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Firm Level Expectations and Macroeconomic Conditions: Underpinnings and Disagreement

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Abstract

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Keywords

forecast disagreement, firm level, labor, professional forecasts, Bureau of Economic Research, South African Reserve Bank

JEL Classification

E37, E31, E47, E32, E58

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FIRM LEVEL EXPECTATIONS AND MACROECONOMIC CONDITIONS:

Underpinnings and Disagreement

Monique Reid* and Pierre Siklos**

This Draft: December 2023

ABSTRACT

Abundant evidence that the inflation expectations of financial analysts differ in economically important ways from those of non-financial specialists, has been followed by increasing demand for firm level data, in an attempt to more accurately capture the views of price setters. The unusually rich firm level survey data from South Africa allows us to explore some of the ways in which the expectations of firms differ from that those of other groups surveyed. We focus specifically on forecast disagreement, which can offer insights about the level of uncertainty reflected in the data, as well as the degree to which expectations are anchored. We find that divergence of inflation forecasts amongst respondents is partly explained by differences in how respondents believe the broader macroeconomy is evolving. We also consider the impact of different types of aggregation of the data. It is when we construct a new measure of macroeconomic disagreement that combines all the variables being forecast that we are able to see that forecasters responded sharply in early 2020 as the pandemic emerged.

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1. Introduction

Abundant evidence that the inflation expectations of financial analysts differ in economically important ways (Binder, 2015) from those of non-financial specialists, has been followed by increasing demand for firm level data (Bernanke, 2007). This is part of a larger attempt to capture the views of price setters and understand how inflation expectations behave[1]. In an attempt to capture the views of the price setters in an economy, the expectations of households have received considerable attention recently, but there remains comparatively little evidence about the forecasting behavior of firms, due at least in part to the small number of data sets available (see Coibion et al. (2020); Reid and Siklos (2022)). The unusually rich firm level survey data from South Africa, which has been collected at a quarterly frequency for over twenty years, allows us to explore some of the ways in which the expectations of firms differ from that those of other groups surveyed.

In this paper, we focus specifically on one characteristic of these expectations – disagreement – which can contribute to providing insights, such as the level of uncertainty survey respondents are experiencing, as well as how well anchored these inflation expectations are. There exists a rich literature that empirically and theoretically examines the nature and behaviour of forecast disagreement. This literature provides substantial empirical evidence showing that forecasters disagree, but it has tended to focus on surveys of professional forecasters. The literature also remains inconclusive about the nature of forecast disagreement and its origins, requiring further empirical evidence to narrow the differences of view.

The present study makes three contributions. Firstly, it employs an under-utilized data set from South Africa (SA) that is exceedingly rich. Our primary focus is to contribute to the body of knowledge about forecast disagreement among firms' expectations, but we also compare this to forecast disagreement of financial analysts and trade unions (trade organisations).[2] Financial

[1] The broader literature on inflation expectations is now vast so we do not try to offer a full review of it in this paper. Instead, we refer readers to Coibion et al (2020) for an overview of the current state of the literature that focuses on firm level data in particular, and see Reid and Siklos (2021) for a review of academic contributions using the South African inflation expectations survey data.

[2] Our study complements an earlier study (Reid et. al., 2021) that looks at household level inflation forecasts of inflation in SA since the introduction of inflation targeting in that country. The results discussed below also fit in the broader literature on forecast disagreement and its sources (e.g., see Siklos, 2019).

analysts provide a natural benchmark, because they have received the most attention in the literature. The comparison with trade union expectations is far less common, but interesting because of the relatively high level of unionisation in South Africa and periodic concerns about the effect of wage pressures on inflation. Unlike much of the extant data used in studies across several economies, we have at our disposal a relatively long time series, consisting of micro data at a quarterly frequency, covering a period of more than twenty years. The data span a sample when a single monetary policy regime, namely inflation targeting, was in place.

Secondly, besides the standard measures of forecast disagreement used in the literature, we also create a new indicator of macroeconomic forecast disagreement. We use a factor model to take advantage of the fact that the dataset also includes forecasts of other macroeconomic variables. Using this factor model is a way of considering the impact of a different type of aggregation. There is a well-established view that consensus style forecasts tend to be superior (i.e., the wisdom of the crowd argument), which is important since central banks cannot tailor the stance of monetary policy to different groups in society. This indicator of macroeconomic disagreement provides evidence of the impact of the COVID-19 pandemic on expectations and reveals how forms of aggregation in inflation forecasts impact our interpretation of the data. Nevertheless, we empirically demonstrate that, even if this is the case, disaggregating expectations data can yield useful information that the monetary authority can use to fine tune how it communicates with different audiences[3] (e.g., see Portelance (2021) and references therein).

Our third contribution is an analysis of differences in disagreement across a number of factors – the industry the respondent is part of, different occupations of respondents (e.g., economists versus CEOs), and differences in respondents' forecasts of other macroeconomic variables.

Our findings reveal that when forecasters disagree about future inflation it is because they also disagree about the future course of other key macro-financial variables, suggesting that the divergence in their forecasts are at least partly due to the fact that they also disagree about how the

[3] For example, the SARB holds a press conference at the end of the monetary policy committee meeting. Monetary Policy Forums are also held at various venues around the country when the Monetary Policy Review is released to engage with the SARB directly.

broader macroeconomy is evolving. Inflation forecast disagreement is also partially driven by past observation of the series being forecast, reflecting a level of persistence in inflation expectations. The source of disagreement is also sensitive to the level of aggregation in the data. It is when we construct a new measure of macroeconomic disagreement that combines all the variables being forecast that we are able to see that forecasters responded sharply in early 2020 as the pandemic emerged. That said, our findings on the determinants of inflation forecast disagreement are uninformative about whether this is due to a form of inattention, to differences in what the past portends for the future, to certain socio-economic characteristics of the forecasters that we are unable to quantify, or to some type of bias in how disagreement about future inflation emerges. Nevertheless, the results do point to the value of analysing individual level forecasts and the potential for these to provide insights into how a central bank might consider communicating differently with different audiences.

While we do not explicitly aim to draw comparisons with other economies in this paper, we do place these findings from South Africa (an emerging market economy) within the larger literature, which has focused primarily on findings from advanced economies. This South African experience holds insights of broader application, the country was an inflation targeter over the entire period and experiences regular supply shocks. South Africa offers a test case for the resilience of inflation targeting under supply shocks at a time when international interest covid19 experience and efforts design systems able to cope with the impacts of climate change have piqued interest in the topic.

The rest of the paper is organized as follows. We provide a brief literature review in the following section, followed by a presentation of the BER dataset. Next, we discuss how disagreement is measured in this paper, including the construction of a macroeconomic forecast disagreement indicator. This is followed by an explanation of the empirical methodology adopted, some stylised facts about the data, and empirical findings. Finally, more formal econometric analysis is used to explore the sources of forecast disagreement, before concluding with a summary, potential limitations of our study and some policy implications.

2. Related Literature

Siklos (2019) provides a recent overview of the literature on forecast disagreement. The literature explores concepts such as the extent to which disagreement can act as a proxy for uncertainty and tries to identify factors which are likely to increase (decrease) disagreement. However, there are several important questions about which a fair amount of divergence remains. Not only do multiple theories seek to explain why forecasters disagree, ranging from differences in implicit or explicit forecasting models to cognitive limitations (e.g. Dovern and Hartmann, 2017), but several indicators have been proposed to quantify forecast disagreement (e.g. Schultefrankenfeld, 2020).

The link between uncertainty and disagreement has attracted considerable interest, but the extent to which disagreement is a useful proxy for uncertainty generates mixed evidence. Bachmann et. al. (2013) report that forecast errors are correlated with forecast dispersion and that uncertainty and disagreement may be treated as proxies for each other.[4] In contrast, Lahiri et. al. (2015) posit that uncertainty is only one element of the concept of disagreement. Boero et. al. (2015) point out, in their survey of the theory and evidence, that "…disagreement is a useful proxy for uncertainty when it exhibits large fluctuations…" (op. cit., p. 1044), perhaps explaining the overall weak link between uncertainty and disagreement (e.g., see Glas, 2020; Rich and Tracy, 2021).

Other difficulties to consider include whether to use point estimate forecasts or density forecasts (e.g., see Knüppel and Krüger, 2019), and the choice of forecast horizon (e.g., see Glas, 2020), where more uncertainty is likely at longer horizons. Clements and Galvão (2014) also propose a distinction between ex ante and ex post measures of uncertainty (i.e., measures determined by models and probabilistic considerations versus those determined by realized data) and conclude that ex ante tracks well ex post uncertainty when the forecast horizon is short.

Even if there is limited consensus on the time series properties of forecast errors, it is widely accepted that they are riddled with biases and inconsistencies. Nevertheless, the existence of a common factor across forecasts or forecast errors is useful because it suggests that forecasters consider comparable sources of information when forming expectations even if they disagree. Jurado et. al. (2015) investigate dispersion versus uncertainty concepts to empirically identify

[4] Based on the German Ifo Survey of Business Climate conducted by the Institute for Economic Research housed at the University of Münich.

salient uncertainty ‘events’ for the US. They find that uncertainty rises in recession as well as when the forecast horizon lengthens. The authors interpret uncertainty as the common latent factor among individual measures of uncertainty.

These findings about how to measure disagreement and how well it proxies uncertainty are related to the question of how information generates disagreement, since signals (e.g., macroeconomic news) are digested differently by different forecasters. Disagreement can reflect differences in views, for example, about predictions about future recessions (e.g., see Bürgi and Sinclair, 2021) or expected future macroeconomic and financial conditions more generally because signal-to-noise ratios can differ.

Glas and Hartmann (2015) rely on data from the Survey of Professional Forecasters (SPF) conducted by the European Central Bank (ECB) to show that rising inflation uncertainty precedes a deterioration of forecasting performance. Bauer (2015) explore the role of news by using US Blue Chip and SPF forecasts to estimate their sensitivity to macroeconomic news. He concludes that targeting inflation contributes to reducing the volatility of inflation expectations, representing an effective anchoring device. Similarly, Badarinza and Buchmann (2009) find that better anchoring of expectations reduces forecast disagreement for evidence from the Eurozone, and using households data, Kamada et. al. (2015), and Nishiguchi et. al. (2014) both report that central bank announcements in Japan (e.g., the introduction of quantitative and qualitative easing or QQE) can shift the distribution of expectations towards the announced objective. Strohsal et. al. (2015), and Strohsal and Winkelmann (2015), also consider the role of news effects and reach the strong conclusion that inflation was almost “perfectly” anchored in the U.S. since 2004.

Empirical results must also confront different views about how households, firms, and professional forecasters form expectations. This is particularly important for policy makers who need to understand how inflation expectations are formed in order to try influence these. Caroll (2003) argues that households acquire information more slowly that their professional counterparts, whereas Coibion and Gorodnichenko (2012) see no systematic differences in the processing of information across different groups. There is, however, substantial evidence that the forecasts of some professional forecasters represent an attractor for those of other professional forecasters.

Clements (2015) demonstrates that forecast differences amongst US SPF forecasts become larger the longer the forecast horizon, although there is a form of herding of forecasts at short horizons.

The global increase in central bank transparency is well-known (Dincer and Eichengreen, 2014; Dincer, Eichengreen and Geraats, 2019, 2022), but there are also differing views about its connection with disagreement. For example, Brito et. al. (2018) finds that disagreement falls with the adoption of IT, but only in developing economies. Given that IT and communication have long been thought to go hand in hand it is less obvious whether the regime, or how it is presented to the public, is what drives changes in forecast disagreement (Seelajaroen et. al., 2020). Forecast disagreement may rise with relatively higher transparency given that more information creates the opportunity for greater noise (Siklos, 2013).[5]

While we do not explicitly test, in this paper, whether forecast disagreement can proxy for uncertainty and whether central bank transparency reduces disagreement, the literature does provide motivation to explore ways to measure disagreement, identify some of the challenges in doing so, and provide context for interpreting our own results. In the sections that follow, we introduce the BER data set, consider ways to measure forecast disagreement using this data, and explore some of the sources of the disagreement.

3. The BER Data Set

Since 2000, when inflation targeting became the monetary policy strategy of the SARB, the BER has surveyed trade unions, businesses, and financial analysts on a quarterly basis on behalf of the SARB.[6] The dataset consists of individual level forecasts at several horizons for a variety of critical macroeconomic and financial time series. Some additional characteristics are also collected about the survey respondents, such as the industry in which a firm operates. Each respondent is identified

[5] Studies that conclude that a negative link exists between forecast disagreement in such regimes and transparency (e.g., Jitmareeroj et. al., 2019) tend to distinguish them from other regimes using a 0,1 dummy. Given the heterogeneity of IT regimes it is debatable whether this is the appropriate specification.

[6] Between 2000 and 2003 the quarterly surveys were conducted in February, May, August, and October. Since that time the February and October surveys were shifted to March and November. The timing of the remaining two surveys is unchanged.

only by an ID number, as they are guaranteed anonymity,[7] but we are able to establish that there are few duplicate individuals surveyed over time.[8]

The principal questions in the BER survey elicit forecasts of inflation (headline). The precise wording for the inflation question is: "What do you expect average headline inflation rate to be during the year." Respondents are then asked to fill in boxes for the current calendar year and the next two. There is some "priming" because respondents are provided with average annual inflation rates (actual inflation outturns) for the calendar year that precedes the survey, as well the mean annual inflation rate over the past five years. Respondents also are asked "What do you expect the average CPI inflation rate to be over the next five years?" to capture longer-term inflation expectations. A scanned copy of the survey is provided in the appendix.

A fixed event horizon is adopted in the survey. This means that a forecast for inflation covering a particular calendar year, rather than a fixed horizon of one quarter or one year ahead. Fixed event data can be converted into a fixed horizon, but we retain the fixed event form and note that, with minor exceptions, either set of forecasts generate similar results (see Reid and Siklos, 2021).

The survey is notable in at least three respects. First, the BER also asks for forecasts for a wide range of key macro-financial variables. Trade unions and firms also provide forecasts for the GDP growth rate, the prime interest rate[9], wage and salary growth, and the rand/US dollar exchange rate. Financial analysts forecast growth rates in the M3 money stock,[10] the yield on long-term government bonds, and the capacity utilization rate in the manufacturing sector (percentage utilisation of production capacity), in addition to questions about inflation and economic growth. Second, as described above, respondents are for forecasts of inflation at 3 horizons and, since 2011Q2, a five year horizon as well. Finally, the data set is one of the longest consistent time series we are aware of (Coibion et. al., 2020; Reid and Siklos, 2022), covering almost 25 years.

[7] The raw expectations data are available from the BER on written request.

[8] More precisely, 7.45% of trade union respondents, 6.50% of businesses, and 5.08% of financial analysts are duplicates over the complete sample.

[9] That is, the interest rate charged by commercial banks for loans to their best customers.

[10] M3 is a broad money supply measure that includes notes, coins, commercial bank deposits, time deposits, money market funds, and other liquid financial assets.

Greater detail about the data for the full sample considered in this study (2000Q2-2020Q4) is available in the appendix, but we highlight a few relevant characteristics here. The number of respondents in the firm component of the survey is far greater than for the other two groups. The BER uses convenience sampling, so the fraction of firms surveyed is not formally linked to the relative size of each sector in the South African economy, although effort it made to ensure that a variety of sectors is adequately represented in the sample. This BER sample composition also appears to be fairly stable over time. Finally, the vast majority of the firm respondents are in senior decision-making positions within the firm, so their forecasts are likely to impact the price setting behavior of the firm.

4. Measures of Disagreement and Econometric Methodology

There is no universally agreed upon measure of inflation forecast disagreement. Commonly used indicators include a measure of forecast dispersion and the inter-quartile range (IQR) of forecasts (e.g., Mankiw, Reis, and Wolfers (2003), Capistrán and Timmermann (2008)), both of which we adopt in the results below. The dispersion indicator has the virtue of retaining all the available information[11] (including the proverbial 'black swan'), but the results are potentially vulnerable to extreme forecasts. That said, sharp changes in forecast disagreement emerge at the same time regardless of the disagreement measure employed, and there are very few extreme forecasts, as measured by the usual 3 or more standard deviations from the mean.

For the squared deviations measure of forecast disagreement (i.e., forecast dispersion),[12] let d_{th}^{j} represent disagreement about forecast F at time t, h periods ahead, for variable z (e.g., CPI inflation) and firm j. Intuitively, forecast disagreement is relative to some benchmark. Typically, the benchmark is the mean or consensus forecast, $\bar{F}$ (e.g., see Glas (2020); Siklos (2019)). Hence, we write

[11] Boxplots (not shown) for several measures of disaggregated expectations among all three groups that confirm: (1) mean and median estimates of expectations are very close to each other. The largest gap between the two measures are for the long-term expectations. However, as explained below, the sample for 5 years ahead inflation expectations is considerably shorter than for the other available horizons and is measured somewhat differently from the other inflation forecast series; (2) the IQRs are extremely narrow in almost all cases examined and a non-negligible portion of the distribution of expectations would be left out from the analysis which could be seen as ad hoc.

[12] The measure used here comes closest to the one used in Lahiri and Sheng (2008) while the transformation applied yields a version that is the normalized absolute deviation of forecasts implemented by Banternghansa and McCracken (2009).

$$d_{th}^{zj} = \frac{1}{N_j - 1} \sum_{i=1}^{N_j} (F_{ith}^{zj} - \bar{F}_{gth}^{zj})^2 \quad (1)$$

where F is the forecasted variable (z), N_j is the number of forecasts, i identifies the forecast, and $\bar{F}^j$ represents the mean forecast across a chosen group g (for example, industries or the position of survey respondents) across firms j. The consensus forecast is typically used for $\bar{F}$, but other groups whose forecasts can provide an influential benchmark can be used (e.g., a central bank forecast or the forecasts of professionals).[13] Alternatively, if the inflation targeting regime is credible, $\bar{F}$ would then represent the announced numerical inflation target.

Most of the results in this paper assume, as is common in the extant literature, that $\bar{F}$ is the consensus forecasts across all groups (i.e., firms, labor, and financial analysts). We did test robustness using the SARB's inflation target (4.5%), as well as grouping[14] by industry and occupation of the respondent, but these did not change the conclusions. There were too few published data of the SARB's inflation and real GDP growth forecasts available (since 2015; see Reid and Siklos, 2022) to enable robustness testing using these.[15]

Once the forecast disagreement measures are obtained, we explore econometrically their determinants. We ask whether the forecast disagreement for macroeconomic variables for which the central bank provides an outlook (inflation and GDP growth), are linked to disagreement in other macroeconomic or financial variables that are believed to be related according to economic theory. We also condition on other information that might be available at the time forecasts are made, that is, lagged observed values of all the variables being forecast. The estimated specification is hence,

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[13] Outside forecasts can be grouped in a variety of ways to generate forecast combinations. These include ones prepared by central banks, survey-based forecasts conducted among households, a set of forecasts by public agencies (i.e., OECD, IMF, Consensus), as well as a group consisting of professional forecasts (e.g., Consensus, Survey of Professional Forecasters).

[14] This is motivated by the considerable evidence that favors simple forecast combinations over other forms of forecast aggregation or forecasts made by specific forecasters (e.g., see Timmermann, 2006).

[15] We also note that equation (1) can also be converted into an indicator that ranges between zero and 1 via normalization. Since none of the conclusions are affected by this transformation, we only mention the effect of normalizing forecast disagreement when providing additional insights into the results. A normalized version of (1) would be written $\tilde{d}_{th}^{zj} = \left| \sqrt{\frac{1}{N_j - 1} \sum_{i=1}^{N_j} (F_{ith}^{zj} - \bar{F}_{gth}^{zj})^2} \right|$ where d_{th}^{j} is bounded between [0,1] using the transformation $(d - d_{min})/(d_{max} - d_{min})$.

$$\tilde{d}_{th}^{zj} = \boldsymbol{\alpha} + \boldsymbol{\Theta}_{\delta}\widetilde{\boldsymbol{D}}_{\boldsymbol{th}}^{\delta j} + \mathbf{B}\boldsymbol{\Gamma}_{t-1} + \eta_{\boldsymbol{t}} \tag{2}$$

where disagreement was previously defined, $\boldsymbol{\alpha}$ are fixed effects, **D** is a vector of variables that includes disagreement other than for inflation. In principle, of course, one can also ask whether disagreement in any of the variables is related to others with a lag, in which case equation (2) could be re-written as a vector autoregression (VAR). However, to conserve space, we limit our analysis to the relationship between disagreement in inflation and the other forecasts respondents are asked to make. $\boldsymbol{\Gamma}$ is a vector of observables (lagged values of the series being forecasted). As noted in the literature review, inattention, to name one explanation, may well lead forecasters to avoid paying attention to outturns in the series being forecasted. Therefore z=[π], while $\boldsymbol{D}^{\boldsymbol{\delta}} \neq z$ represents the vector of other variables that are forecasted. We provide the details in the next section.

As discussed above, the series respondents are asked to forecast are endogenous in which case it can be appropriate to estimate a VAR. Expectations are usually modelled as being partially dependent on past inflation, but the response of expectations may also partially fuel future inflation.[16] A potential disadvantage of the VAR approach is that identification is needed to recover the structural coefficients. Strategies for doing so are often tailored to the question at hand, but given that there is no established theory about how disagreement between different macro-financial variables are causally related, we exploit the information content about disagreement for the available time series.

A popular alternative to a VAR is estimating a factor model. A single series is created by linearly combining related series that are believed to be linked to inflation. The technique offers a parsimonious way of utilizing considerable amounts of data (in this case across the different macroeconomic and financial variables being forecasted). We restrict attention to factor models

[16] The clearest case is the adaptive expectations model where expectations are determined by the past history of inflation and previous forecast errors. Similarly, when expectations are self-fulfilling then changes in expectations impact future inflation. An illustration is when certain prices are expected to rise in future (e.g., goods or services) this may prompt economic agents to raise their demand for them today. Other things equal, this would generate more inflation.

for each available horizon (h) and socio-economic groupings (κ). We write the model to be estimated as follow:

$$\mathbf{X}_{th}^{\kappa} = \mathbf{\Lambda}\mathbf{\Omega}_{th}^{\kappa} + e_{th}^{\kappa} \tag{3}$$

where **X** is the vector of disagreement in all the variables that are forecasted, κ are the socio-economic groupings for which factor models are estimated, h is the forecast horizon, **Λ** are the factor loadings, and **Ω** are the factors. Our results below show that this approach yields new insights into how forecast disagreement evolves when forecasts of different, but related, macro-financial variables are combined.

5. Stylized Facts about the Data and Empirical Results

4.1 Summary Statistics and Stylized Facts

Table 1 and Figure 1 provide some stylized facts. Table 1 captures the mean inflation forecast (and standard deviation) for each of the 3 groups, at the different forecast horizons. For all the horizons, the mean forecasts of the financial analysts were the lowest and those of the businesses were the highest. The standard deviation of the forecasts of all three groups decreases as the horizon lengthens, and this happens most rapidly for the financial analysts. It is, however, interesting to note that financial analysts do perform the worst along this metric for the current year forecasts. To conserve space, we do not show the average forecasts of the other macroeconomic variables in the survey (e.g., GDP growth), but these are available in the appendix. .[17] Financial analysts' forecast of inflation are, on average, the lowest of the three groups with businesses forecasting higher average inflation at all horizons.[18]

TABLE 1 – Aggregate Expectations for Different Macro-Financial Variables from the BER Survey: Full Sample 2000Q2-2020Q4

Forecast		***Labor***	***Businesses***	***Financial Analysts***
Definition	**Label**	**Mean (SD) - %**	**Mean (SD) - %**	**Mean (SD) - %**
Current year inflation	CPI_T0	6.07 (1.52)	6.29 (1.56)	5.70 (1.81)
Year ahead inflation	CPI_T1	6.16 (1.32)	6.39 (1.27)	5.46 (0.82)
Two years ahead inflation	CPI_T2	6.22 (1.23)	6.41 (1.09)	5.28 (0.44)

[17] Obviously, the same individual need not generate the highest and/or lowest forecasts through time.
[18] Tables providing comparisons between means and medians for groups across the full sample are shown in the appendix.

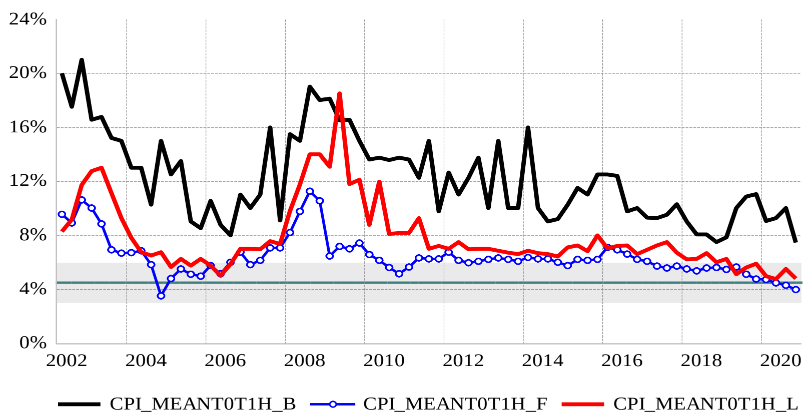
Five years ahead inflation	CPI5a	5.75 (0.64)	6.15 (0.48)	5.34 (0.35)

Source: BER and authors' calculations.

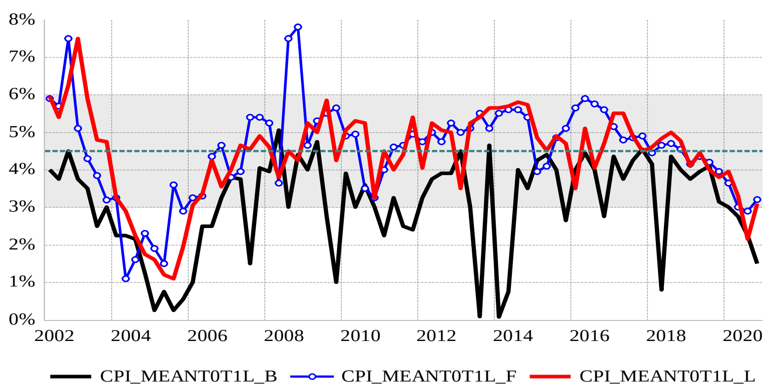
Figure 1, divided into two parts, depicts the range of inflation forecasts across the different groups surveyed, focusing on the current and one year ahead expectations that dominate the literature. The top portion of Figure 1 plots the highest individual inflation forecasts followed by the lowest individual inflation forecast displayed in the lower figure.

FIGURE 1 – Highest and Lowest Inflation Forecasts: Trade Union, Businesses, and Financial Analysts, 2000Q2-2020Q4

(a) Highest



(b) Lowest



Note: MEANT0T1 is the simple average of current and one year ahead inflation forecasts. B represents the business sector, F the financial analysts, and L is for labor (trade unions). The shaded horizontal area is the SARB's inflation target of 3 to 6%.

The figures reveal considerable variation over time and across the three groups surveyed. Firm respondents who forecasted the lowest inflation rates are relatively more responsive to major economic events compared with the same respondents who predicted higher inflation. For example, we observe higher volatility in inflation expectations during 2013 and 2014 at the time of severe labor unrest in the mining industry. High volatility between the end of 2015 and 2018 is very likely influenced by local political turmoil caused by the sudden firing of the Minister of Finance in December 2015 (Nenegate), followed by events leading up to the resignation of the State President, Jacob Zuma in February 2018. Problems with electrical generation capacity leading to load shedding (from about 2007 to the present day), as well as the mounting costs from an severe drought (peaking in 2017-2018) are also likely to have contributed. The impact of these events is less noticeable from the group of firms that expected relatively higher inflation. The sensitivity of different groups to the COVID-19 pandemic is, again, higher among the respondents who forecast lower inflation than among those whose inflation expectations are highest.

4.2 Patterns in Forecast Disagreement

The SARB's mandate over the sample is an inflation target defined by a 3 to 6% range and, since 2017, the SARB has explicitly targeted the mid-point at 4.5%. Figures 2 to 4 provide key details of the evolution of inflation forecast disagreement over time and across various levels of disaggregation of the data.[19] Unsurprisingly, the most visible impact on forecast disagreement, at all forecast horizons, is the period of the GFC (2009-2010).[20] Respondents from the businesses display levels of disagreement that are only marginally lower than those of trade unions and far higher than financial analysts at the three shorter horizons. At the 5-year horizon, the pattern is similar, but forecast disagreement of labour is more volatile and slightly lower than that of firms. This slight change may simply be due to the smaller sample size of the labor group.

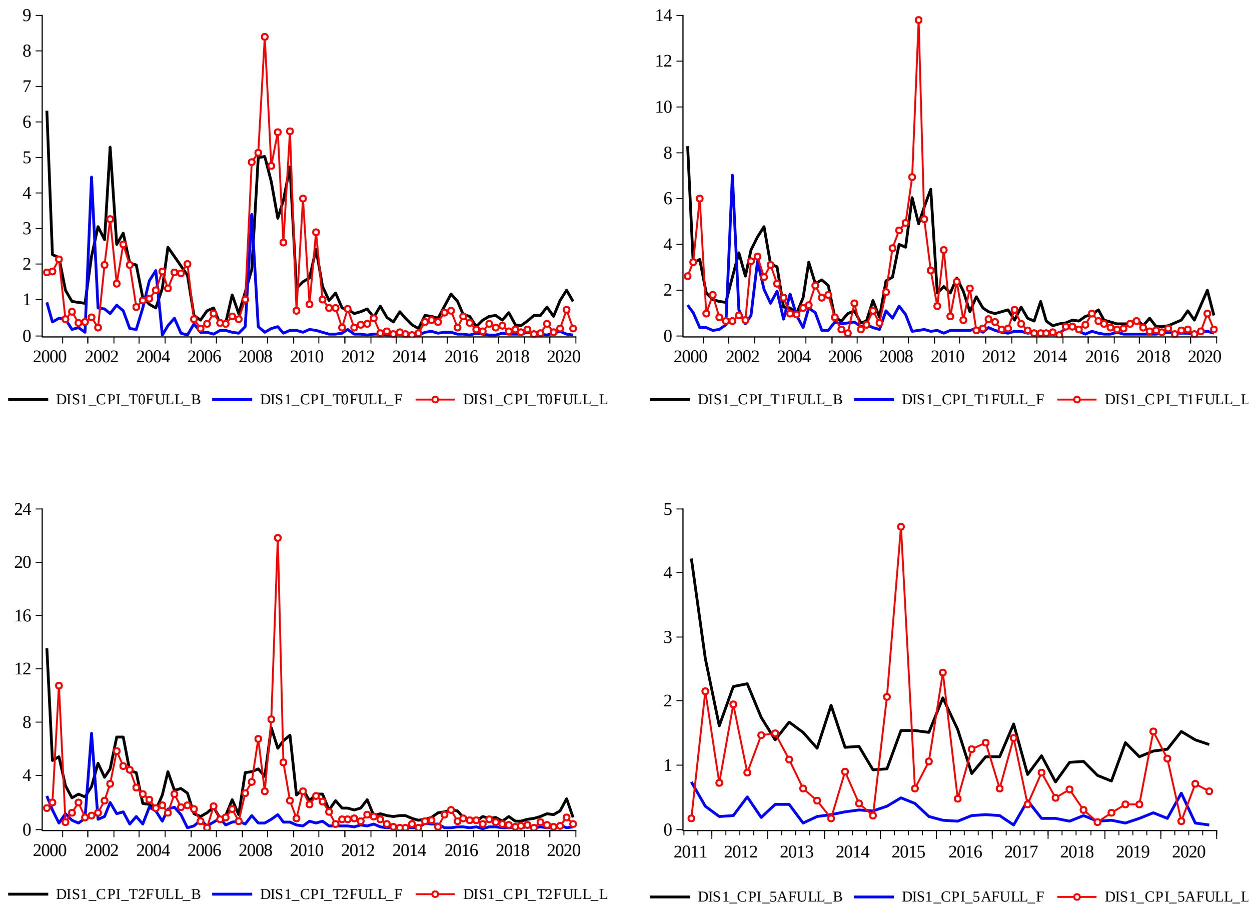
Generally, disagreement is far more volatile during the early years of the IT regime, with notable increases in 2001/2002 at the time of the exchange rate crisis, in 2004/2005 at a time when inflation was surprising observers at levels lower than any seen in approximately 35 years, and then in 2009/2010 as the effects of the GFC were experienced in SA. Disagreement is both lower and more stable post-GFC, particularly after approximately 2012. The arrival of the COVID-19

[19] Unless stated, the conclusions drawn from Figures 2 and 3 are the same even if the various measures of forecast disagreement are disaggregated.

[20] Unfortunately, long-run inflation expectations data begin after the GFC period so we are unable to examine how longer horizon expectations may have been impacted by the financial crisis.

pandemic sees only a small impact on forecast disagreement, although a visible decline in disagreement begins to emerge beginning the second quarter of 2020.

FIGURE 2 – Overall Disagreement By Major Groups Surveyed



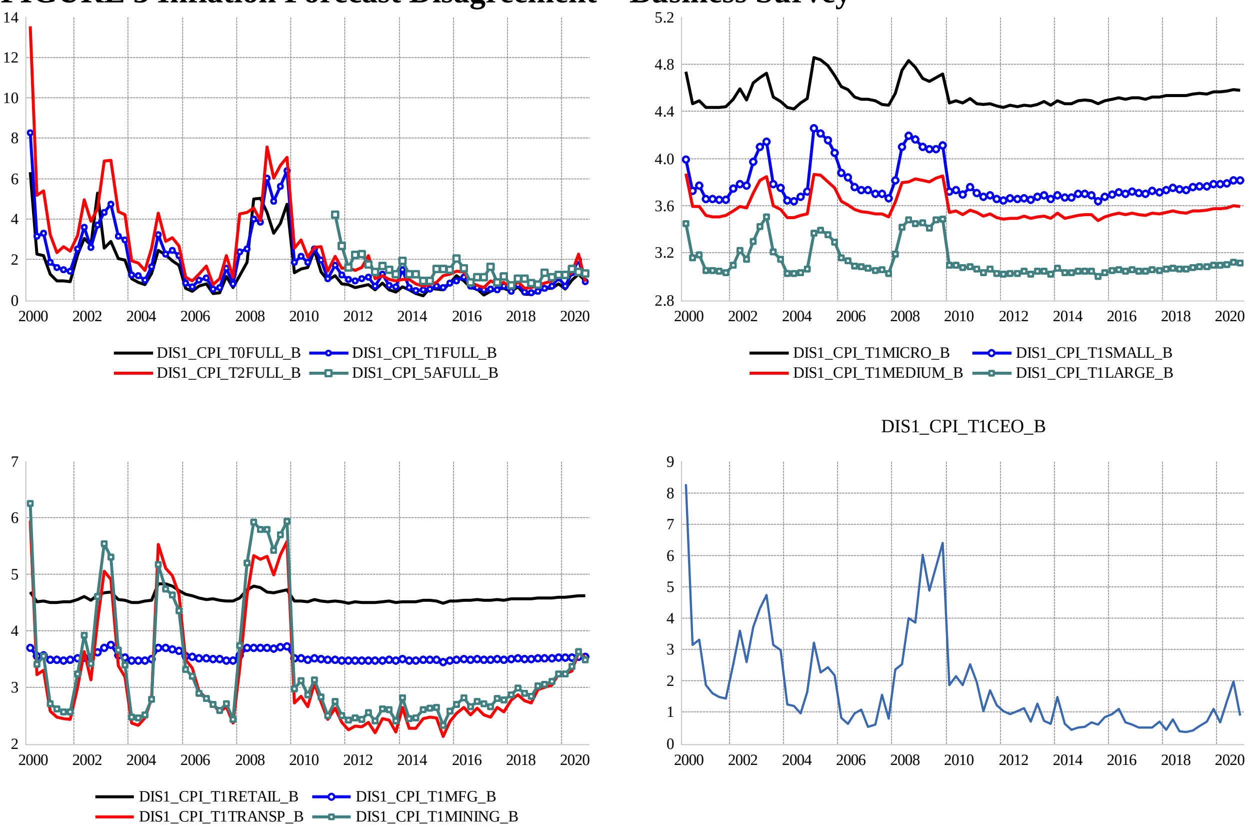
Note: Disagreement measured according to equation (1). Also, see Table 3 for the benchmark used in the calculations.

In Figure 3 we consider examples of forecast disagreement for more disaggregated data. We plot the indicator of inflation forecast disagreement for the entire business sector and all horizons (top left-hand side figure) against one year ahead forecast disagreement (i.e., for year T+1) according to firm size (top right hand side figure), selected industries (bottom left-hand side), and CEOs of the businesses surveyed (bottom right-hand side).

A common feature across horizons, and various levels of disaggregation, is that the period of the GFC no longer stands out as much as it did when the other three sectors are compared as in Figure

2. The impact of the exchange rate crisis at the end of 2001 and into 2002, which was the subject of commission of Inquiry,[21] is visible in the inflation disagreement of 2002-03. Following this, 2004-5 was a time when the South African Rand was strengthening significantly again. At the same time, the oil price increased sharply so, at least in early 2004, two key inflation drivers were moving in opposite directions. Disagreement amongst survey respondents about inflation forecasts could therefore quite reasonably be due to the movements in these two macroeconomic factors which were both large and uncertain. Average headline CPI measured 1.4% in 2004, which was the lowest CPI reading in approximately 35 years.

FIGURE 3 Inflation Forecast Disagreement – Business Survey



Note: DIS1 is the disagreement metric used in Siklos (2013). T0, T1, T2 refers to the forecast horizon (current year, one year ahead, two years ahead). FULL means that the mean of all respondents' forecasts is used. MICRO refers to businesses with fewer than 21 employees; SMALL 21-50 employees; MEDIUM 51 to 200 employees; LARGE more than 200 employees. RETAIL is the wholesale and retail sector (SIC 61-64); MFG is manufacturing (SOC 30-39); TRANSP is transportation and communication (SIC71-75); MINING is mining (SIC 13). CEO means that the respondent to the Business (B) survey is the CEO/Manager/Owner. The higher the estimate the greater is the forecast disagreement.

[21] The South African Rand weakened by 42% between 1 September and 31 December 2001 (Department of Justice and Constitutional Development, 2002). The President of the Republic of SA appointed the Commission of Inquiry into the rapid depreciation of the Rand and related matters, which was released on 1 August 2002.

Figure 3 also reveals that there is rising forecast disagreement after 2012 in the transportation and mining industries, although levels are lower than in the other industries shown. Disagreement is much also less volatile across all the industries after the worst of the GFC has passed. Levels of forecast disagreement also are highest for the smallest firms and lowest for the largest firms. Finally, note that levels of disagreement in mining and transportation catch up to ones shown in the manufacturing sector by the end of the sample.

It is conceivable firms respondents from different sectors may not equally contribute to the aggregate level of forecast disagreement. Recognising this, the US Federal Reserve publishes an index of common inflation expectations based on 21 indicators of inflation forecasts (Ahn and Fulton, 2021). While the simplest way of aggregating is the simple arithmetic mean, we can consider other several other measures of common inflation expectations. In the case of the BER survey, it is not unreasonable to think that the forecasts of other macro-financial variables are related to each other (e.g., interest rates and inflation, exchange rates and inflation, and so on). Hence, we estimate, via principal components analysis (PCA)[22], a simple factor model that provides an alternative and, arguably, richer estimate of respondents' forward-looking views about the South African economy[23]. Next, we use the resulting estimates to generate a new measure of forecast disagreement using, as before, equation (4).

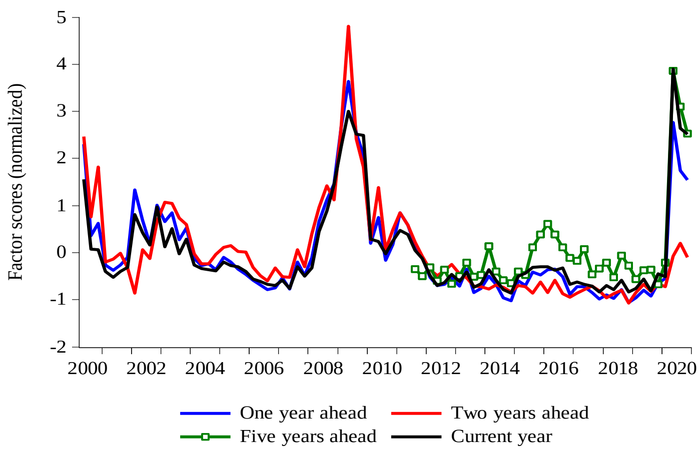
Figure 4 plots this resulting disagreement indicator that summarizes the views of the three groups surveyed. In contrast to the earlier calculations, inflation forecast disagreement combines forecast disagreement across the different variables and all three groups. The estimates are normalized and can be interpreted as an indicator of macro-financial disagreement about the outlook for the South

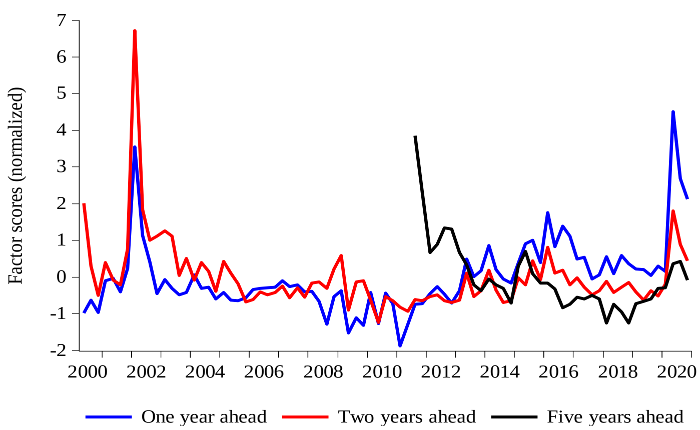
[22] PCA is a widely used statistical method that generates a linear combination among several variables. Accordingly, it is a means to simplify the relationship that exists among time series. Several textbooks provide details (e.g., Joliffe (2002), but see also Joliffe and Cadima (2016)). When more than one linear combination satisfies a statistical relationship (e.g., maximum likelihood) it is common to clarify (and simplify) the relationship between the series still more. This requires a rotation that ensures that the estimated factors remain uncorrelated. The varimax approach is a popular technique (see Kaiser (1958)).

[23] The current year factor model (T0) includes 15 variables; the one year ahead model (T1) includes 30 variables; and 18 variables are in the two (T2) and five year (5a) ahead models. In the case of 2 factors the scores are estimated following a rotation via the Varimax method. More detailed estimates of the PC are relegated to the Appendix.

African economy. Two results stand out in the Figures. When data are aggregated across the sectors surveyed (top figure), the COVID-19 pandemic clearly results in a surge in overall forecast disagreement in early 2020. In contrast, macro-financial disagreement does not rise at the two year and five years horizons, perhaps an indication that the impact of the pandemic is seen as temporary. The same interpretation holds when the factor model is estimated using firm level data only (i.e., business sector). Next, whereas the period of the GFC continues to stand out for the case where disagreement across the separate groups surveyed are combined, the same is not true when data are aggregated by firm size. Instead, it is the exchange rate crisis in the early IT period, the political turmoil in the mid-2010s and the covid pandemic which generate rises in macro-financial disagreement.

FIGURE 4 Disagreement Based on Factor Models





Note: The top figure is based on forecasts for all variables and survey groups. The bottom figure relies only on firm level data (business sector). Estimation is via principal components (PC) with the number of factors set to 1 for the current year model and 2 for the remaining factor models.

5.4 Econometric Evidence about the sources of disagreement

Figures 2 to 4 provide only unconditional insights into the sources of disagreement. Hence, we next turn to econometric evidence. Table 2 provides estimates of equation (2). Representative measures of inflation forecast disagreement for each of the three groups surveyed and every available forecast horizon are included. The specifications also allow for the possibility that disagreement at shorter horizons is a potential determinant of longer term forecast disagreement.

The Table is divided into two parts. The first set of determinants of inflation forecast disagreement consist of disagreement in the set of other variables respondents are asked to forecast (i.e., real GDP growth, Rand/USD exchange rate, prime interest rate, average salary and wage increase, long-term government bond yield, money supply growth, capacity utilization rate. The second set of determinants are levels of the variables observed in the previous quarter to capture the well-known persistence of macro-financial time series (Jordà, Schularick, and Taylor, 2017).

With only two exceptions, current year inflation forecast disagreement between financial analysts and five year ahead disagreement among respondents from labor, inflation forecast disagreement is well explained by the combination of disagreement in all the variables forecasted and lagged observed values of these same variables. Lagged disagreement about expected inflation is also significant, implying persistence in inflation forecast disagreement. Only firms at the shortest horizon show a significant and sizeable response to the Rand, perhaps reflecting the fact that for some sectors exchange rate movements can have a sizable immediate impact on inputs costs etc., but that this impact is not expected to pass-through to prices in general.[24] Increased disagreement about future interest rates contributes to more disagreement about inflation for firms at all horizons except the five year horizon, probably reflecting a view that there is a connection between interest rates and inflation within the typical policy horizon.[25] Disagreement about the outlook for wage growth contributes positively to disagreement about future inflation at all horizons except the 5-year horizon for firms, reflecting their importance as an input cost. This relationship is far less evident for labor and financial analysts, which might be more surprising.

[24] The fact that the BER Survey asks for forecasts of the level of the Rand and not its rate of change may also play a role. Economic theory links inflation to currency appreciation or depreciation.

[25] The data do not permit us to disentangle the direction of causality between inflation and interest rates.

TABLE 2 Sources of Forecast Disagreement

Forecast Disagreement By Horizon (T0,T1,T2, 5a), and Groups Surveyed (Business, Financial Analysts, Labour)

Determinants	CPIT0_B	CPIT0_F	CPIT0_L	CPIT1_B	CPIT1_F	CPIT1_L	CPIT2_B	CPIT2_F	CPIT2_L	CPI5a_B	CPI5a_F	CPI5a_L
CPIT2										.49(.34)	**.72(.32)@**	1.57(.98)
CPIT1							**1.44(.09)***	**.59(.08)***	**1.75(.10)***	.58(.42)	.28(.44)	.49(1.42)
CPIT0				**.57(.07)***	**.72(.13)***	**.38(.10)***	**-.40(.07)***	**.21(.10)@**	**-.48(.09)***	.01(.62)	**-1.31(.86)@**	-.24(1.33)
GDPT0	-.05(.03)	-.10(.15)	.08(.08)	**-.12(.07) ¶**	.16(.29)	-.05(.06)	.01(.05)	-.02(.17)	.07(.05)	**-.25(.13) ¶**	-.08(.21)	-.03(.13)
RANDT0	**.55(.24)¶**	.05(.17)	.03(.27)	-.04(.22)	-.45(.30)	.18(.35)	-.18(.15)	-.10(.18)	-.32(.29)	.37(.24)	.16(.11)	-.21(.54)
PRIMET0	**.72(.19)***	.34(.25)	**.17(.08)@**	**.78(.18)***	-.02(.36)	-.005(.11)	**-.47(.15)***	**-.52(.21)***	-.15(.13)	.16(.37)	-.15(.18)	.12(.44)
WAGEST0	**.23(.09)***	.09(.09)	.15(.09)	**.30(.18) ¶**	.45(.13) ¶	-.05(.15)	-.06(.11)	-.07(.08)	-.19(.13)	**.51(.19)***	-.09(.08)	.14(.41)
M3T0	-	-.03(.02)	-	-	.05(.02)@	-	-	-.07(.08)	-	-	-.03(.03)	-
R153T0	-	**.23(.14) ¶**	-	-	.32(.25)	-	-	-.02(.01)	-	-	-.11(.08)	-
CAPT0	-	-.001(.004)	-	-	.01(.03)	-	-	.02(.02)	-	-	-.01(.02)	-
GDPT1	-	-	-	.21(.14)	**-.83(.48) ¶**	.29(.18)	-.02(.10)	-.01(.29)	-.03(.15)	.38(.64)	.47(.33)	.25(.30)
RANDT1	-	-	-	.11(.12)	**.54(.25) @**	-.07(.16)	.005(.09)	.16(.16)	.15(.13)	.08(.07)	-.13(.09)	.04(.35)
PRIMET1	-	-	-	.02(.14)	.23(.27)	**.29(.11)***	**.40(.10)***	**.69(.16)***	-.03(.09)	.06(.18)	-.09(.15)	-.37(.37)
WAGEST1	-	-	-	.10(.18)	-.03(.13)	.11(.09)	.10(.13)	.02(.08)	**.18(.08)@**	-.05(.20)	**.14(.07) ¶**	.04(.38)
M3T1	-	-	-	-	-.01(.03)	-	-	.03(.02)	-	-	-.001(.03)	-
R153T1	-	-	-	-	-.24(.21)	-	-	-.04(.12)	-	-	.08(.08)	-
CAPT1	-	-	-	-	-.01(.04)	-	-	-.03(.02)	-	-	.02(.02)	-
RGDPG(-1)	-.05(.05)	-.01(.04)	-.01(.08)	**-.05(.03) ¶**	**-.08(.04) ¶**	.01(.07)	.02(.02)	.02(.03)	.05(.05)	**-.22(.11) ¶**	.04(.02)	.13(.12)
RAND (-1)	**-.09(.05) ¶**	-.04(.04)	**-.12(.07)¶**	**-.09(.03)***	-.06(.04)	.03(.06)	.03(.03)	-.001(.03)	.04(.05)	**-.23(.15)***	.01(.03)	.16(.16)
PRIME(-1)	**.12(.06)@**	**.15(.08)@**	**.19(.07)***	-.01(.05)	-.02(.08)	**.14(.07)@**	**.06(.03) ¶**	-.01(.05)	.03(.06)	.25(.17)	.03(.06)	-.39(.36)
CPI(-1)	**.07(.04) ¶**	**-.07(.04) ¶**	**.11(.06) ¶**	**.05(.02)@**	.02(.04)	-.0005(.05)	-.003(.02)	-.03(.02)	-.004(.04)	-.02(.09)	.003(.03)	-.12(.21)
RLT(-1)	-	-.03(.08)	-	-	.09(.09)	-	-	.03(.05)	-	-	-	-
M3G(-1)	-	.02(.02)	-	-	.02(.03)	-	-	-.01(.02)	-	-	-	-
CAP(-1)	-	.01(.02)	-	-	-.02(.02)	-	-	.01(.010	-	-	-	-
Constant	-.49(.82)	-1.68(1.63)	-.94(1.09)	**.88(.56)***	1.16(1.62)	**1.91(.97)@**	-.86(.40)	-.57(.97)	-.87(.83)	0.71(1.46)	-.37(.36)	2.28(2.96)
R^2-adj.	.68	.17	.48	.92	.61	.80	.97	.85	.93	.75	.55	.00
F-statistic	22.36(.00)	2.17(.02)	11.70(.00)	69.82(.00)	6.99(.00)	25.46(.00)	224.97(.00)	20.77(.00)	81.66(.00)	8.35(.00)	3.11(.01)	.88(.59)
Obs.	83	83	83	83	83	83	83	83	83	38	38	38

Note: Least squares estimation of equation (3). Also, see notes to Table1 and 2. RGDPG is the growth rate in real GDP; NER is the Rand/USD exchange rate; PRIME is the observed prime rate; CPI(-1)is the inflation rate; M3G is the growth rate in M3; CAP is the capacity utilization rate. Obs. is the number of observations before any transformation and lags. The full sample is 2000Q2-2020Q4; 2011Q3-2020Q4 for CPI5a. Forecast disagreement is given by equation (1) and the mean forecast across all three groups (i.e., business, labor, financial analysts) is represented as $\bar{F}$. Coefficient estimates in bold characters are respectively statistically significant at the 1% (*), 5% (@), and 10% (¶) levels of significance.

Another extension to the specifications presented in Table 2 was also considered (not shown). We added other variables from outside of this survey that might impact forecast disagreement but are not among the series being forecast. We included the return on the Johannesburg stock exchange (lagged one quarter), credit growth, the US policy rate, the VIX and economic policy uncertainty (i.e., Baker et. al., 2015). These additional series were not found to be statistically significant at the longer forecast horizons (two and five years), but share prices, credit growth and the US policy rate can partially explain inflation forecast disagreement at shorter horizons.[26]

The foregoing results suggest that when forecasters disagree about future inflation it is because they also disagree about the future course of other key macro-financial variables. The relationship is strongest for shorter term disagreement about inflation. Inflation forecast disagreement is also partially driven by how the series being forecast evolved in the past. We cannot tell whether this reflects a form of inattention, differences in how the past portends for the future, certain socio-economic characteristics of the forecasters we are unable to quantify, or some type of bias in how disagreement about future inflation emerges. Nevertheless, we can conclude that forecasters not only disagree about future inflation, because they also have different expectations about other key variables, but that the source of disagreement is sensitive to the level of aggregation in the data.

6. Conclusions

Despite the centrality of low and stable inflation as a desirable goal of monetary policy, central bankers around the world have repeatedly stressed that we do not know enough about the dynamics of inflation and inflation expectations. Until fairly recently models and professional forecasts were typically used to interpret the effectiveness of monetary policy. There is a growing literature that underscores the value of understanding how households form expectations, but comparatively little data that measures the expectations of firms. As institutions that are, in a sense, both price takers and makers, it would appear critical for policy makers to better understand what firms think about the economic outlook.

[26] We also examined the possibility that a remaining structural break in equation (2) not captured by the available data was omitted. Using the Bai and Perron (2003) methodology we found almost none.

This paper uses rich micro level firm data over a period of more than a twenty years, during which inflation targeting has been in place in SA, to add to our understanding of firm level inflation expectations. These data are complemented with similar data about the expectations of trade unions as well as financial analysts. We are especially interested in the extent to which forecasters disagree and attempt to explore the sources of their disagreement. The data set is rich in that it includes forecasts of inflation as well as forecasts for a set of other macro-financial variables provided by the same individuals and offers forecasts of inflation for several time horizons ranging from current to five years ahead.

Focusing on inflation, although there are common features in the behavior of inflation expectations over time and across forecast horizons, disaggregating the data highlights important differences in how expectations behave across various groups. For example, the mining and manufacturing industrial sectors are far more sensitive to macroeconomic developments than other sectors such as retail. Similarly, there are persistent differences in forecast disagreement displayed that are sensitive to firm size and the occupation of the respondents (e.g., economists versus CEOs). Finally, it appears that forecasts of inflation alone are insufficient to understand how forecast disagreement evolves over time. Thus, aggregated and disaggregated forecast disagreement does not rise greatly at the onset of the COVID-19 pandemic, unless one examines an indicator we create (which we call macroeconomic forecast disagreement) that utilizes forecasts for all available variables jointly modelled via a factor model. The same is true for the impact of the global financial crisis. Combining all forecasts, and disaggregating the data, shows that disagreement in some sectors or industries did not rise as sharply as in the data aggregated across sectors surveyed and for the entire data set combined.

The principal policy implication is that the SARB in particular, but central banks more generally, should consider disagreement in the outlook more broadly than just focusing on inflation and GDP growth. Forecasts for other macro-financial variables generate insights that an investigation of inflation forecast disagreement alone can miss. In addition, the heterogeneity of inflation expectations suggests that central bank communication should include elements that are targeted to particular audiences in addition to conveying information intended for the broader public.

In spite of our findings there are limitations in our analysis and potential extensions. We have too few socio-economic variables to reliably determine what drives the formation of inflation expectations in the three groups for which we have survey data. Moreover, it would be interesting to provide a comparison with similar survey data available for South African households. Unfortunately, we only have a small selection of the available time series of household forecasts (Reid, Siklos, and Du Plessis, 2021). Another extension would be to try and identify the respective roles of uncertainty versus policy stances taken by the SARB over time. This would require a different econometric approach and the imposition of a priori restrictions. Finally, there is scope for a deeper analysis of the performance of various forecasts at different levels of disaggregation as well as the possibility of developing a better understanding of the role of rational inattention, noise, or other behavioural limitations respondents face when forecasting inflation and the other macro-financial variables they are asked to forecast. We leave these extensions to future research.

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