercept term, a time trend and country of origin fixed-effects as defined in section 4. Standard errors are panel and heteroskedasticity robust. Significance level: * 10%, ** 5%, *** 1%.

Table 5: Dynamic random effects Double Hurdle for remittances: Wooldridge (2005)'s initial conditions

	Double Hurdle			**Double Hurdle** - $T \geq 6$		
	coeff	(stderr)		coeff	(stderr)	
Main eq.						
y_{t-1}	0.076	(0.028)	***	0.075	(0.030)	**
d_{t-1}	-0.245	(0.088)	***	-0.240	(0.094)	**
sex	0.026	(0.063)		0.019	(0.073)	
education yrs	-0.004	(0.013)		0.004	(0.015)	
yrs since mig	0.012	(0.004)	***	0.012	(0.005)	***
age at mig	0.086	(0.032)	***	0.094	(0.035)	***
stay&citiz$_1$: ref.						
stay&citiz$_2$	-0.129	(0.115)		-0.181	(0.123)	
stay&citiz$_3$	-0.036	(0.047)		-0.062	(0.050)	
stay&citiz$_4$	-0.237	(0.075)	***	-0.250	(0.080)	***
n_adults	-0.025	(0.039)		-0.031	(0.041)	
n_children	-0.069	(0.044)		-0.062	(0.046)	
individual income	0.033	(0.026)		0.038	(0.024)	
household income	0.295	(0.071)	***	0.280	(0.074)	***
Per capita GDP diff.	0.382	(0.225)	*	0.420	(0.249)	*
Per capita GDP diff.^{2}	0.068	(0.053)		0.073	(0.060)	
Wald test for state dependence $\chi^2(2)$	7.863		**	6.704		**
Selection eq.						
y_{t-1}	0.210	(0.019)	***	0.211	(0.020)	***
sex	0.055	(0.068)		0.095	(0.079)	
education yrs	0.020	(0.013)		0.022	(0.015)	
yrs since mig	0.006	(0.004)		0.004	(0.005)	
age at mig	0.113	(0.028)	***	0.112	(0.032)	***
stay&citiz$_1$: ref.						
stay&citiz$_2$	0.191	(0.141)		0.183	(0.152)	
stay&citiz$_3$	-0.290	(0.059)	***	-0.301	(0.064)	***
stay&citiz$_4$	-0.054	(0.100)		-0.088	(0.109)	
n_adults	-0.036	(0.044)		-0.034	(0.046)	
n_children	-0.029	(0.043)		-0.045	(0.043)	
individual income	0.039	(0.043)		0.036	(0.044)	
household income	0.198	(0.095)	**	0.153	(0.100)	
Per capita GDP diff.	-0.772	(0.269)	***	-0.847	(0.296)	***
Per capita GDP diff.^{2}	-0.154	(0.067)	**	-0.170	(0.071)	**
partner_hc	3.096	(0.653)	***	3.518	(0.583)	***
children_hc	4.613	(0.289)	***	4.753	(0.336)	***
parents_hc	4.245	(0.171)	***	4.535	(0.225)	***
employed	0.213	(0.102)	**	0.194	(0.109)	*
mixed family	0.016	(0.168)		-0.067	(0.173)	
Wald test for state dependence $\chi^2(3)$	139.508		***	110.465		***
ϖ	-0.063	(0.057)		-0.002	(0.064)	
ρ	-0.332	(0.042)	***	-0.321	(0.043)	***
σ^*_α	0.657	(0.031)	***	0.659	(0.034)	***
σ^*_η	1.056	(0.050)	***	1.065	(0.057)	***
σ_ϵ	0.740	(0.019)	***	0.739	(0.019)	***
Log-lik		-10964.137			-9650.442	
N. obs.		5054			2408	

Models specifications include an intercept term, a time trend and country of origin fixed-effects as defined in section 4. w_i includes individual time averages of: n_adults, n_children, individual and household income, partner_ch, parents_hc, children_hc, employed, mixed family. Coefficients associated to w_i, y_{i0}, d_{i0} are not reported and available upon request. Standard errors are panel and heteroskedasticity robust. Significance level: * 10%, ** 5%, *** 1%.

$$\begin{aligned}\alpha_i &= \vartheta_{11} y_{i0} + \vartheta_{12} d_{i0} + \boldsymbol{w}_i' \boldsymbol{\xi} + \alpha_i^* \\ \eta_i &= \vartheta_{21} y_{i0} + \vartheta_{22} d_{i0} + \boldsymbol{w}_i' \boldsymbol{\zeta} + \eta_i^* \quad \text{for} \quad i = 1, \ldots, n\end{aligned}$$

where α_i^*, η_i^* are distributed as a bivariate normal with zero mean, standard deviations equal to $\sigma_\alpha^*, \sigma_\eta^*$ and correlation coefficient ϖ. The vector $\boldsymbol{w}_i$ includes individual time averages of personal characteristics such as labour and household income, composition of the migrant's family living in Germany and the composition of the family living in the country of origin. The first column of Table 5 reports the estimation results confirming the presence of a strongly significant *true* state dependence in both the main and selection equation, where the coefficients associated with lagged dependent variables also maintain the same sign and similar magnitude compared to our preferred specification in Table 3. The most striking difference is probably in the magnitude and significance of κ in Table 3 and ϖ in Table 5, both denoting the correlation between the time invariant unobserved heterogeneity: clearly the different specification for the random-effects adopted here is itself able to capture the cross-equation dependence between α_i and η_i.

Some simulation studies (Akay, 2012) for the probit model found Wooldridge's estimator to exhibit inferior finite sample properties than Heckman's estimator with short T. Since our panel is strongly unbalanced and the median number of periods a migrant is followed is 7, we further investigate this issue by estimating the same model on a trimmed sample so as to keep only migrants observed for 6 years or more.[21] The second column in Table 5 reports the results of this last exercise and it shows that the significance of the state dependence parameters is closer to that in Table 3.[22] Despite the robustness of these results, we argue that Heckman's strategy is still preferable in our case: as opposed to Heckman (1981b), the approach proposed by Wooldridge (2005) relies on the stronger assumption of strict exogeneity of covariates. Such a restriction may hardly be tenable when modelling migrants behaviour, where mechanisms of feedback from past remittance decisions may easily affect the migrant's personal and family characteristics.

6 Conclusions

In order to perform a comprehensive analysis of the determinants of remittance behaviour, we develop a dynamic double hurdle model based on a general

[21] Keeping only individuals observed for a number of consecutive periods much larger than 6 would make our sample too small for the model estimation to give reliable results.

[22] We also repeated the exercise using Heckman's estimator. Results are again very similar to those presented in Table 5, are available upon request but not reported here for brevity.

random-effects formulation that accounts for the double censoring nature of the dependent variable, unobserved heterogeneity, and state dependence. We argue that our proposed model offers several advantages in the field of remittance modelling when compared to other approaches: all the information on the history of highly persistent remittance decisions is retained and we are able to strongly identify the impacts of migrants' characteristics with little time variation, that are often the focus of empirical works on remittance determinants.

Accounting for state dependence in the model formulation allows us to capture the possible intertemporal nature of remittance decisions. Even though we are not able to discern between the different possible reasons to remit, the presence of persistence in transferred amounts would be consistent with intertemporal allocation of savings due to motivations such as investment, loan repayment, subsidising consumption of the household back home.

The estimation results of the random-effects dynamic double hurdle model on the GSOEP data provides novel evidence on the dynamic nature of remitting behaviour. A positive and significant state dependence in the amounts remitted confirms intertemporal planning while, at the same time, the cost of sending money limits the migrants ability to remit, thereby reducing the frequency of transfers.

The formulation of our model is such that it can be extended to embed a more detailed description of the migrants behaviour. For instance the assumption of exogeneity of explanatory variables can be relaxed and, following Bettin et al. (2012), we may allow for reverse causation between remittance amounts, income and consumption. In such a case, the modelling framework can accommodate additional first-step equations; alternatively, the extension to a correlated random-effects approach is straightforward. This further analysis is, however, left for future research as it requires and additional, non-trivial computational effort.

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