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Forecasting Inflation and Inflation Expectations in Small Open Economies: A Comparison of Market and Survey based Approaches for Jamaica

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BANK OF JAMAICA

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# Forecasting inflation and inflation expectations in small open economies: A comparison of market and survey based approaches for Jamaica

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**Abstract**

This paper builds a dynamic factor model to obtain both in-sample and out-of-sample forecasts of inflation in Jamaica. The model is estimated with both survey and market data. For the latter, a global latent factor is first extracted from international financial data and then included as an exogenous variable in the estimations with Jamaican data. The results indicate that the estimations with market data provide a much better fit for in-sample and out-of-sample values of inflation and inflation expectations. The dynamic factor, under a parsimonious representation, also outperforms univariate models, Bank of Jamaica's in-house forecasts of inflation obtained from an ARIMA-X model and those obtained from an estimated DSGE model.

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# 1 Introduction

Since the early 90s most central banks, in both advanced and emerging market economies, have made price stability the overriding goal of their monetary policies. Although this widespread transition to full-fledged and implicit inflation targeting is deemed successful given the track record since the 90s, accurately forecasting inflation is still the most important challenge to ensuring price stability. Specifically, all pillars of inflation targeting policies such as the announced inflation targets, forward guidance measures and the adjustment of policy instruments have an inflation forecast as a foundation. These policies, therefore, are less credible and less meaningful if inflation forecasts are inaccurate.

Unlike the general agreement that inflation targeting is the best practice, there is no consensus on the best methodology to forecast inflation. Forecasts made by using backward and forward looking Phillips curves, medium scale dynamic stochastic general equilibrium models, univariate time series models, and inflation expectations inferred from surveys have not revealed a clear winner. As we discuss below, findings do, however, indicate that the univariate time series approach such as an ARIMA model, have had the most success and it is therefore perceived as the approach to beat.

In this paper, we build a dynamic factor model (DFM), estimate it with Jamaican data and find that it can outperform both univariate models and survey based measures in predicting the in-sample and out-of-sample values of inflation. This relative accuracy of DFM forecasts of inflation is even more evident when we make a comparison with Bank of Jamaica's in-house forecasts of inflation obtained from an ARIMA-X model and those produced by an estimated dynamic stochastic general equilibrium (DSGE) model. There are two distinct contributions in this paper. First, we extract a latent common factor in inflation survey data by using a DFM. We then do the same by using market data. Finally we compare the accuracy of the two models in forecasting inflation. This study, therefore, is a first attempt at comparing the predictive power of inflation survey data and market data by using a DFM framework. Second, we follow a two-layer method that incorporates external factors when estimating the DFM with market data for a small open economy. Specifically, we first estimate a global latent factor by using international variables that are commonly associated with global financial cycles. We then incorporate this factor into the

DFM with Jamaican endogenous variables as an exogenous variable. As we discuss below, this two-layer method is unique and it contributes to the infant literature on inflation forecasting with DFM in emerging market economies.

Availability of inflation survey data makes Jamaica a good fit for the analysis in our paper. The survey data are available from January 2013 to April 2023 and they represent statistics computed by quantifying and aggregating the responses to various questions related to inflation, including statistics at the sector level. The most critical variable is the survey takers' expectations of 12-month ahead inflation. We include this variable, the actual level of inflation and other aggregated survey statistics, and find that the dynamic latent factor extracted from survey data is significantly related to inflation, inflation expectations and most other survey variables. Checking goodness of fit, however, we find that the factor has small explanatory power over both inflation and inflation expectations.

We also estimate the DFM with several market data that are closely related to inflation such as the Jamaican dollar / US dollar exchange rate, fuel prices and Bank of Jamaica (BOJ) policy rate. Before doing so, we first extract a global latent factor from international data, including volatility indices such as the Chicago Board Options Exchange Volatility Index (VIX), VSTOXX and the Emerging Markets ETF Volatility Index, and various commodity prices indices, and incorporate this latent factor in our estimations with Jamaican market data as described above. The results reveal a slightly closer association between Jamaica's endogenous variables and the domestic latent factor, with 7 and 5 out of the 10 endogenous variables significantly related to the domestic and foreign latent factor, respectively. The CPI inflation variable, however, is only significantly related to the domestic latent factor. A more central finding for our paper is that the DFM estimated with market data, relative to its survey data counterpart, provides a much better fit to the fluctuations of CPI inflation during our sample period. While the dynamic latent factor in the DFM estimated with survey data explains roughly 22 per cent of the historical variation of inflation, the domestic latent factor in the DFM model with market data explains 76 per cent of inflation.

The inferences above remain the same when we include the expected value of inflation compiled from surveys into the model with market data with no noticeable improvements in the models goodness of fit with respect to inflation. The estimations do, however, counterintuitively reveal that the DFM model with market data does a better job of forecasting the in-sample variation of the inflation expectations variable compared to the DFM model with survey data. Simply put, the results imply that the dynamic common factor in market data is a more important driver of inflation expectations than the dynamic common factor in survey data. We also find that the dynamic factor model is a better fit for inflation data than a static factor model. Specifically, using a principal component analysis with different numbers of factors we uncover an inferior fit to inflation data.

We proceed by assessing the out-of-sample forecasting performance of the different DFM models. We find that the DFM model estimated with market data, consistent with its in-sample forecasting performance, outperforms the model estimated with survey data at both short-term and long-term forecast horizons. Compared to a univariate ARMA(2,1) specification (the univariate specification with the least root mean squared errors), however, the DFM model's forecasts are more accurate only for short-term horizons. Similar inferences are drawn for the forecasting accuracy of expected inflation and when we use different number of factors and lags.

Alternative tests with market data reveal that a more parsimonious model with only three Jamaican variables can outperform the ARMA(2,1) specification at both short and long horizons. This finding is also robust to using rolling windows for comparing forecasting performance. As we discuss below, this relative success of the parsimonious model is consistent with some recent evidence on DFM forecasting. While outperforming a univariate model is the ultimate pursuit of any forecasting model, we also check how our DFM forecast compare with those obtained from an estimated DSGE model (following the framework in Aysun, 2023) and the in-house inflation forecasts of the BOJ generated by an ARIMA-X specification that uses disaggregated data. These comparisons, more evidently, reveal the better forecasting performance of our DFM model with market data.

### 1.1 Literature review

DFM models have increasingly become a popular method for macroeconomic forecasting given the overfitting and the degrees of freedom issues associated with competing multivariate and structural methodologies such as vector autoregressive and dynamic stochastic general equilibrium models. Early revelations of these models' forecasting advantages in studies such as Stock and Watson (2002) and Bai and Ng (2002) is more widely documented today, especially with higher data availability and computational power. Compared to the univariate methods such as ARMA, ARIMA, ARIMA-X, however, DFM models demonstrate mixed success according to evidence. While studies such as Das et al. (2011) Kotlowski (2008), Stock and Watson (2016), Pierzak (2013), Gosselin and Tkacz (2010) find that DFM models can outperform univariate models, findings of Lee (2012), Gil-Alana et al. (2012), Bennett and Owyang (2022), Elliot and Timmerman (2008) and Faust and Wright (2013) demonstrate that univariate models are the most accurate macroeconomic forecasting tools.[1,2]

A majority of the earlier literature on the comparison of inflation forecasting methodologies focuses on advanced economies partially due to data availability. Given improvements in the latter there has been a recent growth in the number of studies on emerging market economies (e.g., Das et. al. 2011; Mandalinci, 2017; Duncan and Martínez-García, 2019; Faust and Wright, 2013; Thu and Leon-Gonzalez, 2021 and Ahmad and Haider, 2019). These numbers, however, remain low, especially for DFM forecasting, also because of the high sensitivity of most emerging

[1] Kotlowski (2008) assesses the inflation forecasting accuracy for Poland, comparing a dynamic factor model against a univariate autoregressive model, VAR model and a model with a leading indicator from the business survey. The results indicate the superiority of DFM forecasts for both 1-period and 3-period ahead forecast. Wang (2009) provide a similar support for the forecasting accuracy of DFM relative to VAR, AR and DSGE models but uncovers a greater accuracy of DFM in short-term forecasting. Pierzak (2013) investigates the use of a dynamic factor model and a large dataset of macroeconomic series commonly used for forecasting inflation. Sub-datasets are created that enabled the extracting of a representative series and the subsequent forecasting of CPI inflation, core inflation, food inflation and fuel inflation. The results show that incorporating extracted information from large datasets can improve inflation forecast accuracy and that dynamic factor models outperform the best autoregressive models. Gosselin and Tkacz (2010) compares the performance of a dynamic factor model against a random walk, an auto-regressive model and a vector error-correction model, in forecasting Canadian inflation. They find that a dynamic factor model outperforms the rest using 334 Canadian and 110 US macroeconomic and financial time-series.

[2] Lee (2012), compares three different inflation forecasting models for seven inflation targeting countries, and finds that the ARIMA model outperforms a Phillips curve and a naïve model in out-of-the-sample inflation forecasts. Gil-Alana et al. (2012) show that ARMA and ARFIMA models perform far better than random walk and a VAR models for predicting US inflation. Bennett and Owyang (2022) investigate the relative performance of three survey-based and four macro-model-based inflation forecasts for the US economy. They find that the Atkeson-Ohanian-type random walk (RW-AO) specification is superior in forecasting one-year-ahead inflation and five-year average inflation compared to VAR models. Elliot and Timmerman (2008) find that out of twelve competing models, the auto-regressive and exponential smoothing techniques were superior to others in the assessment, including BVARS. Similarly, Faust and Wright (2013) compare a large set of traditional and recently developed inflation forecasting methods which include conventional models based on domestic factors, existing open-economy Phillips curve-based specifications, factor-augmented models, and time-varying parameter models. They find that the AR method (an AR(1) in gap form with a fixed slope coefficient) is hard to beat consistently over the 8-quarter horizon for US data and several alternative inflation measures.

market economies to external factors. Specifically, a common latent factor amongst domestic variables may not be sufficient for capturing business cycle dynamics given the substantial impact of external variables on these cycles. In our paper, we build a methodology that can account for global financial cycles when describing and forecasting inflation of an emerging market economy. We also find evidence that our DFM can beat univariate specifications in accurately predicting inflation under a parsimonious specification. The latter finding is consistent with the compelling evidence that increasing the number of variables can diminish the forecasting power of DFM and that including a limited number of data series that are more closely related to inflation would produce better outcomes. Studies such as Boivin and Ng (2006), Bai and Ng (2008), Schumacher (2010), Caggiano et al. (2011), Alvarez et al. (2012), and Bessec (2013) show the advantages of using smaller number of variables to estimate DFM models.

Our results also illustrate that the DFM model is more accurate for forecasting inflation than a DSGE model both in the short-run and the long-run. This finding informs the well-documented comparisons of DSGE forecasts with those obtained from bayesian vector autoregressive and univariate models. While the literature (e.g. Edge and Gurkaynak, 2010; Edge et al., 2010, Christoffel et al., 2008) typically finds that DSGE models can outperform BVAR specifications, especially in the long-run, they cannot beat the accuracy of univariate specifications. In our paper, we find that a DFM model can outperform a DSGE model and a univariate model both in the short-run and the long-run.

While managing and tracking inflation expectations is a key component of monetary policy, its measurement is often difficult due to its unobservable nature (see, Figlewski and Wachtel, 1981 for a detailed discussion). Although there have been attempts at inferring and quantifying inflation expectations from observed variables, an inflation survey is the more commonly used method (see, Mankiw and Reis 2018; Cunningham, 2010). This is also justified by some findings that demonstrate the usefulness of inflation expectations obtained from surveys in forecasting the future levels of inflation (Ang et al., 2007; Chan et al., 2018; Coibion et al. 2018; Rondina, 2018). A subset of these studies use factor models to extract common factors in inflation expectations survey to aid the forecasting of inflation (e.g., Álvarez and Sánchez-García, 2018; Nishino et al., 2016). Unlike the literature cited above, we use survey data from an emerging market economy, and find that surveys are not too informative for neither in-sample nor out-of sample forecasting of inflation. Specifically, we find that forecasts of inflation obtained by using market data are much more accurate than those obtained by survey data. We should also point out that the main methodology in our paper is a DFM in contrast to the commonly used static principal component methodology in literature. Ahn and Fulton (2020) and Baumann et al. (2021) are two rare examples of extracting common components in advanced economy surveys by using DFM.

## 2 Methodology and data

In our paper, we mainly use a dynamic factor analysis to draw inferences for inflation and inflation expectations. To do so we estimate the parameters of the following model by maximum likelihood:

$$\begin{aligned} Y_t &= \Lambda F_t + \Psi X_t + u_t \\ F_t &= \Omega\left(L\right) F_t + \varepsilon_t \end{aligned} \tag{1}$$

$Y_t$ here represents a vector of observed dependent variables. We describe these variables below but it is useful to note here that we conduct two separate estimations that populate the $Y_t$ vector with market and survey data, respectively. $F_t$ in equation (1) is a $T$ by $N^f$ vector of unobserved factors with $T$ and $N^f$ denoting the total number of time periods and factors, respectively. The coefficient matrix corresponding to these factors, $\Lambda$, represents the factor loadings that capture the per cent of variance in an observable variable, $Y_{j,t}$, that is explained by the factors. In our estimations, we also introduce exogenously determined variables (vector $X_t$). These variables, by design, do not share a common factor with observed variables but do have an impact on them. Following standard practice, we assume that the factors follow an AR(p) process with $p$ representing the number of lags. The coefficients of these lags are captured by $\Omega\left(L\right)$. $u_t$ and $\varepsilon_t$ are *i.i.d.* error terms following a Normal distribution.

To estimate the state-space form of our dynamic factor model in equation (1), we use a Kalman filter to derive a log likelihood function and then find the parameters that maximize this function. It should be noted here the optimization routine that we use is designed for models with a relatively small number of factors, lags and observed variables and it requires all observed variables to be stationary for convergence. We, therefore, choose 1 factor and 1 lag in our baseline estimation and restrict the set of observed variables to those most closely associated with inflation. We do, however, estimate models with different number of factors and lags in our sensitivity analysis. All variables populating the $Y_t$ and $X_t$ vectors are log differenced and checked for stationarity prior to estimation.

It is also important to mention that, we conduct three sets of analyses after estimating the model. First, we gauge the goodness of fit by measuring the share of variation in observed variables explained by the common factors, and compare this statistic across the two approaches, market-based and survey-based. Second, we assess the forecasting performance of the two approaches by making out-of-sample predictions for both inflation and inflation expectations. Finally, we follow a hybrid approach and include both market and survey variables to determine whether unobserved factors that are common to these two types of variables are stronger drivers and predictors of inflation and inflation expectations. To assess prediction performance, we use the previous period's observation for $Y_t$, the joint distribution of $Y_t$, $X_t$ and $F_t$, and a Kalman filter to make 1-period ahead iterative forecasts.

To estimate our model with market data, we first obtain 10 monthly Jamaican data series for the 2012:1 - 2023:4 period. The reason we choose January 2012 as the start date of our sample with market observations is to match the sample with survey data as the first survey is conducted in January of 2013 (we need data for 2012 to compute year-on-year differences). This allows us to more accurately compare the inferences from the estimations with survey and market data. The 10 data series are the monthly consumer price index (CPI), Jamaican dollar - US dollar exchange rate, fuel prices, industrial electricity fuel sales, Jamaican Stock Exchange (JSE) index, commercial bank loans, M1 money supply, 3-month Treasury bills, Bank of Jamaica policy rate and a rainfall variable. These nominal variables are typically related to inflation and our choices are also determined by data availability. The variable definitions are provided in Table A.1 of Appendix A. All variables are log-differenced so that they reflect year-on-year growth rates with the exception of the T-bill and policy rates that are linearly detrended.

We compare the estimation results obtained by using the market data described above with those obtained by using survey data. The survey data that we use are compiled from Bank of

Jamaica's Survey of Businesses' Inflation Expectation (SBIE) that are conducted eight times a year with an inception date of January 2013. The survey data consist of numerical values that describe the responses to questions related to inflation, the exchange rate, business conditions, growth and input costs. The responses to most questions are expressed in terms of a balance of opinion, which is calculated by subtracting the proportion of negative responses from the proportion of positive responses and then adding 100. While the survey data are rich and available for nine industry groups, we use aggregate data given that our estimation strategy requires that the number of observables is less than the number of time periods. Once again all data series are checked for stationarity prior to estimation. The variables that we use are described below and their definitions are provided in Table A.1 of Appendix A.

## 3 Estimations

We begin by estimating equation (1) with market data. In so doing, we first include monthly observations for the variables that are commonly associated with inflation and that are described above. It should be noted that we do not include survey data in these estimations to facilitate an unambiguous comparison with the estimations that use survey data.

For a small open economy such as Jamaica it is critical to also account for the drivers of inflation that are determined externally. We incorporate these factors by following a unique strategy. We first collect monthly data for global variables that can potentially impact the Jamaican economy and inflation. The set of global variables are also listed in Table A.1 of Appendix A and they include two bond yields (emerging market and Latin American corporate bonds), two US specific variables (inflation and the federal funds rate), an exchange rate index variable that describes the real value of the US dollar against Emerging Market currencies, three financial market volatility measures (Chicago Board Options Exchange's VIX, and Emerging Markets ETF Volatility Index and the VSTOXX index measuring the implied volatility of the EURO STOXX 50) and eight commodity prices obtained from the World Bank (oil, gold, a total commodity index, energy and non-energy commodity price indices, agriculture, grains and precious metals indices). We then estimate a dynamic factor model with these variables to extract a common global factor that describes the evolution of the global variables. Finally, we use this factor as the exogenous variables in our estimations with market data. It should be noted here that while the rainfall variable is exogenously determined it is included in the set of Jamaican variables as our goal is to extract the dynamic component that is common to all Jamaica specific variables.

The results from the estimations that use market data are reported in Table 1. The coefficients represent the relationship between the domestic and external factors with the macroeconomic variables listed in the first column. The results demonstrate that the domestic factor is significantly related to 7 out of the 10 variables. This proportion is 5 out of 10 for the external factor. More importantly, for the variable that is the focal point of our analysis, CPI inflation rate, the domestic factor is the primary driver. The coefficient value of 0.0088 in the first row implies that a one per cent change in the domestic factor corresponds to a 0.88 percentage point increase in the inflation rate. While interpreting the size of the coefficient is not straightforward as the latent factor is an index summarizing all domestic variables, the coefficients values for the two factors can be compared to infer their relative importance for the macroeconomic variables. Although the comparison can be misguided if the two factors have considerably different volatilities, the standard deviations of the two factors that we extract are similar (2.87 and 3.25 for the domestic and external factors, respectively). Taking the significance and the magnitudes of the coefficients into account, the domestic factor is more strongly related to inflation, exchange rate, the JSE index, commercial bank lending and the M1 money aggregate in Jamaica. The external factor is more strongly related to fuel prices, electricity fuel sales, the Jamaican 3 month T-bill rate and the BOJ policy rate. The diagnostic tests imply that the estimated parameters indicate a stationary model and that these parameters are jointly significant. It should also be noted that out of the 10 Jamaican variables only rainfall is not significantly related to either factor.

We proceed by using survey data to estimate the dynamic factor model in equation (1). The survey variables that we include in the equation are the expectation of future inflation (12-month ahead), the expected average monthly inflation for the next 12 months (annualized by BOJ), an index describing how satisfied survey takers are with the BOJ's management of inflation (inflation control), 2 indices that describe present business conditions and expected business conditions in the future, expected annual GDP growth rate, expected T-bill rate, expected change in wages, expected annual change in the USD/ Jamaican dollar exchange rate, 5 variables that include the shares of survey takers that report utilities, wages & salary, fuel & transport, stock replacement and raw materials as the largest cost of production.

Notice here that most of the survey responses are forward looking and thus can be used to predict future inflation. It is, however, also probable that future expectations can affect today's inflation as agents factor in these expectations in making decisions today. To accommodate these two possibilities we estimate equation (1) by using both future inflation and current inflation. The goodness of fit, the forecasting performance and the main inferences that we observe with the two specifications are very similar. We therefore report one set of estimation results obtained by using current inflation. These results are displayed in Table 2 and they too indicate a significant relationship between the latent factor and the annual inflation rate. The factor is also significantly related to all the other survey variables with the exception of the expected growth rate. The positive relationship between the factor and all these variables indirectly imply that an increase in the survey variables listed in Table 2 are positively associated with inflation.

To assess how well the latent factor in the two estimations describe the propagation of inflation, we first compare the model fitted values with actual inflation. As depicted in the first two plots of Figure 1, the domestic latent factor extracted from market data tracks inflation much more closely than the latent factor extracted from survey data. The bottom plot indicates that the market based factor also does a better job of tracking inflation than the inflation expectations variable in the survey. To produce this plot we match current inflation with the inflation expectations 12 months ago in the surveys. The plot demonstrates that while inflation expectations closely track inflation when its relatively stable between 2017 and 2021, prior to and after this period the swings in inflation are captured only with a lag. We observe a similar disparity between the performance of the models for tracking inflation expectations. To predict inflation expectations in the estimations with market data, we add the expected future inflation variable (expected inflation 12-month ahead) obtained from the surveys into the specification with the market variables. Doing so, we find that the predicted value of inflation expectations represents its survey-based counterpart fairly well as displayed in the top plot of Figure 2. A more compelling case for using market data to predict inflation can be made from the bottom plot in the figure. This figure shows that data from the inflation expectation survey, that reveals inflation expectations, cannot predict expectations as well as market data.

Consistent with the inferences from Figures 1 and 2, we find that market data provide a much better fit for inflation than survey data. Specifically, we find, as displayed in panel A of Table 3, that the adjusted R-squared is relatively higher when inflation is regressed on the predicted inflation extracted from the estimations with market data compared to the corresponding statistic obtained by using survey data (displayed in the first row of Panel B). This is also true for inflation expectations as the R-squared in the fourth row of Panel A is much larger than its value in the second row of Panel B. Similar to the inferences from the figures, we find, comparing rows 1 and 2 of Panel A, that market-based predictions of inflation provide a much better fit to the actual values of inflation than the inflation expectations variable from Jamaica's Survey of Businesses' Inflation Expectation.

Although, survey data appear to be less informative for inflation, it is plausible that they can elevate the goodness of fit if they are incorporated into our estimations with market data. Our estimations that use both market and survey data show that this is not true. We draw this inference by conducting two separate tests. First, we incorporate the survey variables that were used in our baseline estimation into the dynamic factor model with market variables. As displayed in Panel C of Table 3, doing so, diminishes the goodness of fit relative to the market based predictions in the first and fourth rows of Panel A. Second, we only add the survey based variable that represents the expected values of inflation into the dynamic factor model with market data. This experiment too reveals, as displayed in the third row of Panel A, an inferior fit to inflation than the baseline estimations with market data.

The main objective of this paper is to accurately forecast future inflation and dynamic factor modelling is chosen for this purpose. The methodology, however, does not allow us to utilize the vast amount of information in the surveys (a total of 420 variables) as the power of the estimations are restricted by the number of time periods. Alternative approach to gauging goodness of fit, that can also utilize all the survey variables, is to use a static factor model. Following this approach by using a principal component analysis, we fail to detect an improvement in the inflation prediction performance of survey data. Figure 3 plots inflation against its predicted values that are obtained by using different number of factors. None of the plots match the close association between inflation and its predicted values inferred from market data.

# 4 Out-of-sample forecasting

To obtain out-of-sample forecasts from our models, we use all observations except the last 12 periods. These periods form our forecast window. We follow a two step approach to obtain forecasts with market data. First, we estimate the dynamic factor model with the external variables described above to obtain forecasts for the latent external factor. We then feed the observations of this latent factor, including the forecasts, into our model with Jamaican market data. Second, we obtain the forecasts for the last 12 months of our sample period (from April 2022 to March 2023). After doing so, we measure the root mean squared error (RMSE) for each forecast horizon as $RMSE = \left[\sum_{h=1}^{H} \left(\pi_{t+h} - \hat{\pi}_{t+h}\right)^2 / H\right]^{1/2}$, where $t$ indexes March 2021 (the end of the estimation period), $\pi_{t+h}$ and $\hat{\pi}_{t+h}$ denote the actual and predicted values of the inflation rate $h$ months after March 2021, and $H$ represents the forecast horizon.

We report the RMSEs obtained by using market and survey data in columns 1 and 2 of Table 4, respectively. Similar to the inferences related to in-sample forecasting, market data allow for a better out-of-sample forecasting performance. Specifically, the RMSEs measured by using market-based forecasts are smaller than those using survey-based forecasts at each horizon. We also find, however, that the DFM model can only outperform an ARMA(2,1) model during the first three periods of the forecast window.[3] The ARMA model is a better predictor of inflation compared to both DFM models at longer horizons. It should also be noted that for the DFM model with market data the average forecast error is minimized at the 3-month horizon. In Table 5, we report the RMSEs obtained from the forecasts of inflation expectations. These statistics too demonstrate that market data are better indicators of inflation expectations than survey data. The difference between the RMSEs obtained from the two DFM models, however, are smaller than those corresponding to inflation forecasts. Also similar to earlier inferences, we find that DFM with market data outperforms an ARMA(2,1) model only during the initial 3 periods of the forecast window.

[3] ARMA(2,1) model had the best overall forecasting performance out of all the different specifications that we considered.

To check the sensitivity of our results, we consider several other model specifications with market data. As reported in Table 6, we observe a similar disparity between the short-run and long-run forecasting performance of the DFM model with market data relative to the ARMA(2,1) model for these alternative tests. Here, we omit the RMSE statistics for the DFM model with survey data here since they were larger compared to the corresponding values for the DFM model with market data under each specification.

To obtain the RMSE statistics reported in the third and fourth rows of Table 6, we incorporated the inflation expectations variable in SBIE into the DFM model with market data. This variation generated inferior forecasts in the short-run and roughly similar forecast in the long-run compared to the baseline DFM model. The implication is that while inflation expectations is positively related to future inflation with a relative strong correlation coefficient, it does not bolster the DFM model's forecasting performance.

Given the small number of time periods in SBIE, so far we estimated the models with survey data by using only one factor that follows an AR(1) process. We followed the same strategy when estimating the model with market data to conduct a fair comparison of the inferences from the two estimations. Here we deviate from this strategy and use a larger number of observations to estimate the DFM model with market data. Doing so allows us to consider two factors and higher-order AR processes. As reported in the fifth and sixth rows of Table 6, we do not detect a clear improvement in the forecasting performance under these alternative specifications. There is however a small improvement in the short-run and long-run forecasting performance when the latent factor follows an AR(2) and AR(4) process, respectively. We proceed by considering a specification that allows for errors in the observables to be autocorrelated. Under this specification we find the smallest forecast errors when the factor follows an AR(2) process. We find that while this variation improves the forecasting performance during the initial period, this comes at the expense of inferior long-run forecasts.

Finally, we consider a model with only three domestic variables: inflation, exchange rates and the T-bill rate and the global latent factor. We choose the USD/Jamaican dollar exchange rate and the T-bill rate as the two determinants of inflation given the strong exchange rate pass-through mechanism in Jamaica's small open economy and that inflation targeting policies are the principal determinant of interest rates in the economy. The results indicate that this parsimonious specification can beat the ARMA model for each period in the forecast window. Further analysis shows that alternative specifications of the parsimonious model cannot improve forecasting performance at the short-run and long-run horizons simultaneously.

So far, we only used the period April 2022 to March 2023 as the forecast window. To draw a more general inference, we obtain out-of-sample forecasts for a rolling 12 month window. Specifically, we use April 2021 to March 2022 as the initial forecast window (using the sample period before April 2021 to estimate the models). We make forecasts for 1 to 12 month horizons within this window. We then move the window one period forward and re-estimate the model and make forecasts. We repeat this procedure until we reach the baseline forecast window (April 2022 to March 2023).

To conduct this experiment, we use the parsimonious DFM model and the ARMA(2,1) model as these produce the lowest forecasts errors amongst the different DFM and ARMA models, respectively. For similar reasons, we omit the results that correspond to the estimations with survey data. After measuring forecast errors, we first compute the RMSE statistic at each horizon. For a 1-month ahead forecast, for example, we add the square of the 1-month ahead forecast errors measured for each of the 12 windows. We then divide this sum by 12 and take the square root to obtain the RMSE statistic. Following the same method produces the results that are reported in columns 1 and 2 of Table 7. While the RMSEs are similar across the two models for the initial periods, we find that the DFM slightly outperforms ARMA as we extend the forecast horizon. Using the forecast errors we also compute cumulative RMSE statistic that reflect average forecasts errors computed across both the horizons but also the 12 forecast windows. These statistics, reported in columns 3 and 4, also indicate that the DFM generally outperforms the ARMA specification.

## 4.1 Other considerations

We compare the forecasting performance of the DFM model to two other models, namely the in-house ARIMA-X model used by the BOJ and a dynamic stochastic general equilibrium (DSGE) model. The results are displayed in Table 8 and they reveal that the DFM model more starkly outperforms the other two models (for which forecasts are reported in columns 2 and 3, respectively). While the forecasting performance disparity is more evident here, the comparisons that we make here are useful.

The model that is used to measure the forecast errors in column 2 are from the in-house model of the BOJ. This model produces forecasts of the CPI at a monthly frequency. We use these projected values of the CPI to measure our inflation variable. We then follow a similar procedure to compute the average RMSE statistic for each forecast horizon. Comparing columns 1 and 2 shows that the DFM model's forecasts are more accurate at each horizon.

As a final analysis, we use the forecasts from a more structural model. We make this comparison since estimated DSGE models are tools that are commonly utilized for macroeconomic forecasting as they are not subject to the Lucas critique. Here we use the estimated DSGE model of Aysun (2022) to produce quarterly forecasts of inflation. The model in Aysun (2022) features a medium scale New-Keynesian framework that includes nominal and real rigidities and it is estimated by using data from Jamaica, the US and the rest of G-7 countries. The forecasts are for quarterly inflation rates. We annualize these forecasts and then measure the average RMSE to compare with the RMSE statistics obtained from the DFM model. This comparison shows that the DFM significantly outperforms the DSGE model. The latter model's forecasting performance is particularly weaker at the longer horizons.

## 5 Conclusion

This paper demonstrated that market data are more informative for projecting future values of inflation and inferring inflation expectations compared to survey data. This inference was drawn by estimating a dynamic factor model in two steps. In the first step, a global latent factor in international financial data was extracted by using a dynamic factor specification. This factor was then incorporated into the model with Jamaican data. Comparing the in-sample and out-of-sample inflation and inflation expectations forecasting performance of the models estimated with market and survey data revealed a better goodness of fit and forecasting accuracy for the model estimated with market data. This inference was robust to using alternative model specifications including different number of lags for the latent factor and endogenous variables, different number of factors, and a more parsimonious specification with only inflation rate, the Jamaican dollar / US dollar exchange rate, the difference between US and Jamaican short-term interest rates and the latent global factor. The inferior performance of the survey-based approach could either be due to deviations from rational expectations or that responses to survey questions may not accurately represent survey takers expectations of future inflation.

Comparing the DFM out-of-sample inflation forecasts with those obtained from a ARMA specification, showed that the DFM can outperform the ARMA model under its parsimonious specification, both in the short-run and the long-run. Further tests revealed that the relative accuracy of the DFM model is even more apparent when its inflation forecasts are compared with Bank of Jamaica's in-house forecasts from a univariate model and those from an estimated medium scale DSGE model.

There are two clear policy implications of our findings. First, inflation surveys in emerging market economies should be revised and tested against market data to improve their usefulness for policy makers and forecasters. In particular, survey variables that are not significantly related to a latent common factor can be investigated more closely to determine their informativeness and adequacy. Second, DFM approach to forecasting inflation should be considered as a replacement for univariate models. Greater availability of data in the future could aid this transition as the DFM model can be calibrated by using different factors and a larger number of lags for both the factors and the endogenous variables.

One shortcoming of all forecasting models considered in this paper is that they are linear in structure and thus the out-of-sample forecasts cannot capture the nonlinearities in future inflation rates, especially the large swings in the inflation rate of emerging market economies. A natural direction for future research would be to account for these nonlinearities by incorporating a nonlinear structure in dynamic factor models. This is a relatively new area of research but there are promising attempts that should be utilized for inflation forecasting in emerging market economies (e.g., Guerron-Quintana et al. 2023).

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# Appendix A. Data

## Table A.1 Data definitions and sources

| Variable | Description | Data Source |
|---|---|---|
| International data | | |
| VIX | Chicago Board Options Exchange, Volatility index reflecting market expectation of near term volatility conveyed by stock index option prices. | Federal Reserve Economic Data |
| VSTOXX | Quantifies investor sentiment and overall economic uncertainty by measuring the 30day implied volatility of the EURO STOXX 50. | Wall Street Journal, Markets Data |
| Emerging Markets Volatility Index | Chicago Board Options Exchange, CBOE Emerging Markets Exchange Traded Fund Volatility Index | Federal Reserve Economic Data |
| Emerging market bond spread | ICE BofA Emerging Markets Corporate Plus Index Option-Adjusted Spread | Federal Reserve Economic Data |
| Latina America bond spread | ICE BofA Latin America Emerging Markets Corporate Plus Index Effective Yield | Federal Reserve Economic Data |
| US inflation | Personal Consumption Expenditures, Y-0-Y Changes in the Price Index, 2012=100 | Federal Reserve Economic Data |
| US policy rate | Federal Funds Effective Rate, Per cent | Federal Reserve Economic Data |
| Oil prices | Crude Oil Prices: West Texas Intermediate (WTI) - Cushing, Oklahoma | Federal Reserve Economic Data |
| Gold prices | $/troy oz, 99.5% fine, London afternoon fixing, average of daily rates | World Bank Commodity Price Data |
| Agricultural good prices | Weighted average of beverage, food, and raw materials | World Bank Commodity Price Data |
| Commodity total index | Weighted average of energy, non-energy and precious metal prices | World Bank Commodity Price Data |
| Energy prices | Weighted average of various coal, crude oil and nautral gas prices | World Bank Commodity Price Data |
| Non-energy prices | Weighted average of agriculture, fertilizers and metals and minerals | World Bank Commodity Price Data |
| Grains prices | Weighted average of various barley, maize, rice, sorghum and wheat prices | World Bank Commodity Price Data |
| Precious metal prices | Weighted average of gold platinum and silver prices | World Bank Commodity Price Data |
| Jamaican market data | | |
| Inflation rate | Y-O-Y changes in the consumer price index (CPI) | Bank of Jamaica |
| Exchange rate | Jamaican dollar to US dollar Spot Exchange Rate, Sales rate | Bank of Jamaica |
| Short term interest rates | 3 month Treasury bills | Bank of Jamaica |
| Money supply | M1 money aggregate | Bank of Jamaica |
| Policy rate | Bank of Jamaica policy rate | Bank of Jamaica |
| Fuel prices | The cost of electricity to residential customers ($ per kwh) | Bank of Jamaica |
| Industrial electricity sales | Electricity sold to non-residential customers in the country (in million megawatt hours) | Bank of Jamaica |
| Jamaican stock exchange index | Monthly average of daily main indices | Bank of Jamaica |
| Bank lending | Non-Business Commercial Bank Loans (J$) | Bank of Jamaica |
| Rain fall | All Jamaica rainfall measured in millimeters | Bank of Jamaica |
| Jamaican inflation survey data | | |
| Inflation expectations | Inflation expectations 12-month ahead | BOJ, Inflation Expectations Survey |
| Inflation control | Degree of satisfaction with BOJ s control of inflation | BOJ, Inflation Expectations Survey |
| Inflation expectations average | Average expected level of 12-month ahead inflation across a 12-month window | BOJ, Inflation Expectations Survey |
| Present business conditions | Index, whether conditions are the same, better or worse compared to the previous period | BOJ, Inflation Expectations Survey |
| Future business conditions | Index, whether responders expect conditions to be the same, better or worse in the future | BOJ, Inflation Expectations Survey |
| Growth | Expected level of economic growth in the next period | BOJ, Inflation Expectations Survey |
| Tbill rate (3 mth) | The projected value of the 3-month ahead Tbill rate | BOJ, Inflation Expectations Survey |
| Wage increase | Projected future wage inflation rate | BOJ, Inflation Expectations Survey |
| Exchange rate depreciation | Projected depreciation rate of the Jamaican dollar / US dollar exchange rate | BOJ, Inflation Expectations Survey |
| Highest cost - utilities | % of responders who identify utilities as the highest cost item in their outlays | BOJ, Inflation Expectations Survey |
| Highest cost - wages & salary | % of responders who identify wages and salary as the highest cost item in their outlays | BOJ, Inflation Expectations Survey |
| Highest cost - fuel & transport | % of responders who identify fuel & transport as the highest cost item in their outlays | BOJ, Inflation Expectations Survey |
| Highest cost - stock replacement | % of responders who identify stock replacement as the highest cost item in their outlays | BOJ, Inflation Expectations Survey |
| Highest cost - raw materials | % of responders who identify raw materials as the highest cost item in their outlays | BOJ, Inflation Expectations Survey |

Table 1. DFM estimation with market data

| Dependent variables | | Coefficients | Standard error |
|---|---|---|---|
| Jamaican CPI inflation | Domestic factor | 0.0088 | (0.0016)*** |
| | External factor | 0.0007 | (0.0008) |
| Rain | Domestic factor | -0.0037 | (0.0088) |
| | External factor | 0.0055 | (0.0189) |
| JMD/USD exchange rate | Domestic factor | 0.0084 | (0.0016)*** |
| | External factor | -0.0050 | (0.0015)*** |
| JSE index | Domestic factor | 0.0082 | (0.0048)* |
| | External factor | -0.0118 | (0.0101) |
| Fuel prices | Domestic factor | 0.0090 | (0.0018)*** |
| | External factor | 0.0412 | (0.0021)*** |
| Electricity fuel price | Domestic factor | 0.0003 | (0.001) |
| | External factor | 0.0115 | (0.0022)*** |
| Commercial bank lending | Domestic factor | 0.0202 | (0.0039)*** |
| | External factor | 0.0012 | (0.004) |
| M1 | Domestic factor | 0.0156 | (0.003)*** |
| | External factor | -0.0049 | (0.0036) |
| T-Bill rate | Domestic factor | 0.0905 | (0.0358)** |
| | External factor | 0.2588 | (0.0671)*** |
| Policy rate | Domestic factor | 0.0452 | (0.0283) |
| | External factor | 0.1902 | (0.0572)*** |
| Number of observations | | 81 | |
| Log likelihood | | 380.5521 | |
| Wald statistic | | 14,106 | |
| p-value | | 0.0000 | |

Note: This table reports the results obtained from the estimation of the model in equation (1) with Jamaican market data. The external factor is the common latent factor extracted from the estimation of a dynamic factor model with international financial variables. *, **, *** significant at 10%, 5%, 1%, respectively.

Table 2. DFM estimation with survey data

| Dependent variables | | Factor coefficients | Standard error |
|---|---|---|---|
| Inflation - annual | Factor | 0.0008 | (0.0002)*** |
| Inflation expectations 12mth | Factor | 0.0994 | (0.0318)*** |
| Inflation control | Factor | 1.2545 | (0.395)*** |
| Inflation Expected Average 12mth | Factor | 0.0999 | (0.032)*** |
| Present business conditions | Factor | 2.4068 | (0.7631)*** |
| Future Business Conditions | Factor | 2.1680 | (0.6822)*** |
| Growth | Factor | 0.0022 | (0.0048) |
| Tbill Projected [3mth] | Factor | 0.0671 | (0.0217)*** |
| Wage Increase | Factor | 0.0992 | (0.0313)*** |
| Exchange rate depreciation | Factor | 0.0400 | (0.0131)*** |
| Highest cost - utilities | Factor | 0.4309 | (0.1366)*** |
| Highest cost - wages & salary | Factor | 0.1301 | (0.0417)*** |
| Highest cost - fuel & transport | Factor | 0.2124 | (0.0673)*** |
| Highest cost - stock replacement | Factor | 0.4113 | (0.1297)*** |
| Highest cost - raw materials | Factor | 0.1758 | (0.0556)*** |
| Number of observations | | 80 | |
| Log likelihood | | -3,324.27 | |
| Wald statistic | | 353,485.73 | |
| p-value | | 0.000 | |

Note: This table reports the results obtained from the estimation of the model in equation (1) with Jamaican inflation survey data. *, **, *** significant at 10%, 5%, 1%, respectively.

Table 3. In-sample forecasting performance

*Panel A: Goodness of fit - market data*

| Dependent variable | Independent variable | Coefficient | Standard error | R-squared |
|---|---|---|---|---|
| Inflation | Predicted inflation | 0.8793 | (0.0552)*** | 0.7594 |
| Inflation | Inflation expectations in survey data | 0.3531 | (0.0933)*** | 0.1527 |
| *Specification that includes inflation expectations from survey data* | | | | |
| Inflation | Predicted inflation | 0.9107 | (0.0653)*** | 0.7114 |
| Inflation expectations | Predicted inflation expectations | 0.8809 | (0.0531)*** | 0.7742 |

*Panel B: Goodness of fit - survey data*

| Dependent variable | Independent variable | Coefficient | Standard error | R-squared |
|---|---|---|---|---|
| Inflation | Predicted inflation | 6.3432 | (1.3235)*** | 0.2198 |
| Inflation expectations | Predicted inflation expectations | 6.2079 | (1.1644)*** | 0.2696 |

*Panel C: Goodness of fit - market and survey data*

| Dependent variable | Independent variable | Coefficient | Standard error | R-squared |
|---|---|---|---|---|
| Inflation | Predicted inflation | 0.7348 | (0.3006)** | 0.0600 |
| Inflation expectations | Predicted inflation expectations | 0.5298 | (0.3640) | 0.0141 |

Note: Predict inflation and inflation expectations are the fitted values of inflation in the estimated dynamic factor models. The inflation expectations variable is compiled from survey responses. *, **, *** significant at 10%, 5%, 1%, respectively.

Table 4. Out-of-sample inflation forecasting performance, Root mean squared errors

| Forecast horizon (months) | Market data | Survey data | ARMA |
|---|---|---|---|
| 1 | 0.559 | 2.485 | 0.576 |
| 2 | 0.409 | 2.592 | 0.407 |
| 3 | 0.336 | 2.442 | 0.359 |
| 4 | 0.454 | 2.267 | 0.330 |
| 5 | 0.471 | 3.115 | 0.300 |
| 6 | 0.711 | 3.681 | 0.356 |
| 7 | 0.719 | 3.891 | 0.341 |
| 8 | 0.677 | 3.944 | 0.455 |
| 9 | 0.735 | 3.891 | 0.434 |
| 10 | 0.959 | 3.899 | 0.463 |
| 11 | 1.165 | 3.943 | 0.513 |
| 12 | 1.556 | 3.838 | 0.787 |

Note: The table displays the accuracy of the three models in predicting inflation. The root mean squared error for a specific horizon, say horizon $x$,is computed as the square root of the sum of squared forecast errors for each period including and preceding period $x$.ARMA(2,1) specification is used for comparison as this univariate specification generates the lowest root mean squared errors.

Table 5. Out-of-sample inflation expectations forecasting performance, Root mean squared errors

| Forecast horizon (months) | Market data | Survey data | ARMA |
|---|---|---|---|
| 1 | 0.111 | 0.415 | 0.465 |
| 2 | 0.676 | 0.942 | 0.735 |
| 3 | 1.074 | 1.353 | 0.783 |
| 4 | 1.601 | 1.861 | 0.809 |
| 5 | 2.639 | 2.853 | 0.760 |
| 6 | 3.321 | 3.538 | 0.778 |
| 7 | 3.805 | 4.017 | 0.818 |
| 8 | 4.045 | 4.250 | 0.881 |
| 9 | 4.113 | 4.314 | 0.958 |
| 10 | 4.161 | 4.352 | 1.038 |
| 11 | 4.193 | 4.371 | 1.119 |
| 12 | 4.221 | 4.387 | 0.839 |

Note: The table displays the accuracy of the three models in predicting inflation expectations. The root mean squared error for a specific horizon, say horizon $x$,is computed as the square root of the sum of squared forecast errors for each period including and preceding period $x$.ARMA(2,1) specification is used for comparison as this univariate specification generates the lowest root mean squared errors.

Table 6. Alternative specifications for inflation forecasting

| | Forecast horizon (months) | DFM | ARMA |
|---|---|---|---|
| Baseline, market data | 1 | 0.559 | 0.576 |
| | 12 | 1.556 | 0.787 |
| Market data with inflation expectations | 1 | 0.652 | 0.576 |
| | 12 | 1.545 | 0.787 |
| Two factors | 1 | 0.557 | 0.576 |
| | 12 | 1.670 | 0.787 |
| AR(2) | 1 | 0.398 | 0.576 |
| | 12 | 1.581 | 0.787 |
| AR(4) | 1 | 0.678 | 0.576 |
| | 12 | 1.229 | 0.787 |
| Endogenous AR(1) and Factor AR(2) | 1 | 0.181 | 0.576 |
| | 12 | 1.733 | 0.787 |
| Parsimonious model | 1 | 0.464 | 0.576 |
| | 12 | 0.736 | 0.787 |
| Parsimonious Endogenous AR(2) and Factor AR(2) | 1 | 0.376 | 0.576 |
| | 12 | 1.348 | 0.787 |

Note: The table compares the accuracy of the DFM and the ARMA(2,1) model for forecasting 1-month ahead and 12-month ahead inflation under different specifications. The DFM model is estimated by using Jamaican market data and the external latent factor as an exogenous variable.

Table 7. Rolling forecasts, DFM versus ARMA

| | Forecast errors for each horizon | | Cumulative forecast errors | |
|---|---|---|---|---|
| Forecast horizon (months) | DFM | ARMA | DFM | ARMA |
| 1 | 1.066 | 1.073 | 1.066 | 1.073 |
| 2 | 1.677 | 1.658 | 1.405 | 1.397 |
| 3 | 2.128 | 2.144 | 1.681 | 1.683 |
| 4 | 2.380 | 2.430 | 1.880 | 1.898 |
| 5 | 2.663 | 2.753 | 2.061 | 2.097 |
| 6 | 2.840 | 2.955 | 2.210 | 2.262 |
| 7 | 3.038 | 3.158 | 2.346 | 2.411 |
| 8 | 3.300 | 3.409 | 2.485 | 2.557 |
| 9 | 3.539 | 3.653 | 2.623 | 2.701 |
| 10 | 3.630 | 3.752 | 2.741 | 2.824 |
| 11 | 3.581 | 3.702 | 2.828 | 2.914 |
| 12 | 3.440 | 3.585 | 2.884 | 2.976 |

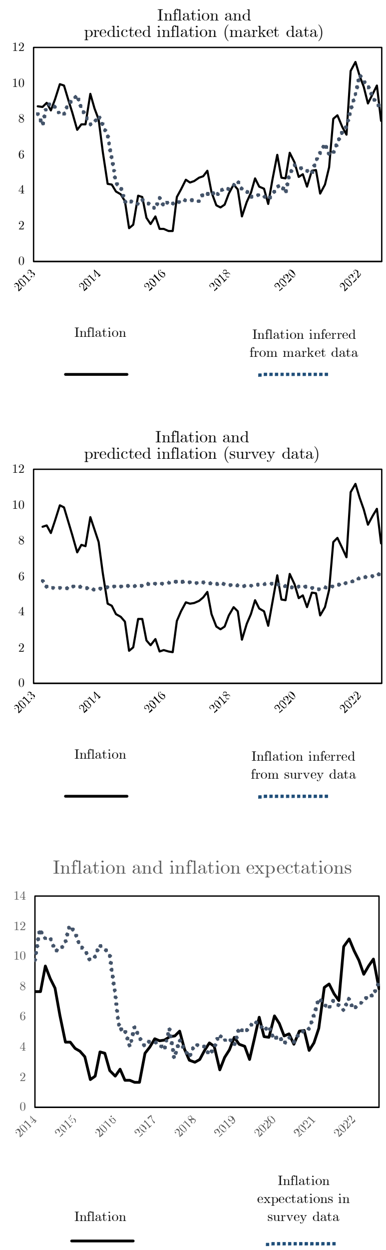
Note: The table shows the average root mean squared errors for the DFM and ARMA models computed across twelve 1 year rolling windows that start with the April 2021 to March 2022 window and end with the April 2022 to March 2023 window.

Table 8. Other comparisons

| Forecast horizon (months) | DFM | BOJ | DSGE |
|---|---|---|---|
| 1 | 0.559 | 0.868 | |
| 2 | 0.409 | 1.619 | |
| 3 | 0.336 | 2.395 | 3.113 |
| 4 | 0.454 | 2.811 | |
| 5 | 0.471 | 2.931 | |
| 6 | 0.711 | 2.926 | 9.825 |
| 7 | 0.719 | 2.800 | |
| 8 | 0.677 | 2.676 | |
| 9 | 0.735 | 2.591 | 10.232 |
| 10 | 0.959 | 2.563 | |
| 11 | 1.165 | 2.505 | |
| 12 | 1.556 | 2.476 | 9.740 |

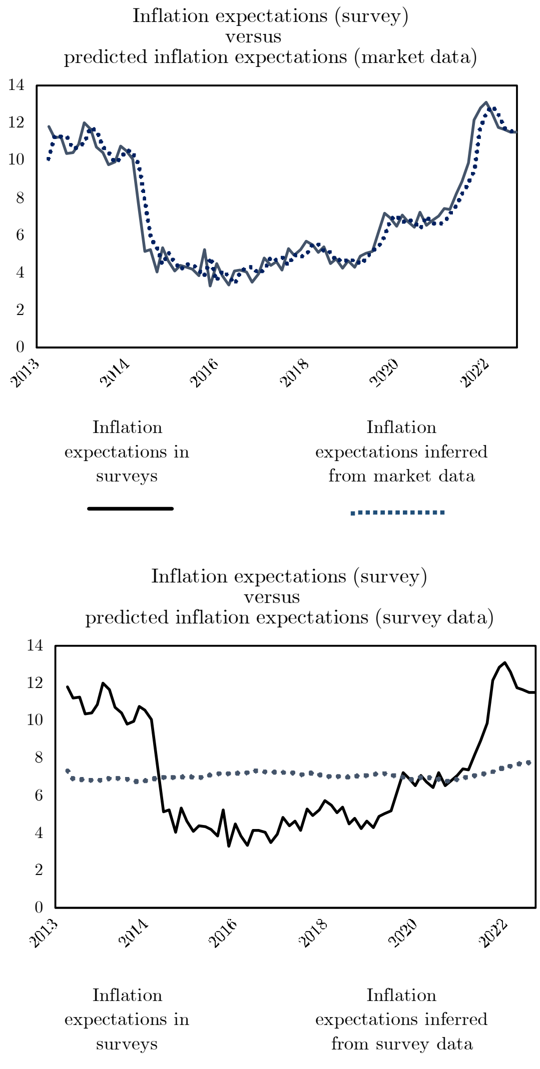
Note: BOJ forecasts are obtained from an ARMA-X specification and the DSGE forecast are obtained by estimating the 3-country model in Aysun (2022).

Figure 1. Market versus survey based prediction of inflation



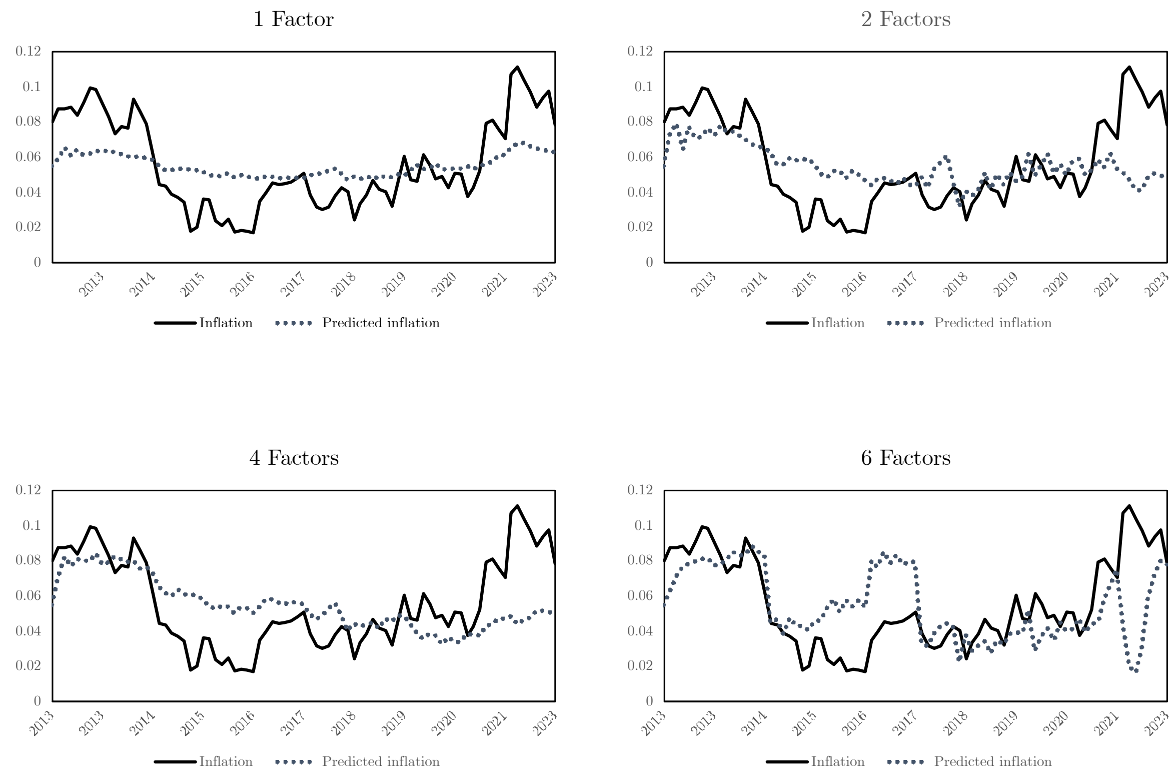

Note: The inferred values of inflation in the first two plots correspond to the fitted values of inflation after estimating the DFM with market and survey data, respectively. The inflation expectations variable is compiled from survey responses.

Figure 2. Market versus survey based prediction of inflation expectations




Note: The inferred values of inflation expectations in the first and second plots correspond to the fitted values of inflation after estimating the DFM with market and survey data, respectively. The inflation expectations variable is compiled from survey responses.

Figure 3. Principal components method of predicting inflation




Note: The predicted values of inflation are obtained by using all 420 survey variables to estimate a static factor model with different principal components.