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ESTIMATING FUNDAMENTAL CROSS-SECTION DISPERSION FROM FIXED EVENT FORECASTS

JONAS DOVERN AND ULRICH FRITSCHE

April 22, 2008

Abstract. A couple of recent papers have shifted the focus towards disagreement of professional forecasters. When dealing with survey data that is sampled at a frequency higher than annual and that includes only fixed event forecasts, e.g. expectation of average annual growth rates measures of disagreement across forecasters naturally are distorted by a component that mainly reflects the time varying forecast horizon. We use data from the *Survey of Professional Forecasters*, which reports both fixed event and fixed horizon forecasts, to evaluate different methods for extracting the "fundamental" component of disagreement. Based on the paper's results we suggest two methods to estimate dispersion measures from panels of fixed event forecasts: a moving average transformation of the underlying forecasts and estimation with constant forecast-horizon-effects. Both models are easy to handle and deliver equally well performing results, which show a surprisingly high correlation (up to 0.94) with the true dispersion.

Keywords: survey data, dispersion, disagreement, fixed event forecasts

JEL Classification: C22, C32, E37

1. Introduction

The extent of disagreement about the future paths of macroecononomic variables is remarkably high – even among professional forecasters (Zarnowitz and Lambros, 1987, Gallo et al., 2002). It can be argued that cross-section dispersion or disagreement is mirroring underlying uncertainty (Giordani and Söderlind, 2003). Measures on the dispersion of predictions are therefore frequently used to proxy the degree of uncertainty surrounding the point forecasts for macroeconomic variables. When derived from fixed event forecasts i.e. forecasts that are repeatedly made for one specific target variable like e.g. the annual growth for a specific calendar year, every measure of fundamental dispersion is distorted by the fact that the forecast horizon is time varying – a problem which is not found in data sharing the same forecast horizon (fixed horizon forecasts). In this paper, we analyze which approach among a group of alternatives is best suited to overcome this problem.

Several theories suggest that increased uncertainty leads to costs in terms of welfare. Friedman (1977) and Ball (1992) demonstrate for instance how increasing inflation uncertainty leads to higher losses in aggregate output. Consequently, it is desirable for economic agents as well as for researchers to have at hand a good proxy for the uncertainty attached to a given forecast of a variable. Giordani and Söderlind (2003) claim that using cross-sectional dispersion measures from survey data on forecasts constitutes a valuable approach for estimating uncertainty that is superior or at least complementary to time series approaches like e.g. GARCH models.

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It should be mentioned, however, that there is a dispute about the validity of this result (Bomberger, 1996, Rich and Tracy, 2003, Döpke and Fritsche, 2006). And a bunch of other theories exist that advocate sources for disagreement, i.e. forecast dispersion, other than pure uncertainty. Models of information transmission stress the role of time lags in the transmission of “news” to different agents in the macroeconomy – a process which is accompanied by shifts in the dispersion of beliefs as e.g. Mankiw et al. (2003) have shown. Recent models by Mankiw and Reis (2002) and Carroll (2003) follow the line of argumentation laid out by the assumption of diverging information sets. In particular, Carroll (2003) proposes a micro-founded model of transmission of inflation expectations between professional forecasters and households.[1]

Another factor explaining disagreement can be found in the usage of differing models and the existence of ideological beliefs. Economists generally have no consensus over “the one and only” model. For example, Fuller and Geide-Stevenson (2003) report that the members of the *American Economic Association* reach no consensus on the time-series properties of real gross domestic product (GDP). Unfortunately, there is little systematic direct evidence on forecasters preferred models and theories. The study of Batchelor and Dua (1990) constitutes an exception and documents considerable differences among forecasters.

In addition it is sometimes argued, that different forecasters face diverging incentives to cheat, to seek rents or to influence the public debate. For those reasons, forecast accuracy might not be the only aim of the forecasters (Laster et al., 1999, Ehrbeck and Waldmann, 1996). A related source of forecasters’ disagreement might be seen in forecasting as part of the policy advice process. In particular, Stege (1989) finds some – at least anecdotal – evidence of so-called “intentional” forecast errors, i.e. the forecaster predicts something to prevent it. Insofar the forecasters represent diverging political and ideological viewpoints the forecasts will differ accordingly. Furthermore, Kirchgässner (1999) argues that under standard assumptions of rent-seeking behavior economic advisers will try to promote their political clients.

Assuming nevertheless that the argument about a reasonably strong connection of dispersion and uncertainty made for instance by Giordani and Söderlind (2003) holds, practitioners and applied researchers are usually interested in a measure of uncertainty that is unaffected by changing institutional factors and more importantly time varying forecast horizons. This is why so far exclusively survey data on fixed horizon forecasts (in most cases twelve months ahead forecasts) have been used for this purpose. It is well documented, that forecast dispersion in fixed event panels has a remarkable proportion which is “non-fundamental” in a sense that this part of cross-section dispersion is driven by the time varying forecast horizons rather than by macroeconomic uncertainty (Gallo et al., 2002, Patton and Timmermann, 2007). Theoretical justifications can be found in early works by Lucas (1973) or Townsend (1983). Unfortunately, a good number of data sets provide only fixed event forecasts rather than fixed horizon forecasts. And given a scarce data situation for a particular country or variable, one would like to use these fixed event forecasts to measure uncertainty. At the same time, one would like to control for “non-fundamental” factors as the influence of the forecast horizon on dispersion. This paper suggests some empirical approaches for this task and assesses their relative performance.

To illustrate the argument treated in this paper, Table 1 shows the correlation coefficients between the cross-sectional standard deviation derived from fixed event forecasts

[1] See Roberts (1997) and Branch (2004), among others, for related work.

	Current year (fixed event)	Next year	12-months (fixed horizon)	Current year (fixed event)	Next year	12-months (fixed horizon)
	drgdp			**unemp**		
Current year	1.00			1.00		
Next year	0.65	1.00		0.75	1.00	
12-Month	0.58	0.61	1.00	0.63	0.85	1.00
	cpi			**tbill**		
Current year	1.00			1.00		
Next year	0.82	1.00		0.81	1.00	
12-Month	0.82	0.94	1.00	0.74	0.85	1.00

Table 1. Correlation of different dispersion measures

and those derived from fixed horizon forecasts.[2] Two observations are worth pointing out. First, the correlation between the dispersions derived from fixed horizon forecasts and those based on predictions for the current year's annual figures are in all cases smaller than those with the dispersion based on predictions for the next year's annual figures. This is not surprising as one would expect that the dispersion across panelists is most affected by the shrinking forecast horizon when the latter comes close to zero and some of the relevant data for the forecast is already in the information set of the forecasters. Patton and Timmermann (2007) indeed show that much of the reduction of cross-sectional dispersion is observed when the forecast horizon becomes smaller than one year rather than during the year before. Second, the correlations are especially low in the case of forecasts for the growth rate of real output.

In the course of the paper we test several methods regarding their appropriateness to filter out the "non-fundamental" dispersion – proxied by the standard deviation and the interquartile range. One of the considered method is applied at the level of the individual panel members, whereas all the other methods are applied directly to the empirical cross-section dispersion.

The remainder of the paper is structured as follows. In section 2, different approaches are presented which serve to extract the forecast-horizon-induced component from the dispersion found in fixed event forecast data. In section 3, we briefly review the data sets we use. In section 4, we present the empirical results that assess the performance of the different approaches. Section 5 concludes the paper.

2. Approaches

In this section, we present different modeling frameworks that seem to be adequate to estimate the "fundamental" component of cross-sectional dispersion derived from fixed event forecasts. Throughout the remainder of this paper we adopt the following notation: Let $\tilde{y}^0_{t,i}$ denote the forecast for a variable for the current calendar year made by forecaster i at time t. Analogously, $\tilde{y}^1_{t,i}$ denotes her forecast for next year's annual figure. In case of growth rates being forecasted, the forecast for the quarter-to-quarter growth rate at time s made by the same forecaster at time t is given by $y^s_{t,i}$. We compute the twelve-months-ahead growth forecast of each panelist as $\hat{y}^{12}_{t,i} = \left[\prod_{k=0}^{3}(y^{t+k}_{t,i}/100 + 1) - 1\right] * 100$.

The different cross-sectional dispersions at each sample point are calculated as the standard deviation across all N forecasts or their interquartile range. We denote them as $D^{\tilde{y}^0}_t$,

[2]Results using alterative measures like the interquartile range are similar. We use the well-known U.S. data set of quarterly macroeconomic forecasts from the *Survey of Professional Forecasters*. For more details see section 3 below.

$D_t^{\tilde{y}^1}$, and $D_t^{\hat{y}^{12}}$ respectively. Since $\hat{y}_{t,i}^{12}$ is unaffected by seasonal influences and the forecast horizon is fixed over time, we don't expect $D_t^{\hat{y}^{12}}$ to show any seasonal patterns. Rather, it should only reflect disagreement due to the prevailing macroeconomic uncertainty.

From the six candidate approaches which we will consider in this paper, one is different from the remaining five approaches in the sense that it tackles the problem at a fundamentally different point. This one approach is non-parametric, intuitive, and simple; it involves approximation of the twelve-months-ahead forecasts in a first step, and calculation of a dispersion measure across those approximative fixed horizon forecasts in a second step. In contrast, all other methods take the dispersion as measured over fixed event forecasts as input and use different parametric time-series approaches to decompose this dispersion into different components one of which represents the fundamental degree of dispersion we are interested in.

2.1. **Estimation via Approximation of fixed horizon forecasts.** If someone is interested in the dispersion across (unobserved) fixed horizon forecasts, a natural way of calculation is based on an approximation of those unknown forecasts. To this end, we construct simple proxies for the twelve-months-ahead forecasts by taking a weighted moving average of fixed event forecasts (Heppke-Falk and Hüfner, 2004, Smant, 2002), namely the forecasts for two subsequent calendar years.

$$\hat{\hat{y}}_{t,i}^{12} = \frac{4-q+1}{4}\tilde{y}_{t,i}^{0} + \frac{q-1}{4}\tilde{y}_{t,i}^{1} , \tag{1}$$

where q is equal to one in each first quarter of the year, equal to two in each second quarter of the year, and so on. As an example, consider the situation in the second quarter of 2007. We would compute a proxy for the twelve-months-ahead forecast with target date 2008Q1 by taking 3/4 of $\tilde{y}_{07Q2,i}^{07}$ and adding 1/4 of $\tilde{y}_{07Q2,i}^{08}$.

In a second step, we compute a measure of dispersion, let's say $D_t^{\hat{\hat{y}}^{12}}$, like the standard deviation or the interquartile range, across all individual forecasters at each point in time.

2.2. **Estimation via Time-Series Decompositions.** The other methods take a different route and start from the dispersion calculated across fixed event forecasts. Formally, we assume that we can write $D_t^{\tilde{y}^k}$, $k \in \{0, 1\}$, as the sum of two components and a residual term

$$D_t^{\tilde{y}^k} = D_t^{\tilde{y}^k\, f} + D_t^{\tilde{y}^k\, h} + \epsilon_t \, . \tag{2}$$

Here $D_t^{\tilde{y}^k\, h}$ denotes the component that is driven by the time varying forecast horizon and contains no valuable information about the fundamental disagreement among the forecasters. On the other hand, $D_t^{\tilde{y}^k\, f}$ is the fundamental component. It is driven by the same underlying factors as $D_t^{\hat{y}^{12}}$ and should follow a sample path with similar dynamic properties. It is this component that we want to use as a proxy for the (in case of survey data on fixed event forecasts) unobserved process $D_t^{\hat{y}^{12}}$.

In the remainder of this section, we present different time series models that can serve to extract the fundamental component, $D_t^{\tilde{y}^k\, f}$, from the observed time series, $D_t^{\tilde{y}^k}$. The basic idea behind all five approaches is to determine the seasonal (forecast horizon dependent) component in some way. The methods differ most crucially in the way residual terms are treated, i.e. whether they are assumed to be part of the fundamental component or not.

2.2.1. *Seasonal Adjustment by X12-ARIMA.* One natural approach to filter out the component, $D_t^{\tilde{y}^k h}$, which moves over the year in a repetitive way due to the varying forecast horizon, is the application of a standard seasonal adjustment method. We have chosen the widely used X12-ARIMA procedure (US-Census-Bureau, 2007) for this purpose.

2.2.2. *Constant Forecast-Horizon-Effects.* Another very simple approach is to assume that the reduction of dispersion caused by a shrinkage of the forecast horizon is constant over time, i.e. there is one $D_t^{\tilde{y}^k h}$ for all first quarters of the years, one for all second quarters of the years, and so on. We can estimate those fixed forecast-horizon-effects by regressing $D_t^{\tilde{y}^k}$ on a set of quarter-dummies each of them being equal to one only in one specific quarter of the year. The regression equation takes on the form

$$D_t^{\tilde{y}^k} = \sum_{i=1}^{4} \beta_i Dum_i + \upsilon_t \ . \tag{3}$$

One can argue that the residuals, $\hat{\upsilon}_t$, of this kind of regression should be a good approximation to $D_t^{\tilde{y}^k f}$. Note that the first two time series approaches do simply filter out a deterministic seasonal component; all residual shocks are attributed to the fundamental component. This will be different for the following two approaches.

2.2.3. *Unobserved Components Model.* Yet another approach is to specify an unobserved components model (Harvey, 1989, Durbin and Koopman, 2001) for $D_t^{\tilde{y}^k}$. This requires some assumptions about the processes behind $D_t^{\tilde{y}^k f}$ and $D_t^{\tilde{y}^k h}$. Since it is not unreasonable to assume that $D_t^{\tilde{y}^k f}$ should exhibit some degree of persistence, we assume here that it follows a random walk process:

$$D_t^{\tilde{y}^k f} = D_{t-1}^{\tilde{y}^k f} + \upsilon_t \ , \tag{4}$$

where we assume that $\upsilon_t \sim NID(0, \sigma_\upsilon^2)$ is independently distributed from ϵ_t above.

For $D_t^{\tilde{y}^k h}$, we assume that it follows a stochastic seasonal pattern. More specifically, we specify it in such a way that it has a trigonometric form:

$$D_t^{\tilde{y}^k h} = \sum_{i=1}^{s/2} \gamma_{j,t} \ , \tag{5}$$

where s is the number of seasonal frequencies in a year (e.g. 4 for quarterly data) and each of the $\gamma_{j,t}$ follows a process

$$\begin{bmatrix} \gamma_{j,t} \\ \gamma_{j,t}^* \end{bmatrix} = \begin{bmatrix} \cos\lambda_j & \sin\lambda_j \\ -\sin\lambda_j & \cos\lambda_j \end{bmatrix} \begin{bmatrix} \gamma_{j,t-1} \\ \gamma_{j,t-1}^* \end{bmatrix} + \begin{bmatrix} \omega_{j,t} \\ \omega_{j,t}^* \end{bmatrix} \ .$$

Here $\lambda = 2\pi j/s$ is the frequency and the disturbances $\omega_{j,t}$ and $\omega_{j,t}^*$ are mutually uncorrelated and $NID(0, \sigma_\omega^2)$. The filtered state estimates (conditional on past information only) of $D_t^{\tilde{y}^k f}$ constitute a proxy for the fundamental dispersion.

2.2.4. *Bivariate Unobserved Components Model.* Whereas we used data on $D_t^{\tilde{y}^0}$ and $D_t^{\tilde{y}^1}$ only separably in the approaches so far, it might be worth specifying a bivariate model to use a richer information set to extract one fundamental component from data on both of the dispersion time series. Such an approach is proposed in this paragraph. More specifically, we assume that $D_t^{\tilde{y}^0 f}$ and $D_t^{\tilde{y}^1 f}$ are equal at each point in time, i.e. we require the fundamental component of disagreement among forecasters to be identical for both the disagreement on current calendar year's annual growth rate and the disagreement on next year's growth rate. Given that these two kinds of forecasts are made by forecasters at the same point in time and facing the same information set about the stance of the economy this is a natural assumption. We denote this common fundamental component by $D_t^{\tilde{y}f}$. The appropriate specification of the data generating process for this fundamental component is data driven and has to be specified for each set of forecasts analyzed. Some restrictions have to be made, however, to limit the number of possible models. We assume that it follows a stationary autoregressive process with a maximum lag order of q.

We capture the changes in dispersion induced by changing forecast horizons by including dummies for each forecast horizon of eight, seven, . . . , one quarter(s) at the appropriate point in the specification taken here in this paragraph. Formally, the model is given by

$$\left[\begin{array}{c} D_t^{\tilde{y}^0} \\ D_t^{\tilde{y}^1} \end{array}\right] = D_t^{\tilde{y}f} \left[\begin{array}{c} 1 \\ 1 \end{array}\right] + \sum_{i=0}^{4} \left(\left[\begin{array}{c} \beta_i \\ \beta_{i+4} \end{array}\right] Dum_i \right) + \left[\begin{array}{c} \epsilon_t^1 \\ \epsilon_t^2 \end{array}\right] , \tag{6}$$

where $D_t^{\tilde{y}f}$ evolves according to

$$D_t^{\tilde{y}f} = L(\beta) D_t^{\tilde{y}f} + \zeta_t \, .$$

$L(\beta)$ is a lag polynomial of order q and the three error terms ϵ_t^1, ϵ_t^2, and ζ_t are assumed to be uncorrelated and independently identically normally distributed with different but fixed variances. Again, the filtered state estimates for $D_t^{\tilde{y}f}$ will serve as a proxy for the fundamental degree of dispersion. Note that in both the univariate and the bivariate unobserved components approach we do not add the residual terms to the fundamental component; this is a conceptual difference to the first two time series approaches above.

3. Data

In this paper we use data from the Survey of Professional Forecasters (SPF).[3] The data set reports forecasts on macroeconomic variables from professional forecasters collected through surveys among the panelists. The SPF is the oldest survey in the US that reports forecasts on macroeconomic variables at a quarterly frequency. Its beginning dates back to 1968 although the set of variables has been continuously extended in later years so that the samples do not reach back to 1968 for all variables.[4] Forecasters are anonymous which should minimize the problem of distorted forecasts due to incentive issues (Kahneman and Tversky, 1979, Ehrbeck and Waldmann, 1996, Batchelor, 2007).

We concentrate in this paper on the most prominent macroeconomic variables of the data set, namely the growth rate of the real gross domestic product (*drgdp*), the inflation rate (*cpi*), the unemployment rate (*unemp*), and the treasury-bill rate (*tbill*). The big advantage of the SPF data set for the purpose of this paper is that it simultaneously provides fixed event and fixed horizon forecasts by all panelists. The forecasters are asked to report not only their predictions for the quarterly development over the next five quarters (from which e.g. four-quarter-ahead forecasts can be deduced) but also their predictions for the annual figures of the current calendar year and those for the next calendar year.

Since panelists are asked to report their beliefs on future levels of GDP rather than the implied growth rates, we need additional information to infer the implied annual growth rate for the current calendar year. It is a natural choice to use real-time data vintages for this purpose as these contain the data which was actually available to the forecasters at

[3]The data can be downloaded at `http://www.phil.frb.org/econ/spf/`.

[4]The survey was taken over by the Federal Reserve Bank of Philadelphia in 1990. The cross-section dimension, i.e. the number of forecasters who take part in the survey, is currently around 30. For more details on the survey see e.g. Croushore (1993).

each time the survey has been conducted. We use information about the level of aggregate output in the previous calender year from the real-time data set provided by the Federal Reserve Bank of Philadelphia.[5]

To get an impression about the data and the problem one is facing when estimating cross-sectional dispersion from fixed event forecasts, we plot the cross-sectional standard deviations over time in Figure 1. The plots show the dispersion of the forecasts for the current and next calendar year respectively together with the dispersion of the 12-months ahead forecasts. It is evident that those dispersion measures based on the two kinds of fixed event forecasts inherit saisonal patterns. These are naturally more pronounced for the results based on the forecasts for the current calendar year. Another observation is that the saisonal effect seems to be weakest for the dispersion of interest rate forecasts.

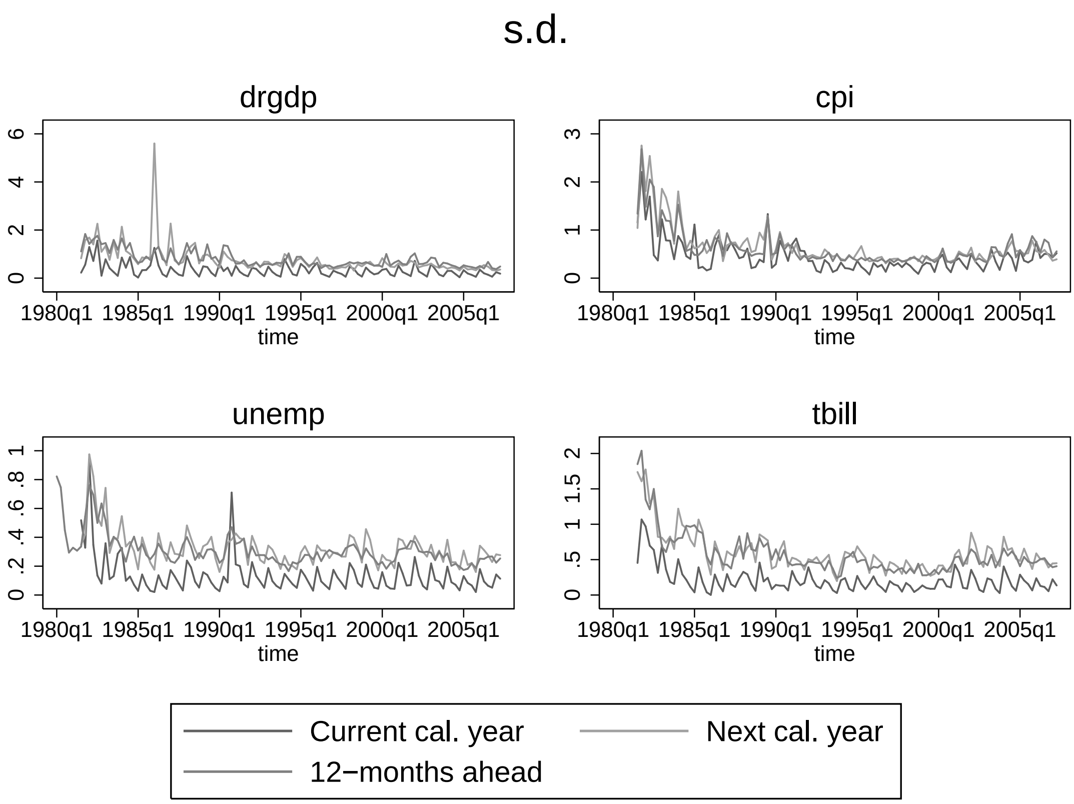

FIGURE 1. Cross-Section s.d. of Forecasts

4. RESULTS

In this section, we briefly review the empirical results obtained using the data from the SPF. Regarding the dispersion measure, we confront the results obtained using the cross-sectional standard deviation (s.d.) and the interquartile range (iqr) respectively. Since we are interested in constructing the best possible measure for fundamental disagreement from fixed event forecasts, we will use the linear correlation between the different potential proxies and the dispersion derived from the fixed horizon forecasts as the performance criterion.

To ease references to the different methods in tables and the following description of the results, we introduce the labeling scheme presented in Table 2. Given its prominence

[5]The real-time data set can be accessed via
`http://www.philadelphiafed.org/econ/forecast/real-time-data/index.cfm`.

Label	Method
M1	Approximation of fixed-horizon FCs
M2	Bivariate unobs. components model
M3	Univ. unobs. comp. model based on FCs for current cal. year
M4	Univ. unobs. comp. model based on FCs for next cal. year
M5	Extraction of sais. comp. by means of dummies based on FCs for current cal. year
M6	Extraction of sais. comp. by means of dummies based on FCs for next cal. year
M7	Saisonal adjustment of FCs for current cal. year by X12-ARIMA
M8	Saisonal adjustment of FCs for next cal. year by X12-ARIMA
M9	Unprocessed dispersion across FCs for current cal. year
M10	Unprocessed dispersion across FCs for next cal. year

Table 2. Labeling of different methods

against the methodologically different other methods and its intuitiveness, we will treat M1 as the reference method, against which we will compare all other methods from here on.

Table 3 contains a bunch of information that describes the empirical results. In what follows, we discuss the different aspects represented in the table. The most important information is given by the first number in each column. Those numbers are the linear correlation coefficient of the proxy obtained by the different methods respectively and the dispersion measure derived directly from the fixed horizon forecasts that are given in the SPF. Ultimately, we would like to know whether the differences in performance according to the correlation coefficient of the different methods are statistically significant. To this end, we use a test based on Fisher's z-transformation (Fisher, 1925) to infer whether we can reject the Null hypothesis that two correlation coefficients are statistically indistinguishable from each other.[6] Information on the test outcomes are given in the table by the numbers in parenthesis. They refer to the p-value of testing the Null hypothesis that the correlation of the corresponding method is equal to the correlation of M1. Values above 5% indicate that we cannot reject the hypothesis of equal correlation coefficients and, hence, equal performance of the two methods.

The test results indicate that the correlation coefficient in the overwhelming number of cases is statistically different, but only in the minority of cases sophisticated methods outperform the simple reference method M1. This result holds for the standard deviation as a common measure of dispersion; it does not hold when using the interquartile range to measure dispersion of forecasts. Considering that the interquartile range is a more appropriate measure of dispersion in those cases where the distribution of forecasts is not symmetric, this could indicate weaknesses of the sophisticated methods relative to M1 when the distribution is for instance skewed.

The methods which indicate a higher correlation with the cross-section dispersion (s.d.) of fixed horizon forecasts compared to M1 are: method M2 in two out of eight cases, method M6 in four out of eight cases, and method M8 in two out of eight cases. In general this does not indicate a clear gain when using quite sophisticated methods. In fact, only M6 looks like a method which is an serious competitor to M1. In case of the interquartile range measure, there is no method which beats the moving-average transformation M1 in terms of a significantly higher correlation coefficient for three out of the four variables.

[6]The test takes into account that we are dealing with dependent correlation coefficients in the sense that for three random variables x_1, x_2, and y we test whether $corr(x_1, y) - corr(x_2, y) = 0$, i.e. both correlations are computed against the same random variable.

	GDP-Growth		Inflation		Unempl. Rate		T-Bill Rate	
	s.d.	iqr	s.d.	iqr	s.d.	iqr	s.d.	iqr
M1	0.82	0.76	0.92	0.60	0.83	0.65	0.89	0.88
M2	0.80 (0.74)	0.74 (0.72)	**0.94* (0.05)**	0.59 (0.88)	**0.90* (0.00)**	0.50* (0.02)	0.85* (0.04)	0.75* (0.00)
M3	0.78 (0.32)	0.64 (0.06)	0.84* (0.00)	0.34* (0.00)	0.80 (0.38)	0.26* (0.00)	0.75* (0.00)	0.67* (0.00)
M4	0.74 (0.08)	0.63* (0.05)	0.86* (0.01)	0.63 (0.78)	0.82 (0.91)	0.44* (0.01)	0.90 (0.61)	0.76* (0.00)
M5	0.67* (0.00)	0.53* (0.00)	0.84* (0.00)	0.24* (0.00)	0.66* (0.00)	0.37* (0.00)	0.79* (0.00)	0.66* (0.00)
M6	0.62* (0.00)	**0.83* (0.05)**	**0.94* (0.04)**	0.68 (0.20)	**0.89* (0.00)**	0.67 (0.64)	**0.93* (0.00)**	0.88 (0.75)
M7	0.54* (0.00)	0.54* (0.00)	0.82* (0.00)	0.28* (0.00)	0.56* (0.00)	0.31* (0.00)	0.80* (0.00)	0.73* (0.00)
M8	0.70* (0.00)	0.82 (0.10)	0.94 (0.08)	0.70 (0.10)	**0.91* (0.00)**	0.66 (0.82)	**0.94* (0.00)**	0.88 (0.92)
M9	0.58* (0.00)	0.40* (0.00)	0.82* (0.00)	0.21* (0.00)	0.62* (0.00)	0.27* (0.00)	0.69* (0.00)	0.54* (0.00)
M10	0.61* (0.00)	**0.83* (0.05)**	0.94 (0.07)	0.68 (0.25)	0.83 (0.94)	0.63 (0.68)	0.90 (0.60)	0.86 (0.45)

Notes: Numbers refer to the correlation to the dispersion of the actual twelve-months-ahead predictions. Number in parenthesis show the p-values corresponding to H_0: Correlation of corresponding method is equal to correlation of M1. An * indicates rejection of H_0 at a 95% confidence level. We marked those cases with bold numbers for which an alternative method delivers a significantly higher correlation coefficient than M1 rather than a significantly lower one.

TABLE 3. Correlation Results

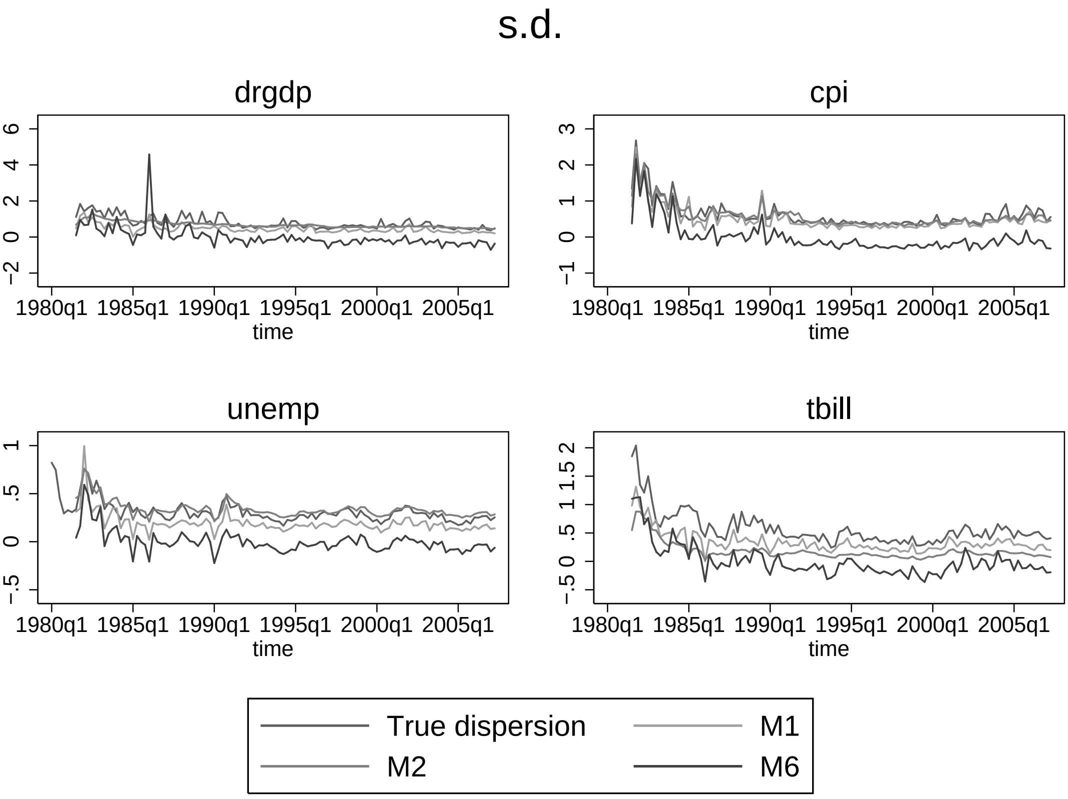

FIGURE 2. Selected Dispersion Measures: s.d.

Figures 2 and 3 visually confirm that some of the mentioned methods perform quite well (up to a level shift/scaling factor). Since most researchers presumingly are interested in the dynamics of the cross-section dispersion over time this fact seems negligible. We leave the discussion on re-scaling the proxies for future research. The dynamics of the dispersion derived from fixed horizon forecasts seem to be appropriately reflected especially for the methods M1, M2 and M6.

To test for the best performing model more rigorously, we made use of the idea outlined by Granger and others (Bates and Granger, 1969, Granger and Ramanathan, 1984) for estimating the optimal weights in forecast combination exercises. To that end, we used a panel regression (SUR) of the following form:

$$D_{it}^{\hat{y}^{12}} = \alpha_i + \sum_{j=1}^{8} \beta_j D_{it}^{\tilde{y}^j\, f} + \varepsilon_{it},\ \sum_{j=1}^{8} \beta_j = 1 \tag{7}$$

where $D_{it}^{\hat{y}^{12}}$ denotes the dispersion from the fixed horizon forecasts and $D_{it}^{\tilde{y}^j\, f}$, $j = 1, \ldots, 8$ are the different dispersion approximations based on the competing models (except the unprocessed dispersion measures); the subscript i refers to the different variables analyzed in this paper ($i \in \{drgdp, cpi, unemp, tbill\}$). We estimated the regressions in levels and first differences of the series and for both dispersion measures. The results are summarized in table 4. Once more it is clear, that $M1$ is by far the most promising method. Although, the results suggest that combining the proxy derived by $M1$ with other proxies (especially from $M4$ and $M8$) can improve the quality, we conclude that for practical work $M1$ constitutes a fairly good approach to proxy the fundamental dispersion from panels of fixed event forecasts.

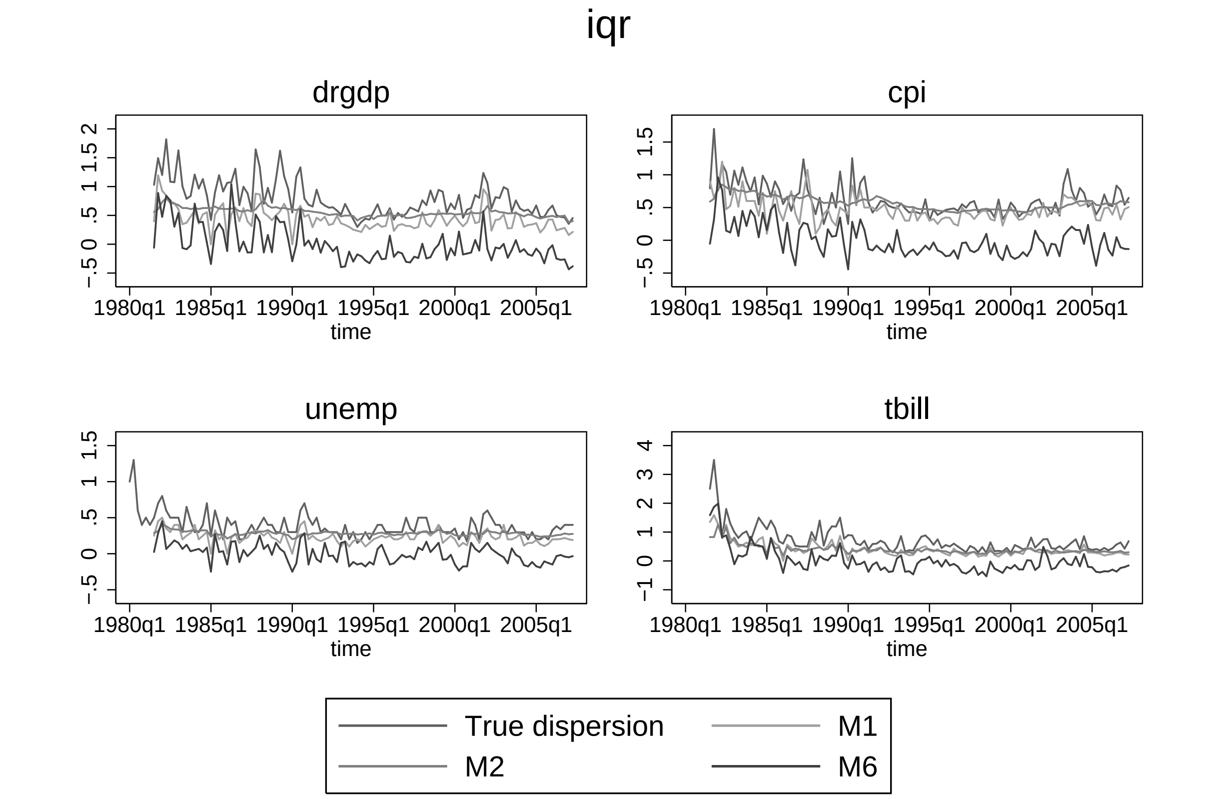

Figure 3. Selected Dispersion Measures: iqr

	β coefficients							
Measure	s.d				iqr			
Specification	Difference		Level		Difference		Level	
M1	0.468	***	0.506	***	0.532	***	0.741	***
M2	0.216	*	0.177		-0.058		-0.338	***
M3	0.128		-0.120		0.303	**	0.111	
M4	0.120		0.273	***	-0.006		0.242	***
M5	-0.305	***	-0.206	*	-0.085	*	-0.143	***
M6	0.106		-0.061		0.156	***	0.198	***
M7	0.175	***	0.139	*	0.035		0.095	*
M8	0.092	NA	0.293	NA	0.123	NA	0.094	NA

Notes: “NA” refers to non-availability of an estimated coefficient value due to the fact that an adding-up constraint was emposed on the sum of the coefficients.*,**,*** denotes significance at 10, 5, 1 per cent levels.

Table 4. Results of Forecast Combination Regressions

5. Conclusion

In this paper we performed a horse-race: we compared different methods to extract a “fundamental” dispersion component from a panel of fixed event forecasts. The methods which we considered belong to two groups: aggregation and transformation on the level of individual forecasts on the one hand and time-series models to extract deterministic and/or seasonal elements out of the cross-section dispersion on the other hand. We based the horse-race on data from the SPF, the only available data set which provides both information simultaneously – fixed horizon and fixed event forecasts. We assume that the true "fundamental" dispersion is given by a measure of cross-section dispersion derived from the reported fixed horizon forecasts. As a benchmark we used the dispersion of the reported fixed horizon forecasts. The correlation coefficient between the true "fundamental" dispersion and the proxies as a criterion were chosen to judge the relative performance of the different methods.

We can conclude that a moving-average transformation of the fixed event predictions on the level of individual forecasters (M1) performs extremely well for interquartile range and standard deviations measures. There are some other methods that perform comparably well in the case of the standard deviation measure, namely a bivariate unobserved components model (M2), the seasonal dummy method (M5, M6), and seasonal adjustment using a standard procedure like X12-ARIMA (M8). Also the forecast combination exercise reveals that the moving-average method seems to outperform all other candidates. It has by far the largest weight associated with any method, which clearly speaks in favor of this method.

All in all, our results are quite useful for practitioners and researchers as a tested benchmark to calculate dispersion measures from panels of survey data on fixed event forecasts.

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