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Inflation forecasts and forecaster herding: Evidence from South African survey data

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ABSTRACT

We use South African survey data to study whether inflation forecasts are unbiased. Depending on a forecaster's information set, we evaluate whether forecasts are biased due to forecaster herding. Forecaster herding is strong when a forecaster's information set contains no information on the contemporaneous forecasts of others. When we randomly allocate forecasters into a group of early forecasters who can only observe the past forecasts of others and late forecasters who can also observe the contemporaneous forecasters of their predecessors, evidence of forecaster herding weakens. Evidence of forecaster (anti-) herding is strong and significant in times of high (low) inflation volatility.

1. Introduction

A key question for monetary policymakers, and anyone who monitors inflation as an indicator of macroeconomic performance, is whether agents form unbiased inflation expectations. Moreover, inflation expectations are a key element of virtually all modern monetary macroeconomic models. Monitoring inflation expectations is particularly important in the case of an inflation-targeting economy like South Africa. South Africa has formally used inflation targeting as its policy framework since February 2000. The Reserve Bank of South Africa targets inflation in a range between 3% and 6% on a continuous basis.[1] Given the key importance of inflation expectations for monetary policy, it is not surprising that much research has been done to shed light on how agents form their inflation expectations (for detailed reviews of the South African experience, see Naraidoo and Gupta, 2010, Kabundi and Schaling, 2013). Because it is impossible to observe inflation expectations directly, researchers have extensively studied survey data to analyze the properties of inflation forecasts (for recent examples, see Castelnuovo, 2010; Adam and Padula, 2011; Del Negro and Eusepi, 2011; Fuhrer, 2012, to name just a few).

An important question in this line of research is whether survey data of agents' inflation forecasts are in line with the rational-expectations hypothesis. In the South African case, Ehlers and Steinbach (2007) provide a comprehensive investigation of the extent to which inflation expectations are rational. They assess the characteristics of expectations formation across three different groups of economic agents using the Bureau for Economic Research's (BER) inflation expectations survey data and data from the Reuters Inflation Expectations (RIE) Survey. Ehlers and Steinbach (2007) conclude that the RIE expectations are unbiased except for the expectations for the current-period forecast horizon. The BER expectations of financial analysts and short-term expectations by the trade unions also appear unbiased, whereas the expectations of the business representatives and the longer-term expectations of trade unions are biased. However, all the groups were found to use information inefficiently, so none of the groups could be viewed as weakly rational, where the forecasts for the current-quarter horizon from the RIE Survey are an exception. Similarly, Kabundi and Schaling (2013) report, also for the BER data, that inflation expectations are closely tied to the lagged inflation rate. They conclude that inflation expectations are not in line with the rational expectation hypothesis. In a recent study,

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[1] The mandate of the South African Reserve Bank is set by the National Treasury, but the South African Reserve Bank has instrument independence in the pursuit of the mandate.

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Kabundi and Schaling (2014) also report that the forecasts of price-setters (business representations and unions) are linked to the lagged inflation rate. This, however, is not true for the forecasts of analysts, consistent with cross-sectional heterogeneity of forecasters. In recent research, Pierdzioch, Reid and Gupta (2015) study the rationality of inflation forecasts under asymmetric loss. They find mixed evidence of an asymmetric loss function, suggesting that inflation forecasters are heterogeneous with respect to the shape of their loss functions. They report that micro-level inflation forecasts are in line with forecast rationality, whereas there is evidence for asymmetry in the loss function and against forecast rationality based on aggregate sectoral inflation forecasts.

Apart from adaptive learning, Ehlers and Steinbach (2007) do not consider potential behavioral sources of the bias they find in the South African inflation expectations other than an absence of rationality. In this research, we study whether behavioral interactions between forecasters may be a source of bias in inflation expectations. The specific behavioral interaction that we focus on is forecaster herding. Forecaster herding arises when forecasters rely not only on private information when forming their inflation forecasts, but also on the forecasts of other forecasters. Forecaster herding has been extensively studied using theoretical models (see for example, Scharfstein and Stein, 1990; Bikhchandani and Hirshleifer, 1992; Ehrbeck and Waldmann, 1996; Teraji, 2003, among others; for related research on preferences for conformism, see, e.g., Klick and Parisi, 2008), in experimental research (Anderson and Holt, 1997; Drehmann and Oechssler, 2005; Morone and Sandri, 2009), and also in empirical research (Chang and Cheng, 2000; Clement and Tse, 2005; Bernhardt and Campello, 2006 among others; for related research on biases in how experts update beliefs, see Sinkey, 2015, among others).[2] While theories of herding behavior have been extensively used in the field of financial economics to study forecasts of stock prices (Chang and Cheng, 2000; Pierdzioch and Rülke, 2012), metal prices (Pierdzioch and Stadtmann, 2013), and exchange rates (Pierdzioch and Stadtmann, 2012; Fritsche et al., 2015), herding behavior has also been studied in a variety of other fields including, for example, macroeconomic modeling (Gaffeo and Canzian, 2011) and the modeling of the foreign direct investment decisions of firms (Pinheiro-Alves, 2011). Forecaster herding arises if, for example, weak forecasters and forecasters in an early stage of their career remain close to the consensus forecast (Lamont, 2002; see, however, Ashiya and Doi, 2001). In contrast, forecaster anti-herding arises if a forecaster's remuneration, in addition to forecast accuracy, depends on the forecaster publicity or on publishing the best forecast at a single point in time (Laster, Bennett and Geoum, 1999).[3]

We apply a test of forecaster herding recently proposed by Bernhardt and Campello (2006) to detect signs of forecaster herding in survey data of inflation forecasts for the South African economy. Recent applications of their test can be found in Frenkel and Rülke (2013), who study whether IMF and OECD forecasts of the inflation rate and other macroeconomic variables influence private-sector forecasts, and in Pierdzioch and Rülke (2013, 2014b), who apply the test to study whether inflation targets and central banks' interest rate projections anchor expectations. The test suggested by Bernhardt and Campello (2006) is easy to implement, the economic interpretation of the test results is straightforward, and the test is robust to various forms of misspecification. We apply their test to study short-term inflation forecasts provided by Bloomberg. A specific feature of the data is that Bloomberg publishes forecasts at the time forecasters submit their forecasts. Forecasters, thus, may or may not observe the forecasts of other forecasters when submitting their own forecasts. While early forecasters are likely to have rather limited information on the forecasts of other forecasters, late forecasters can take into account a potentially large number of forecasts when submitting a forecast. A direct consequence is that we have to make an assumption as to what forecasters know about the forecasts of others when making their forecasts. When we assume that forecasters mainly rely on past information to estimate the forecasts of others, the test results suggest that forecasters herd. The relevance of past information for the formation of inflation expectations has been documented for different types of forecasters in earlier research by Ehlers and Steinbach (2007), Reid (2012), and Kabundi and Schaling (2013). In the past-information scenario, we detect forecaster herding not only for the full sample of data covering the sample period 2000–2014, but also for various subsample periods including those periods during which the inflation rate fluctuated inside and outside the inflation-targeting band announced by the South African Reserve Bank. Evidence of forecaster herding becomes weaker when we assume that forecasters' information set consists of a mix of past and current information on the forecasts of others, but also in this mixed-information scenario our results provide hints that forecasters herd. Furthermore, we find, in line with results reported by Bewley and Fiebig (2002) and Pierdzioch and Rülke (2014a), that forecaster herding becomes stronger in times of high inflation volatility. Evidence of forecaster herding in times of high inflation volatility is strong and significant. Uncertainty, thus, seems to trigger forecaster herding. When inflation volatility is low, in contrast, we find evidence that forecasters anti-herd.

We organize the remainder of our research as follows. In order to derive our results, we first lay out the test for forecaster herding in Section 2. We then describe our data in Section 3 and our empirical results in Section 4. We conclude in Section 5.

2. Empirical method

We use a test developed by Bernhardt and Campello (2006) to study forecaster herding. To set up their test, we first introduce some notation. We let π_t denote the inflation rate, and we let π_t^e denote the forecast of the future inflation rate formed in time t. Moreover, we let π_t^p denote a forecaster's unobservable private forecast. Suppose that a forecaster forms, given an information set available when a forecast is made, a median-unbiased private forecast of inflation. Then the probability that this unbiased private forecast overshoots (undershoots) the future inflation rate should be equal to 0.5, and this probability should be unrelated to the consensus (average) forecast, $\tilde{\pi}_t^e$. If a researcher assumes that a forecaster's information set includes information on the contemporaneous inflation forecasts of others (together with past inflation forecasts), the formation of the time t consensus forecast can include these contemporaneous inflation forecasts. If, in contrast, a forecaster's information set does not contain information on the contemporaneous inflation forecasts of others, the consensus forecast is computed based on inflation forecasts made in some earlier period.[4] Regardless of the precise definition of the consensus forecast, the conditional probability, P, that a forecast overshoots (undershoots) the future inflation rate should be 0.5. We have

$$P(\pi_{t+1} < \pi_t^e \mid \pi_t^e > \tilde{\pi}_t^e, \pi_{t+1} \neq \pi_t^e) = 0.5, \tag{1}$$

$$P(\pi_{t+1} > \pi_t^e \mid \pi_t^e < \tilde{\pi}_t^e, \pi_{t+1} \neq \pi_t^e) = 0.5. \tag{2}$$

[2] See Bikhchandani and Hirshleifer (1998) and Bikchandani and Sharma (2001) for detailed surveys of the vast literature on theoretical and empirical studies of forecaster herding.

[3] A behavioral bias could also arise, for example, if forecasters try to please their employer (Ito, 1990), or through media communication (Reid and Plessis, 2011).

[4] As we shall document in detail in Section 4, the precise assumption made with regard to a forecaster's information set has important implications for the test results.