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

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Abstract

The empirical modelling of remitting behaviour has been the object of a considerable amount of micro-level literature. The increasing availability of panel datasets makes it possible to explore the persistence in transfer decisions as a result of intertemporal choices, that may be consistent with several motivations to remit. Building a dynamic model with panel data poses the additional problem of dealing properly with permanent unobserved heterogeneity; morever, the specific censored nature of international transfers must be accounted for as well.

In this paper, we propose a dynamic, random-effects double hurdle model for remittances: we combine the Maximum Likelihood estimator of the traditional double hurdle model for cross-section data (Jones, 1989) with the approach proposed by Heckman (1981b) for dealing with state dependence and unobserved heterogeneity in a non-linear setting. Our empirical evidence based on the German SOEP dataset suggests that there is significant state dependence in remitting behaviour consistent with migrants' intertemporal allocation of savings; at the same time, transaction costs are likely to affect the steadiness of transfers over time.

JEL codes: F22, F24, C23, C34, C35
Keywords: Migration, Remittances, State dependence, Double hurdle, Intertemporal choices.

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 multiperiod 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's 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.

The aim of the present paper is to propose a dynamic empirical setting where the intertemporal nature of remittance decisions possibly due to the different motives mentioned above. To this purpose, we need to properly identify and estimate "true state dependence", that is the causal effect of past remittance decisions on their present value, seperately 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. 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

[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.

addressed within the decision to remit only.

On the other hand, the literature has long taken into account that a large non-random share of migrants do not remit money (see, among others, Banerjee, 1984; Hoddinott, 1994). 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 constaint (or high transaction costs) (Sinning, 2011; Bettin et al., 2012; Brown et al., 2014b).

We therefore proposed a dynamic, random-effects double-hurdle model for remittances. We extend the Maximum Likelihood estimator introduced by Jones (1989), building on earlier work by Cragg (1971), 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 evidence on the dynamic nature of remitting behaviour. We find a positive and signifcant state dependence in the amounts remitted, cosistent with the intertemporal planning 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 should be more accurately represented as a mixture distribution, with a non-null probability mass at zero.

The choice of the appropriate econometric model to deal with the large amount of zero–remittances depends on the interpretation of the individual 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. Funkhouser, 1995; Cox et al., 1998; Aggarwal and Horowitz, 2002; Amuedo-Dorantes and Pozo, 2006; Bouyiour and Miftah, 2015) often relying also on the

[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.

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). This amounts to interpreting the observed zeros as the outcome of corner solutions to the budget contraint.

More recently, the double-hurdle model (Cragg, 1971; 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, migrants who do not remit might not simply be individuals that 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) and Brown et al. (2014b) used a double-hurdle model in its restricted independent version, while Bettin et al. (2012) propose 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).

With longitudinal data, 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) use GSOEP data to 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 instrumenting the intention to return with past realisations of either the probability to remit or the size of the transfer.

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. Strong evidence of true state dependence was found: the propensity to remit at time t depends on what the migrant actually did at $t-1$, even after controlling for persistence in observable and unobservable characteristics. Therefore, time allocation of remittances seems to follow a multi-period scheme.

3 A random-effects Double Hurdle model

We discuss the specification and Maximum Likelihood estimation of a static and dynamic random-effects the double hurdle model that extends the traditional setting for cross-section data put forward by Cragg (1971); Jones (1989); Blundell et al. (1987). We further illustrate a simple specialisation that extends the sample selection model proposed by Heckman (1974) toembed unobserved heterogeneity and state dependence. We first consider a general formulation for the pooled models that we then extend to random-effects static and dynamic models.

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

$$y_{it}^* = \mu_{it}\left(\mathscr{F}_{it}, \alpha_i; \boldsymbol{\psi}\right) + \varepsilon_{it} \quad (1)$$

$$s_{it}^* = \nu_{it}\left(\mathscr{F}_{it}, \eta_i; \boldsymbol{\psi}\right) + u_{it}, \quad \text{for } i = 1, \ldots, n \quad t = 1, \ldots, T \quad (2)$$

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 of the information set at time t available to individual i, $\mathscr{F}_{it}$, of the individual time-invariant unobserved heterogeneity α_i and η_i, and of the model parameters $\boldsymbol{\psi}$. Finally, ε_{it} and u_{it} are iid error terms.

The decision to remit depends on the binary variable $s_{it} = \mathbb{I}\left(s^*_{it} > 0\right)$, where $\mathbb{I}\left(\cdot\right)$ is an indicator function, with $s_{it} = 1$ if the migrant sends remittances and zero otherwise. 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 the transaction costs $y_{\min}$. In the special case of the sample selection model $d_{it} = s_{it}$, that is whether positive amounts are observed depends only on the decision to remit. 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 specifying the density functions with 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 $\mathrm{E}\left(\varepsilon_{it}\varepsilon_{is}\right) = \sigma^2_\varepsilon$, $\mathrm{E}\left(u_{it}u_{is}\right) = 1$, $\mathrm{E}\left(\varepsilon_{it}u_{is}\right) = \sigma_\varepsilon\rho$ if $t = s$, 0 otherwise, for $t, s = 2, \ldots, T$.
- 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).

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

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

where $\boldsymbol{\beta}$ and $\boldsymbol{\gamma}$ are regression parameters, and $\boldsymbol{x}_{it}$ and $\boldsymbol{z}_{it}$ 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 closely related sample selection model has brought forward a great deal alternatives to Maximum Likelihood estimation under the assumption of bivariate normality of the error terms. 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. [3] Nevertheless, the fully parametric specification and the bivariate normality assumption allows for a general formulations that lends itself to a straightforward extension to include unobserved heterogeneity and state dependence, none of this for the DH model.

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

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

[3] 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.

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 $\boldsymbol{X}_i$ and $\boldsymbol{Z}_i$, $\boldsymbol{Z}_i = [z_{i1}, \ldots, z_{iT}]$, 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 re-specify 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

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

The 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

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

where $f(y_{it}, d_{it} | \mathscr{F}_{it}, \alpha_i, \eta_i; \boldsymbol{\psi})$ 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 model (1) - (2) becomes

$$y_{it}^* = \mu_{it} + \varepsilon_{it}, \quad \mu_{it} = \phi_{11} y_{it-1} + \phi_{12} s_{it-1} + \mathbf{x}_{it}' \boldsymbol{\beta} + \alpha_i \tag{9}$$

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

for $t = 2, \ldots, T$, 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

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

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

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 appear either in the primary and the selection equations. Differently from Raymond et al. (2010), we model initial conditions by specifying to 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). However, Akay (2012) showed that, with short T, Heckman's estimator has superior finite sample properties.

Our proposed model also relates to other random-effects approaches to the estimation of the sample selection model so far brought forward by the econometric literature. Vella and Verbeek (1999) adopt a two-step estimation approach where they first derive estimates of the unobserved heterogeneity 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.

4 Data

Our empirical analysis is based on data from the German Socio-Economic Panel (SOEP) for the period between 1996 and 2012[4]. 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[5]. 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. The only available information is about the family structure, i.e. what relatives live in the origin country. This shortcoming partly explains why, despite its longitudinal natural and the wide usage in the literature on migrants' assimilation and performance in the labour market,

[4]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.

[5]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.

the SOEP has not been employed in many empirical contributions on remittance behaviour.[6] The sample used in the empirical analysis is restricted to the 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 living either in Germany or abroad. In the definition of the amount remitted, our dependent variable in the main equation, we consider all remittances towards close and distant relatives in the home country and express them in natural logarithm[7]. 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.

On average, 11% of migrants in our sample remit (Figure 1). However, it is interesting to note that most non-zero remittances are relatively far 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 as the observable outcome of a corner solution at 0 in the migrant's optimisation process.

[6]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.

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

Figure 1: Distribution of amounts remitted

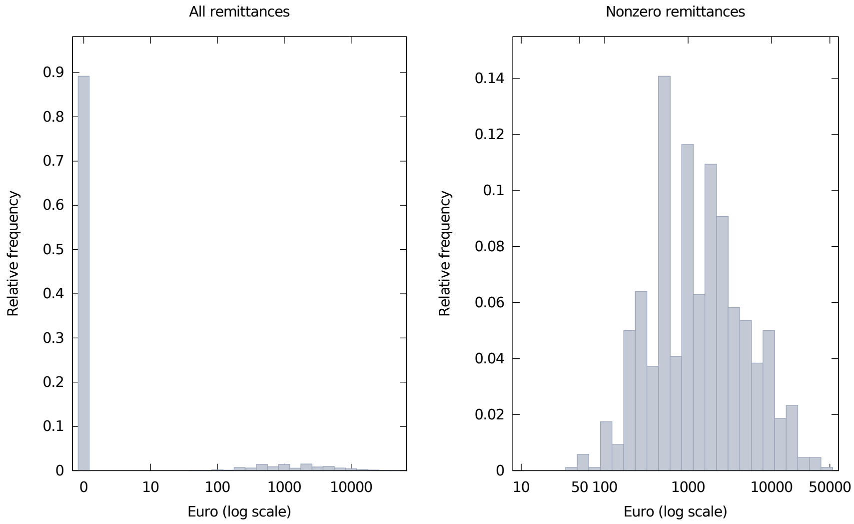
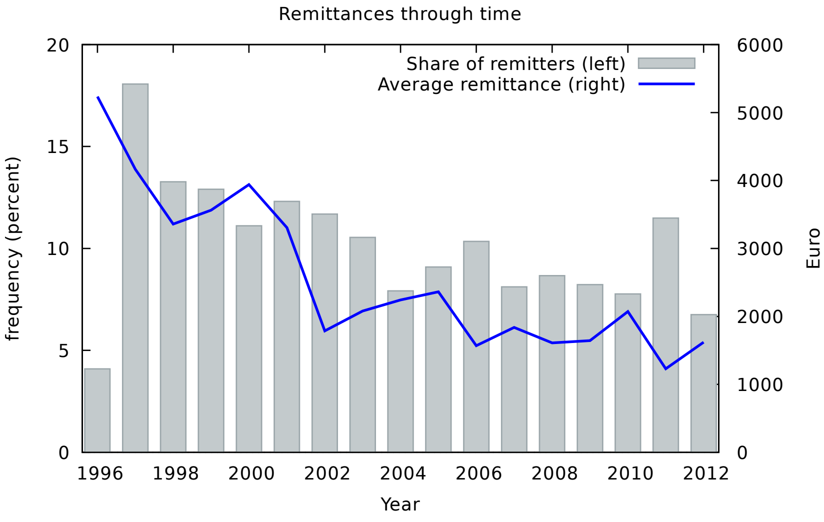


Figure 2: Share of remitters and average amount remitted by year, 1996-2012



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; even adjusting our data for the Euro adoption from 2002 onwards, there seems to be a sensible gap in the size of transfers before and after that date. As a matter of fact, the highest value is registered in 1996, 4.276 Euros, while the lowest in 2011, 1269 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

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 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[8], 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) and their square terms, a time trend. 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 survey. The ratio between per capita GDP[9] in the home country[10] 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 nonlinear effects. In addition, we also include a set of "pseudo-country" dummies[11] 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[12] or to factors which cannot be disregarded *a priori* as determinants of the amount remitted[13].

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

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

[10]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.

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

[12]Hoddinott (1992); Gubert (2002); 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.

[13]Hoddinott (1992); Aggarwal and Horowitz (2002) consider the years of absence from the

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, partner and siblings in the home country.

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 utility gain related to international transfers. Following the approach by Bettin et al. (2012), positive amounts of remittances are therefore observed according to (3) in section 3 where $y_{\min}$ is the minimum remittance below which the amount to be sent would not cover the transaction costs. In our baseline specification this threshold is set to 50 euros. Notice that migrants' behaviour is properly described by two non-independent processes, the first one governing the choice as to whether to remit and the second one the decision on how much to transfer. This 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

home country, which are likely to have an impact also on the size of transfers as predicted by Poirine (1997).

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

	Static			Dynamic		
	coeff	(stderr)	p-value	coeff	(stderr)	p-value
Main eq.						
y_{t-1}				0.077	(0.031)	**
d_{t-1}				-0.237	(0.101)	**
sex	0.053	(0.059)		0.089	(0.075)	
age	0.008	(0.003)	***	0.012	(0.004)	***
education yrs	0.007	(0.012)		0.013	(0.017)	
yrs since migration	0.005	(0.004)		-0.003	(0.005)	
stay&citiz$_1$: ref.						
stay&citiz$_2$	-0.187	(0.117)		-0.063	(0.139)	
stay&citiz$_3$	-0.044	(0.048)		-0.022	(0.055)	
stay&citiz$_4$	-0.262	(0.072)	***	-0.294	(0.091)	***
n_adults	-0.097	(0.028)	***	-0.066	(0.034)	*
n_children	-0.061	(0.024)	**	-0.083	(0.030)	***
individual income	0.055	(0.019)	***	0.044	(0.021)	**
household income	0.398	(0.063)	***	0.379	(0.077)	***
Per capita GDP diff.	0.174	(0.246)		0.273	(0.077)	
Per capita GDP diff.^{2}	0.028	(0.061)		0.045	(0.245)	
Wald test for state dependence $\chi^2(2)$				6.307		**
Selection eq.						
y_{t-1}				0.072	(0.048)	
d_{t-1}				0.109	(0.137)	
sex	0.141	(0.092)		0.149	(0.105)	
age	0.009	(0.003)	***	0.003	(0.005)	
education yrs	0.021	(0.018)		0.007	(0.017)	
yrs since migration	0.015	(0.005)	***	0.024	(0.007)	***
stay&citiz$_1$: ref.						
stay&citiz$_2$	0.378	(0.134)	***	0.213	(0.174)	
stay&citiz$_3$	-0.262	(0.060)	***	-0.335	(0.074)	***
stay&citiz$_4$	0.092	(0.101)		0.085	(0.122)	
n_adults	-0.046	(0.033)		-0.022	(0.054)	
n_children	-0.091	(0.027)	***	-0.109	(0.038)	***
individual income	0.114	(0.037)	***	0.081	(0.045)	*
household income	0.184	(0.079)	**	0.059	(0.107)	
Per capita GDP diff.	-1.416	(0.318)	***	-1.486	(0.378)	***
Per capita GDP diff.^{2}	-0.344	(0.076)	***	-0.268	(0.107)	***
partner_hc	1.658	(0.709)	**	1.139	(0.371)	***
children_hc	3.657	(0.248)	***	3.773	(0.248)	***
parents_hc	2.920	(0.121)	***	3.163	(0.191)	***
employed	0.215	(0.089)	**	0.315	(0.112)	***
Wald test for state dependence $\chi^2(2)$				26.433		***
Wald test for state dependence $\chi^2(4)$				34.791		***
κ	-0.221	(0.056)	***	-0.219	(0.058)	***
ρ	-0.487	(0.040)	***	-0.477	(0.049)	***
σ_α	0.745	(0.025)	***	0.735	(0.040)	***
σ_η	1.444	(0.086)	***	1.611	(0.121)	***
σ_ϵ	0.772	(0.017)	***	0.732	(0.020)	***
Log-lik		-12964.4			-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%.

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 some kind of comittement to send steady amounts over time.

Second, the sign of d_{t-1} denotes a 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 transfered 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. This result also carries an interpretation in terms of budget contraints generated by trasfer 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 obviously positive 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. We choose to focus on the latter specification as our preferred one, because more information on the dynamics in the extensive margin is preserved. Notice 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 a strong individual unobserved heterogeneity, that emerges 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 [14].

5.2 The other determinants of remitting behaviour

Regarding the other determinants of remitting behaviour, the indications we got 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 lower 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.

There is also evidence of a non linear relationship between household income and the probability to remit, with a negative coefficient on the squared term. Non linearity characterises the effect of the GDP differential between the home country and Germany, which is negative both in its linear and its squared 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 other-

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

wise would rely on non-linearity only. In our case, both migrants' employment status and the variables related to the household structure in the country of origin are all extremely significant and positively affect the probability to remit.

Although non reported in the tables, the time trend variable 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.

5.3 Robustness checks

In this section we illustrate two robustness exercises that check for the sensitivity of our results to the choice of the threshold $y_{\min}$. This is the minimum above which positive remittances are observed, as it represents the transaction fee that makes it not worthwhile for the migrant to send money back home.

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) that is a special case where 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. In this case, $y_{\min} = 0$ represents a necessary condition for the sample selection model.

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 5.1 still apply. Moreover, we argue that the double hurdle model is still 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.

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 random-effects formulation that accounts for the double censoring nature of the dependent variable, unobserved heterogeneity, and state dependence. We argue

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)	p-value	coeff	(stderr)	p-value
Main eq.						
y_{t-1}	0.071	(0.027)	***	0.074	(0.026)	***
d_{t-1}	-0.257	(0.101)	**	-0.522	(0.182)	***
sex	0.093	(0.074)		0.105	(0.072)	
age	0.011	(0.004)	***	0.011	(0.003)	***
education yrs	0.013	(0.017)		0.015	(0.016)	
yrs since migration	-0.003	(0.005)		-0.003	(0.005)	
stay&citiz$_1$: ref.						
stay&citiz$_2$	-0.057	(0.136)		-0.113	(0.139)	
stay&citiz$_3$	-0.017	(0.055)		-0.017	(0.054)	
stay&citiz$_4$	-0.286	(0.090)	***	-0.259	(0.089)	***
n_adults	-0.058	(0.033)	*	-0.062	(0.033)	*
n_children	-0.085	(0.030)	***	-0.084	(0.029)	***
individual income	0.040	(0.021)	*	0.040	(0.021)	*
household income	0.371	(0.077)	***	0.367	(0.075)	***
Per capita GDP diff.	0.246	(0.230)		0.219	(0.223)	
Per capita GDP diff.^{2}	0.042	(0.055)		0.036	(0.054)	
Wald test for state dependence $\chi^2(2)$						
	6.961		**	8.270		**
Selection eq.						
y_{t-1}	0.092	(0.018)	***	0.047	(0.009)	***
sex	0.134	(0.102)		0.130	(0.101)	
age	0.003	(0.005)		0.003	(0.005)	
education yrs	0.003	(0.018)		0.003	(0.017)	
yrs since migration	0.024	(0.007)	***	0.024	(0.007)	***
stay&citiz$_1$: ref.						
stay&citiz$_2$	0.188	(0.169)		0.225	(0.168)	
stay&citiz$_3$	-0.332	(0.073)	***	-0.331	(0.072)	***
stay&citiz$_4$	0.082	(0.120)		0.072	(0.119)	
n_adults	-0.023	(0.053)		-0.021	(0.053)	
n_children	-0.107	(0.038)	***	-0.110	(0.038)	***
individual income	0.081	(0.045)	*	0.080	(0.045)	*
household income	0.095	(0.109)		0.094	(0.108)	
Per capita GDP diff.	-1.380	(0.365)	***	-1.352	(0.357)	***
Per capita GDP diff.^{2}	-0.246	(0.085)	***	-0.241	(0.083)	***
partner_hc	1.151	(0.357)	***	1.152	(0.355)	***
children_hc	3.731	(0.246)	***	3.739	(0.245)	***
parents_hc	3.128	(0.179)	***	3.130	(0.180)	***
employed	0.333	(0.110)	***	0.334	(0.109)	***
Wald test for state dependence $\chi^2(3)$						
	36.413		***	37.658		***
κ	-0.212	(0.056)	***	-0.199	(0.050)	***
ρ	-0.474	(0.049)	***	-0.481	(0.049)	***
σ_α	0.739	(0.036)	***	0.739	(0.033)	***
σ_η	1.594	(0.114)	***	1.591	(0.116)	***
σ_ϵ	0.732	(0.020)	***	0.733	(0.019)	***
Log-lik		-10100.6			-10767.2	
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%.

that our proposed model offer several advantages in the field of remittance modelling with respect to other available approaches: all information on the history of highly persistent remittance decisions is retained and we are able to strongly identify the impact of migrants' characteristics with little time variation, that are often the focus of empirical analyses 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 transfered 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. 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 an additional, substantial computational effort.

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