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Heterogeneous Expectations and the Predictive Power of Econometric Models

by

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ABSTRACT

A recent literature questions the mainstream omniscient rational agent, suggesting that agents act as, and have the same bounded rationality of, econometricians. Heterogeneous expectations may then arise because of the different forecasting models used by individuals, who select disparate predictors according to the peculiar net benefits of each model. Net benefits are assumed to be a function of mean square forecasting errors (MSE). Consequently, as in Carroll's epidemiological approach, an implicit assumption is that the level of disagreement across agents cannot Granger cause model-based MSE. Instead, survey expectations on GDP growth show that the information flow runs exclusively from heterogeneity to MSE. Moreover, variance decompositions point out that survey expectations entropy and MSE are not contemporaneously correlated, enforcing the detected causal chain. Results are robust to several predictors, nonlinearities, and suggest looking also at other possible causes of disagreement.

Keywords and Phrases: Survey Expectations, Forecasting Models.

JEL Classification: C53, D84, E27.

NON TECHNICAL SUMMARY

L'economia è una scienza eminentemente comportamentale e le aspettative ne sono un elemento cruciale. Fin dagli anni '70 l'approccio standard è stato quello di assumere che le aspettative sono formate in modo razionale. L'ipotesi delle aspettative razionali (REH) è particolarmente utile per gli economisti poiché, tra l'altro, semplifica di molto la soluzione di modelli comportamentali altrimenti oltremodo complicati. Di converso, tuttavia, la REH impone che gli agenti abbiano un livello di conoscenza del sistema economico così elevato da essere altrettanto implausibile. Nel tentativo di ridurre l'eccessiva astrattezza della REH, alcuni autori hanno suggerito di assumere che gli agenti abbiano gli stessi limiti informativo/computazionali degli economisti di professione.

A differenza dell'approccio standard, dove per assunzione tutti usano il medesimo modello e hanno le stesse informazioni tanto da giungere inevitabilmente alle stesse previsioni, in questo filone di ricerca le aspettative potrebbero essere non uniformi. La logica è che gli agenti, attraverso un'analisi dei relativi costi e benefici, potrebbero trovare ottimo basarsi su modelli previsivi diversi. In particolare, i benefici netti derivanti dall'uso di un dato modello sono una funzione dell'errore quadratico medio (MSE) di previsione: da un lato, evitare errori di valutazione può ridurre l'insorgere di costi o procurare dei benefici; dall'altro, contenere il MSE implica un'attività di elaborazione, aggiornamento delle informazioni, ecc. tanto incessante quanto costosa. Quando il modello usato realizza un beneficio netto non ottimale, allora lo si cambia. Però il beneficio netto è soggettivo e, dunque, non tutti gli agenti selezionano in ogni istante lo stesso modello. Ciò da luogo ad aspettative razionalmente eterogenee. Una conseguenza implicita in questo modo di ragionare è che l'entità del disaccordo esistente tra gli agenti segue il livello del MSE generato dal modello, poiché per cambiare modello - e di qui le attese - si deve prioritariamente calcolare il MSE. Questa catena causale che va dal modello alla formazione delle aspettative si ritrova anche nell'approccio "epidemiologico" proposto da Carroll. Costui modella le attese assumendo che gli agenti aggiornano il proprio set informativo sulla base delle notizie fornite dai mass media i quali, a loro volta, pubblicano le previsioni elaborate dagli economisti professionisti attraverso modelli econometrici.

Curiosamente, l'analisi empirica di questa recente letteratura è usualmente rivolta verso le aspettative inerenti l'inflazione negli USA. Eppure è immediato osservare che andrebbero studiate anche altre variabili cruciali e altri contesti economici. Ma è ancor più importante notare che la catena causale sopra menzionata potrebbe non essere l'unica possibile. Indicazioni dell'esistenza di una opposta (Granger-)causalità sono rinvenibili, ad esempio, nella teoria delle aspettative auto-realizzantesi dove, infatti, gli shock che colpiscono le attese potrebbero essere una fonte indipendente delle dinamiche economiche. Similmente, l'eterogeneità delle aspettative può provocare i cosiddetti equilibri sunspots, cioè situazioni in cui variabili casuali esogene influenzano il sistema economico esclusivamente attraverso le attese delle persone.

Questo articolo si è perciò proposto di studiare le aspettative sulle dinamiche del PIL nel Regno Unito, evidenziando se, come e quanto gli MSE - generati dai modelli - e le attese - dichiarate dagli agenti in survey ad hoc - sono intercorrelati. A questo fine si sono dapprima stimati, ricorsivamente e con finestre scorrevoli, svariati modelli tra quelli comunemente utilizzati nella pratica econometrica. Da essi sono stati poi calcolati altrettanti MSE "un passo avanti" ottenendo dunque, alla fine del processo, molte serie storiche degli errori previsivi commessi dai modelli econometrici. Ci si è poi rivolti ai dati qualitativi contenuti nelle survey presso i consumatori, quantificando le tendenze centrali e l'eterogeneità delle aspettative sull'evoluzione tendenziale del PIL. Invero, tra l'altro, le survey chiedono all'intervistato: "Come evolverà, secondo te, la situazione economica generale del Paese nei prossimi 12 mesi?". Il rapporto tra le due summenzionate statistiche fornisce un'indicazione dell'entropia relativa (SNR) presente nelle aspettative dei cittadini inglesi. Dato che esistono più modi di quantificare le risposte qualitative raccolte nelle survey, si sono elaborati diversi SNR alternativi. Così calcolate le varie serie storiche "MSE" e "SNR", si è poi proceduto ad esaminarle attraverso vettori autoregressivi bivariati composti da un MSE e un SNR. Se le assunzioni della citata teoria sono valide allora, come notato, gli MSE dovrebbero "precedere temporalmente" gli indicatori SNR. Ovvero, le aspettative dovrebbero conformarsi ex post ai risultati realizzati dai modelli econometrici.

Tuttavia, i dati per il Regno Unito evidenziano nessi causali opposti: la capacità previsiva dei modelli è influenzata dal, ma non influenza il, grado di entropia presente nelle survey. Oltretutto, la scomposizione della varianza mostra che il livello di eterogeneità e il MSE sono contemporaneamente incorrelati. Tutto ciò implica che né i valori passati, né quelli presenti e neanche quelli futuri del MSE aiutano a spiegare l'eterogeneità che caratterizza le aspettative dei consumatori. Questi risultati valgono sia usando vari modelli econometrici che considerando eventuali non linearità, facendo ritenere che aspettative eterogenee possono realizzarsi anche a prescindere dal fatto che gli agenti usano modelli previsivi diversi.

SINTESI IN ITALIANO

Un piccolo ma crescente numero di autori sta ipotizzando che gli agenti elaborano previsioni economiche come se fossero degli econometrici di professione con i quali, pertanto, condividono gli inevitabili limiti informativo/computazionali di simili esercizi. Discostandosi dall'ipotesi di aspettative razionali, essi arguiscono che le aspettative potrebbero essere non uniformi. La logica è che gli agenti, analizzandone in modo soggettivo i relativi costi e benefici, potrebbero trovare ottimo basarsi su modelli previsivi difformi. In particolare, i benefici netti derivanti dall'uso di un dato modello sono ipotizzati essere una funzione dell'errore quadratico medio (MSE) di previsione. In questo quadro, similmente a quanto accade nell'approccio "epidemiologico" proposto da Carroll, l'entità del disaccordo esistente tra gli agenti "razionalmente eterogenei" sarebbe Granger-causato dal MSE. Nel Regno Unito, tuttavia, le aspettative sull'evoluzione del PIL raccolte nell'ambito delle survey sul clima di fiducia dei consumatori mostrano un nesso causale opposto. L'analisi della scomposizione della varianza indica poi che il livello di eterogeneità presente nelle survey e il MSE derivante dai modelli econometrici sono contemporaneamente incorrelati. Tutto ciò vuol dire che i valori presenti, passati e futuri del MSE non aiutano a spiegare l'entropia che caratterizza le aspettative dei consumatori. Questi risultati valgono sia usando vari modelli econometrici che considerando eventuali non linearità, facendo ritenere che aspettative eterogenee possono realizzarsi anche a prescindere dal fatto che gli agenti usano modelli previsivi diversi.

Parole chiave: Aspettative, Survey, Modelli Previsivi.

Classificazione JEL: C53, D84, E27.

CONTENTS

"There is a communism of models.
All agents inside the model, the econometrician,
and God share the same model"

T.J. Sargent

1 INTRODUCTION[1]

Economics is a behavioral science and expectations play a crucial role in it. Since the seminal papers of Muth (1961), Lucas (1972) and Sargent (1973), the standard approach has been to assume that expectations are formed rationally. The rational expectation hypothesis (REH) is very helpful for professional economists allowing, inter alia, to simplify the solution of economic models. For common people, instead, REH is very demanding: Muthian agents must know the correct form of the model, all parameters, that other agents are rational, etc. In an attempt to step back from the hard-to-defend omniscience of rational agents, a recent strand of the theoretical research has proposed modeling agents as econometricians (Evans and Honkapohja, 2001). The idea is that the skill/knowledge necessary to act as a Muthian agent is too much even for professional economists who, in fact, relentlessly must estimate economic models. Therefore, this approach suggests assuming that agents are as boundedly rational as econometricians are, and that they form their expectations by using some adaptive updating rule. Following the theoretical indications of Brock and Hommes (1997), Branch (2004) points out that individuals are uncertain about the correct model for the economy and so each period they rationally select the predictor according to its relative benefit, assumed to be a function of the mean squared error (MSE). In this approach, agents may choose different optimal forecasting models because some of them may not fully respond to change in relative net benefits. People may also have inherent predisposition to use one predictor over another, which again leads to disagreement. In any case, since relative net benefits and preferences are agent-specific, individuals have their own optimal model and may form rationally heterogeneous expectations (RHE). From the empirical standpoint, Branch shows that survey expectations are distributed heterogeneously across univariate and multivariate forecasting models, and that there is dynamic

[1] The opinions expressed herein are those of the author and not necessarily reflect the views of the ISAE. I would to tank an anonymous referee for the useful comments. The usual disclaimers apply.

switching between predictors that depends on relative MSE. Extending his 2004 paper, Branch (Branch, 2007) contrasts models of heterogeneity in survey expectations, showing that model uncertainty is a more robust factor of heterogeneity than the sticky information setting conceptualized by Mankiw and Reis (2002). Branch and Evans (2006) compare some time-varying parameter vector autoregressive (VAR) models, finding that a constant gain algorithm provides the best fit to the Survey of Professional Forecasters. Other papers reporting heterogeneity across forecasting models include Aadland (2004), Brock and Durlauf (2004) and Orphanides and Williams (2005).

Typically, the empirical literature on heterogeneous expectations deals with inflation in the US. This leaves unexplored expectations formation in other countries and on other key macroeconomic variables. Most importantly, the empirical bounded rationality setting implies a specific Granger causality relating model-based forecast errors and the degree of disagreement across people's expectations. In the RHE framework, agents switch from one model to another after having computed the MSE of the predictors: expectations formation cannot precede realizations.[2] In the limit case of fully rigid forecasters, i.e. one-model-for-life agents, survey expectations heterogeneity and MSE should be orthogonal. A similar time sequence is also implied by the epidemiological approach proposed by Carroll (2003). He models households' expectations assuming that agents update their information set from mass media which, in turn, report economists' forecasts. For the US, Carroll finds that professional expectations on inflation Granger cause those of lay people.

There exist, nonetheless, several approaches providing theoretical justification of different causal chains. Farmer (1999) explains how shocks to agents' self-fulfilling beliefs can be an independent source of economic dynamics. Alike, heterogeneity of beliefs is a source[3] of sunspot equilibria, situations where extraneous random variables influence the economy solely through the expectations of the agents (Shell, 2008). It is worth recalling that Branch (2007) concludes that neither the RHE nor the sticky information setting can significantly match the data generation process behind survey expectations. In addition, many empirical papers have been looking, with some success, for

2 Another paper implicitly suggesting an information flow running from fundamentals to expectations is that of Capistran and Timmermann (2009). They suggest the presence of heterogeneous asymmetries in the forecasters' costs of over or under predicting inflation, showing that inflation uncertainty affects dispersion of beliefs.

3 Proper sunspot equilibria can exist in a number of economic situations, including asymmetric information, externalities in consumption or production, imperfect competition, etc. In this paper we take an agnostic view of the exact channel through which agents' beliefs may affect economic activity and we relegate this topic in the agenda.

the additional information content of survey expectations, whereby the adjective "additional" stands exactly for extra economic factors and/or independent information (for a survey, see Ludvigson, 2004).

Against this background, we see our contribution and aim to examine the links between the disagreement across agents, as captured by survey data, and the forecasting performance of standard econometric models, as measured by MSE. Specifically we estimate, both recursively and with MSE-minimizing rolling windows, several standard univariate and multivariate econometric models of UK GDP growth that we use to perform one-step-ahead forecasting exercises. So, we end up with several time series made up by one-quarter-ahead MSE (Section 2). We then turn our attention to "corresponding" survey data (Section 3), in order to compute some indicators of the relative disagreement across people's replies (Section 4). These measures are signal-to-noise ratios (SNR), based on survey expectations, that are natural survey counterparts of model-based MSE. As far as we know, this is the first attempt to examine this kind of statistics. After having studied separately econometric forecasts and survey expectations, we perform bivariate VARs to address the statistical significance, the direction and the sign of the links between MSE and SNR (Section 5).

Results exhibit a significant and univocal causal chain connecting MSE and SNR, with the latter preceding the former. In particular, the sign of the coefficients shows that signal-noise ratios are negatively correlated with MSE. Otherwise stated, the greater the level of entropy in the surveys, the larger the MSE of econometric models is. In addition, variance forecast error decompositions suggest that there is no significant instantaneous causality between MSE and SNR, so that they are exogenous to each other. It turns out that SNR is a "real" cause for MSE, i.e. it is a cause in a stronger sense than that implied by the simple Granger "predictability". These results are robust to nonlinearities and to several predictors. In particular, evidence indicates that a random walk turns out to be the best predictor of the GDP growth rate over most of the sample. Therefore, should heterogeneity depend only on the net benefits of using different models, UK citizens' expectations should likely converge because naïve forecasting exercises are so easy and cheap to be quickly available for any forecaster. Since this does not happen even in this sort of natural experiment, in the sense that it remains enough disagreement such that SNR significantly causes MSE, then there must be some additional explanation behind the formation of disparate expectations. The identification of these disagreement-widening factors is in the agenda.

2 ECONOMETRIC MODELS FORECASTING PERFORMANCES

2.1 Econometric Models

In this section we estimate and compare the forecasting power of a battery of standard econometric models aimed to predict the GDP annual growth[4] in the UK: $y_t \equiv (gdp_t - gdp_{t-4})/gdp_{t-4}$. Quarterly GDP data cover the period 1955.Q1-2009.Q1. The exercise cannot and does not want to be exhaustive. Each model is chosen for its widespread use in econometric practice and is designed to be representative of a larger class of predictor functions (Branch, 2004). Even more so considering that we also perform several alternative rolling windows estimations, which should account for the possible presence of nonlinearities.[5] In addition, our set includes the models used in previous works (Williams, 2003; Branch, 2004 and 2007; Forsells and Kenny, 2005; Branch and Evans, 2006). As for our VAR predictors, which are frequently employed bi- and tri-variate Phillips curves (Henry and Pagan, 2004), it is also worth noting that they are often cited as an approximation to rational and to professional economists' expectations. Table 1 collects and summarizes the predictors used in this paper.

Table 1 **The Competing Predictors**

Model (Mnemonic)	*Model Specification (abstracting from the error term)*
Naïve=Random Walk (RW)	$y = y_{-1}$; $y \equiv (gdp_t - gdp_{t-4})/gdp_{t-4}$
Adaptive Expectations (AE)	$y_t = \gamma y_{t-i} + (1-\gamma) y_{t-i-1}$ $0<\gamma \leq 1$; $i,t=1,\ldots,T$; $y_0 = y_{1956Q1}$
First Order Autoregression[6] (AR1)	$y_t = \alpha + \beta y_{t-1}$
Vector Autoregression 1 (VARPC)	$z_t = \sum_{i=1}^{\infty} \Psi_i z_{t-i}$ $z=\{y,\pi\}$; π = CPI inflation; Ψ=Coeff. matrix
Vector Autoregression 2 (VAR)	$z_t = \sum_{i=1}^{\infty} \Psi_i z_{t-i}$ $z=\{y,\pi,r\}$; r=3M Treasury bill rate

Note. Source of data: OECD, Datastream. Sample: 1955.Q1-2009.Q1. $y_0 = y_{1956Q1}$ because y=annual growth, and the first data for GDP is 1955Q1. The other two variables (π,r) are quarterly averages of the corresponding monthly values.

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4 We focus on annual growth rates for reasons that will be clear in the following section.

5 Under certain assumptions, the MSE-minimizing window size is equal to the reciprocal of the optimal gain parameter of Kalman filter estimation (Branch and Evans, 2006). So, our results are robust to parameter estimates generated by gain algorithms.

6 We have also estimated AR(4) and ARMA(1,1) models. Not-reported Wald-tests on coefficient restrictions and usual information criteria show that AR(1) is the best specification for this kind of models.

To compute the relative predictive fitness of the models we rely on the mean squared error statistic. Several reasons are behind this choice. First, the MSE is a standard tool in econometric practice and, if agents really act as econometricians, it is likely that they consider it. Second, it is based on the same statistic that is minimized in least squares estimations, namely the residual sum of squares (RSS): MSE=RSS/T (T=number of observations). Third, the MSE constitutes a natural counterpart for the survey signal-to-noise ratios elaborated in Section 4. Finally, the Granger causality tests used to establish the direction of information flows are built on the comparison of the mean square error statistic (Section 5).

When comparing econometric models and survey expectations, the former should be estimated in real time using, each time, the vintage of data actually available to agents (Croushore and Stark, 2003). Nonetheless, Orphanides and van Norden (2005) have argued that the relative usefulness of real-time dataset is small when dealing with simple forecasting models which, as ours, use past inflation and output growth. In addition, we do recursive estimations to reduce the effects of assuming that individuals use information which will be available only in future dates. This is in accordance with the adaptive learning literature (Evans and Honkapohja, 2001). Lastly and importantly, the recursive procedure is close to the forecasting exercise actually faced by the survey respondent. As for the rolling windows estimation variants, we set the smaller window size[7] to thirty-two quarters and the largest to sixty quarters. We therefore perform twenty-eight separate rolling regressions (the first with thirty-two, the second with thirty-three up to the last with a sample of sixty quarters) for each model in order to ascertain the optimal, i.e. MSE-minimizing, window size. Alike, to find out the parameter of the AE model, we perform a grid search over all $\gamma \in (0,1]$, with stepsize 0.1, and we choose the value of γ that minimize the mean square error. Results show that setting $\gamma=1$ delivers the best AE predictor. So, in our sample, the naïve and the AE predictor are equivalent. For all VAR models, Akaike's and Schwarz Bayesian information criteria[8] suggest that one lag is optimal for virtually all models.[9]

Once estimated a model we perform one-step-ahead forecasts, computing the relative MSE. We limit our analysis to one-step-ahead predictions because

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7 In VAR models we must estimate at least four parameters and it suggests to keep enough observations.

8 It is worth recalling that these information criteria are based on the MSE statistic, too.

9 We have also estimated more generously lagged (up to four lags) models. Results show that the MSE stemming from VAR models only differing because of their different lag length, are very highly correlated and in no case outperform their most parsimonious version (i.e. that with only one lag).

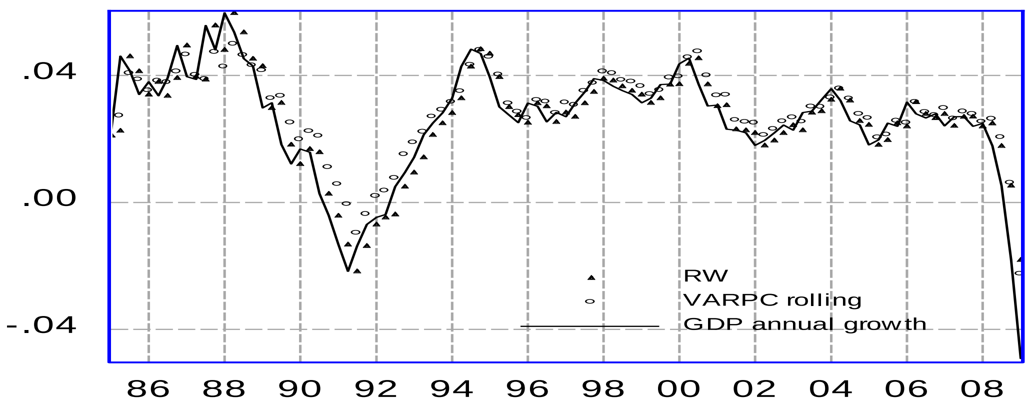
this is what naïve expectations do. Given the benchmark role of RW in testing the relative forecasting accuracy tests (Section 2.2), we proceed with one-quarter-ahead forecasts for all models. Finally, the wording of the survey question seems to support this kind of predictive exercise (Section 3). Table 2 reports the averages of the mean squared forecast percent errors (MSPE) of the models over the full sample period for which survey data are available[10] (1985:1-2009:1) and over three equally long sub-samples. Figure 1 offers the visual impact of the predictive ability of the models with the lowest (RW) and the largest (VARPCR) MSPE.

Table 2 The Forecasting Performance (MSPE) of GDP growth rate Predictors

Model	*1985-1992*	*1993-2000*	*2001-2009*	*1985-2009*
RW = MSE-minimizing AE	102.1	2.4	25.5	43.2
AR1	155.5	1.9	33.1	63.2
AR1R (=AR1 rolling)	121.1	2.2	29.0	50.5
VARPC	193.1	1.5	41.3	78.3
VARPCR (=VARPC rolling)	218.2	2.2	34.6	84.5
VAR	100.4	1.5	51.1	51.0
VARR (=VAR rolling)	126.3	3.3	32.0	53.6

Note. The MSPE refers to one-step-ahead forecasts of GDP annual growth. The MSE-minimizing AE coincides with RW. The rolling variants of each kind of model are those showing the MSE-minimizing window size. Other details under Table 1.

Figure 1. Best (RW) and Worst (VARPCR) one-step-ahead forecasts of the UK GDP growth



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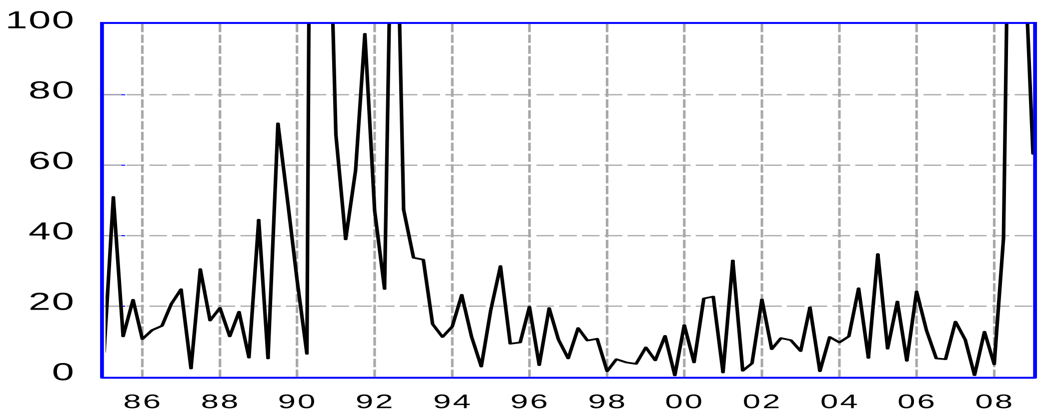
[10] It is worth noting that VAR models have been proposed for the first time in 1980 by Sims (Sims, 1980): it is hard to think that common people used VARs before that year.

Table 2 informs that the minimum MSPE is obtained by the naïve model but, with the possible exemption of the VARPC models, the overall forecasting accuracy is not dissimilar across models. Some sub-periods display larger discrepancies, unveiling that peculiar periods may impinge on the relative forecasting accuracy of models. Another robust outcome is that the first two sub-periods are featured by very different predictive performances: as compared to the first sub-sample, in the second period the MSPE of all models shrinks dramatically. A possible explanation may be found in the so-called "Great Moderation" (GM), a stylized fact on the significant reduction in the macroeconomic volatility around the industrialized world during the last decades[11] (Stock and Watson, 2003). In fact, as already noted, the MSE is strictly linked to the residual sum of squares and many authors suggest looking for the presence of the GM working on estimated residuals.[12] As for the naïve model, the MSE is equal to $(y_t-y_{t-1})^2$ and the following Figure 2 clarifies the U-path of the GDP growth rate volatility as (less easily) observable from Table 2.

Figure 2 Random Walk Forecasting Accuracy (RMSPE) as a Proxy of the Great Moderation



Note. The RMSPE refers to one-step-ahead forecasts of UK GDP annual growth. See also Tables 1 and 2.

11 Several authors have shown that, in the UK, the Great Moderation started in the early '90s (Benati, 2008; Bean, 2009).

12 For instance, Kim, Nelson and Piger (2004) use the residuals of autoregressive models. Note that, using MSEs stemming from the naïve model to proxy the GDP volatility, a constant GDP implies by construction a zero MSE.

2.2 Relative Forecasting Performances

In the previous section we have shown that the forecasting fitness of many models is similar. The full-sample correlations between the MSE relative to the different models vary from a minimum of 92.8% (RW vs. VAR) and a maximum of 99.8% (VARPC vs. VARPC rolling). To formally test the relative forecast ability of the models we perform Diebold-Mariano-type tests (Diebold and Mariano, 1995). We do that because there are no a priori on which forecasting model performs better, while it is likely that the costs related to models increase with their complexity (Brock and Hommes, 1997). Therefore model, and hence survey expectations, heterogeneity may depend on the kind of the best model. For instance, if the MSE-minimizing forecasting model turns out to be a VAR, as it somewhat implicitly assumed for the price dynamics in the US (Carroll, 2003), common people may feel the forecasting exercise as a costly and hard-to-perform activity. In this case, people may actually perform the cost and benefit analysis argued by the RHE approach or they may wait to be "contaminated" by news as in the Carroll's setting. If it happens, instead, that naïve models systematically outperform other forecasting models, individuals should quickly converge towards these predictors because they are the cheapest/easiest to use: both a "communism of models" and homogeneous expectations should eventually emerge. So, setting aside the limit case of one-for-life model agents, model-induced heterogeneous expectations may be model-conditional. In Section 5 we better clarify the implications of that.

Following the logic of this paper, we maintain the MSE as loss criterion and we run the following rolling regressions[13] (abstracting from the error term):

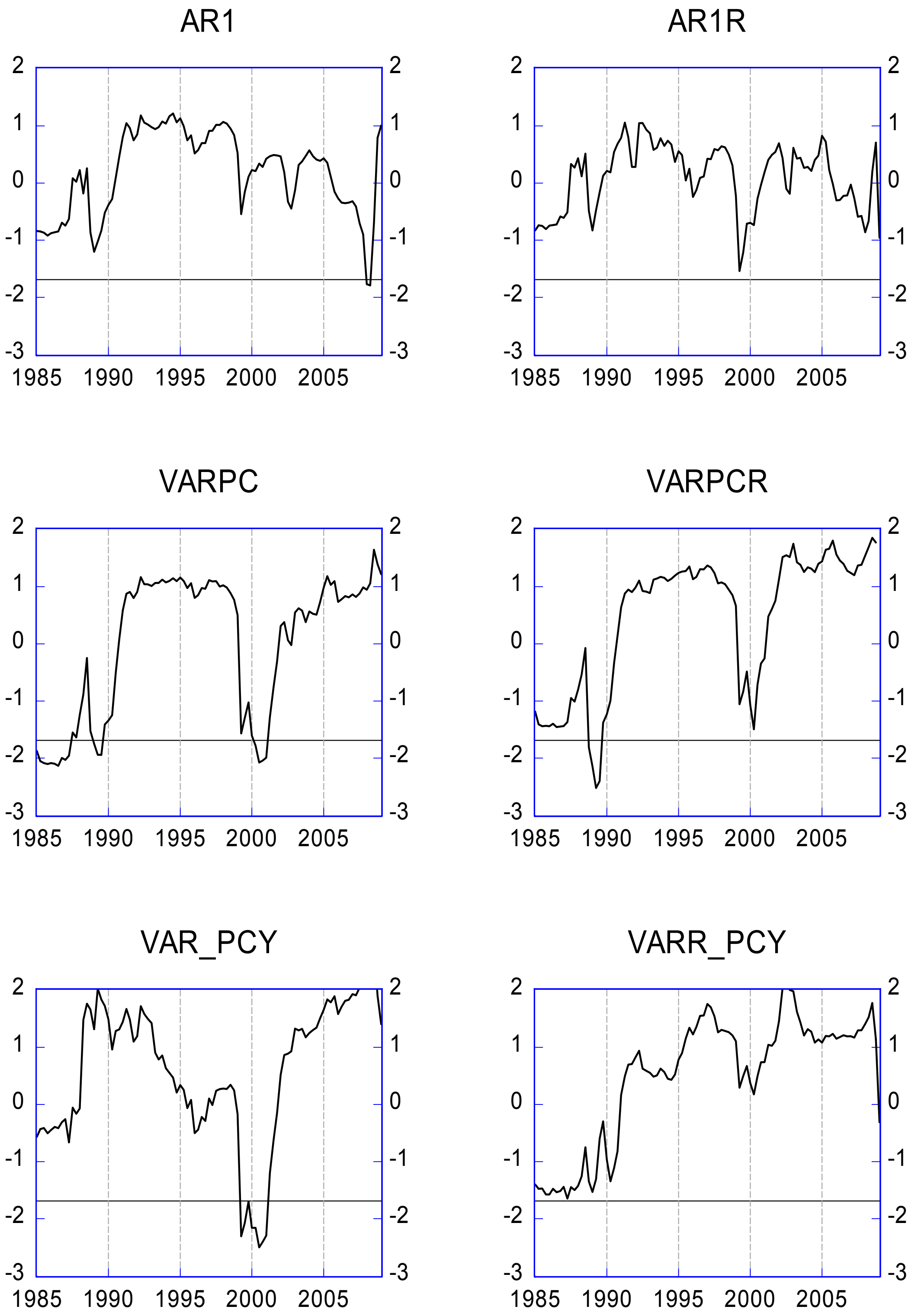
$$MSE_{t,j} - MSE_{t,rw} = const \qquad (1)$$

where J=AR1, VARPC, VAR, and their corresponding rolling versions (see Table 2).

As usual in the literature (Theil, 1966), we take the RW as the pivotal model: it is the easiest/cheapest/quickest, so it is likely that agents shift to another model only if this latter significantly MSE-dominates the naïve predictor. The null is "Model J has better predictive accuracy than RW" and, because it is a one-sided test, we reject it if the t-statistic of the intercept is greater than -1.69 (corresponding to a p-value of 5%). Figure 3 collects the results:

[13] In the main text we report the results obtained using window size of thirty-two quarters. Other window sizes do not substantially change the outcomes. All tests relies on Newey-West HAC dispersion matrices (Newey and West, 1987).

Figure 3 The Relative Forecasting Accuracy of Standard Econometric Models



Note. The benchmark model is the RW, the loss criterion is the MSE. When a curve is below the -1.69 horizontal line then the corresponding model dominates the naïve predictor at 95% significance level.

Evidence indicates that there is some model uncertainty over the sample:[14] in terms of MSE, no model beats all the others all the times. Nonetheless, the naïve model turns out to be the optimal predictor for most part of the sample. The worst performances are obtained by AR models, which practically never outperform the predictions of the benchmark model. As for professional predictors, i.e. the VAR models, they beat naïve forecasts only in the 80s and at the beginning of the current century.

3 DATA

After having examined model-based expectations, in this section we deal with survey expectations. For our aim, a unique dataset can be obtained from the Business Surveys Unit of the European Commission (European Commission, 1997, 2007). The survey is based on monthly surveys, it starts from January 1985 and it is still running. The survey is not a genuine panel, i.e. there are no re-interviews, though it is designed to capture the representative consumer. So, respondents are not professional economists, which is perfectly in line with our target.[15] In particular, each nation-wide monthly survey for the UK is based on two-thousand interviews. Thought the survey ask several questions, the relevant query in the present setting is:

"How do you expect the general economic situation in the country to develop over the next 12 months? It will…".

Surveyed individuals have six reply options:

LB=…get a lot better;
B=…get a little better;
E=…stay the same;
W=…get a little worse;
LW=…get a lot worse;
N=don't know.

[14] Following Branch (2007), here model uncertainty attains to forecasting: given costly estimation, what is the ideal predictor?

[15] It is worth noting that, given that we deal with the representative agent in all surveys, demography-related heterogeneous expectations should disappear. On that, Bryan and Venkatu (2001a,b) and Souleles (2004) detect strong evidence that survey expectations are different across demographic groups.

LB, B, E, etc., are the shares of respondents having chosen the corresponding option so that they sum up to one. Only these six aggregate shares are available, and only five of them form the basis of this study. Following existing literature, we have excluded the proportion relative to the option[16] "don't know", rescaling the other shares accordingly. Our dataset covers the period January 1985-March 2009. The correlations collected in Tables 3 and 3a suggest that the national account concept closer to what people have in mind when elicited on macroeconomic evolutions is the GDP annual growth.

Table 3 Forward-Looking Survey Question and GDP evolutions: Correlations

		Measures of GDP dynamics			
		$a=(gdp_t-gdp_{t-1})/gdp_{t-1}$	$(gdp_t-gdp_{t-4})/gdp_{t-4}$	$[1+a]^4$	Output gap
Survey Central Tendency	$y_{t-4}^{e,BAL}$	0.33	0.45	0.33	0.15
	$y_{t-4}^{e,BAL3}$	0.33	0.42	0.33	0.09
	$y_{t-4}^{e,CP}$	0.32	0.46	0.32	0.20
	$y_{t-4}^{e,CP3}$	0.36	0.47	0.35	0.12

Note: Central tendency indicators, all computed with unitary multipliers, are defined in Section 4.
They are lagged because the survey question refers to one-year-ahead GDP growth: "How do you expect the general economic situation in the country to develop over the next 12 months?"
Output gap=Log(gdp/gdp*); gdp*=Hodrick-Prescott GDP trend (λ=100).

Table 3a Backward-Looking Survey Question and GDP evolutions: Correlations

		Measures of GDP dynamics			
		$a=(gdp_t-gdp_{t-1})/gdp_{t-1}$	$(gdp_t-gdp_{t-4})/gdp_{t-4}$	$[1+a]^4$	Output gap
Survey Central Tendency	$y_t^{e,BAL}$	0.65	0.77	0.65	0.33
	$y_t^{e,BAL3}$	0.63	0.75	0.63	0.28
	$y_t^{e,CP}$	0.70	0.81	0.70	0.39
	$y_t^{e,CP3}$	0.73	0.82	0.72	0.33

Note: Survey question: "How do you think the general economic situation in the country has changed over the past 12 months?". See also under Table 3.

[16] Possibly, it is a "non response", i.e. it is not the outcome of an explicit elaboration but, rather, a declaration of no information. In this regard, the European Commission Users' Manual (1997, p. 18) states that: "(…) there are six reply options: five "real" ones and a 'do not know' option".

Given the wording of the questions faced by the interviewed, the finding that survey data are more related to the annual growth rate than to other GDP dynamics is expected and, hence, somewhat reassuring about the reliability of the answers. So, in the following sections, we limit the analysis to the GDP annual growth rate (y_t). Given that GDP data are available only at quarterly frequency, we aggregate monthly survey data via quarterly averages. In view of the VAR analyses reported in Section 5, it is worth mentioning that time aggregation may reduce noise in series, but may also increases contemporaneous correlation (Spencer, 1989).

4 SURVEY EXPECTATIONS SIGNAL-TO-NOISE RATIOS

In this section we elaborate some alternative quantitative indicators of the mean and dispersion of survey expectations. We do not rely on a single measure because all of them have pros and cons and none has emerged as being definitively superior to the others (Pesaran and Weale, 2006). Needless to say, then, univocal results stemming from different indicators increase the robustness of the findings.

As for the central tendency, one of the most used quantification method is the balance statistic (Anderson, 1952; Theil, 1952). In the three-category scheme (e.g., with only “up”, “same”, “down” option replies), it is defined as the difference between the share of respondents that expect “up” and the share of respondents that expect “down”. Within this approach it can be also computed a measure of disagreement between agents’ expectations. To calculate these two moments in the three-category version of the method we, somewhat following Berk (1999), aggregate the EU consumer survey replies. Defining: $s_t^B = LB_t+B_t$; $s_t^W = LW_t+W_t$; $s_t^E = E_t$, the balance and disconformity statistics suggested by Anderson are, respectively:

$$y_t^{e,BAL3} = \alpha(s_t^B - s_t^W) \tag{2}$$

$$\sigma_t^{e,BAL3} = \alpha^2[(s_t^B + s_t^W) - (s_t^B - s_t^W)] \tag{3}$$

We then reckon a slightly modified version, also used by the European Commission (1997), when the survey permits five option replies:

$$y_t^{e,BAL} = \alpha(LB_t+0.5*B_t-0.5*W_t-LW_t) \quad (4)$$

$$\sigma_t^{e,BAL} = \alpha^2[(LB_t+0.5*B_t+0.5*W_t+LW_t)^2 - (LB_t+0.5*B_t-0.5*W_t-LW_t)^2] \quad (5)$$

The parameter α can be chosen to ensure that the balance has the same average value as the GDP growth rate. This is an arbitrary choice and it may be misleading (Nardo, 2003; Pesaran and Weale, 2006). As for the balance statistic, the European Commission (2007) put a unitary weight.[17] Later on we will clarify why we do not address the issue of specifying this multiplier.

Another well-known conversion method is that of Carlson and Parkin (1975, henceforth CP), which we work out in the five option replies version of Batchelor and Orr (1998), too. The CP method interprets the share of respondents as maximum likelihood estimates of areas under the density function of aggregate expectations, that is as probabilities. The relative mean and standard deviation of expectations across individuals are:

$$y_t^{e,CP} = -y_t^r \left(\frac{z_t^3 + z_t^4}{(z_t^1 + z_t^2 - z_t^3 - z_t^4)} \right) \quad (6)$$

$$\sigma_t^{e,CP} = y_t^r \left(\frac{2}{(z_t^1 + z_t^2 - z_t^3 - z_t^4)} \right) \quad (7)$$

where:

y_t^r = agent's reference GDP growth rate;

$z_t^1 = N^{-1}[1-LB_t]$; $z_t^2 = N^{-1}[1-LB_t-B_t]$; $z_t^3 = N^{-1}[1-LB_t-B_t-E_t]$; $z_t^4 = N^{-1}[1-LW_t]$;

$N^{-1}[]$=inverse of the cumulative normal distribution.[18]

17 In fact, this is the solution usually adopted to publish the index.

18 Dasgupta and Lahiri (1992), Smith and McAleer (1995), and Berk (1999) find that the accuracy of the quantified series does not significantly vary between any of the common parametric distributions.

With three shares, the first two CP moments are:

$$y_t^{e,CP3} = \delta\left(\frac{N^{-1}[s_t^n] + N^{-1}[1 - s_t^p]}{N^{-1}[s_t^n] - N^{-1}[1 - s_t^p]}\right) \tag{8}$$

$$\sigma_t^{e,CP3} = \left(\frac{2\delta}{N^{-1}[1 - s_t^p] - N^{-1}[s_t^n]}\right) \tag{9}$$

The constant δ is a critical value that can be recovered by equating the mean of the expected (or perceived) GDP growth to average actual GDP growth in the sample period. Just like for the multiplier α in the Anderson setting, even the quantification of the critical value is as important as tricky.[19]

Another possible disconformity indicator is the Index of Qualitative Variation (IQV). It is based on the ratio of the total number of differences in the distribution to the maximum number of possible differences within the same distribution:

$$\mathrm{IQV}_t = \frac{K}{K-1}\left(1 - \sum_{i=1}^{K} s_{t,i}^2\right) \tag{10}$$

where $K=5$ is the number of option replies, and $i=LB_t, B_t, E_t, W_t, LW_t$. The scaling factor ensures that $0 \le \mathrm{IQV} \le 1$. Unlike the previous methods, the IQV does not account for the ordered nature of the data.

With central tendency and standard deviation indicators at hand, we are eventually able to calculate signal-to-noise ratios aimed to capture the relative heterogeneity in survey expectations. Table 4 shows the definitions of the SNR, their cross-correlations and those with the GDP volatility.

[19] For instance, when respondents have five options replies, it is not possible to assume that δ is constant (Pesaran and Weale, 2006).

Table 4 Survey Signal-to-Noise Ratios and GDP Volatility: Correlations

		Correlations (1985:1-2009:1)				
Definition	*Name*	SNR_BAL_t	SNR_BAL3_t	SRN_CP_t	SRN_CP3_t	GDP volatility
$y_t^{e,BAL} / \sigma_t^{e,BAL}$	SNR_BAL_t					-0.17
$y_t^{e,BAL3} / \sigma_t^{e,BAL3}$	SNR_BAL3_t	0.80				-0.17
$y_t^{e,CP} / \sigma_t^{e,CP}$	SNR_CP_t	0.74	0.86			-0.39
$y_t^{e,CP3} / \sigma_t^{e,CP3}$	SNR_CP3_t	0.80	0.99	0.89		-0.23
$y_t^{e,CP3} / IQV_t$	SNR_IQV_t	0.72	0.95	0.91	0.97	-0.37

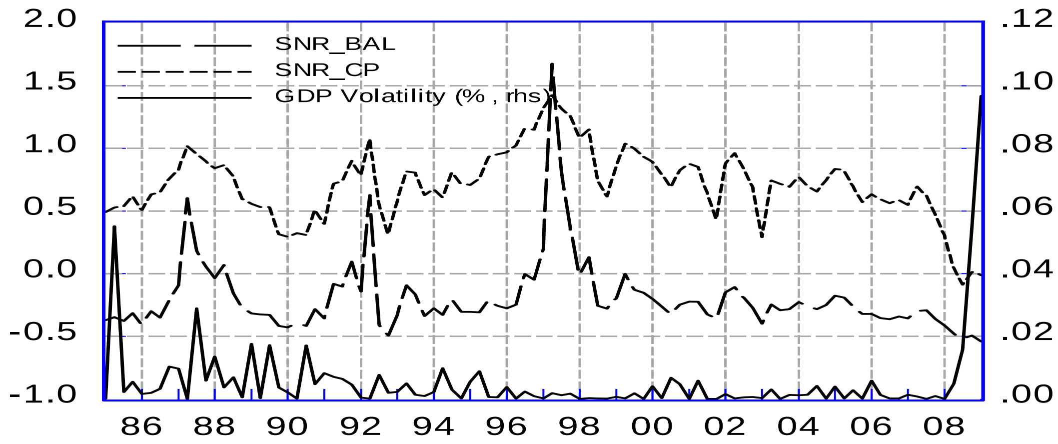
Note: GDP volatility = $(y_t - y_{t-1})^2$, $y_t=(gdp_t - gdp_{t-4})/gdp_{t-4}$. In computing SNR_IQV we have set $\delta=1$. For other definitions see the main text.

Before commenting the figures of Table 4, it is important to note that the proposed SNR afford to overcome some of the difficulties linked to their components. As for the five and three categories probability methods respectively, the factors y_t^r and δ disappear in the ratio. In the balance approach, the remaining α is no more a problem because any linear transformation leaves the correlation unchanged. This said Table 4 emphasizes that, with the possible exemption of SNR_BAL, all measures are strongly correlated. So, notwithstanding the different nature of the indexes, all SNR seem to contain similar information, which is a comforting outcome: it may be the effect of the relatively reduced number of crucial assumptions behind these ratios. Moreover, since our goal of contrasting a survey measure with model-based MSE, SNR are a natural choice because both criteria assess the quality of an estimator in terms of its variation and unbiasedness.[20] We also propose a hybrid SRN, namely SNR_IQV (computed by setting δ=1). The reason is that this latter, according to the findings of Maag (2009), might be the best signal-to-noise ratio in order to quantify survey expectations. Relying on micro-data from the Swedish consumer survey that asks for both qualitative and quantitative responses on expected inflation, Maag contrasts the fitness of the CP method with alternative approaches. Evidence suggests that whereas the three-

[20] The MSE of an estimator $\bar{\theta}$ with respect to the estimated parameter θ can be written as the sum of the variance and the squared bias of the estimator: $MSE(\bar{\theta}) = Var(\bar{\theta}) + Bias[(\bar{\theta},\theta)]^2$.

category probability method is the best in describing the central tendency, the IQV most closely tracks the actual heterogeneity of quantitative replies. The last column of Table 4 reports the correlations between SNR and GDP volatility. As expected, they are negative and suggest that the Anderson measure is the poorest one.[21] SNR_CP and SNR_IQV do a better and similar job. Finally, possibly due to their more detailed information content, the five-category indicators appear to be superior to the others. Figure 4 gives a first look at both survey and "hard" data.

Figure 4 **Signal-to-Noise Ratios and GDP Volatility**



Specifically, Figure 4 gives a visual impression of the mentioned (and expected) inverse relationship between GDP growth rate volatility, as proxied by the MSE stemming from naïve expectations, and the disconformity of survey expectations. Figure 4 reports only the SNR less/more correlated with GDP volatility, respectively SNR_BAL and SNR_CP (cfr. Table 4), so that the missing information can be roughly drawn by these extreme bounds.

5 GRANGER CAUSALITY TESTS AND FORECAST ERROR VARIANCE DECOMPOSITION

So far, we have examined survey and econometric predictions separately. Here we study their linear relationships, testing the presence, the direction, and the sign of causal links between them. We limit the analysis to the naïve model

21 It is based on hard-to-defend assumptions (Batchelor, 2006).

and to the models that are not systematically MSE-dominated by it (i.e., we exclude AR models). The logic is that it may be possible that nobody uses these models, so that it seems better to focus on really competing predictors. Specifically, we estimate bivariate VAR models involving one SRN and one (log) MSPE.[22] We then perform Granger block causality tests to see the direction of the causal chain relating these two indicators. Table 5 summarizes the results.

Table 5 Model-based MSPE and Survey-based Signal-to-Noise Ratios. Granger Causality Tests.

SNR	*BAL*		*BAL3*		*CP*		*CP3*		*IQV*	
Model	SNR => MSPE	MSPE => SNR	SNR => MSPE	MSPE => SNR	SNR => MSPE	MSPE => SNR	SNR => MSPE	MSPE => SNR	SNR => MSPE	MSPE => SNR
Naïve	.000	.182	.109	.255	.004	.618	.103	.420	.030	.226
VARPC (y,π)	.014	.386	.014	.067	.000	.428	.020	.103	.009	.154
VARPC (y,π) rolling	.034	.696	.002	.238	.000	.906	.011	.140	.001	.148
VAR (y,π,r)	.006	.965	.034	.542	.000	.230	.038	.105	.001	.662
VAR (y,π,r) rolling	.000	.941	.020	.196	.000	.285	.051	.187	.048	.346

Note. Cells report the p-values of Granger Block Exogeneity Tests, which are based on bivariate VAR made up by one SNR and one model-based (log) MSPE. E.g., the (zero) p-value in the upper left cell suggests that SNR_BAL significantly enter the equation with dependent variable “RW-based MSPE”. All residuals are multivariate normal but for six out of ten combinations relating VARPC and VARR to SNR. In these cases p-values are computed using Newey-West HAC matrices. To obtain multivariate normal residuals all the four VARs involving BAL start from 1998:1.

A robust message emerges from Table 5: no matter the survey indicator nor the econometric model on which the MSE is based, SNR always Granger-cause MSE. That is to say, people’s relative disagreement on macroeconomic evolutions affects the forecast accuracy of standard econometric models. Furthermore, there is no significant information flow in the opposite direction. This causal chain is in sharp contrasts with the timing behind the RHE and the epidemiological approach, whereas the “news” coming from econometric models “infect” survey expectations.

Another intriguing finding stemming from our analysis refers to the sign of the correlations relating SNR to MSE. The algebraic sum of the SNR coefficients significantly entering the MSE equation of the VARs is negative in

[22] Henceforth, to avoid confusion, when we write MSE in capital letter we refer to one of the time series computed in section 2. Just to mention, the Granger causality is based on the mean-squared error so that when we say that “SNR Granger causes MSE” we mean that the variable SNR helps to reduce the mean-squared forecast error referring to the variable MSE.

all the combinations between the proposed SNR and MSE. It implies that when the signal coming from the surveys is relatively perturbed, then econometric models exhibit greater difficulty in achieving good predictions. This result is in line with the papers of Mankiw and Reis (2001, 2002) and Roberts' (1995, 1997), which show that empirical macro models perform better when survey-based (inflation) expectations are used in place of constructed model-consistent rational expectations. To save space we do not report the above mentioned algebraic sums. Rather, we offer a quantification of the improvement in the predictive fitness of econometric models once the information contained in SNR is taken into account. To this end, we estimate the GDP growth rate equation of the trivariate VAR (Table 2) where we have also inserted the variable SNR_IQV:

$$y_t = \alpha_t + \sum_{i=1}^{h} \Psi_i z_{t-I} \tag{11}$$

$z=\{y,\pi,r,SNR\_IQV\}$; the optimal lag (h) is based on Akaike's and Bayesian information criteria.

A full-sample static (one-step-ahead) forecast of this model gives a RMSE of 0.54% and a mean absolute percentage error (MAPE) of 19.6. Deleting SNR from equation (11), that is regressing only the GDP growth rate component of the standard "fundamental" trivariate VAR ($z=\{y,\pi,r\}$), the foregoing statistics worsen: RMSE becomes 0.64%, the MAPE rises to 25.5. Similar findings, here not reported, hold for other combinations of SNR and econometric models.

The definition of Granger causality did not mention anything about the possible instantaneous correlation between time series. It can only establish whether, as found in this paper, past and current values of SNR help predict the future value of MSE. One way to test instantaneous correlations in VAR settings is via variance forecast error decompositions (VFED). If the percentage of the variance forecast error of MSE explained by innovations in SNR is zero and vice versa, then the two variables are exogenous and there is no instantaneous causality between them. We collect some of the VFED, and the relative Monte Carlo standard error bands, in Appendix. To save space we report only the VFED referring to the two best models (Figure 3), namely RW and PEAPC.[23] No matter the Choleski ordering, evidence univocally displays that MSE is exogenous with respect to SNR. That is to say, not only MSE does not Granger causes SNR, but it cannot explain current and future values of SNR either. It

[23] All not reported variance decompositions stemming from the other possible SNR-MSE combinations confirm the findings of Appendix 1.

turns out that the detected causal chain is stronger than a simple Granger "precedence".

6 CONCLUDING REMARKS

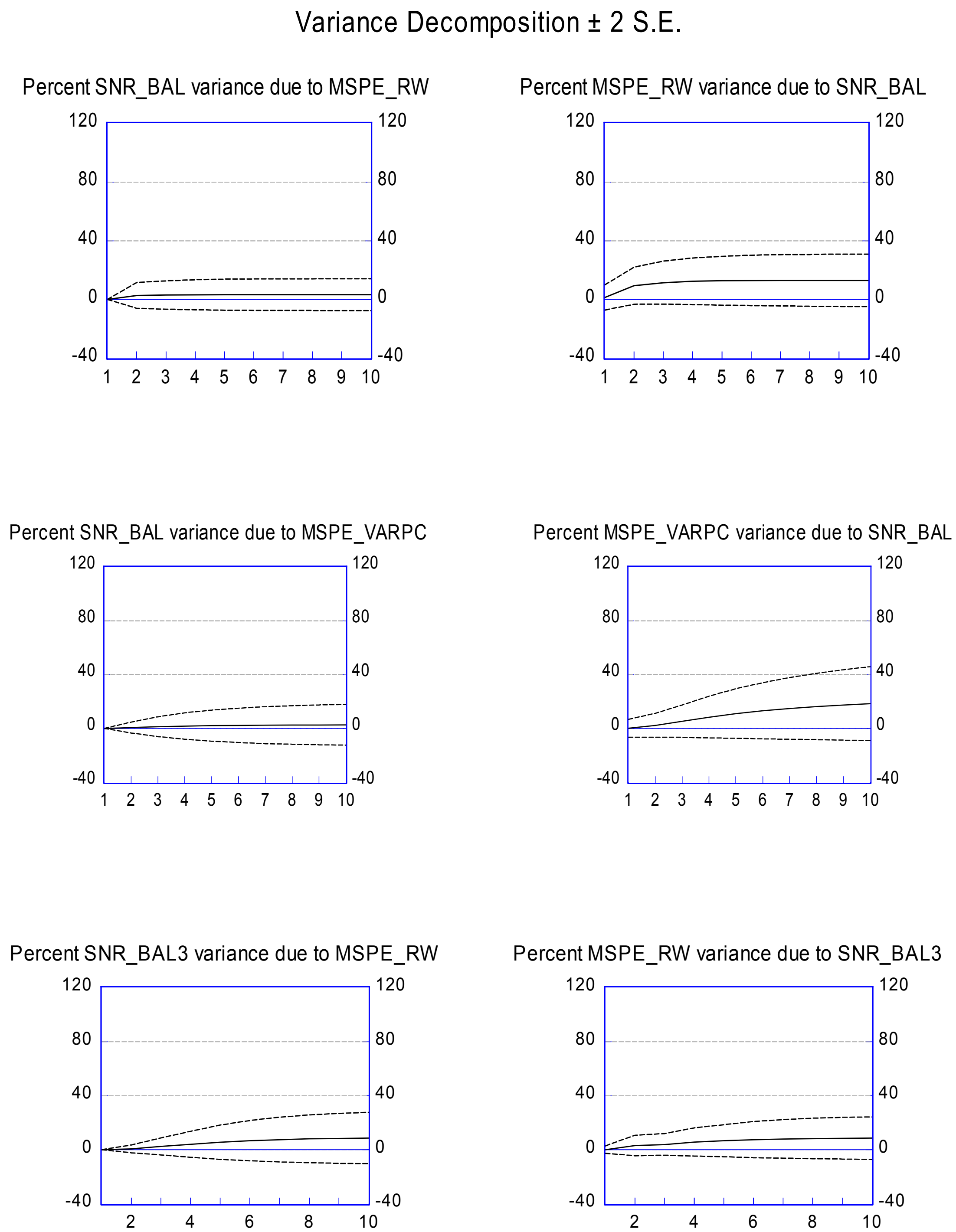
Mainstream economics usually turn a blind eye to the limitations of human rationality. Possibly because of that, we still know little about how people form their expectations. Yet, agents' expectations play a pivotal role in economics. In particular, heterogeneous expectations are a fact of life all over the world that seems overlooked by standard economic models.

A recent strand of the literature has been exploring whether the presence of heterogeneous expectations, as gathered by surveys, may be explained by the forecasting power of econometric models. Relying on macroeconomic and survey data for the UK this paper allows even the reverse engineering process, testing whether the causal chain runs from survey expectations to model fitness or vice versa. Whereas the predictive accuracy of models is based on the widespread mean square forecasting error statistic, the relative disagreement in survey expectations is measured by unusual signal-to-noise ratios. These ratios allow to tackle some of the issues impinging on methods of quantification of qualitative survey observations. Also, they are survey natural counterparts for the model-based MSE statistic.

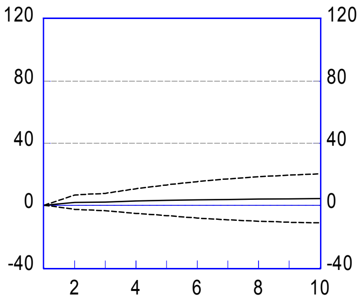
Evidence points univocally to information flows going from survey to econometric models. Specifically, Granger and variance decompositions tests suggest that past, present and future values of model-based MSE are not a determinant of the signal/noise ratios emerging from survey expectations. In contrast, divergent expectations affect the forecasting accuracy of macroeconomic models. Results are robust to several models/ratios combinations, including univariate and multivariate models estimated both recursively and via optimal-size rolling windows. All in all, our findings suggest looking at other possible causes of disagreement across agents' expectations beyond model uncertainty. The identification of these causes is the topic of future research.

APPENDIX. VARIANCE DECOMPOSITION

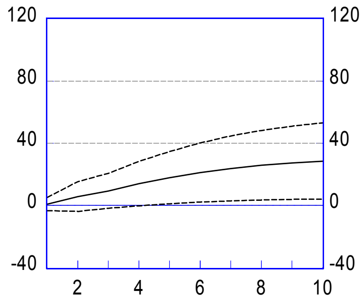
VARIABLES (CHOLESKI) ORDERING: SNR => MSE
(Monte Carlo Standard Error Bands, 1000 repetitions)



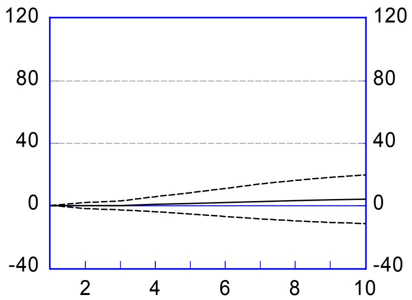
Percent SNR_BAL3 variance due to MSPE_VARPC



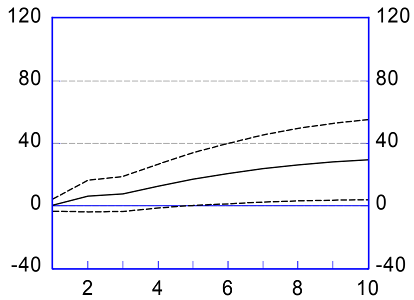
Percent MSPE_VARPC variance due to SNR_BAL3



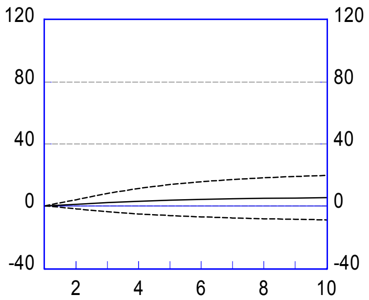
Percent SNR_CP variance due to MSPE_RW



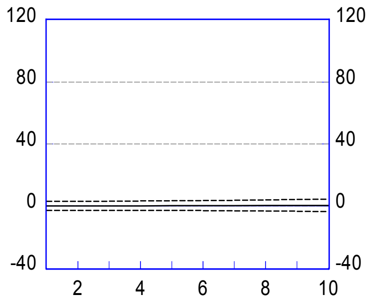
Percent MSPE_RW variance due to SNR_CP



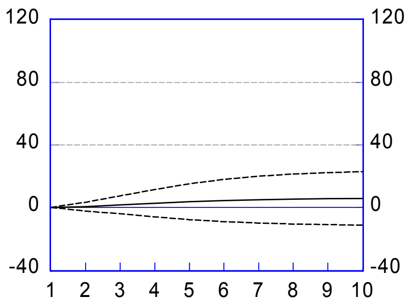
Percent SNR_CP variance due to MSPE_VARPC



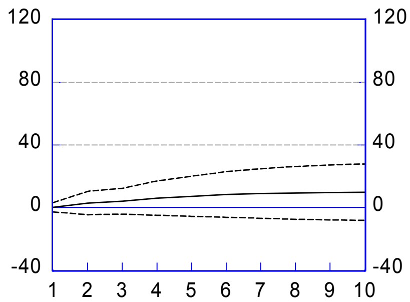
Percent MSPE_VARPC variance due to SNR_CP



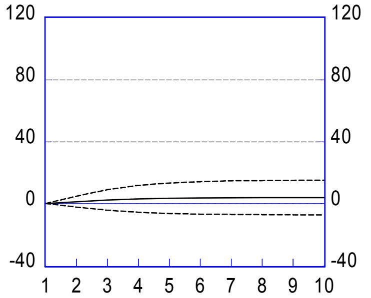
Percent SNR_CP3 variance due to MSPE_RW



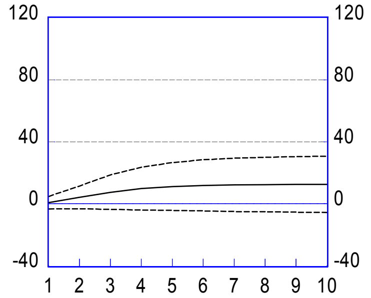
Percent MSPE_RW variance due to SNR_CP3



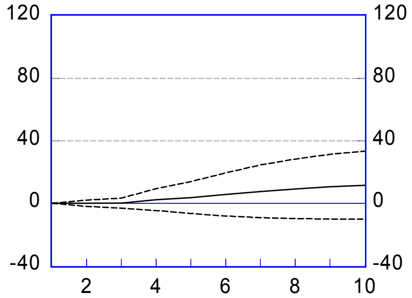
Percent SNR_CP3 variance due to MSPE_VARPC



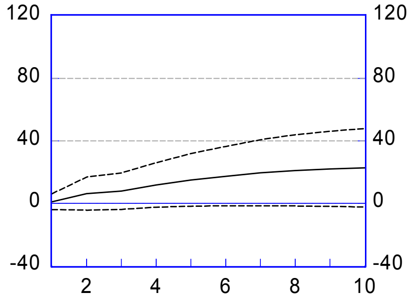
Percent MSPE_VARPC variance due to SNR_CP3



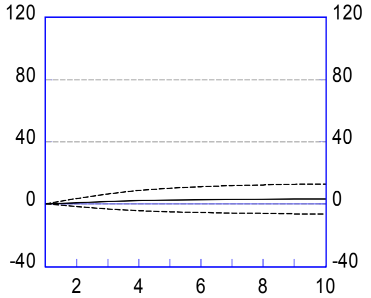
Percent SNR_IQV variance due to MSPE_RW



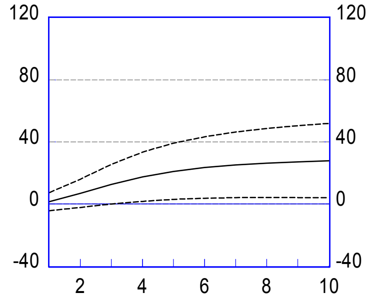
Percent MSPE_RW variance due to SNR_IQV



Percent SNR_IQV variance due to MSPE_VARPC

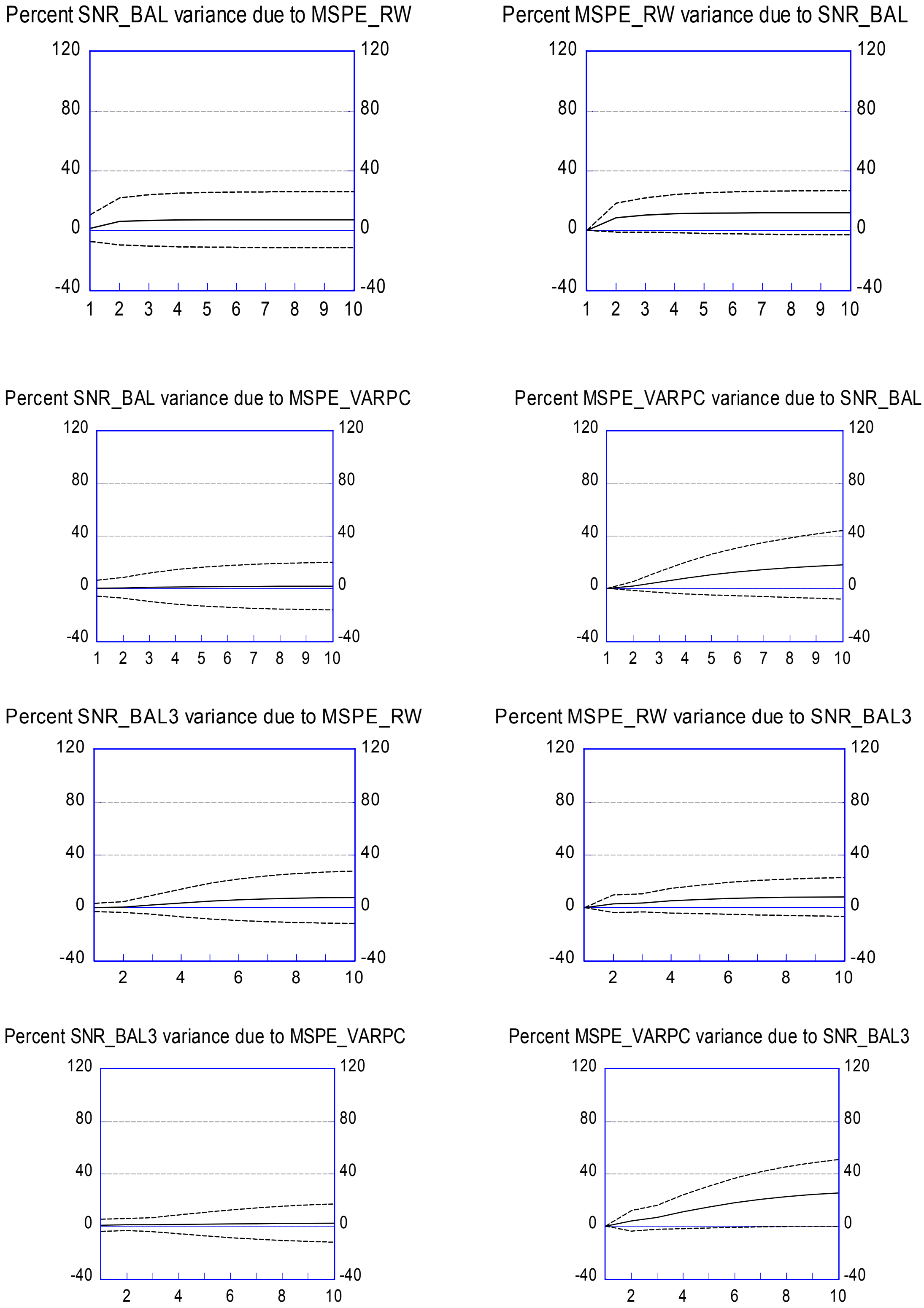


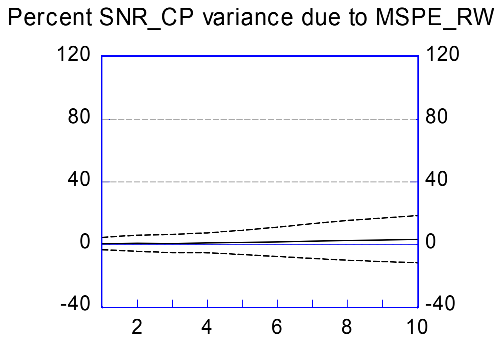
Percent MSPE_VARPC variance due to SNR_IQV

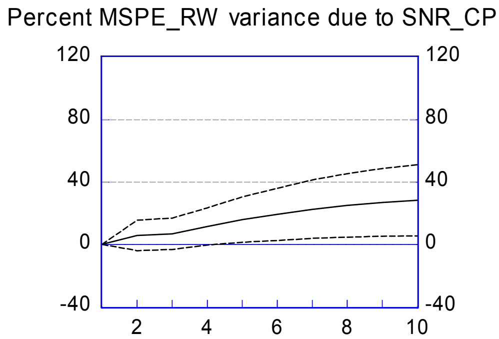


VARIABLES (CHOLESKI) ORDERING: MSE => SNR

Variance Decomposition ± 2 S.E.




Percent SNR_CP variance due to MSPE_RW
120
80
40
0
-40
2 4 6 8 10


Percent MSPE_RW variance due to SNR_CP
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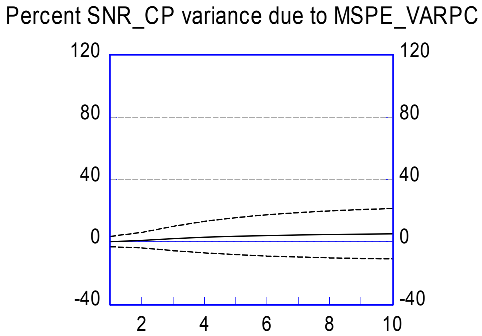
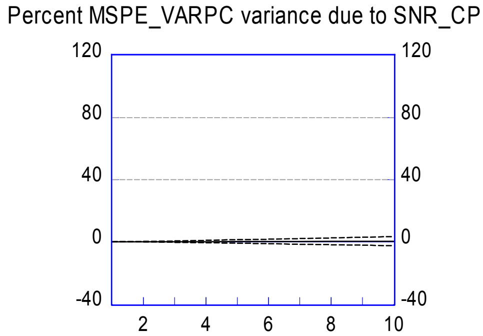
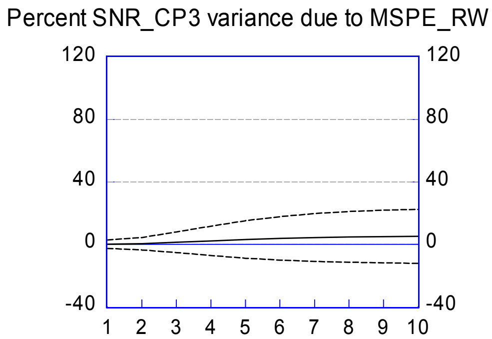
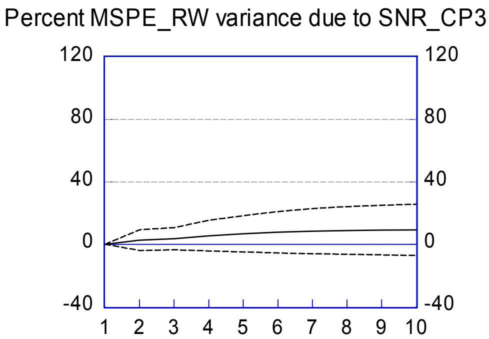
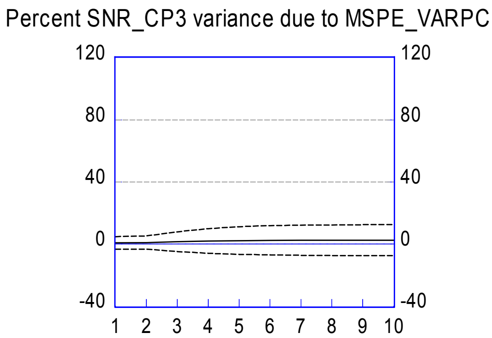
80
40
0
-40
2 4 6 8 10

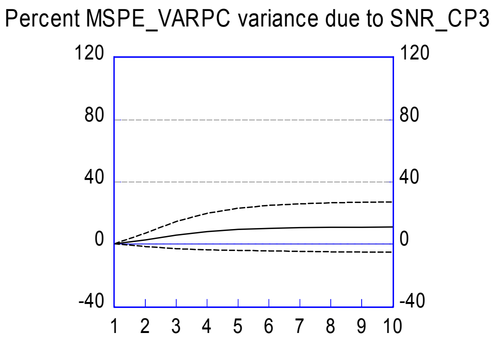

Percent SNR_CP variance due to MSPE_VARPC
120
80
40
0
-40
2 4 6 8 10

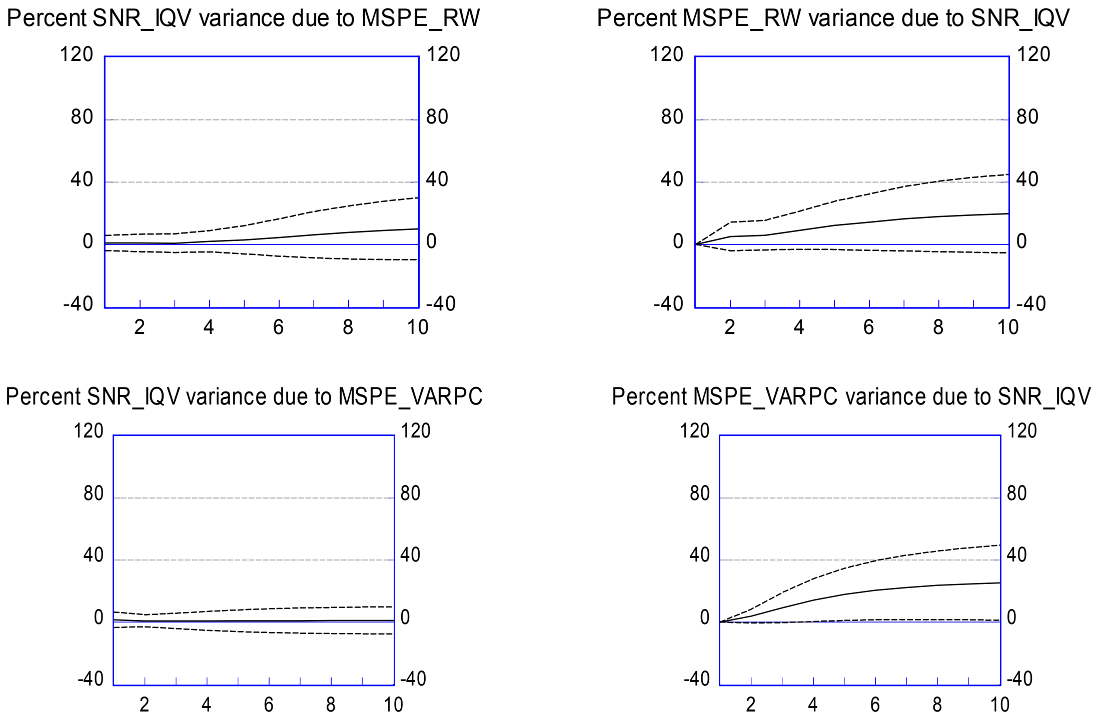

Percent MSPE_VARPC variance due to SNR_CP
120
80
40
0
-40
2 4 6 8 10


Percent SNR_CP3 variance due to MSPE_RW
120
80
40
0
-40
1 2 3 4 5 6 7 8 9 10


Percent MSPE_RW variance due to SNR_CP3
120
80
40
0
-40
1 2 3 4 5 6 7 8 9 10


Percent SNR_CP3 variance due to MSPE_VARPC
120
80
40
0
-40
1 2 3 4 5 6 7 8 9 10


Percent MSPE_VARPC variance due to SNR_CP3
120
80
40
0
-40
1 2 3 4 5 6 7 8 9 10


Percent SNR_IQV variance due to MSPE_RW
Percent MSPE_RW variance due to SNR_IQV
Percent SNR_IQV variance due to MSPE_VARPC
Percent MSPE_VARPC variance due to SNR_IQV
120
80
40
0
-40
2
4
6
8
10

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