RATIONALITY OF SURVEY BASED INFLATION EXPECTATIONS OF EIGHTEEN EMERGING ECONOMIES[1]

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ABSTRACT:

This study investigates rationality of inflation expectations of 18 emerging countries inflation rates using ten years (11/2001 – 5/2012) of inflation data. Given the nature of the data, we use the panel method to assess the relation between actual and the expected inflation rates. We perform various diagnostic tests to identify the appropriate panel test for the data. We use a recently developed panel regression method based on simple OLS techniques but derive standard errors corrected for serial correlation, panel heterogeneity and cross-sectional dependence. Results of the unbiasedness test and the efficiency test indicate that forecasts are rational for one month ahead forecast horizon.

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1. Introduction

Forecasting of future asset prices is an important activity of all financial analysts. Actively managed portfolios require forecasting of interest rates, exchange rates, inflation rates, etc. to rebalance the positions. Forecasting is a large and growing industry at present. Consensus survey forecast has become a popular way to assess the future movement in a variable. This method surveys the opinions of experts in a field about the future change in a variable. This allows the consensus forecast to be more accurate since the survey takes the opinions of experts only, not public in general. Because of its importance, consensus survey data is now collected by many central banks, businesses, and academic institutions on different macroeconomic variables, like, interest rate, exchange rate, GDP growth rates, inflation rates, current account, unemployment rate, industrial production, etc. A number of businesses and newspapers, including Wall Street Journal, Economists, Financial Times, etc. collect and publish consensus survey of many economic and financial variables of interest to the readers. The data can provide valuable information about the efficiency of expectations by the experts. Thus, it has caught attention of many researchers in economics and finance in the recent past.

Survey data on expectations are useful in testing various economic hypotheses. Survey data is used as a proxy to unobservable expectations in economic and finance models, for example, efficient markets theory of security prices, theory of dynamics of hyperinflations, permanent income and life-cycle theories of consumption, etc. It is also used by Central Banks, practitioners in business and financial markets and policy makers to understand the influence of expectations on agents' behavior.

Researchers try to understand the accuracy of forecasting by analyzing the forecasted data as many of these methods are kept secret by experts. The central question that researchers try to investigate is whether the forecast correctly predict the future. This line of research is known as rationality of expectations. John Muth (1961) first proposed the idea of rational expectations, which asserts that outcome of an economic activity, will not differ systematically from what people expected them to be. Expectations will drive agents to act accordingly and bring the outcome to its expected value. He argued that agents are utility maximizer and will process information efficiently to predict the future. Mestre (2007) derives the properties of a rational expectations solution as follows:

1. Expectations should differ from actual values by an unforecastable residual.
2. Expectations should be formed using all relevant information in the available data set, i.e. all observed pre-determined variables that matter for the model solution should enter the expectations formation mechanism and nothing more.
3. Expectations should be efficient, in the sense that alternative forecasts should lead to errors with higher variance than rational expectations.

There are two versions of rationality: weak form and strong form. If expectations are strong form, then expectations meet all three above mentioned conditions. Weak form amounts to allowing for some degree of error auto-correlation in the forecasts and may be some amounts of bias in forecasting. Weak form tests of rationality examine if expectations of an economic variable are unbiased predictors of future realized values of the variable. It also examines whether past values of the variable can be used to explain the error between the expected the realized value (forecast error) and whether the forecast errors can be explained by other theoretically relevant variables.

This research investigates the rationality of inflation expectations of 18 emerging economies using consensus survey data published by a source (www.Fx4casts.com) previously unexploited by researchers. Data on actual rates are also provided in the publication. The time period of the study is November 2001 to May 2012.

2. Literature Review

There are many studies related to rationality of survey expectations of inflation using both survey of experts as well as general public. The literature on testing the rationality of inflation or price forecasts is old and extensive. The literature on this topic has attempted to test rational expectation of price or inflation expectations either indirectly by using proxy for expectations using various econometric methods, or by using direct survey data that asks surveyors explicitly about their expectations. The use of survey data in empirical studies of inflation and price forecasts can be broadly divided into two parts. First, many researchers have used consumer survey data to test for rational expectations. Papers in this category include, but not limited to, Rich (1989), Smyth (1992) and Thomas (1999). Second, the most popular data sources have been the so-called *professional surveys* where experts are surveyed. There are four main data sources that have been used in the literature. First, many papers which include, but not limited to, Rich (1990), Mullineaux (1978), Pearce (1979), Thomas (1999), Fama and Gibbons (1984) used *Livingstone Price Expectation* survey data. Second, other papers such as Gil-Alana et al (2011) have used Survey-based Expectations survey conducted by the Federal Reserve Bank of Philadelphia. Third, Pearce (1987) used survey data compiled by the Money Market Services Inc. (MMS). Finally, the most popular data has been the ASA-NBER data on professional forecasts which has been used extensively in papers that include, but not limited to, Keane and Runkle (1990), Zarnowitz (1969, 1974, 1984, 1985), Baghestani and Nelson (2011) and Dovern and Weisser (2011). Regardless of the data set that was used, the most prevalent results that emerged from almost all the papers, with very few exceptions, is that price forecasts are not rational. Recently, Oral et al (2011) used consensus survey data collected from professionals published by Turkish Central Bank, and they could not find evidence of rationality of expectations. Curtin (2006) concluded that consumers do not fulfill rational expectations hypothesis while forming inflation expectations. Bakshi (1998) also found similar results using inflation expectations drawn from a survey of UK employees by Gallup. Souleles (2002) conducted a comprehensive study using Michigan micro data and found that consumer expectations are biased and it is also time varying. He also found that expectations are inefficient. However, Keane and Runkle (1990) tested the rationality of individual price forecasts in a panel of professional forecasters and rational expectation hypothesis in this case was accepted. As Keane and Runkle (1990) argued, further testing of price or inflation forecast rationality is warranted because of severe problems in almost all existing tests, which suffer from one or more of the following four flaws. First, some use average survey response data rather than individual data. This can bias tests in two ways. It can lead to false rejection of rational expectations because average forecasts that are conditional on different information sets are not rational forecasts conditional on any particular information set. Furthermore, it can lead to false acceptance of rational expectations by masking systematic individual bias that may be randomly distributed in the population. Second, many tests fail to deal properly with the pervasive problem of systematic data revision. Tests of forecast rationality depend upon correct assumptions about what the forecasters tried to predict and what they knew when they made their predictions. Much work has implicitly tested whether forecasters rationally forecast revised data conditional on other revised data, none of which was available until long after the forecasts were made, Third, most studies of forecast rationality use predictions from individuals who are not professional forecasters; these people have few economic incentives to report their expectations precisely. Finally, many studies that use micro data fail to account properly for the covariance structure of the forecast errors. This failure can take two forms. First, some studies assume that forecast errors must be white noise. In fact, lags in the availability of relevant data can produce serially correlated errors even when agents are rational. Second, most studies fail to account for the fact that shocks to the aggregate economy produce forecast errors that are correlated across individuals. In either case, improperly assuming independent, identically distributed errors can produce severely biased results. Finally, other than Mullineaux (1978), all other studies assumed forecast error variance to be homogeneous. Furthermore, almost all the studies on forecast rationality have focused on survey data available for the USA.

In this study, we use a new international dataset that surveys and collects monthly inflation forecasts on average inflation rate for 40 countries. We select only 18 of these countries which are considered emerging, Argentina, Brazil, Chile, China, Colombia, Czech Republic, Hong Kong, Hungary, India, Indonesia, Mexico, Philippines, Poland, Russia, South Africa, Thailand, Turkey and Venezuela. We collected 10 years of monthly data on these 18 countries. However, we only focused on forecast efficiency of one- month ahead inflation forecast. With 180 panel observations, we used a panel approach to investigate the rationality of inflation forecast. However, we used a recently developed panel estimation techniques pioneered by Parks (1967) but used in a more general setting by Beck and Katz (1995) which is suitable for a small panel with more countries than country-specific observations. Our estimation technique is based on OLS which bypasses the problem of inapplicability of Generalized Least Square Methods (GLS) in small panel setup. Furthermore, our test of hypotheses used panel corrected standard errors that corrected for three problems that researchers regularly encounter in panel study; serial correlation of the error term, group or panel specific heteroskedastcity and cross-sectional dependence. Finally, with our panel corrected standard errors method, we show inflation forecasts are strongly unbiased and weakly efficient.

3. Economic Theory and Econometric Specification for the Test of Rationality of Inflation Forecast

Form the onset, we will assume that expectations are rational in Muth's sense (Muth, 1961) if they are equal to mathematical expectations conditional on the set of all information relevant for forecasting. Following Keane and Runkle (1990), for an individual forecaster in an individual country, we can express this relationship as:

$$ {}_t\pi_{i,j,t+k} = E\left(\pi_{t+k} \mid I_{i,j,t}\right) \tag{1} $$

where π_{t+k} is the realized value of the time series π at time $t+k$, ${}_t\pi_{i,j,t+k}$ is a k-step ahead prediction of π made at time t by forecaster i in country j, $I_{i,j,t}$ is the information available at time t to a forecaster i in country j, and E is the mathematical expectation operator. This is equivalent to the statement: $E\left(\varepsilon^{i,j}{}_{t,k} \mid I_{i,j,t}\right) = 0$ where $\varepsilon^{i,j}{}_{t,k} = \pi_{t+k} - {}_t\pi_{i,j,t+k}$. This statement can be broken down into the separate hypotheses that forecasts are unbiased and efficient.

For an individual forecaster, a test of rationality can be performed by running the following regression:

$$ \pi_{t+k} = \alpha_0 + \alpha_1 {}_t\pi_{i,j,t+k} + \alpha_2 X_{i,j,t} + \varepsilon^{i,j}{}_{t,k} \tag{2} $$

where $X_{i,j,t}$ is any variable in forecaster I in country j’s information set at time t. Unbiasedness requires that, in a regression without $X_{i,j,t}$ variables, the coefficients in equation (2) may be restricted to:

$$ \alpha_0 = 0, \alpha_1 = 1 \tag{3} $$

Efficiency requires that any variable known at time t or before be orthogonal to $\varepsilon^{i,j}{}_{t,k}$, that is, in equation (2), $\alpha_2 = 0 \forall X_{i,j,t} \in I_{i,j,t}$

Next, the estimate of the regression co-efficient will be based on multi-country data where each data reports survey means of the forecasts for each country. Hence, if we use ordinary least square estimate methods, our estimates would look like:

$$ \alpha_1 = \frac{1}{J} \sum_{j=1}^{J} \frac{\sum_{t=1}^{T} \pi_{t+k} \left(\frac{1}{N} \sum_{i=1}^{I} {}_t\pi_{i,j,t+k} \right)}{\sum_{t=1}^{T} \left(\frac{1}{N} \sum_{i=1}^{I} {}_t\pi^2{}_{i,j,t+k} \right)} \tag{4} $$

Where subscript j indexes country from 1 to J, i indexes individuals in country 1 to N and t indexes time from 1 to T. It should be mentioned that using cross section-time series data can help us to detect systematic country specific bias which could be modeled either as a fixed effect or as a random effect. Furthermore, using panel data would increase degrees of freedom which would make our tests of hypothesis on rationality more powerful. However, using panel data would create two complications which would have to be dealt with very carefully. First, forecast error variances might be heteroskedastic in cross sections. Second, although each country faces different forecasters and forecasting targets, common or global shocks such world recessions, common currency unions and such could create cross sectional dependence among the forecasts errors. The general remedy for both, as suggested by the literature, is to use GLS (or more specifically FGLS) methods corrected for the above mentioned problems. However, there are two problems in our data that make the use of GLS infeasible. First, in our data, $N > T$ and both N and T are small (T=10, N=18). As a result, the weighting matrix used for transformation in the GLS method would not have a full rank and would not be invertible. Second, Keane and Runkle (1990) argued that the regressors in equation (3) are not strictly exogenous. Hence the GLS transformation cannot be used. Therefore, the only solution to the above mentioned problems would be to use OLS method corrected for heteroskedasticity and cross sectional dependence. While Keane and Runkle (1990) only dealt with the latter, we will use a methodology developed by Beck and Katz (1995) to address both problems in an OLS setup. Finally, special attention needs to be paid to the nature of serial correlation, if any, that exists in our data. Keane and Runkle (1990) pointed out that if π_t, itself is known when the forecast ${}_t\pi_{i,j,t+k}$ is made (such as our data), then neither π_t nor lagged one-step ahead forecast error ${\varepsilon^{i,j}}_{t-1,1} = \pi_t - {}_{t-1}\pi_{i,j,t}$ should be orthogonal to ${\varepsilon^{i,j}}_{t,k}$. Therefore, the forecast errors will be $MA(k)$ rather than $MA(k-1)$ as they would be if the forecasters knew π_t, when they made their forecasts.

4. Estimation Method Corrected for Serial Correlation, Cross-Sectional Dependence and Heteroskedasticity

We will now describe the least square method that we will use to estimate regression coefficients defined in equation (2). In our empirical exercise, we will use the panel estimation technique developed by Beck and Katz (1995) that corrects for serial correlation, cross-sectional dependence and panel heteroskedasticity and estimates regression coefficients and standard errors which are more efficient that either simple OLS or GLS method. The estimation technique will follow several steps. First, since our country specific data only reports average forecast for a given time, we will drop the subscript I and write our regression model in more compact form:

$$y_{j,t} = x_{j,t}\beta + \varepsilon_{j,t};\ j = 1,......J;\ t = 1,......T \tag{5}$$

In this case, $y_{j,t}$ is π_{t+k}, $x_{j,t}$ is a constant and $\pi_{j,t+k}$. We will assume that the data is stacked by country. Therefore, the vector of dependent and independent variables can now be defined as Y and X. Finally, define the NT x NT covariance matrix of the errors with a typical element $E\left(\varepsilon_{i,t},\varepsilon_{j,t}\right)$ by Ω[3]. Following Keane and Runkle (1990) and Beack and Katz (1995), we will make the following assumptions about serial correlation, cross-sectional dependence and heteroscedasticity. First, we will assume MA (1) serial correlation:

$$\varepsilon_{j,t} = \mu_{j,t} - \lambda_j \mu_{j,t-1} \tag{6}$$

where the $\mu_{j,t}$'s are (mean zero) variables independently distributed across time. Here λ_j's unit or country specific. Some analysts impose the additional assumption that the λ_j's are homogeneous across countries, that is, $\lambda_j = \lambda$. Ordinary least squares residuals are used to estimate either the common λ or the λ_j; this estimate is then used to transform the data, using the well-known Prais- Winsten transformation (see, e.g., Kmenta 1986, 304). Next, we will write the variance-covariance matrix Ω as follows:

$$\Omega = \Sigma \otimes I_T \tag{7}$$

where Σ is the N x N matrix of contemporaneous covariances, with typical element $E\left(\varepsilon_{i,t},\varepsilon_{j,t}\right)$. The notation $\otimes$ is the Kronecker product. For example, if N = 2 and T = 3, the variance covariance matrix of the errors is:

[3] Here the subscript i and j refers to two countries.

$$\Omega = \begin{pmatrix} \sigma^2{}_1 & 0 & 0 & \sigma^2{}_{12} & 0 & 0 \\ 0 & \sigma^2{}_1 & 0 & 0 & \sigma^2{}_{12} & 0 \\ 0 & 0 & \sigma^2{}_1 & 0 & 0 & \sigma^2{}_{12} \\ \sigma^2{}_{12} & 0 & 0 & \sigma^2{}_2 & 0 & 0 \\ 0 & \sigma^2{}_{12} & 0 & 0 & \sigma^2{}_2 & 0 \\ 0 & 0 & \sigma^2{}_{12} & 0 & 0 & \sigma^2{}_2 \end{pmatrix}$$

Next we will assume panel heteroscedasticity:

$E\left(\varepsilon^2{}_{i,t}\right) \neq E\left(\varepsilon^2{}_{j,t}\right)$ but $E\left(\varepsilon^2{}_{i,t}\right) = E\left(\varepsilon^2{}_{i,t'}\right)$. Therefore, we can write:

$$E\left(\varepsilon^2{}_{i,t}\right) = \sigma^2{}_i \tag{8}$$

Next, we will assume contemporaneous or cross sectional dependence among the error terms:

$E\left(\varepsilon_{i,t}\varepsilon_{j,t}\right) = E\left(\varepsilon_{i,t'}\varepsilon_{j,t'}\right) \neq 0$ but $E\left(\varepsilon_{i,t}\varepsilon_{j,t'}\right) = 0.$ Therefore, we can write:

$E\left(\varepsilon_{i,t}\varepsilon_{j,t}\right) = \sigma_{ij}$.with all other covariances being zero. (9)

Finally, we will estimate regression coefficients and standard errors of our model by using two step sequential FGLS procedure developed by Parks (1967) for serial and contemporaneously correlated error terms and applied by Beck and Katz (1995) in a general setting involving panel heteroscedasticity. In step 1, equation 5 is initially estimated by OLS. The residuals from this estimation are used to estimate the unit-specific serial correlation of the errors, which are then used to transform the model into one with serially independent error. In step 2, residuals from this estimation are then used to estimate the contemporaneous correlation of the errors. The correct formula for the sampling variability of the OLS estimates is given by the square roots of the diagonal terms of:

$$Cov(\hat{\beta}) = \left(X'X\right)^{-1}\left\{X'\Omega X\right\}\left(X'X\right)^{-1} \tag{10}$$

If the errors obey the spherical assumption (Ω has 1 in diagonal and O in off-diagonal elements), this simplifies to the usual OLS formula, where the OLS standard errors are the square roots of the diagonal terms of $\hat{\sigma}^2\left(X'X\right)^{-1}$, where $\hat{\sigma}^2$ is the usual OLS estimator of the common error variance, σ^2. If the errors obey the panel structure, then this formula provides incorrect standard errors. Equation (10), however, can still be used, in combination with that panel structure of the errors, to provide accurate, panel-corrected standard errors (PCSEs). For panel models with contemporaneously correlated and panel heteroscedastic errors, Ω is an NT x NT block diagonal matrix with an N x N matrix of contemporaneous covariances, Σ, along the diagonal. To estimate equation (10), we need an estimate of Σ. Since the OLS estimates of equation (5) are consistent, we can use the OLS residuals from that estimation to provide a consistent estimate of Σ. Let $\varepsilon_{i,t}$ be the OLS residual for country (unit) i at time t. We can estimate a typical element of Σ by:

$$\hat{\Sigma}_{i,j} = \frac{\sum_{t=1}^{T} \varepsilon_{i,t}\varepsilon_{j,t}}{T} \tag{11}$$

with the estimate of $\hat{\Sigma}$ being comprised of all these elements. We then use this to form the estimator $\hat{\Omega}$ by creating a block diagonal matrix with the $\hat{\Sigma}$ matrices along the diagonal. In symbols, if E denotes the T x N matrix of the OLS residuals, we can estimate Σ by:

$$\hat{\Sigma} = \frac{E'E}{T} \tag{12}$$

Hence estimate of Ω will be given by:

$$\hat{\Omega} = \hat{\Sigma} \otimes I_T = \frac{E'E}{T} \otimes I_T \tag{13}$$

As the number of time points increases $\hat{\Omega}$ becomes an increasingly better estimator of Ω.

5. Description of the Data

Data for the study is collected from www.fx4casts.com. There are several features of the data that that are being collected. First, FX4casts.com collects data on inflation forecasts from a group of experts in every country that survey and the pool of the surveyors are kept unchanged.

Second, FX4casts.com uses the geometric mean when computing consensus currency forecasts. By exponentially reducing the weight given to extreme forecasts, this reflects more accurately the contributors' predominant expectations. The arithmetic mean, by contrast, is often misleading. For example, the average of 1, 2, 3 and 10 is 4. If the 10 is given equal weight, the arithmetic mean would not reflect the group's primary expectations as well as would the geometric mean. Third, the forecast data that are published are for the average rate of annual inflation year over year. For example, in December 2010, the forecasts are for the average rate of inflation in 2011 and 2012. In January 2011, when the actual data is available, inflation for January 2011 is revised and we publish forecasts for 2012 and 2013. Fourth, the forecast is done during the third week of every month. The original survey data contains forecasts for 40 countries. Therefore, the publication of the timing of the actual inflation rate will vary from country to country. In our study we will use data for 18 emerging countries where we have ten years (11/2001 – 5/2012) of monthly forecasts for the yearly inflation rate. So, we only have ten years of actual yearly inflation rate. Forecasts are revised every month, and forecast starts two years earlier. So, there are 24 observations for each actual yearly inflation rate. Thus, we concluded that a panel study is more appropriate for the nature of the data. We have 180 observations for each horizon for the panel. In this study, we only investigate rationality of one month ahead forecast. We perform all necessary diagnostic investigation of data for the appropriate panel test before conducting the unbiasedness and the efficiency test.

6. Empirical Results

Our empirical results will be reported on several steps. First, we will report a series of diagnostic tests to understand the nature and properties of our cross-section-time series data. Our diagnostic tests will shed light on the necessity of using the PCSEs method outlined in the previous section. Finally, we will present hypothesis tests related to the unbiasedness and efficiency of inflation forecasts for the panel of countries into question. In order to be consistent with Keane and Runkle (1990) and other studies, all the empirical results would be presented at the one-step-ahead horizon. Thus our regression model would look like:

$$\pi_{t+1} = \alpha_0 + \alpha_{1\,t}\pi_{i,t+1} + \alpha_2 X_{i,t} + \varepsilon^{i}{}_{t,1} \tag{14}$$

6.1 Diagnostic Tests

6.1.1 Panel Unit Root Tests

Table 1 reports six panel unit roots to access the time series property of the actual inflation rate, π_{t+1}. We report results from five popular panel unit root tests, Levin- Lin- Chu (2002), Pesaran-CADF, Im-Pesaran- Shin (IPS 2003), Dicky-Fuller and Phillips-Perron (PP) test summarized by Choi (2001). Test statistics used by different methods and their values are reported in column 3 and 4. Parentheses in column 4 indicate p-values associated with each test. All the tests overwhelmingly reject the null hypothesis of a unit root either in the panel or for any individual country. Therefore, we conclude that π_{t+1} is a stationary panel. Table 2 reports time series property of the expected or forecasted inflation rate, ${}_t\pi_{t+1}$. All the tests overwhelmingly reject the null hypothesis of a unit root either in the panel or for any individual country. Therefore, we conclude that forecasted inflation rate, ${}_t\pi_{t+1}$ is also a stationary panel.

6.1.2 Co-Integration Tests

Although unit root tests in previous sub section indicated that actual and expected inflation are both I (O), we know that π_{t+1} and ${}_t\pi_{t+1}$ would be co-integrated. Table 3 reports one of the most popular co-integration tests by Westerlund (2007). Table reports various test statistics calculated by the test. The p-values of respective test statistics strongly reject the null hypothesis if no co-integrated. Therefore, we can conclude that π_{t+1} and ${}_t\pi_{t+1}$ are co-integrated.

6.1.3 Test for Fixed and Random Effects

Table 4 reports tests for fixed and random effect in the model of equation (14) without the X variables. For testing the presence of country-specific fixed effect, we carried out two tests. First, we conducted an F-test suggested by Greene (2000). Here a model with fixed effect is tested against a model without such effect. The calculated value of the F-test, compared against the 95% critical values suggest that we accept the null hypothesis of no fixed effect. Second, we estimated a least square dummy variable model following Greene (2000) and tested whether country dummy variables are jointly equal to zero (no fixed effect). The high p-values of the test statistic suggest that we cannot reject the null hypothesis of no fixed effect. Table 4 also reports test for random effects in our regression model. We perform the famous Breusch and Pagan (1980) Lagrange multiplier test for random effects. This will be a chi-square test. The high p-value associated with the calculated test statistics indicates that we cannot reject the null hypothesis of no random effect in our regression model.

Table 1: Panel Unit Root Tests

Name of the Tests			π_{t+1}	π_{t+1} **(Demeaned)**	π_{t+1} **(With Trend)**	$\Delta\pi_{t+1}$	$\Delta\pi_{t+1}$ **(Demeaned)**	$\Delta\pi_{t+1}$ **(With Trend)**
Levin-Lin-Chu	Hypothesis: H_o: Panels contain unit roots. H_a: Panels are stationary							
	Test Stat	Adjust t*	-12.54 (0.0)	-11.84 (0.0)	-13.04 (0.0)	-13.16 (0.0)	-15.61 (0.0)	-14.59 (0.0)
Pesaran-CADF	Pesaran's CADF panel unit root test in presence of cross section dependence. Ho: There is unit root							
	Test Stat	t-bar	-2.742 (0.00)		-4.067 (0.00)			
IPS	Ho: All panels contain unit roots. Ha: Some panels are stationary							
No serial correlation	Test Stat	Z-t-tilde-bar	-3.884 (0.00)	-3.914 (0.00)	-4.1998 (0.00)	-5.2304 (0.00)	-4.6407 (0.00)	-4.9751 (0.00)
Serial correlation		W-t-bar	-5.993 (0.00)			-7.0391 (0.00)		
Dicky-Fuller	Ho: All panels contain unit roots. Ha: At least one panel is stationary							
	Test Stat	Inv chi-squared	189.56 (0.00)		131.66 (0.00)	202.73 (0.00)		158.016 (0.00)
Phillips-Perron	Ho: All panels contain unit roots. Ha: At least one panel is stationary							
	Test Stat	Inv chi squared	218.90 (0.00)		137.16 (0.00)	248.90 (0.00)		169.48 (0.00)

Table 2: Panel Unit Root Tests (Contd)

Name of the Test			${}_t\pi_{t+1}$	${}_t\pi_{t+1}$ (Demeaned)	${}_t\pi_{t+1}$ (With Trend)	$\Delta_t\pi_{t+1}$	$\Delta_t\pi_{t+1}$ (Demeaned)	$\Delta_t\pi_{t+1}$ (With Trend)
Levin-Lin-Chu	Hypothesis: H_o: Panels contain unit roots. H_a: Panels are stationary							
	Test Statistics	Adjusted t*	-6.69 (0.00)	-11.76 (0.00)	-8.23 (0.00)	-11.40 (0.00)	-5.61 (0.00)	-15.71 (0.00)
Pesaran-CADF	Pesaran's CADF panel unit root test in presence of cross section dependence. Ho: There is unit root							
	Test Statistics	t-bar	-2.25 (0.00)		-3.23 (0.004)			
IPS	Ho: All panels contain unit roots. Ha: Some panels are stationary							
No serial correlation	Test Statistics	Z-t-tilde-bar	-4.17 (0.00)	-3.60 (0.0002)	-4.98 (0.00)	-5.89 (0.00)	-5.17 (0.00)	-5.52 (0.00)
Serial correlation		W-t-bar	-3.51 (0.00)			-7.81 (0.00)		
Dicky-Fuller	Ho: All panels contain unit roots. Ha: At least one panel is stationary							
	Test Statistics	Inverse chi-squared	96.55 (0.00)		142.81 (0.00)	249.01 (0.00)		250.95 (0.00)
Phillips-Perron	Ho: All panels contain unit roots. Ha: At least one panel is stationary							
	Test Statistics	Inverse chi-squared	227.22 (0.00)		175.17 (0.00)	327.68 (0.00)		286.02 (0.00)

6.1.4 Test for Serial Correlation

Table 4 also reports a test for serial correlation following Wooldridge (2002). In this test, we tried to find evidence of first order serial correlation for the forecast errors, defined in equation (14) without the X variables. The low p-value of the calculated F-test statistic indicated that we cannot accept the null hypothesis of no first order auto-correlation.

Table 3: Panel Co-Integration test of Westerlund (2007)

Null Hypothesis: H_0: No error correcting relationship between π_{t+1} and ${}_t\pi_{t+1}$ for any member country in the panel (No co integration)

Alternative Hypothesis: H_a: Error correcting relationship between π_{t+1} and ${}_t\pi_{t+1}$ for at least one member country in the panel (co integration for at least one member country)

Statistics	**Value**	**Z-Value**	**P-Value**
G_t	-2.14	-4.77	0.000
G_a	-3.75	0.05	0.521
P_t	-3.75	-7.21	0.000
P_a	-5.82	-7.03	0.000

6.1.5 Test for Group Wise (Panel) Heteroskedasticity

Table 4 also reports a test for group wise heteroscedasticity following Greene (2000). In this test, we calculated a modified Wald test for group wise heteroskedasticity from the residuals of the regression model defined in equation (14) without the X variables. The high value of the chi-squared test statistics and low p-value indicates that we cannot accept the null hypothesis of no group-wise heteroskedastcity.

6.1.6 Test for Cross Sectional Dependence (CD Test)

Table 5 reports two tests that we conducted to test for cross sectional dependence among the panel of countries. First, we calculated a stand-alone test based on Pesaran (2004) where we tried to detect cross sectional dependence in the data for both π_{t+1} and ${}_t\pi_{t+1}$. Second, we calculated a test statistics based on Pesaran (2006) based on the estimated residuals from cross-section time series pooled regression model defined in equation (14) without the X variables. The low p-values in both of the tests indicated that we cannot accept the null hypothesis of no cross-sectional dependence in either of the test.

Table 4: Other Diagnostic Tests

Name of the Tests	Type of Tests	Test of Hypothesis	Test Statistics	P-value	Decision
Test for Fixed Effect	F-test	Ho: There is no fixed effect	F (17,161) = 0.659		Reject Null Hypothesis at 95% level
Test for Fixed Effect	Least Square Dummy Variable model (F-test)	H_0: All dummy variables are zero (no FE)	F (17, 161) = 0.66	Prob > F = 0.84	Accept Null Hypothesis at all levels
Test for Random Effect	Chi-square test	H_0: There is no random effect	$\chi^2(1) =$ 0.00	$p > \chi^2(1)$ = 1.0000	Accept Null Hypothesis at all levels
Test for Serial Correlation	F-test	H_0: No first order autocorrelation	F(1, 17) = 19.35	Prob > F = 0.0004	Reject Null Hypothesis at all levels
Test for Group-wise (panel) Heteroscedasticity	Modified Wald Test	H_0: No group wise heteroscedasticity	$\chi^2(18) =$ 768.38	$p > \chi^2(18)$ = 0.00	Reject Null Hypothesis at all levels

Table 5: Test for Cross-Sectional Dependence

Test	Variable	Hypothesis	CD-Test	p-value	Corr	Abs(corr)	Decision
Test-1	π_{t+1}	H_0: No CD	5.89	0.000	0.150	0.372	Reject H_0
Test-1	$_t\pi_{t+1}$	H_0: No CD	5.61	0.000	0.143	0.377	Reject H_0
Test-2	$\hat{\varepsilon}_{t,1}$	H_0: No CD	8.63	0.00			Reject H_0

Table 6: Test for Unbiasedness Based on GEE and FGLS Methods

Method	α_0	α_1	**Correlation Corrected**	**Hetero Corrected**	**C-D Corrected**	**Test Statistics**	**Decision**
GEE population -averaged model	0.65 (0.24)	0.94 (.027)	No	No	No	$\chi^2(2)$ = 7.13	P= 0.0283. Accept null at 98% significance level
GEE population -averaged model	0.76 (0.33)	0.92 (0.04)	MA(1)	No	No	$\chi^2(2)$ = 6.07	P= 0.0481 Accept null at 96% significance level
FGLS	0.79 (0.34)	0.92 (0.03)	No	No	No	$\chi^2(2)$ = 6.03	P= 0.049 Accept null at 96% significance level
FGLS	0.66 (.27)	0.93 (.05)	No	Yes	No	$\chi^2(2)$ = 6.54	P= 0.0381 Accept null at 97% significance level
FGLS	0.81 (.3511)	0.92 (.0366)	MA(1)	No	No	$\chi^2(2)$ = 6.01	P= 0.049 Accept null at 96% level.

6.2 Test for Unbiasedness

Table 6 and 7 reports the results that we derived for unbiasedeness of inflation forecasts based on equation (3). This means that we estimated our regression equation defined in equation (14) by using alternative methods under alternative hypothesis about the data without the X-variables. In order to show the significance of using our panel-corrected standard errors based on OLS method explained in section 4, we first ran several counter-factual models which have been used in other papers in the literature. Table 6 reports all these counter-factual methods. The two models that were used were the GEE population average model and the FGLS method. We systematically corrected for autocorrelation and heteroscedasticity but made no assumptions about cross-sectional dependence. Figures in the parentheses show standard errors. We see that correcting for serial correlation (row 3 and 6) or correcting for heteroscedastcity (row 5) increases the probability of accepting the null hypothesis, although none of the models allowed us to accept the null hypothesis of unbiasedness at a conventionally accepted level of significance of 95%.

Table 7 reports regression results based on OLS and test of hypothesis results based on the panel-corrected standard errors. We conducted several estimations each time correct for specific feature that was elaborately discussed in section 4. Immediately, we see that our null hypothesis of unbiasedness is accepted in every possible case. However, several results stand out. First, each assumption appears to be important for the test of hypothesis. Correcting for at least for one of three assumptions; serial correlation, panel heteroskedasticity and cross-sectional dependence appear to help us to accept the null hypothesis of unbiasedness. At the same time, when one of the three features of the data is not corrected, it decreases the probability of accepting the null hypothesis. Second, cross-sectional dependence appears to be the most important features of the data that needs to be corrected for the unbisedness test. If we compare results from last three rows of table 7 with the first three, we see that correcting for cross-sectional dependence immediately increases the probability of accepting the null hypothesis. Third, it appears that the assumption of common versus panel specific serial correlation terms seems to be important. When serial correlation is assumed to be panel or country specific (row 3 and 5), it increases the probability of accepting the null hypothesis of unbiasedness. Fourth, in our final results, when we correct for all features of our data and use panel specific serial correlation strcuture, the null hypothesis regarding unbiasedness of inflation forecasts appear to be strongly accepted at all level of significance.

6.3 Test for Efficiency

Since we cannot reject unbiasedness, we must test the further implication of rational expectations that forecasts be efficient, that is, that no readily available information could have improved forecast accuracy. This involves testing the hypothesis that $\alpha_0 = 0, \alpha_1 = 1, \alpha_2 = 0$ in equation (14). Table 8 gives the results of our efficiency tests. Figures in the parentheses show

Table 7: Test for Unbiasedness Based on Panel-Corrected Standard Error (PCSE) Estimates

Method	α_0	α_1	Correlation Corrected	Hetero Corrected	CD Corrected	Test Statistics	Decision
Panel-Corrected Standard Error (PCSE) Estimates	0.79 (0.51)	0.92 (0.08)	No	Yes	Yes	$\chi^2(2)$ = 2.44	P= 0.296 Strongly accept null at all level
Panel-Corrected Standard Error (PCSE) Estimates	0.82 (0.53)	0.92 (0.08)	MA(1): Common for all cross section	Yes	Yes	$\chi^2(2)$ = 2.39	P= 0.30 Strongly accept null at all level
Panel-Corrected Standard Error (PCSE) Estimates	0.61 (0.54)	0.92 (0.08)	MA(1): Panel specific	Yes	Yes	$\chi^2(2)$ = 1.42	P= 0.49 Strongly accept null at all level
Panel-Corrected Standard Error (PCSE) Estimates	0.79 (0.36)	0.92 (0.06)	No	Yes	No	$\chi^2(2)$ = 5.58	P= 0.061 Accept null at 95% level
Panel-Corrected Standard Error (PCSE) Estimates	0.82 (0.38)	0.92 (0.065)	MA(1): Common for all cross section	Yes	No	$\chi^2(2)$ = 5.48	P= 0.063 Accept null at 95% level
Panel-Corrected Standard Error (PCSE)	0.61 (0.37)	0.92 (0.06)	MA(1): Panel specific	Yes	No	$\chi^2(2)$ = 2.68	P=0.262 Strongly accept at all level.

standard errors. In table 8, we see three important results. First, results from table 8 suggests that one lag actual inflation rate or one lag money growth or one lag oil price change does not improve inflation forecasts. This is because null hypothesis for efficiency in terms of lag money growth rate (row 3) is strongly accepted while for lag inflation rate and lag oil price change, it is accepted at 98 % and 99% significance level (row 1 and row 5) respectively. Hence our inflation forecasts appear to be efficient in terms of these variables which have been used by other previous studies and except for Keane and Runkle (1990), found to be improving inflation or price forecasts (rejection of null hypothesis). Second, forecast error (row 7), one lag forecast error (row 8) or just one lag forecast (row 9) improves the efficiency of inflation forecasts. Therefore, our inflation forecasts are not efficient with respect to these three variables as the null hypothesis of forecast efficiency is rejected at all levels of significance. This result contradicts with Keane and Runkle (1990) but is supported by other studies such as Pearce (1987), Rich (1990) and Thomas (1999). Finally, due to the special nature of the data, the inflation forecast is made for an average annual rate. Therefore, average lag variables might be more informative for the forecasters than just one period lag variables. Surprisingly, we find this intuition to be correct in at least two instances. , we find that one period lag average (11 month average) inflation rate (row 2) and one period lag average oil price change (row 6) improves forecasts. Hence, our inflation forecasts are not efficient in terms of these two sources of information as the null hypothesis for efficiency is rejected at all levels. However, one period (one month) lag average money growth rate (row 4) adds no information to the forecasters as the null hypothesis for efficiency with respect to this information is strongly accepted at all levels of significance.

Table 9 reports results for joint efficiency. The objectives of the hypothesis testing in table 9 is to understand whether forecasts are rationale with respect the entire set of the important variables that other studies have used to test forecast rationality. This test is due to Keane and Runkle (1990) is considered to be the strictest form of test of efficiency of forecasts. Since we already showed that inflation forecasts are not efficient in terms of forecast error, lag forecast error and lag forecasts, we exclude them from our list variables that were used for joint efficiency tests. Row 1 shows that jointly lag inflation rate, lag money growth rate and lag oil price change add some information to the forecaster. Hence hypothesis of joint efficiency in terms of these three variables are rejected at all significance levels. Furthermore, the joint hypothesis in terms of the lag average of these variables (row 2) is also rejected. Although the latter strong test of efficiency has only been tested by Keane and Runkle (1990) and has been found in favor efficiency, this result is not without controversy (Bonham and Cohen 1995).

Table 8: Test for Efficiency Based on Panel-Corrected Standard Error (PCSE) Estimates

New Variable	α_0	α_1	α_2	**Correlation Corrected**	**Hetero Corrected**	**C-D Corrected**	**Test Stat**	**Decision**
One Lag Inflation Rate	0.39 (0.54)	0.89 (0.08)	0.525 (0.18)	MA(1): Panel specific	Yes	Yes	$\chi^2(3) =$ 9.12	P = 0.028 Accept null at 98% level of significance
One Lag Average Inflation Rate	0.198 (0.48)	0.80 (0.07)	2.07 (0.29)	MA(1): Panel specific	Yes	Yes	$\chi^2(3) =$ 53.92	P = 0.00 Reject null at all levels
One Lag Money Growth Rate	0.45 (0.56)	0.88 (0.07)	0.12 (0.08)	MA(1): Panel specific	Yes	Yes	$\chi^2(3) =$ 4.83	P=0.1847 Strongly accept null at all levels
One Lag Average Money Growth Rate	0.66 (0.54)	0.92 (0.08)	-0.05 (0.12)	MA(1): Panel specific	Yes	Yes	$\chi^2(3) =$ 1.67	P = 0.6434 Strongly accept null at all levels
One Lag oil price change	0.51 (0.59)	0.90 (0.08)	-0.08 (0.03)	MA(1): Panel specific	Yes	Yes	$\chi^2(3) =$ 10.19	P = 0.017 Accept null at 99% level of significance
One lag Average Oil Price Change	1.59 (0.48)	0.91 (0.08)	-0.42 (0.87)	MA(1): Panel specific	Yes	Yes	$\chi^2(3) =$ 27.84	P = 0.000 Reject Null at all level
Forecast Error	0.54 (0.44)	0.87 (0.08)	0.76 (0.11)	MA(1): Panel specific	Yes	Yes	$\chi^2(3) =$ 54.74	P = 0.0000 Reject Null
One Lag Forecast error	1.2 (0.41)	0.81 (0.05)	0.07 (0.12)	MA(1): Panel specific	Yes	Yes	$\chi^2(3) =$ 19.85	P = 0.0002 Reject Null
One Lag Forecast	1.2 (0.31)	0.81 (0.05)	0.07 (0.1)	MA(1): Panel specific	Yes	Yes	$\chi^2(3) =$ 15.88	P = 0.0012 Reject Null

Therefore, we can conclude that our results did derive some strong evidence in support of unbiasedness of inflation forecasts and weak yet generally acceptable support in favor of efficiency.

Table 9: Test for Joint Efficiency

Method	α_0	α_1	**New Variables**	**Corr Correct**	**Hetero Correct**	**C-D Correct**	**Test Stat**	**Decision**
PCSE	0.03 (0.62)	0.8090 (0.1)	Lag inflation, Lag money growth, Lag oil price change	MA (1): Panel Specific	Yes	Yes	$\chi^2(5) =$ 39.81	P = 0.0000 Reject null at all level
PCSE	1.04 (0.43)	0.82 (0.1)	Lag Average inflation, Lag Average money growth, Lag Average oil price change	MA (1): Common for all cross section	Yes	Yes	$\chi^2(5) =$ 90.28	P= 0.0000 Reject null at all level

Table 10 and 11seeks to understand the source of efficiency loss in terms of forecast error, lag forecast error, lag forecast, average lag inflation rate and lag average oil price change. Bonham and Cohen (1995) argued that any X variable that is to be tested for efficiency in equation (14) has to be stationary and cointegrated with our main regressor and regressand, inflation forecast and actual inflation. West (1988) argued that standard inference (conventional normal asymptotic theory) can only be applied to cointegrated series. Based on this, Bonham and Cohen (1995) argued that if any of the additional X variables are at least not cointegrated with the main regressor (inflation forecast), we might reject (or accept) the null hypothesis due to improper distributional assumptions, not because the additional variables did (or did not) provide additional information to improve the inflation forecasts. Table 10 reports the unit root tests of Pesaran-CADF, IPS (with and without assumption of serial correlation) and the Fisher type Dicky-Fuller tests. Parenthesis shows p-values associated with the test statistics for the null hypothesis unit root in the panel. For lag inflation rate (row 1), lag average inflation rate (row 2), lag oil price change (row 5), lag average oil price change (row 6) and lag forecast (row 9), the null hypothesis cannot be rejected only based on the Pesaran-CADF test. More importantly, we notice that cross sectional dependence might be the cause of the non-stationarity which is reported by the Pesaran-CADF test.

Table 10: Unit Root test for Efficiency Variables

Variables\Tests	Pesaran- CADF (Cross Sectional Dependence)	Im-Pesaran-Shin (No Serial Correlation)	Im-Pesaran-Shin (Serial Correlation)	Dicky-Fuller (Fisher Type)
Lag Inflation Rate	**-1.89 (0.26)**	-5.77 (0.00)	-4.96 (0.00)	143.55 (0.00)
Lag Average inflation rate	**-1.49 (0.74)**	-4.27 (0.00)	-3.25 (0.00)	81.02 (0.00)
Lag Money Growth Rate	-2.10 (0.00)	-5.0047 (0.00)	-3.46 (0.00)	86.66 (0.00)
Lag Average Money Growth	-2.544 (0.00)	-4.1558 (0.0)	-6.6831 (0.00)	143.68 (0.00)
Lag oil price change	**2.61 (1.00)**	-6.33 (0.00)	-6.45 (0.00)	73.32 (0.00)
Lag Average Oil Price change	**1.70 (1.0)**	-7.75 (0.0)	-5.26 (0.00)	109.18 (0.0)
Forecast Error	-3.20 (0.00)	-4.16 (0.00)	-4.68 (0.00)	102.63 (0.00)
Lag Forecast Error	-4.14 (0.00)	-3.63 (0.00)	-4.26 (0.00)	124.08 (0.00)
Lag Forecast	**-1.99 (0.17)**	-3.74 (0.00)	-4.28 (0.00)	125.95 (0.00)

Table 11reports cointergation tests on the list of variables considered for the efficiency test by using the Westerlund (2007) test. We only reported G_t and G_a statistics which assumes no cointegration in any of the member country in the panel as null hypothesis. Parenthesis shows p-values associated with the test statistics for the null hypothesis of no cointegration in the panel between any of the X variables, actual inflation rate (regressand) and the forecasted inflation (main regressor). Lag average inflation rate, lag average money growth rate, lag average oil price change and lag forecast appear to have no contegrating relationship with actual inflation rate (regressand) while lag average inflation rate and lag forecast appears to have no cointegrating relationship with also the inflation forecasts (main regressor).

Table 11: Panel Cointegration Tests of Westerlund (2007) for Efficiency Variables

Null Hypothesis: H_0: No error correcting relationship between variables defined in column 1 for any member country in the panel (No co integration) **Alternative Hypothesis**: H_a: Error correcting relationship between variables defined in column 1 for at least one member country in the panel (co integration for at least one member country)					
Variables	**Statistics: Gt**	**Statistics: Ga**	**Variables**	**Statistics: Gt**	**Statistics: Ga**
π_{t+1}, Lag inflation Rate	-1.382 (0.05)	-2.634 (0.862	${}_t\pi_{t+1}$, Lag inflation	-1.202 (0.179)	-1.473 (0.985)
π_{t+1}, Lag Average inflation rate	**-3.593** **(0.00)**	**-7.595** **(0.00)**	${}_t\pi_{t+1}$, Lag Average inflation rate	**-2.265** **(0.00)**	-3.370 (0.657)
π_{t+1}, Lag Money growth	-1.213 (0.167)	-1.837 (0.967)	${}_t\pi_{t+1}$, Lag Money growth	-1.051 (0.381)	-1.057 (0.995)
π_{t+1}, Lag Average Money growth	**-1.612** **(0.005)**	-2.235 (0.928)	${}_t\pi_{t+1}$, Lag Average Money growth	-0.953 (0.538)	-1.465 (0.985)
π_{t+1}, Lag oil price change	-0.358 (0.994)	-0.349 (0.999)	${}_t\pi_{t+1}$, Lag oil price change	-0.453 (0.984)	-0.260 (1.00)
π_{t+1}, Lag Average oil price change	**-1.49** **(0.02)**	-2.10 (0.94)	${}_t\pi_{t+1}$, Lag Average oil price change	-0.73 (0.84)	-4.23 (0.99)
π_{t+1}, Forecast Error	-0.246 (0.999)	-0.035 (1.00)	${}_t\pi_{t+1}$, Forecast Error	-0.604 (0.936)	-0.599 (0.999)
π_{t+1}, Lag forecast error	0.855 (1.0)	0.442 (1.0)	${}_t\pi_{t+1}$, Lag Forecast error	-1.033 (0.409)	-0.198 (1.00)
π_{t+1}, Lag Forecast	-1.951 (0.000)	-2.709 (0.846)	${}_t\pi_{t+1}$, Lag Forecast	-2.701 (0.00)	-2.399 (0.905)

We can therefore, make several conclusions about the efficiency tests for our inflation forecasts. First, the null hypothesis for efficiency was rejected for lag average oil price and lag forecast because of absence of cointegrating relationship among the regressors which resulted in improper distributional assumptions, not because these information actually improved inflation forecasts. Second, non-stationarity of the lag oil price and lag average oil price might have prompted a weak acceptance of efficiency for the former and a strong rejection for the latter. Our results are somewhat in favor of Bonham and Cohen (1995) who argued that large fluctuations in the oil price makes it difficult for forecasters to efficiently utilizing oil price change information in their inflation forecasts. Finally, our results indicate that forecast errors and lag forecast errors improve inflation forecasts. This contradicts Keane and Runkle (1990) but is supported by Pearce (1987) and Thomas (1999). We might conclude, similar to them, that our inflation forecasters, regardless of their professional background, fail to learn from their previous forecasts. For an international data set where data is collected from a wide range of emerging countries with significant economic and political differences, the failure seem to be quite general, mimicking failures by professional forecasters from more advanced countries. Our study also re-iterates some of the concerns about inflation forecasting in international data sets highlighted by Oral et al (2011) and Bakshi (1998).

7. Conclusion

In this paper, we have made an effort to test and understand the rationality of inflation forecasts of professional forecasters by using a consensus based forecast survey data including 18 emerging countries. With our short panel data involving 18 countries with 10 one-month ahead forecast data per country, we used a recently developed panel data estimation technique popularized by Beck and Katz (1995) that corrects for serial correlation, panel heteroskedastcity and cross sectional dependence. We used the panel corrected standard errors derived from our estimation results to test for the unbiasedness and efficiency of inflation forecasts, two of the most popular test of rationality of expectations. We found forecasts made by the forecasters in our panel data sample are strongly unbiased and efficient to most commonly used source of information to improve professional forecasts. The results of this study will enhance our understanding of forecast efficiency, which will be useful to both researchers and policy makers.

This research will contribute to the area significantly as there are no comprehensive studies that investigate emerging market inflation rates using a large number of countries.

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