Exchange rate forecasting using a new dynamic panel estimator

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Abstract

This study investigates the effectiveness of a newly proposed dynamic panel estimator, Panel Fully Aggregated Estimator (PFAE, see Han, Phillips and Sul, 2011) in the forecasting context. Our simulation results show that forecasts from PFAE-based estimator generally outperforms forecasts from the least squares dummy variables (LSDV) based method especially when the data series is approaching unit root or when the data series are correlated. The exchange rate forecasts from the monetary fundamentals and the Taylor-rule models for a sample of OECD countries also show superiority in outperforming forecasts generated using LSDV and a random walk benchmark in the short horizon.

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1. Introduction

This paper analyzes the forecasting performance of a new dynamic panel estimator proposed by Han, Phillips and Sul (2011, HPS hereafter). HPS (2011) develop a novel approach for estimating dynamic parameters in pure autoregressive models that they call “X-differencing”. X-differencing eliminates the idiosyncratic fixed effects but retains information in the presence of stationary or unit root dynamics. HPS (2011) refer to the new estimator as “panel fully aggregated estimator” (PFAE) which is obtained using pooled least squares on the system of X-differenced equations. HPS (2011) show that PFAE is easy to implement, is consistent across a range of parameter values including unit root and possess strong asymptotic and finite sample properties which makes it better than the other dynamic estimators, viz., biased corrected least squares (LSDV), GMM and system GMM.

Given the strong asymptotic and finite sample properties of PFAE, one interesting issue would be to explore how this new estimator performs in the context of forecasting. We look at this issue using a two-pronged approach. First, we use a simulation exercise with the data generating process being a panel autoregressive model to generate forecasts using PFAE. We also report results on the parameter estimation of fixed effects. The way the fixed effects are eliminated and then estimated might matter for forecasting.1 Afterwards, we compare the one-period ahead, out-of-sample forecasting performance of the PFAE estimator against the widely used LSDV estimator.2 We want to explore whether LSDV is a reasonable choice for forecasting (compared to PFAE and under which N, T combinations), whether estimation of fixed effects is affected by the choice of estimation method for the dynamic parameters and whether the forecasting performance of the two estimators is similar. Second, we apply the new estimator to generate one-period ahead, out-of-sample forecasts for exchange rates in a sample of nine non-Eurozone OECD countries using models based on macroeconomic fundamentals.

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1See Clements and Hendry (1998) for the importance of intercepts in forecasting.
2Both the PFAE and the LSDV estimators are very easy to compute, being linear estimators, and they do not require any assumptions on the choice of, e.g., instrumental variables.
Thereafter, we compare the forecasting performance with forecasts generated using LSDV estimator and a random walk benchmark.

Starting with the seminal work of Messe and Rogoff (1983), a large number of influential papers use time-series regression models based on macroeconomic fundamentals to generate out-of-sample forecasts of exchange rates (see Cheung, Chinn and Pascual, 2005 for a recent survey). Exchange rate models with economic fundamentals cover Taylor-rule models (see, among others, Molodtsova and Papell, 2009), uncovered interest rate parity or interest rate differential model (see, among others, Clark and West, 2006), monetary fundamentals model (see, among others, Engel, Mark and West, 2007, and Mark, 1995), purchasing power parity model (see, among others, Rogoff and Stavrakeva, 2008), as well as external balance model (see, among others, Gourinchas and Rey, 2007). However, all these models, in general, are set-up against a difficult-to-beat opponent: the random walk benchmark. The extant literature report evidence of mixed success of outperforming forecasts generated from the benchmark with those of the fundamentals in short horizons (see, among others, Sarno and Velante, 2009).

In contrast, studies using pooled regression models and estimated with panel data after allowing for fixed effects generally obtain better forecasting performance within the long horizon. Important contributions by Mark and Sul (2001), Rapach and Wohar (2004), Groen (2005), Engel, Mark and West (2007) and Rogoff and Stavrakeva (2008) employ panel data and use the monetary fundamentals model to forecast exchange rates. The above studies, in general, employ the pooled fixed-effects or LSDV estimator to generate out-of-sample forecasts. However, there is an ongoing debate on a number of aspects of panel data models and associated estimation techniques. Mark and Sul (2011) deal with the issue of using pooled panel-data regression versus time-series regression to generate superior forecasts. Westerlund and Basher (2007) show how pooling across individual prediction tests as well as across forecasting parameters lead to better forecasting power.

\[^3\] Groen (2000) also uses panel data but the focus is not on predictability. Similarly, a number of studies like Frankel and Rose (1996), Papell and Theodoris (2001), and Papell (2006) use panel data to investigate the long-run purchasing power parity. Recently, Engel, Mark and West (2009) employ a factor model embedded in a panel setup and report superior exchange rate forecasts for OECD countries in the longer horizon.
in the long horizon when the researcher uses the monetary model with a benchmark random walk model. Some studies like Rapach and Wohar (2004) and Groen (2005) argue that the researcher needs to take care of the heterogeneity in the regression slopes as well as pooling in presence of heterogeneous slopes may affect the asymptotic properties of the LSDV estimator. Mark and Sul (2011) also point that ignoring cross-sectional and serial correlations may distort the asymptotic variance of the pooled regression.

Recently, several seminal empirical papers have focused on investigating which estimator is the “best” when the specified model has to be used for forecasting purposes. Baltagi and Griffin (1997), Baltagi, Griffin, and Xiong (2000), Baltagi, Bresson, and Pirotte (2002) and Baltagi, Bresson, Griffin, and Pirotte (2003) apply dynamic panel specifications to industrial level data and find that the predictive ability of homogeneous estimators are better than the predictive ability of heterogeneous and Bayesian estimators over any forecast horizon. Among the homogeneous estimators, GLS and within-2SLS emerge as the best estimators for forecasting purposes, especially when forecasting over a long time period. The superiority of the homogeneous estimators can appear reasonable when the panel is short, and when the degree of heterogeneity across units is limited, but it is rather puzzling when the time length $T$ of the panel is large or when the degree of heterogeneity is high. This genuine empirical finding is particularly interesting because models where homogeneity is imposed are, in general, rejected by the data. A first interpretation of this apparent counter-intuitive empirical regularity is that a model that is “simple and parsimonious” offers a better forecasting performance. However, using a different dataset, Baltagi, Bresson, and Pirotte (2002) find that Bayesian estimators provide the best forecasting performance.

Trapani and Urga (2009) compare the forecasting accuracy of several estimators belonging to each of the three classes (homogeneous, heterogeneous and shrinkage/Bayesian) for a routinely applied model (the dynamic specification with one or more exogenous covariates) under various circumstances, through a broad Monte Carlo simulation exercise. The “circumstances” are the pair $(N, T)$, the level of heterogeneity
among units, the dynamic specification of the error term, and the existence and degree of cross-sectional dependency across units. These issues are of paramount importance in determining the estimator properties.

An important related question is how to assess the forecasting performance of a model. Earlier papers by Baltagi and his co-authors use the standard Root Mean Squared Error (RMSE) to measure forecasting accuracy. However, the literature on forecasting has developed quite a critical attitude towards this classical statistical measure. To assess the predictive performance, Trapani and Urga (2009) use traditional measures of forecast accuracy approach based on different specifications of the loss function (Diebold and Mariano, 1995), and Pesaran and Timmermann’s (1992) nonparametric statistic that evaluates the ability to forecast change points. Their main findings show that the degree of heterogeneity plays a very important role, while other data features have a very limited impact on the predictive ability of various panel estimators. In cases where heterogeneity is low or mild, homogeneous estimators have the best predictive ability. On the other hand, when heterogeneity is high, shrinkage/Bayesian procedures are preferable.

Our study makes a number of novel contributions after addressing some of the important issues highlighted above. First of all, the paper augments the PFAE setup, beyond allowing for heterogeneity, by having contemporaneous cross-sectional correlation in the error term and by adding exogenous variables. Based on the findings from Groen (2005), Westerlund and Basher (2007), and Trapani and Urga (2009), allowing for heterogeneity across units (for this paper, countries) is important. This also makes practical sense, as country characteristics are quite different even if they all belong to the OECD group. Second, as pointed out by Mark and Sul (2011), we incorporate the contemporaneous cross-sectional correlation in our forecasting setup. In terms of practicality, contemporaneous cross-sectional correlation, in general, represents countries susceptibility to common shocks which may lead to some amount of policy coordination across OECD countries. Incorporating exogenous variables is another novel contribution of the paper. HPS (2011) posit that consistent estimation of PFAE would be useful for panels with exogenous regressors. Therefore, exchange rate models based on macro
fundamentals are used in the forecasting exercise using PFAE as well as LSDV. To the best of our knowledge, we are the first in extending and applying PFAE in a multi-dimensional setup.

Our results show some interesting features. First, from the simulation exercise, it appears that when forecasting is the aim, LSDV performs well, even for relatively small number of time periods or small panels, but only when we are dealing with stationary series. As we approach the unit root case PFAE overruns LSDV and is superior. Second, in presence of cross-sectional correlation, the simulations show that estimates of fixed effects and forecasts from PFAE are more robust than those produced by LSDV. Third, the above findings from the simulation exercise are largely corroborated by the one-period ahead out-of-sample forecasts using nine non-Eurozone OECD countries exchange rates at monthly, quarterly and annual frequencies. To be specific, we find that, using data at monthly and quarterly frequencies, the PFAE forecasts are better more than 50% of the time than the LSDV forecasts when we use the root mean squared error for evaluation with this result being independent of whether or not the data are correlated. In comparison to forecasts generated from random walk benchmark model, PFAE always performs better. Fourth, PFAE-based forecasts dominate forecasts from LSDV estimators and forecasts from benchmarks when we use the monetary fundamentals model of exchange rate for nine non-Eurozone OECD countries with the data in both quarterly and monthly frequencies. PFAE-based forecasts also perform well when we use the Taylor-rule model for these nine non-Euro zone countries. Overall, the researcher can rely on PFAE as a good alternative estimator for generating superior forecasts in the short-horizon as well especially when the nature of correlation in the dataset is unknown.

The rest of the paper is organized in the following way. In section 2, we outline the dataset. Section 3 describes the model, estimation and forecasting methodology. Section 4 reports the simulation design and results. In section 5, we discuss the empirical results from the exchange rate dataset for nineteen OECD countries. Section 6 concludes.
2. Data

Our data consists of 10 currency pairs, vis-à-vis the US dollar. The choice of countries is guided by data availability and relevance today – so we do not use the now extinct currencies of the Euro-zone countries.\(^4\) Besides the euro/US dollar exchange rate we have the following currencies: Australian dollar, Canadian dollar, Danish kroner, Japanese yen, South Korean won, Norwegian kroner, Swedish kronor, Swiss franc and the British pound. All exchange rate data are at the monthly frequency and, as we will explain in the next section, we use monthly, quarterly and annual changes in them and all other variables for the analysis. The data range is from 1970 to 2010 and we use a rolling window that: (a) varies based on the frequency of changes used and (b) is defined by the nominal range of 1970 to 2002 (data length may differ slightly per country, especially when exogenous variables are used). The rest of the observations from 2003 to 2010 are used as the evaluation period.

IMF’s International Financial Statistics database is the primary source of data for exchange rates and other exogenous variables in the macroeconomic fundamentals models. Following Molodtsova and Papell (2009) and Engel, Mark and West (2007), we use the nominal exchange rate as the end of period observation. The seasonally adjusted industrial production index (IFS line code 66) is used as a proxy for national income as quarterly GDP data are not available for all sample countries.\(^5\) The money supply is measured as the sum of money (IFS line code 34) and quasi-money (IFS line code 35) for Australia, South Korea and Switzerland. For Canada, Denmark and Japan, the money supply is measured as the sum of M1 and M2. Following Engel, Mark and West (2007), we use M2 as the money supply for Norway, M3 as the money supply for Sweden and M0 as the money supply for UK. The price level is measured by the consumer price index (IFS line code 64).\(^6\) The short-term interest rate is the Treasury bill rate (IFS line

\(^4\) Mark and Sul (2011) point that some of the earlier findings in the exchange rate forecasting literature which support the forecasts from the random walk model against the macroeconomic fundamental based models may happen due to the small sample size. Since we do not want this to happen, we rely on the sample of nine non-Eurozone countries to gather more data points.

\(^5\) Following Molodtsova and Papell (2009) we employ the “quadratic matching average” option in E-Views 7.0 to convert the quarterly IIP series into monthly frequency for Australia and Switzerland.

\(^6\) In line with Molodtsova and Papell (2009), for Australia, the original quarterly CPI has been converted to monthly frequency using the “quadratic matching average” option in E-Views 7.0.
For the Taylor-rule model, the output gaps are calculated as in Molodtsova and Papell (2009).

3. Model, Estimation & Forecasting Methodology

3.1. Model

Our starting point is the model of HPS (2011) with the addition of exogenous variables. Consider the dependent variable of interest $y_{it} = s_t - s_{t-h}$, the $h$-th difference in the logarithm of the exchange rate, for $i=1,2,...,N$ and $t=1,2,...,T$, which is assumed to follow the model:

$$
y_{it} = \alpha_i + x_{it}^T \beta + u_{it}$$
$$u_{it} = \sum_{j=1}^{p} \rho_j u_{i,t-j} + \epsilon_{it}
$$

where $x_{it}$ is a ($k \times 1$) vector of exogenous variables and $\beta$ is its associate parameter vector. The innovations $\epsilon_{it}$ are assumed to be uncorrelated across $t$ but exhibit cross sectional heterogeneity across $i$ and are allowed to have different variances, say $\sigma_i^2$. The exact conditions are given in HPS (2011). Alternatively, the model of equation (1) can be written as a (non-linear in the parameters) dynamic panel as:

$$
y_{it} = a_i(\rho) + \sum_{j=1}^{p} \rho_j y_{i,t-j} + x_{it}^T(\rho) \beta + \epsilon_{it}
$$

where we have that $a_i(\rho) = \alpha_i \left(1 - \sum_{j=1}^{p} \rho_j \right)$ and $x_{it}^T(\rho) = \left(x_{it}^T - \sum_{j=1}^{p} \rho_j x_{i,t-j}^T \right)$ with $\rho = (\rho_1, ..., \rho_p)$ being a ($p \times 1$) vector. As HPS (2011) note, if we have available a consistent initial estimator for $\beta$ we can proceed to consistently estimate $\rho$ by PFAE.

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7 The results remain the same if we use the money market rate instead of the Treasury bill rate for all countries.
3.2. Estimation and computation of forecasts

To compute the forecasts we need estimators for the parameters and forecasts for the exogenous variables. For simplicity let us consider the practical case where the exogenous variables are all predetermined, i.e. they enter with a lag so that \( x_{it} = \tilde{x}_{i,t-1} \), where \( \tilde{x}_i \) are the original variables. Denoting the estimators from method \( m \) by \( \hat{\alpha}^{(m)}_i, \hat{\beta}^{(m)}_i, \hat{\rho}^{(m)}_i \) and following the above convention for the exogenous variables, the forecasts are computed as the sum of the static part and the dynamic part of the model. However, the sequence of operations for estimating the cross-sectional heterogeneity due to the fixed effects is not the same in LSDV and PFAE. For LSDV, the cross-sectional means are used first and then the dynamic estimation takes place while for PFAE, the dynamics are estimated first (after x-differencing) and then fixed effects are computed from the x-differenced residuals. We describe the above steps below. First, for LSDV we have:

\[
\begin{align*}
\hat{\delta}_{it}^{(OLS)} &= y_{it} - x_{it}^{T} \hat{\beta}^{(OLS)} \\
\hat{\alpha}^{(LSDV)}_i &= (1/T) \sum_{t=1}^{T} \hat{\delta}_{it}^{(OLS)} \\
\hat{u}_{it}^{(LSDV)} &= \hat{\delta}_{it}^{(OLS)} - \hat{\alpha}^{(LSDV)}_i \\
\hat{u}_{i,t+1}^{(LSDV)} &= \sum_{j=1}^{p} \hat{\rho}_j^{(LSDV)} \hat{u}_{i,t+1-j}^{(LSDV)} \\
\hat{\delta}_{i,t+1}^{(LSDV)} &= \hat{\alpha}^{(LSDV)}_i + \hat{u}_{i,t+1}^{(LSDV)} \\
\hat{y}_{i,t+1}^{(LSDV)} &= x_{i,t+1}^{T} \hat{\beta}^{(OLS)} + \hat{\delta}_{i,t+1}^{(LSDV)}
\end{align*}
\]

It can be seen that the fixed effects estimation comes first and then the estimation of the dynamics – both of which are done using OLS. Now, for the PFAE we have the following sequencing:
\[ \hat{\delta}_{it}^{(OLS)} = y_{it} - x_{it}^T \hat{\beta}^{(OLS)} \]

The estimation of the dynamics is done first – and without reference to the fixed effects – and only after the estimates of the dynamic part are computed we estimate the fixed effects. According to the theory of HPS (2011), the PFAE method should be \textit{ex ante} superior in estimation of both components as it handles all cases of underlying dynamic structure.

### 3.3. Forecast evaluation

In addition to the forecasts from LSDV and PFAE, \( \hat{y}_{i,t+1}^{(LSDV)}, \hat{y}_{i,t+1}^{(PFAE)} \), we also compute the benchmark random walk with drift forecast, \( \hat{y}_{i,t+1}^{(RWD)} \), in line with the extant exchange rate forecasting literature. The benchmark forecasts are computed using a rolling window of \( R \) observations and are evaluated on the rest \( P = T - R \) observations. Afterwards, we estimate the forecast errors, that is:

\[
\begin{align*}
e_{i,t+1}^{(LSDV)} &= y_{i,t+1} - \hat{y}_{i,t+1}^{(LSDV)} \\
e_{i,t+1}^{(PFAE)} &= y_{i,t+1} - \hat{y}_{i,t+1}^{(PFAE)} \\
e_{i,t+1}^{(RWD)} &= y_{i,t+1} - \hat{y}_{i,t+1}^{(RWD)}
\end{align*}
\]

and evaluate them as follows.

First, for each cross-section \( i \) we compute the mean error, the mean squared error and the mean absolute error of the forecasts in a conventional fashion, for each method \( m \):
These time-series measures are next averaged across cross-sections and then expressed as ratios with respect to the benchmark as follows:

\[
ME_{i,P}^{(m)} = \frac{1}{P} \sum_{t=1}^{T-1} e_{i,t+1}^{(LSDV)}
\]

\[
RMSE_{i,P}^{(m)} = \frac{1}{P} \sqrt{\frac{1}{T-1} \sum_{t=1}^{T-1} \left( e_{i,t+1}^{(LSDV)} \right)^2}
\]

\[
MAE_{i,P}^{(m)} = \frac{1}{P} \sum_{t=1}^{T-1} |e_{i,t+1}^{(LSDV)}|
\]

(4a)

These latter measures \( ME_{p}^{(m)} \), \( MSER_{p}^{(m)} \) and \( MAER_{p}^{(m)} \) are the main output of the forecasting exercise and our results are presented in aggregate (averaged) form across combinations of lags used in estimation for each group of explanatory variables. That is, if we use a sequence of lags \( p_1, p_2, \ldots, p_Q \) then we first present the results on the relative performance of LSDV against PFAE:

\[
AME_{p}^{q} = \frac{1}{Q} \sum_{q=1}^{P} 1\left[ ME_{p}^{(PFAE)}(q) < ME_{p}^{(LSDV)}(q) \right]
\]

\[
ARMSE_{p}^{q} = \frac{1}{Q} \sum_{q=1}^{P} 1\left[ RMSE_{p}^{(PFAE)}(q) < RMSE_{p}^{(LSDV)}(q) \right]
\]

\[
AMAE_{p}^{q} = \frac{1}{Q} \sum_{q=1}^{P} 1\left[ MAE_{p}^{(PFAE)}(q) < MAE_{p}^{(LSDV)}(q) \right]
\]

(5a)

Thereafter, we report the results on the relative performance of PFAE against the benchmark, that is:
Note that the above estimation approach does not fully utilize the cross-sectional heterogeneity assumed in the model of equation (1), i.e., it does not account for the cross-sectional error correlation. Furthermore, the theory in HPS (2011) does not deal with this case where there is cross-sectional, contemporaneous correlation.

To partially address these two important issues we repeat the all the analysis above (which is done via OLS and the application of PFAE as can be seen in equations (3a) and (3b)) by first uncorrelating the data – a “simple” approach than performing non-linear GLS. Specifically, let \( \hat{\delta}^{(\text{OLS})}_i(t) \) denote the \((R \times 1)\) vector of the (rolling) first stage residuals for the \(i\)-th cross-section (where \(t\) runs from \(R\) to \(T-1\) during estimation) and let \( \hat{\delta}^{(\text{OLS})}(t) = \left[ \hat{\delta}^{(\text{OLS})}_1(t), \hat{\delta}^{(\text{OLS})}_2(t), \ldots, \hat{\delta}^{(\text{OLS})}_N(t) \right] \) be the \((R \times N)\) matrix of all dependent variables. The sample variance-covariance matrix of residuals are denoted by \( \hat{\Sigma}(t) = R^{-1} \left[ \hat{\delta}^{(\text{OLS})}(t)^T \hat{\delta}^{(\text{OLS})}(t) \right] \). Also denoting \( \hat{U}^T(t) \) as the transpose of the Cholesky factor of the inverse covariance, we can uncorrelate the data using \( \hat{\delta}^{(\text{UCR})}(t) = \hat{\delta}^{(\text{OLS})}(t) \hat{U}^T(t) \) and pass those for estimation. Once the vector of \(N\) forecasts is computed using the uncorrelated data we can revert the forecasts back to their original scaling by applying the inverse of the Cholesky factor appropriately.

3.4. Selection of explanatory variables

The set of explanatory variables that we use is the same one as in Molodtsova and Papell (2009) and in Engel, Mrak and West (2007), to which we refer for a complete discussion. We do not present the models but rather the set of variables in \(x_u\). First, for the Taylor-rule model the variables include domestic and foreign inflation, domestic and foreign
output gap, and the real exchange rate (all these at lag one), and the domestic and foreign
interest rates (at lag two):

\[ x_{it}^{(TR)} = (\pi_{t-1}, \bar{\pi}_{t-1}, y_{t-1}, \bar{y}_{t-1}, q_{t-1}, i_{t-1}, \bar{i}_{t-1}) \] (6a)

The output gap is calculated under three alternative scenarios: (a) using deviations from a
linear trend, (b) using deviations from a quadratic trend and (c) using deviations from the
Hodrick-Prescott filter.
Next, we have the variable from the interest rate differential model which is just:

\[ x_{it}^{(IR)} = i_{t-1} - \bar{i}_{t-1} \] (6b)

Afterwards, we have the variable entering the price fundamentals model given by:

\[ x_{it}^{(PF)} = p_{t-1} - \bar{p}_{t-1} - s_{t-1} \] (6c)

And, finally, the monetary fundamentals model is given by:

\[ x_{it}^{(MF)} = m_{t-1} - \bar{m}_{t-1} - s_{t-1} \] (6d)

The interest rate, price fundamentals and monetary fundamentals variables can be
obtained via parametric restrictions on the Taylor-rule model variables.

4. Simulation design and results

4.1. Design

To further enhance our understanding of the properties of the PFAE estimator in the
context of forecasting we perform a simulation exercise, using the same methodological
approach as in the previous section.
The data generating process is the panel autoregressive model of order $p$ AR($p$) with fixed effects, cross-sectional heterogeneity but no exogenous variables, i.e.:

$$y_{it} = \alpha_i + \sum_{j=1}^{p} \rho_{ij} y_{i,t-j} + u_{it}$$

(7)

We assume the error term either (a) follows the standard assumption $u_{it} \sim \sigma, \epsilon_{it}$, with $\epsilon_{it}$ being an i.i.d. (across $i$ and $t$) sequence with zero mean and variance one, or (b) allows for contemporaneous cross-sectional correlation in the errors, i.e., $\text{Cov}(u_{it}, u_{jt}) = \sigma_{ij}$ for $i \neq j$, $t = s$ and zero otherwise. Note that when there is contemporaneous cross-sectional correlation we do not follow the method described above but rather we ignore it during estimation. In this way we try to understand the effects of this type of misspecification on estimation and forecasting performance.

We consider both AR(1) and AR(2) models. For AR(1), we take values of $\rho_1 = \{0.2, 0.5, 0.7, 0.9, 1.0\}$ and for AR(2) we set $\rho_1 = \{0.5, 0.7, 0.9, 1.0, 1.2\}$ and $\rho_2 = -0.2$, as in HPS (2011). For the number of cross-sections and the length of the time series we work with values in $N = \{5,10,15,30,50\}$, $T = \{5,10,15,30,50\}$ and all the resulting combinations thereof. The fixed effects and error variances are drawn from the normal and uniform distributions as $\alpha_i \sim N(2,2^2)$ and as $\sigma_i \sim U(0,1,2)$. These parameters are kept fixed for the replications involving the same number of cross sections.

For each $(N, T)$ combination we simulate data from the model of equation (7), allowing for a 100-observation burn-in period and for an extra observation that is held out for forecasting evaluation. Each simulation involves $R=1,000$ replications (and we thus have available 1,000 out-of-sample forecasts) and at each replication $r$ we store the squared difference of the estimates and forecasts with the true values, so that we have:

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8 Increasing $N$ and $T$ produce qualitatively similar results. We are therefore reporting the results with the above dimensions of $N$ and $T$. 

\[ D_r^{(m)}(\alpha) = \sum_{i=1}^{N} \left( \tilde{x_i}^r - x_i \right)^2, \text{ and } D_r^{(m)}(y_{i,T+1}) = \left( \hat{y}_{i,T+1} - y_{i,T+1} \right)^2 \] (8)

Note that we are not presenting (they are available though) the results from the accuracy in the estimation of the autoregressive parameters since this has been explored at length in HSP (2011). At the end of each simulation run we compute the following MSE-based performance measures of the above quantities:

\[ MSE^{(m)}(\alpha) = R^{-1} \sum_{r=1}^{R} D_r^{(m)}(\alpha) \]
\[ MSE^{(m)}(y_{i,T+1}) = R^{-1} \sum_{r=1}^{R} D_r^{(m)}(y_{i,T+1}) \] (9)

where we also track the performance of the estimators of the fixed effects. Then, similar to the methods outlined in equations (4) to (5) before, we consider the average MSE of the forecasts across all cross-sections. This is expressed as a ratio for the two methods, and the percentage of cross-sections where the MSE of the PFAE method is smaller than the MSE of the LSDV method:

\[ MSE^{(m)}(\alpha) = N^{-1} \sum_{i=1}^{N} MSE^{(m)}(\alpha) \]
\[ MSE^{(m)}(y_{T+1}) = N^{-1} \sum_{i=1}^{N} MSE^{(m)}(y_{i,T+1}) \]
\[ MSE(\alpha) = MSE^{(PFAE)}(\alpha) / MSE^{(LSDV)}(\alpha) \]
\[ MSE(y_{T+1}) = MSE^{(PFAE)}(y_{T+1}) / MSE^{(LSDV)}(y_{T+1}) \]
\[ CMSE(y_{T+1}) = N^{-1} \sum_{i=1}^{N} \left[ MSE^{(PFAE)}(y_{i,T+1}) < MSE^{(LSDV)}(y_{i,T+1}) \right] \] (10)

We summarize the results in figures using the measures as follows: for each \( N \) we plot the MSE-ratios of the two methods across all values of \( T \), i.e., we plot \( MSE(\alpha) \) and \( MSE(y_{T+1}) \) and then we plot the comparison measure \( CMSE(y_{T+1}) \). In this way one has an immediate visual understanding of the relative performance of both methods.
4.2. Discussion of simulation results
We report results for AR(2) models. The AR(2) parameter combinations are indicated above each figure and the time series observations are plotted on the horizontal axis. We discuss in turn the two cases of absence and presence of contemporaneous cross-sectional correlation.

4.2.1. Results without any cross-sectional correlation

For the case of no cross-sectional correlation the results are given in Figures 1a to 3a. In Figure 1a, the fixed effect parameters are always estimated more accurately using LSDV rather than PFAE, except for the unit root case. This is an interesting result and relevant to forecasting. Note that there is a difference in the way fixed effects are treated in the two methods: in LSDV the fixed effects are estimated first while in PFAE they are estimated last. Therefore, we have a better performance of PFAE compared to LSDV only when the cross-sectional means are not well defined and are closer to the non-stationarity region.

Figure 2a compares the average forecasting performance within a panel of PFAE and LSDV. We want to explore which method gives us the most accurate forecast for the majority of the cross sections in the panel. The results again depend on the strength of autocorrelation and the number of time periods in the panel. When there is low autocorrelation and the number of time periods is small (less than 10 or 15), the LSDV approach gives consistently better forecasts for more cross sections in the panel. As the number of time periods and the degree of autocorrelation increases the performance of the PFAE improves as well. However, note that, when the number of time periods is small at $T = 5$ we still have the LSDV producing more accurate forecasts for more cross sections, even for the unit root case.

Figure 3a shows the results on the average (across the cross sections) MSE ratio of the forecasts produced by PFAE and LSDV. The findings here also follow the patterns as in the previous figures. When the number of time periods is less and the strength of

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9 We have generated a large number of qualitatively similar results for AR(1) and AR(2) models. AR(1) results are available on request.
autocorrelation is relatively small, the average forecasting performance of LSDV is better than PFAE. After $T = 15$ the two methods give identical or almost identical forecasting performance for the stationary cases.

4.2.2. Results in presence of cross-sectional correlation

Figures 1b to 3b report results where there is contemporaneous cross-sectional correlation, but is ignored during estimation. In the estimation of the fixed effects we note some changes in comparison to the previous results where we had no correlation. Comparing the top and bottom panel of Figure 1b we find that the fixed effects parameters are still more accurately estimated when the strength of autocorrelation is low, but now the effect of the ignored cross-sectional correlation is substantial when we consider the cases with higher autocorrelation or a unit root. It is interesting to note that even when the sum of the autoregressive coefficients is 0.7, the PFAE performs way better, as it does in the unit root case.

Figure 2b compares the average forecasting performance within a panel of PFAE and LSDV. Except for the unit root case, where the PFAE approach performs uniformly better, we could not find a clear case in favor or against the two methods. In general, and as we have seen before, for small number of time periods the LSDV produces more accurate forecasts in most of the cross sections within a panel. But for the case of $\rho_1 + \rho_2 = 0.5$ the performance of LSDV is practically uniformly better than that of PFAE.

Looking finally at Figure 3b, we find that, except for the case of $N = T = 5$, where the LSDV outperforms PFAE, the two methods give almost identical average forecasting MSE ratio for $T$ greater than 15. Based on the above in the case of cross-sectional correlation the PFAE might be more robust compared to LSDV.

These simulation results can now be summarized as follows. First, LSDV will estimate the fixed effects better than PFAE when the autoregressive parameters are within the stationarity region; the opposite is true as we get closer to the unit root case. Second, LSDV produces more accurate forecasts than PFAE in most of the cross sections within a
panel, when the number of time periods is small and when the autoregressive parameters are well within the stationarity region; again, the opposite is true as we get closer to the unit root case. Third, both approaches produce similar forecasting performance, averaging across cross sections, when the number of time periods is greater than 15. Fourth, in presence of cross-sectional correlation, estimates of fixed effects and forecasts from PFAE appear to be more robust than those produced by LSDV. This result may have some important practical implication.

Therefore, when forecasting is the aim, LSDV performs well, even for relatively small number of time periods or small panels, but only when we are dealing with stationary series. As we approach the unit root case PFAE overruns LSDV and is superior. Since the strength of autocorrelation is unknown in advance, it might be practical to use both of them in applications.

5. Discussion of Empirical Results

The empirical results are summarized in Tables 1 through 3. In the tables we present aggregate performance measures as described in equation (5) for monthly changes, quarterly changes and annual changes in the exchange rates (that is for $h = 1, 3$ and 12 in $y_{it} = s_t - s_{t-h}$). The aggregation is across the values of the lags used in estimation, across the three evaluation measures and also across the three different groups at each table. For Table 1 where there are no exogenous variables the three groups are those defined by the different values of $h$. In Tables 2 and 3 where there are exogenous variables, the four groups are those defined by the different types of exogenous variables used.

5.1. Results with no exogenous variables

The results in Table 1 show a wealth of performance information about PFAE which we discuss now in detail. First, and foremost, we clearly see that PFAE easily outperforms the random walk benchmark by well over 50% of the time across all relevant entries in columns 4 and 5. The PFAE dominates the benchmark when we consider quarterly exchange rate changes, followed by the annual changes and the last the monthly changes. This holds true irrespective of whether we have uncorrelated the data before estimation.
and forecasting. The lowest performance can be found in the averaged RMSE for the monthly changes. Note that from these first results the researcher can conclude that uncorrelating the data is not important for outperforming the benchmark. The performance goes well with what the simulation results pointed before, especially if one looks at the evaluations based on the RMSE.

The results in column 3 of the table show that the usefulness of uncorrelating the data for PFAE alone is probably data-specific. For several entries we see that in more than 50% of the time the performance measures with uncorrelated data is higher than the corresponding ones without the transformation. Just counting across all entries in column 3 of the table we find that in only 6 of 16 entries does the uncorrelating transformation provides better performance for PFAE.

However, and this matters more in our context, the situation is different when we compare the performance of PFAE with LSDV. Looking at columns 1 and 2 of Table 1 we can see that PFAE outperforms LSDV in 8 out of 16 entries when we perform uncorrelation but only 6 in 16 entries when we do not. Furthermore, note that the percentages are higher in column 1, particularly for the quarterly and annual exchange rate changes. Next, note that when monthly and quarterly changes are used the performance of PFAE is clearly better for the variance measures of RMSE and MAE but clearly worse for the bias measure of ME, overall, though PFAE provides a better performance. The situation is not the same when we look at annual changes, or when we combine all three groups. In these instances, it is only when we uncorrelate the data and concentrate on RMSE, the PFAE is providing good performance.

Summarizing so far, we find that the PFAE-based forecasts can easily outperform the random walk benchmark – practically all the time – but they do not dominate LSDV forecasts all the time; the latter is data-specific. For the most straightforward case, that of forecasting the one-month (or short horizon) ahead change, the PFAE forecasts are better more than 50% of the time when we look at variance measures but are worse when looking at the bias measure, with this result being independent of whether or not we
uncorrelate the data. The findings under quarterly changes also support the above conjecture. Note that most of the panel forecasting studies uses data at quarterly frequency; therefore, this finding is consistent with the extant studies. The above findings are in line with the simulation results presented in the earlier section.

5.2. Results from models based on macroeconomic fundamentals

The results with macroeconomic fundamentals where exogenous variables are used have an important dimension. The researcher can explore whether the combined usage of appropriate fundamentals with PFAE gives superior performance. These results are given in Tables 2 and 3 and are clearly more interesting than those without the use of exogenous variables.

5.2.1. Results from monthly data

In Table 2 we have the results from the use of monthly changes, the most relevant case for practical forecasting in the short horizon. In presence of the Taylor-rule fundamentals, the dominance of PFAE with uncorrelated data is evident. The PFAE-based forecasts with uncorrelated data always outperform the benchmark, always outperform the PFAE-based forecasts with correlated data and always outperform the LSDV-based forecasts. However, it is interesting to note that when the errors are correlated, the LSDV-based forecasts are always better.

A similar situation emerges, but not as strong, when we consider the interest rate and price fundamentals, although the superior performance of PFAE is not all around as before. The use of price fundamentals does a slightly better job when we consider the MAE measure with correlated data while the use of interest rate fundamentals does a better job when considering the ME and MAE measures with uncorrelated data.

The monetary fundamentals model, which is the widely used model in exchange rate forecasting with panel data techniques show remarkable results when PFAE-based forecasts with uncorrelated data are used. In this scenario, the forecasts always outperform the forecasts from the benchmark model, the PFAE-based predictions with
correlated data and the LSDV-based forecasts. This is an interesting finding especially in the context of the short horizon predictions.

A closer look at the last panel of the table, where we pool together performance across the four fundamental groupings, the overall picture emerges that, with four exceptions, the PFAE-based forecasts are always better.

5.2.2. Results from quarterly data

The results from quarterly data in Table 3 show additional support for PAFE-based forecasts. In general, we see that the performance of PFAE-based forecasts is better even for the case where the data are not uncorrelated, especially in column 2 of the table.

The most interesting case is that of the monetary fundamentals model. This model is the most used in the context of exchange rate forecasting with dynamic panel data where in general LSDV is employed. Now once we use PFAE estimator, there is overwhelming support for using PFAE in both the cases where the data are uncorrelated and correlated. In all cases, the forecasts based on PFAE outperforms forecasts from the LSDV model, forecasts from the benchmark and forecasts from PFAE when the data is uncorrelated. Our earlier conjecture of cross-correlation in the error terms which possibly captures the presence of common shocks affecting the countries in the dataset gets supported by this finding from the monetary model. This result also reassures the faith in using monetary fundamentals model when the researcher is interested in forecasting exchange rates using panel data.

In general, the PFAE-based forecasts from the Taylor rule fundamentals model show better performance when one uses the monthly data than the quarterly data and in absence of any correlation in the data. However, if we use the RMSE criterion, then PAFE-based forecasts using quarterly data outperforms PFAE-based forecasts using monthly data with or without controlling for correlation in the data.
The PFAE-based forecasts using the interest rate fundamentals also work well in terms of generating superior forecasts when the researcher uses quarterly data as opposed to monthly data. The PFAE-based forecasts are always better than the benchmark model forecasts when we use RMSE and MAE as the evaluating criteria. Similar conclusion can be made from the price fundamentals model as well.

Looking at the last panel of Table 3, where we pool together performance across the four fundamental groupings, it becomes apparent that PFAE-based forecasts are always better except for three occasions.

6. Concluding Remarks

This study presents the forecasting performance of a newly proposed dynamic panel estimator, the Panel Fully Aggregated Estimator (PFAE a la HPS, 2011) which has better finite sample and asymptotic properties than the widely used least squares dummy variable estimator (LSDV) or the GMM or the system-GMM. The forecasting literature with panel data identifies a number of concerns involving the ways the fixed effects are estimated and eliminated, the ways slope coefficients are treated (homogeneous versus heterogeneous), as well as addressing the potential correlation in the error term. The above issues affect the properties of the estimator and subsequently have an adverse impact on the forecasting performance.

We address the above concerns and explore the forecasting performance of PFAE using both simulation and empirical data for exchange rates. The exchange rate forecasts are generated from four macroeconomic fundamental models, viz, the Taylor-rule model, the interest rate model, the purchasing power parity model and the monetary model. We generate one-period ahead out-of-sample forecasts with data at the monthly, quarterly and annual frequencies. The comparison forecasts are generated from two sources: (i) using simulations and using above four macro fundamentals models where LSDV estimator is used and (ii) a random walk benchmark model. The empirical analysis is carried out for nine non-Eurozone OECD countries for the post Bretton Woods period.
Our simulation results show general support for PFAE as an alternative estimator if the aim is to generate superior forecasts where the data series is approaching unit root or the data series are correlated but the researcher has no a priori knowledge of the correlation. The empirical results reveal that the PFAE-based forecasts generated from the monetary fundamentals model at the quarterly and monthly frequencies outperform forecasts from the LSDV-based estimation as well as forecasts from the benchmark model. The above empirical result holds true in presence of potential correlation in the data in the quarterly frequency. The PFAE-based forecasts generated from the Taylor-rule model, in general, also provides better outcome. It is interesting to note that these findings are all in short horizons whereas the extant literature generally finds forecasts from monetary fundamentals model outperform forecasts from the benchmark model in the long horizon. Therefore, the researcher can use PAFE-based estimation as an alternative to the LSDV-based estimation to generate superior forecasts based on some of the macroeconomic fundamentals model as well.

In this paper, we present only short horizon results and results from a small non-Eurozone OECD panel of countries. One extension of the paper will be to look at the long horizon results after incorporating all OECD countries in the dataset. Another possible extension will be exploring the short and long horizon results from a number of emerging countries exchange rates. We leave these for future research.
References


Appendix: Simulation Pictures and Empirical Tables

**SIMULATION PICTURES**

**Figure 1a.** MSE ratio for estimates of $a_i$ no cross-sectional correlation

- $\rho_1 = 0.3$
- $\rho_2 = 0.5$
- $\rho_1 = 0.7$
- $\rho_2 = 1$
Figure 2a. Percentage of times \( \text{MSE(PFAE)} < \text{MSE(LSDV)} \) across \( N \), no cross-sectional correlation

\[ \rho_1 \rho_2 = 0.3 \]

\[ \rho_1 \rho_2 = 0.5 \]

\[ \rho_1 \rho_2 = 0.7 \]

\[ \rho_1 \rho_2 = 1 \]
**Figure 3a.** Average (across N) forecasting MSE ratio, without the cross-sectional correlation

\[ \rho_1 \rho_2 = 0.3 \]

\[ \rho_1 \rho_2 = 0.5 \]

\[ \rho_1 \rho_2 = 0.7 \]

\[ \rho_1 \rho_2 = 1 \]
Figure 1b. MSE ratio for estimates of $\alpha_i$, with cross-sectional correlation but ignored during estimation.
Figure 2b. Percentage of times MSE(PFAE) < MSE(LSDV) across N, with cross-sectional correlation but ignored during estimation

$\rho_1 \rho_2 = 0.3$

$N=5$ $N=10$ $N=15$ $N=30$ $N=50$

$\rho_1 \rho_2 = 0.5$

$N=5$ $N=10$ $N=15$ $N=30$ $N=50$

$\rho_1 \rho_2 = 0.7$

$N=5$ $N=10$ $N=15$ $N=30$ $N=50$

$\rho_1 \rho_2 = 1$

$N=5$ $N=10$ $N=15$ $N=30$ $N=50$
Figure 3b. Average (across N) forecasting MSE ratio, with cross-sectional correlation but ignored during estimation.
### Table 1. Summary results for exchange rates, no exogenous variables

<table>
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<tr>
<th>Forecast Evaluations</th>
<th>PFAE &lt; LSDV uncorrelated</th>
<th>PFAE &lt; LSDV correlated</th>
<th>PFAE (uncorrelated) &lt; PFAE (correlated)</th>
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**Notes:** Table entries contain the percentages for which the conditions of the column labels hold true. These reported percentages are averages across results with different number of lags for these nine countries: Australia, Canada, Denmark, Japan, South Korea, Norway, Sweden, Switzerland and UK. Uncorrelated and correlated denote the data were uncorrelated before estimation and were correlated before estimation, respectively. PFAE < LSDV stands for PFAE being better than LSDE. PFAE (uncorrelated) < PFAE (correlated) refers to PFAE with uncorrelated data being better than PFAE with correlated data. PFAE/BENCH < 1 stands for PFAE being better than the corresponding benchmark.
Table 2. Summary results for exchange rates, monthly, with exogenous variables

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Table 3. Summary results for exchange rates, quarterly, with exogenous variables

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Notes: Table entries contain the percentages for which the conditions of the column labels hold true. These reported percentages are averages across results with different number of lags for these nine countries: Australia, Canada, Denmark, Japan, South Korea, Norway, Sweden, Switzerland and UK. Uncorrelated and correlated denote the data were uncorrelated before estimation and were correlated before estimation, respectively. PFAE < LSDV stands for PFAE being better than LSDE. PFAE (uncorrelated) < PFAE (correlated) refers to PFAE with uncorrelated data being better than PFAE with correlated data. PFAE/BENCH < 1 stands for PFAE being better than the corresponding benchmark.