A Framework for Decomposing Shocks and Measuring Volatilities Derived from Multi-Dimensional Panel Data of Survey Forecasts

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Abstract

This work applies previously published frameworks developed for analyzing multi-dimensional panel data of survey forecasts to IPD forecasts from the Survey of Professional Forecasters. The paper expands on these frameworks, demonstrates that the frameworks imply the existence of new and richer measures of shocks and volatilities, and shows how these measures can be extracted from multi-dimensional forecast panels. Three distinct types of economic shocks (cumulative shocks, cross-sectional shocks, and discrete shocks) and implied volatility measures based on these shocks are calculated for IPD inflation over the period 1969 through 2004. GMM tests for forecaster biases are conducted using the expanded framework.

Keywords:

Panel data, shocks, volatility, multidimensional, Survey of Professional Forecasters, inflation, rationality, error measures, evaluating forecasts, inflation forecasting, volatility forecasting

1. Introduction

The existence of multi-dimensional panel data sets significantly predates methodologies for extracting maximal information from the data sets. The Survey of Professional Forecasters (SPF), instituted in late 1968, is a three-dimensional panel data set in which multiple forecasters forecast macroeconomic variables over multiple quarters and at multiple quarterly horizons (Croushore 1993; Zarnowitz and Braun 1993). Similarly, the Livingston Survey (LS), instituted in 1946, asks participants to forecast variables semi-annually and at multiple semi-annual horizons (Croushore 1997). While the SPF and the LS have long histories, the relative infrequency of the forecasts (particularly in the case of the LS) combined with the facts that the forecasts are anonymous and that the participant memberships have changed over time limits the usefulness of the data. In contrast, the Blue Chip Survey of Professional Forecasters (BCS), instituted in 1976, asks multiple participants to forecast variables monthly and at multiple monthly horizons. Because the BCS forecasts are not anonymous, researchers have suggested that the BCS forecasters have greater incentive to produce accurate forecasts. While these (and other) multi-dimensional panel surveys have long histories, the first methodologies that fully utilized the multi-dimensionality did not appear until the 1990's.[1]

Batchelor and Dua (1991) and Swindler and Ketcher (1990) were among the first to perform panel data analyses on the BCS. However, because they employed then-typical panel data techniques, they were forced to restrict their analysis to two of the three dimensions the data set offered (Batchelor and Dua used multiple targets and multiple

[1] See Lahiri (1981), Visco (1984), Lovell(1986), Pesaran (1988) and Maddala (1990) for reviews of earlier studies using these and other survey data sets.

horizons, but single individuals, while Swindler and Ketcher used multiple individuals and multiple targets, but single horizons). Keane and Runkle (1990) perform a panel data analysis on the SPF, but similarly restrict their analysis to two of the three available dimensions (they use multiple individuals and multiple targets, but single horizons) as do De Bont and Bange (1992) who analyze the LS (they use multiple targets and multiple horizons, but aggregate individuals into consensus forecasts).[2] Keane and Runkle's (1990) attempt to analyze the SPF data set is noteworthy for the use of the generalized method of moments despite the fact that the results of their analysis are invalid due to unaddressed non-stationarity (Bonham and Cohen, 1995). Davies and Lahiri describe a methodology for analyzing what they term "multi-dimensional" panel data (i.e. panel data with more than two dimensions) and apply the methodology to the BCS data (Davies and Lahiri, 1995) and the SPF data (Davies and Lahiri, 1999). They show that by employing techniques that account for all three of the data sets' dimensions, additional information can be obtained that would not otherwise be available.[3]

The purpose of this paper is to build on the Davies-Lahiri multi-dimensional analysis framework in an attempt to better describe shocks and the volatilities of shocks. In the next section, I describe the data sets I use in this paper. In section 3, I show how the Davies-Lahiri framework implies the existence of three distinct measures of shocks. In sections 4 and 5, I employ these measures to calculate shocks and volatilities for IPD inflation. Section 6 offers a conclusion and suggestions for future research.

[2] For a more recent, though not panel, analysis of the LS data, see Thomas (1999).

[3] For example, Davies and Lahiri (1999) show that restricting a three-dimensional data set to two-dimensions is equivalent, among other things, to imposing restrictions on components of the error covariance matrix.

2. Measuring Implied Inflation Forecasts and Actual Inflation

The SPF asks forecasters to forecast, each quarter, the level of the implicit price deflator (IPD) for the last quarter, the current quarter, and the each of the next four quarters. Forecasters are assigned identification numbers and are thus anonymous. From 1968-IV (the inception of the survey) to 1991-IV, individuals forecasted the level of the GNP deflator. From 1992-I to 1995-IV, individuals forecasted the level of the GDP deflator, and from 1996-I to the present, individuals have forecasted the chain-weighted GDP deflator. This paper focuses on the 52 forecasters who responded at least 25% of the time over the period 1968-IV through 2005-I.[4] Each forecaster (when responding) reported one forecast for each of six forecast horizons. Fifty-two forecasters reporting six forecasts for each of 147 quarters, results in 45,864 potential data points. Because all forecasters occasionally failed to respond to the survey, the data set contains 13,510 forecasts. I arrange these forecasts by individual, target (the quarter being forecast), and horizon (the number of quarters prior to the realization of the target).

To avoid problems associated with integrated data, I look at the forecasters' implied inflation forecasts (Bonham and Cohen, 1995). At a given point in time, an individual forecasts the level of IPD for the previous quarter (horizon -1), the current quarter (horizon 0), and each of the next four quarters (horizons 1 through 4). After making the appropriate adjustments for base year changes, I compute the implied inflation forecast for quarter *t* as:[5]

[4] Given the amount of data manipulation required, computer limitations required that we not use the entire data set. The individuals' survey identification numbers of the forecasters in our data set are: 7, 8, 15, 20, 22, 30, 31, 32, 34, 35, 38, 40, 43, 44, 49, 51, 54, 60, 62, 64, 65, 66, 69, 70, 72, 73, 77, 78, 82, 84, 86, 87, 89, 94, 98, 99, 109, 125, 144, 407, 411, 420, 421, 426, 428, 429, 431, 433, 439, 446, 456, and 463.
[5] Base year changes occur in 1976–I, 1986–I, 1992–I, and 1996–I.

$$F_{i,t,h} = \frac{L_{i,t,h} - L_{i,t-1,h-1}}{L_{i,t-1,h-1}} \quad (1.1)$$

where L_{ith} is the IPD level forecast made by individual i for target quarter t at a horizon of h quarters, and F_{ith} is the implied inflation forecast for target quarter t at a horizon of h quarters. **Figure 1** provides a graphical depiction of the implied inflation forecast. In the figure, the individual provides forecasts at the beginning of quarter 7. The individual forecasts IPD for the end of quarter 8 (at a horizon of two quarters), $L_{i,8,2}$, and the end of quarter 9 (at a horizon of three quarters), $L_{i,9,3}$. The two IPD forecasts imply an inflation forecast for quarter 9 (at a horizon of three quarters), $F_{i,9,3}$.

[**Figure 1**]

Note that the forecasts are made, and the official IPD figures are released, around the middle of the second month of the quarter. For simplicity, let us speak of the "beginning of the quarter" understanding that it is really the "middle of the second month of the quarter." Since both the forecasts are made and the targets are realized at the same time, the simplification does not affect our analysis.

In evaluating monetary policy rules that are based on forecasts, Orphanides (1997) notes that the evaluation should account for the fact that forecasts are based on preliminary, not revised, data as forecasts based on revised information can be expected to differ from forecasts based on real-time data. As such, to compute the actual inflation, I use the so-called Real Time data set compiled by the Federal Reserve Bank of Philadelphia (cf. Croushore and Stark, 2001). The Real Time data set lists historical (going back to 1947) nominal and real GNP (GDP from 1992 forward) that was known at each quarter from 1965–IV to the present.[6] Dividing the nominal by the real yields the appropriate deflator as it was known at each quarter. Taking the quarter-over-quarter change yields the actual (known) inflation rate for each quarter.[7]

3. The Forecasting Process and Types of Shocks

Following Davies and Lahiri (1999), let the actual quarterly inflation rate that existed *h* quarters prior to the end of quarter *t* be A^*_{th}. From the perspective of the forecasters, A^*_{th} is a latent variable in that while A^*_{th} exists (i.e. there *was* some true level of inflation *h* quarters prior to the end of quarter *t*), A^*_{th} may not be observed (as is, strictly speaking, always the case because inflation on a specific date is not measured), may be observed but only at a future date (as is the case when forecasts are made before the official inflation figures are announced), or may be observed but with error (as in the case of preliminary vs. revised inflation measures). Because A^*_{th} eventually drops out of the equations, the issue of whether or not it is observed is moot. Consider a hypothetical "representative rational forecaster" who correctly utilizes all pertinent and available information, and who forecasts without bias. Let γ_{th} be the change in A^*_{th} the representative rational forecaster, forecasting at *h* quarters prior to the end of quarter *t*, would expect to observe by the end of quarter *t*. By definition, unanticipated changes in A^*_{th} over the period from *h* quarters prior to the end of quarter *t* to the end of quarter *t* are shocks, λ_{th}. We can write the actual inflation rate from the beginning to the end of quarter *t* as:

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[6] By "known", we mean the latest data revision available to forecasters at each point in time.

$$A_t = A^*_{th} + \gamma_{th} + \lambda_{th} \qquad (1.2)$$

where shocks (λ_{th}) can include both changes in A^*_{th} that were not anticipated (i.e. $\gamma_{th} = 0$ $\Rightarrow \lambda_{th} = \Delta A^*_{th}$), and changes in A^*_{th} that were anticipated yet never materialized (i.e. $\gamma_{th} = \Delta A^*_{th} \Rightarrow \lambda_{th} = -\Delta A^*_{th}$).

Figure 2 shows the relationships among the forecasts with respect to known information and shocks. The brackets above the time line labeled $\lambda_{10,4}$ through $\lambda_{5,-1}$ show the times over which shocks can occur which will affect the accuracy of the six forecasts made at the beginning of quarter 7 for various horizons.[8] The solid sections of the brackets show all points in the future in which shocks can affect the accuracy of each forecast. The dotted sections of the brackets show all points in the past in which shocks (in the form of data revisions) can affect the accuracy of each forecast. For example, the bracket associated with $\lambda_{8,2}$ indicates that revisions in the IPD data for quarters 5 and 6 as well as news that occurs in quarters 7 and 8 can affect the accuracy of the forecast $F_{i,8,2}$.. Data more than two quarters old is considered "certain" (i.e. no significant revisions are expected).[9]

[Figure 2]

A specific forecaster can deviate from the representative rational forecaster for three reasons: (1) the specific forecaster can exhibit a bias, (2) the specific forecaster can have access to private information or fail to access available information, or (3) the

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[7] This raises the question of which "vintage" (i.e. revision) of actuals data to use. Patterson (2000) provides evidence that the youngest vintage of data is most appropriate.

[8] Note that the brackets do not show the range over which the forecaster is forecasting (every forecast is for the *single* quarter ending at the end of the target quarter). Rather, the brackets show the range of dates over which the *accuracy* of the forecast can be affected by events external to the forecaster.

[9] We ignore here benchmark revisions, which can be systematic and occur as many as five years after the fact.

specific forecaster can incorrectly process information. Let forecasters' biases, ϕ_{ih}, vary according to the individual forecasting and to the horizon at which the individual stands. Batchelor and Dua (1991) assume a common bias across individuals and horizons. Davies and Lahiri (1999) relax Batchelor and Dua's (1991) restriction and assume a common bias only across horizons. Because it is reasonable to expect that, whatever inherent bias a given forecaster may exhibit, the bias would decline as the horizon declines, in this model, I relax Davies and Lahiri's (1999) restriction and allow for the possibility of a change in forecast bias over both individuals and horizons.

Let deviations in the forecaster's information set from the publicly available information set be reflected in ε_{ith}. Note that it is impossible for the model to allow for individual, target, and horizon specific biases (i.e. ϕ_{ith}) because the biases become indistinguishable from the idiosyncratic errors, ε_{ith} (Clements et al., 2004). Holding information constant, a forecaster's inability to process information efficiently will be reflected in a higher variance of ε_{ith} for that forecaster. Further, ε_{ith} also reflects idiosyncratic forecast errors – that is, forecast errors that have no systemic or informational cause.

Adding the actual inflation rate at *h* quarters prior to the end of quarter *t* to the rationally anticipated change in the actual, and including the individual forecaster's biases and deviations from public information, we have the following:

$$F_{ith} = A^{*}_{th} + \gamma_{th} + \phi_{ih} + \varepsilon_{ith} \tag{1.3}$$

Notice that all forecasters produce the same forecast when (1) all forecasters have zero biases (i.e. $\phi_{ih} = 0 \ \forall \ i, h$), and (2) all forecasters have access to the same information and suffer no idiosyncratic errors (i.e. $\varepsilon_{ith} = 0 \ \forall \ i, t, h$).

Figure 3 shows time divided into quarters. The numbers in the boxes above the time line are examples of shocks to IPD inflation. Each number on the figure identifies shocks uniquely associated with a given occurrence and impact. The horizontal position of the numbers indicates the quarter in which the shocks occurred. For example, in quarter 6, there occurred four shocks: -1, -2, +3, and +5. The vertical position indicates the quarter in which the shock will *impact* IPD inflation. For the four shocks occurring in quarter 6, the +5 shock impacts inflation in quarter 6, the +3 shock impacts inflation in quarter 7, etc. For example, an event that occurs in quarter 6 may impact inflation over time in a decaying fashion such that inflation in quarter 6 is impacted greatly, inflation in quarter 7 is impacted somewhat less, etc.

[Figure 3]

The shocks depicted in Figure 3 can be grouped according to definitions in our model. Figure 4 provides some examples. Let us call the aggregation of all shocks that occur from *h* quarters prior to the end of quarter *t* to the end of quarter *t cumulative shocks* and denote them as λ_{th}. Let us call the sum of all shocks that occur in the single quarter *h* quarters prior to the end of quarter *t* and that impact IPD inflation at any point up to the end of quarter *t cross-sectional shocks* and denote them as u_{th}. Shocks that occur in the single quarter *h* quarters prior to the end of quarter *t* and that impact IPD inflation only in quarter *t* are *discrete shocks* and denoted as v_{th}. Figure 4 provides examples of these three types of shocks. The definitions of the shocks are summarized in Table 1.

[Figure 4]

[Table 1]

From Figure 4, we can see the relationships among the three types of shocks. Cumulative shocks are all the shocks that occur starting *h* quarters prior to the end of quarter *t* and ending at the conclusion of quarter *t*. Decomposing a single cumulative shock measure, λ_{th}, according to the times at which the shocks occur yields cross-sectional shocks. Cross-sectional shocks, u_{th}, are the components of a cumulative shock that occur in the single quarter that is *h* quarters prior to the end of quarter *t*. Mathematically, we have:

$$\lambda_{th} = \sum_{j=0}^{h-1} u_{t,h-j} \tag{1.4}$$

Decomposing a single cross-sectional shock measure, u_{th}, according to the times at which the shocks will impact yields discrete shocks. Discrete shocks, v_{th}, are the components of a cross-sectional shock that will impact at various points in the future. Mathematically, we have:

$$u_{th} = \sum_{j=0}^{h-1} v_{t-j,h-j} \tag{1.5}$$

Combining (1.4) and (1.5) yields an expression for the relationship between cumulative shocks and discrete shocks.

$$\lambda_{th} = \sum_{j=0}^{h-1} \sum_{k=0}^{h-j-1} v_{t-k,h-j-k} \tag{1.6}$$

For example, the cumulative shock $\lambda_{9,4}$ is the set of all shocks that occur from the beginning of quarter 6 to the end of quarter 9 (see Figure 4). This cumulative shock is the sum of the cross-sectional shocks: $u_{9,4}$, $u_{9,3}$, $u_{9,2}$, and $u_{9,1}$, or the sum of the discrete shocks: $v_{9,4}$, $v_{8,3}$, $v_{7,2}$, $v_{6,1}$, $v_{9,3}$, $v_{8,2}$, $v_{7,1}$, $v_{9,2}$, $v_{8,1}$, and $v_{9,1}$.

4. Estimating Shocks

We can estimate the three types of shocks by looking at changes in forecasts over different horizons and for the same target. For example, differencing (1.3) over *h* we have:

$$F_{ith} - F_{i,t,h-1} = A^*_{th} - A^*_{t,h-1} + \gamma_{th} - \gamma_{t,h-1} + \phi_{ih} - \phi_{i,h-1} + \varepsilon_{ith} - \varepsilon_{i,t,h-1} \tag{1.7}$$

Solving (1.2) for A^*_{th} and incrementing the horizon, we have

$$A^*_{th} = A_t - \lambda_{th} - \gamma_{th} \quad \text{and} \quad A^*_{t,h-1} = A_t - \lambda_{t,h-1} - \gamma_{t,h-1} \tag{1.8}$$

Substituting (1.8) into (1.7), we have

$$F_{ith} - F_{i,t,h-1} = \left(A_t - \lambda_{th} - \gamma_{th}\right) - \left(A_t - \lambda_{t,h-1} - \gamma_{t,h-1}\right) + \gamma_{th} - \gamma_{t,h-1} + \phi_{ih} - \phi_{i,h-1} + \varepsilon_{ith} - \varepsilon_{i,t,h-1} \tag{1.9}$$

Simplifying (1.9) yields

$$F_{ith} - F_{i,t,h-1} = -\lambda_{th} + \lambda_{t,h-1} + \phi_{ih} - \phi_{i,h-1} + \varepsilon_{ith} - \varepsilon_{i,t,h-1} \tag{1.10}$$

Subtracting (1.3) from (1.2) we find the forecast error for forecaster *i* standing *h* quarters prior to the end of target quarter *t*:

$$A_t - F_{ith} = \lambda_{th} - \phi_{ih} - \varepsilon_{ith} \tag{1.11}$$

Assuming the idiosyncratic errors and deviations from public information represented by ε_{ith} are white noise over all dimensions, and that the shocks are white noise, we can estimate the forecaster biases, ϕ_{ih}, by taking the mean of the forecast errors in (1.11) over *t* as follows:

$$-\hat{\phi}_{ih} = \frac{1}{T}\sum_{t=1}^{T}\left(A_t - F_{ith}\right) \tag{1.12}$$

Substituting the estimates in (1.12) into equation (1.10) and averaging over i (again assuming the ε_{ith} are white noise) yields estimates of the changes in shocks over horizons. We have:

$$\hat{\lambda}_{th} - \hat{\lambda}_{t,h-1} = \frac{1}{N}\sum_{i=1}^{N}\left(-F_{ith} + F_{i,t,h-1} + \hat{\phi}_{ih} - \hat{\phi}_{i,h-1}\right) \tag{1.13}$$

The differences in the cumulative shocks over horizons,

$$\hat{u}_{th} = \hat{\lambda}_{th} - \hat{\lambda}_{t,h-1} \tag{1.14}$$

are the cross-sectional shocks impacting the economy over the single quarter beginning h quarters prior to the end of quarter t. From (1.14), we can estimate the discrete shocks as

$$\hat{v}_{th} = \hat{u}_{th} - \hat{u}_{t-1,h-1} \tag{1.15}$$

Figure 5 depicts graphically the derivation of the shock measures.

[Figure 5]

Following similar logic to that shown above, we can estimate discrete anticipated changes in the actual. Taking the appropriate difference in (1.3) we have:

$$F_{ith} - F_{i,t-1,h-1} = A^*_{th} - A^*_{t-1,h-1} + \gamma_{th} - \gamma_{t-1,h-1} + \phi_{ih} - \phi_{i,h-1} + \varepsilon_{ith} - \varepsilon_{i,t-1,h-1} \tag{1.16}$$

Because "h quarters prior to the end of quarter t" is the same point in time as "$h - j$ quarters prior to the end of quarter $t - j$," we have $A^*_{th} = A^*_{t-j,h-j} \ \forall j$. Incorporating this into (1.16) causes the actual inflation terms to cancel and we have:

$$F_{ith} - F_{i,t-1,h-1} = \gamma_{th} - \gamma_{t-1,h-1} + \phi_{ih} - \phi_{i,h-1} + \varepsilon_{ith} - \varepsilon_{i,t-1,h-1} \tag{1.17}$$

Estimating the forecaster biases and averaging (1.17) over i yields estimates of the difference in cumulative anticipated changes over horizons as:

$$\hat{\gamma}_{th} - \hat{\gamma}_{t-1,h-1} = \frac{1}{N}\sum_{i=1}^{N}\left(F_{ith} - F_{i,t-1,h-1} - \hat{\phi}_{ih} + \hat{\phi}_{i,h-1}\right) \tag{1.18}$$

where the cumulative anticipated change (γ_{th}) is the sum of changes the representative rational forecaster anticipates occurring from *h* quarters prior to the end of quarter *t* to the end of quarter *t*. The first difference in the cumulative anticipated changes,

$$\hat{a}_{th} = \hat{\gamma}_{th} - \hat{\gamma}_{t-1,h-1} \tag{1.19}$$

is the change in IPD inflation anticipated, at *h* quarters prior to the end of quarter *t*, to occur in quarter *t*. As a_{th} are analogous to v_{th} in terms of the timing of occurrence and impact, we can refer to them as *discrete anticipated changes*. The definitions of cumulative and discrete anticipated changes are summarized in Table 2.

Finally, we can find the relationship between discrete shocks and discrete anticipated changes by combining (1.10) and (1.17) with (1.15) and (1.19). We see that the estimate of a discrete shock is the change in the estimate of the discrete anticipated changes in the target variable.

$$\hat{v}_{th} = -\hat{a}_{th} + \hat{a}_{t,h-1} \tag{1.20}$$

Figure 6 depicts several examples of anticipated changes. The numbers in boxes are changes in IPD inflation that the representative rational forecaster anticipates. The horizontal position of a number indicates the quarter in which the forecaster generated the expectation. The vertical position indicates the quarter for which the forecaster anticipates the change. For example, in Figure 6, the representative forecaster, standing at the start of quarter 6, anticipates that IPD inflation will change by +3 in quarter 6, +2 in quarter 7, +1 in quarter 8, and not change in quarter 9.

[Figure 6]

[Table 2]

Employing the estimation techniques shown above, one can show the discrete shocks to IPD inflation (Figure 7). The vertical bars show the shocks according to the quarters that the shocks impacted (as distinct from the dates that the shocks *occurred*) for the period 1969-III through 2004-IV. Due to the randomness of news, we would expect that some of the discrete shocks would reinforce each other, while others would counteract each other. Adding the discrete shocks according to their times of impact yields a measure of the net impact of discrete shocks at each point in time, *t*. The line graph in Figure 7 shows the net impact of the three discrete shocks, $v_{t,4} + v_{t,3} + v_{t,2}$, across time.

[Figure 7]

Noteworthy is the difference between the summed discrete shocks and changes in IPD inflation (Figure 8). Changes to inflation from one period to the next will either be anticipated, in which case the changes will show up in the calculations as discrete anticipated changes, or unanticipated, in which case the changes will show up in the calculations as discrete shocks. As such, one would expect to see a stronger correlation between changes in the actual and discrete shocks during periods of greater uncertainty, and a stronger correlation between changes in the actual and discrete anticipated changes during periods of lesser uncertainty. The implication is that the use of changes in the macroeconomic variable as a proxy for shocks can lead to a misinterpretation of the economic climate, but that this misinterpretation is ameliorated during periods of greater uncertainty. This finding is consistent with approaches to modeling, for example, monetary shocks (Bernanke & Mihov, 1998, and Christiano et al., 1997) and trade shocks (Chang and Velasco, 2001). For example, in 2000-IV, the economy experienced a marked increase in IPD inflation. According to the discrete shock measures, however, this increase was almost entirely expected. Hence, although there was a significant *change* in the macroeconomic measure, there was almost no *shock* to the economy in 2000-IV. Conversely, in 2002-I, the economy experienced IPD inflation slightly below the long-term average despite the fact that, in that same quarter, shocks impacting IPD inflation were significantly negative – the implication being that the economy expected a rise in inflation that never materialized.

[Figure 8]

5. Estimating Volatility

Each of the shock measures implies a corresponding volatility measure that we can refer to as, respectively, *cumulative volatility*, *cross-sectional volatility*, and *discrete volatility*. The definitions of the volatility measures are analogous to the definitions of the shock measures shown in Table 1. Combining (1.13) through (1.15), we have

$$\hat{v}_{th} = \frac{1}{N}\sum_{i=1}^{N}\left(-F_{ith} + F_{i,t,h-1} + F_{i,t-1,h-1} - F_{i,t-1,h-2} + \hat{\phi}_{ih} - 2\hat{\phi}_{i,h-1} + \hat{\phi}_{i,h-2}\right) \tag{1.21}$$

Taking the sample variance across *i* of the expression inside the summation of (1.21) yields the volatility measures for discrete shocks. We have:

$$\widehat{\text{var}}\left(v_{th}\right) = \frac{1}{N-1}\sum_{i=1}^{N}\left(-F_{ith} + F_{i,t,h-1} + F_{i,t-1,h-1} - F_{i,t-1,h-2} + \hat{\phi}_{ih} - 2\hat{\phi}_{i,h-1} + \hat{\phi}_{i,h-2} - \hat{v}_{th}\right)^2 \tag{1.22}$$

As with the discrete shocks, we must make a distinction between when the volatility *occurred* and when the volatility *impacted* the target variable. Following the definition of v_{th}, var(v_{th}) is the volatility of shocks that occurred in the single quarter *h* quarters prior to the end of quarter *t* and that impact the target variable only in quarter *t*. Figure 9 shows the discrete volatilities occurring two through four quarters in the past, arranged according to the quarter in which the volatility impacted the target variable.

Figure 10 shows the discrete volatilities separated by horizon.[10]

[Figure 9]

[Figure 10]

6. Estimating Forecaster Biases

In their original framework, Davies and Lahiri allowed biases to vary across forecasters, but held the biases constant over targets and horizons for the same forecaster. The model specification in (1.3) generalizes the Davies-Lahiri multi-dimensional panel framework by allowing forecaster biases to vary across forecasters and horizons. Note that this is the most general specification possible as allowing the biases to vary across all three dimensions would make the bias measures indistinguishable from the idiosyncratic errors.

Let the data be ordered first by individual, then target (in ascending order), then horizon (in descending order) so that the vector of forecasts takes the form:

$$F' = \left(F_{1,1,4},\ F_{1,1,3},\ \ldots,\ F_{1,1,-1},\ F_{1,2,4},\ \ldots,\ F_{1,147,-1},\ F_{2,1,4},\ \ldots,\ F_{52,147,-1}\right) \qquad (1.23)$$

To estimate the standard errors of the forecasters' biases, I employ GMM analogously to the application outlined in Davies and Lahiri (1995 and 2000). For the regression model in (1.11), they specify the error covariance matrix as (using their notation):

$$\mathbf{\Sigma} = \begin{bmatrix} \mathbf{A}_1 & \mathbf{B} & \mathbf{B} & \ldots & \mathbf{B} & \mathbf{B} \\ \mathbf{B} & \mathbf{A}_2 & \mathbf{B} & \ldots & \mathbf{B} & \mathbf{B} \\ \vdots & & & & & \\ \mathbf{B} & \mathbf{B} & \mathbf{B} & \ldots & \mathbf{B} & \mathbf{A}_N \end{bmatrix}_{NTH \text{ x } NTH} \quad \text{where } \mathbf{A}_i = \sigma_{\varepsilon_i}^2 \mathbf{I} + \mathbf{B} \qquad (1.24)$$

[10] For display purposes, the volatilities are shown as standard deviations, not variances.

$\sigma^2_{\varepsilon_i}$ is the variance of the idiosyncratic error for forecaster i, and **I** is an identity matrix. In (1.24), the TH x TH matrix $\mathbf{A}_i$ contains the covariances of error terms across targets and horizons for forecaster i, and the matrix **B** contains the covariances of error terms across targets and horizons and forecasters. I expand the components of their matrix **B** to account for the six forecast horizons included in this data set. We have:

$$\mathbf{B} = \begin{bmatrix} \mathbf{b}_{1,1} & \mathbf{c}_{1,2} & \mathbf{d}_{1,3} & \mathbf{e}_{1,4} & \mathbf{f}_{1,5} & \mathbf{g}_{1,6} & \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} & \cdots & \mathbf{0} \\ \mathbf{c}'_{2,1} & \mathbf{b}_{2,2} & \mathbf{c}_{2,3} & \mathbf{d}_{2,4} & \mathbf{e}_{2,5} & \mathbf{f}_{2,6} & \mathbf{g}_{2,7} & \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} & \cdots & \mathbf{0} \\ \mathbf{d}'_{3,1} & \mathbf{c}'_{3,2} & \mathbf{b}_{3,3} & \mathbf{c}_{3,4} & \mathbf{d}_{3,5} & \mathbf{e}_{3,6} & \mathbf{f}_{3,7} & \mathbf{g}_{3,8} & \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} & \cdots & \mathbf{0} \\ \mathbf{e}'_{4,1} & \mathbf{d}'_{4,2} & \mathbf{c}'_{4,3} & \mathbf{b}_{4,4} & \mathbf{c}_{4,5} & \mathbf{d}_{4,6} & \mathbf{e}_{4,7} & \mathbf{f}_{4,8} & \mathbf{g}_{5,9} & \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} & \cdots & \mathbf{0} \\ \mathbf{f}'_{5,1} & \mathbf{e}'_{5,2} & \mathbf{d}'_{5,3} & \mathbf{c}'_{5,4} & \mathbf{b}_{5,5} & \mathbf{c}_{5,6} & \mathbf{d}_{5,7} & \mathbf{e}_{5,8} & \mathbf{f}_{6,9} & \mathbf{g}_{6,10} & \mathbf{0} & \mathbf{0} & \mathbf{0} & \cdots & \mathbf{0} \\ \mathbf{g}'_{6,1} & \mathbf{f}'_{6,2} & \mathbf{e}'_{6,3} & \mathbf{d}'_{6,4} & \mathbf{c}'_{6,5} & \mathbf{b}_{6,6} & \mathbf{c}_{6,7} & \mathbf{d}_{6,8} & \mathbf{e}_{7,9} & \mathbf{f}_{7,10} & \mathbf{g}_{7,11} & \mathbf{0} & \mathbf{0} & \cdots & \mathbf{0} \\ \mathbf{0} & \mathbf{g}'_{7,2} & \mathbf{f}'_{7,3} & \mathbf{e}'_{7,4} & \mathbf{d}'_{7,5} & \mathbf{c}'_{7,6} & \mathbf{b}_{7,7} & \mathbf{c}_{7,8} & \mathbf{d}_{8,9} & \mathbf{e}_{8,10} & \mathbf{f}_{8,11} & \mathbf{g}_{8,12} & \mathbf{0} & \cdots & \mathbf{0} \\ \vdots & & & & & & & & & & & & & & \\ \mathbf{0} & \cdots & \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{g}'_{T,T-5} & \mathbf{f}'_{T,T-4} & \mathbf{e}'_{T,T-3} & \mathbf{d}'_{T,T-2} & \mathbf{c}'_{T,T-1} & \mathbf{b}_{T,T} \end{bmatrix}_{TH \text{ x } TH} \quad (1.25)$$

The matrices **b**, **c**, **d**, **e**, **f**, and **g** contain the covariances of the error across horizons and the indicated targets. The descriptions of the matrices are summarized in Table 3.

[Table 3]

The elements of the matrices can be inferred from an examination of the overlapping of cumulative shocks. Figure 11 shows the ranges over which the occurrences of cross-sectional shocks are incorporated into various cumulative shocks. For example, the cumulative shock $\lambda_{10,2}$ is comprised of cross-sectional shocks $u_{8,1}$, $u_{8,0}$, and $u_{8,-1}$.[11] Employing the definition for cumulative shocks in (1.4) (adapted for the fact that our horizons run from –1 to 4), and via examination of Figure 11, we can map out the

[11] When the duration of a single horizon is the same as the duration of a single target (as in this data set), the pairing (t,h) does not uniquely define a quarter, though the scalar $t - h$ does, (see Davies and Lahiri (1995) for an example of a data set in which the durations of target and horizon are not the same). For example, $u_{8,-1}$, $u_{9,0}$, $u_{10,1}$, $u_{11,2}$, $u_{12,3}$, and $u_{13,4}$ all refer to the same cross-sectional shocks – those occurring in quarter 9. For ease of exposition, I have chosen the subscripts that set the latest occurring common shock to a horizon of –1.

cross-sectional shocks that are common to cumulative shocks for target quarters 9 and 10. These commonalities are detailed in Table 4.

[Table 4]

Similarly, using Figure 12, we can map out the cross-sectional shocks that are common to cumulative shocks for target quarters 8 and 10. These commonalities are detailed in Table 5.

[Table 5]

Cross-sectional shocks occurring in the quarters have variances $\sigma^2_{u_{t,h}}$. Where two ranges of cumulative shocks, λ_{t_1,h_1} and λ_{t_2,h_2}, overlap, the cross-sectional shocks that occur within the overlap create a correlation between the two λ's. Deconstructing the cumulative shocks into their cross-sectional components yields

$$\operatorname{cov}\left(\lambda_{t_1,h_1}, \lambda_{t_2,h_2}\right) = \operatorname{cov}\left(\sum_{j_1=-1}^{h_1} u_{t_1,j_1}, \sum_{j_2=-1}^{h_2} u_{t_2,j_2} \right) \tag{1.26}$$

Assuming rationality implies that

$$\operatorname{cov}\left(u_{t_1,h_1}, u_{t_2,h_2}\right) = \begin{cases} \sigma^2_{u_{t_1,h_1}} = \sigma^2_{u_{t_2,h_2}} & \forall\ t_1 - h_1 = t_2 - h_2 \\ 0 \text{ otherwise} \end{cases} \tag{1.27}$$

Combining (1.27), (1.26), the patterns shown in Table 4 and Table 5, and extrapolating for cases in which the targets are separated by more than two quarters, we have definitions for the matrices **b**, **c**, **d**, **e**, **f**, and **g** which are analogous to those described in Davies and Lahiri (1999) show below.[12] Note that, while I show the constructs for matrices **b**, **c**, **d**, **e**, **f**, and **g**, for my data set, matrices **f** and **g** are zero matrices because

[12] Davies and Lahiri (1999) identified shocks as occurring "in quarter *t*," rather than "*h* quarters prior to the end of quarter *t*." As such, the elements of their matrices show one subscript only whereas mine show two. The choice is a matter of clarity only.

horizons –1 and 0 drop out due to missing data. The missing data are caused by (1) the differencing across horizons of IPD level forecasts to obtain the implied inflation forecasts in (1.1), and (2) the differencing of the inflation forecasts across horizons necessary for obtaining estimates of the cross-sectional shocks in (1.13).

$$\mathbf{b}_{t_1,t_2} = \begin{bmatrix} \sum_{h=-1}^{4}\sigma^2_{u_{s,h}} & \sum_{h=-1}^{3}\sigma^2_{u_{s,h}} & \sum_{h=-1}^{2}\sigma^2_{u_{s,h}} & \sum_{h=-1}^{1}\sigma^2_{u_{s,h}} & \sum_{h=-1}^{0}\sigma^2_{u_{s,h}} & \sum_{h=-1}^{-1}\sigma^2_{u_{s,h}} \\ \sum_{h=-1}^{3}\sigma^2_{u_{s,h}} & \sum_{h=-1}^{3}\sigma^2_{u_{s,h}} & \sum_{h=-1}^{2}\sigma^2_{u_{s,h}} & \sum_{h=-1}^{1}\sigma^2_{u_{s,h}} & \sum_{h=-1}^{0}\sigma^2_{u_{s,h}} & \sum_{h=-1}^{-1}\sigma^2_{u_{s,h}} \\ \sum_{h=-1}^{2}\sigma^2_{u_{s,h}} & \sum_{h=-1}^{2}\sigma^2_{u_{s,h}} & \sum_{h=-1}^{2}\sigma^2_{u_{s,h}} & \sum_{h=-1}^{1}\sigma^2_{u_{s,h}} & \sum_{h=-1}^{0}\sigma^2_{u_{s,h}} & \sum_{h=-1}^{-1}\sigma^2_{u_{s,h}} \\ \sum_{h=-1}^{1}\sigma^2_{u_{s,h}} & \sum_{h=-1}^{1}\sigma^2_{u_{s,h}} & \sum_{h=-1}^{1}\sigma^2_{u_{s,h}} & \sum_{h=-1}^{1}\sigma^2_{u_{s,h}} & \sum_{h=-1}^{0}\sigma^2_{u_{s,h}} & \sum_{h=-1}^{-1}\sigma^2_{u_{s,h}} \\ \sum_{h=-1}^{0}\sigma^2_{u_{s,h}} & \sum_{h=-1}^{0}\sigma^2_{u_{s,h}} & \sum_{h=-1}^{0}\sigma^2_{u_{s,h}} & \sum_{h=-1}^{0}\sigma^2_{u_{s,h}} & \sum_{h=-1}^{0}\sigma^2_{u_{s,h}} & \sum_{h=-1}^{-1}\sigma^2_{u_{s,h}} \\ \sum_{h=-1}^{-1}\sigma^2_{u_{s,h}} & \sum_{h=-1}^{-1}\sigma^2_{u_{s,h}} & \sum_{h=-1}^{-1}\sigma^2_{u_{s,h}} & \sum_{h=-1}^{-1}\sigma^2_{u_{s,h}} & \sum_{h=-1}^{-1}\sigma^2_{u_{s,h}} & \sum_{h=-1}^{-1}\sigma^2_{u_{s,h}} \end{bmatrix}, \; s=\min\left(t_1,t_2\right)-1 \tag{1.28}$$

$$\mathbf{c}_{t_1,t_2} = \begin{bmatrix} \sum_{h=-1}^{3}\sigma^2_{u_{s,h}} & \sum_{h=-1}^{2}\sigma^2_{u_{s,h}} & \sum_{h=-1}^{1}\sigma^2_{u_{s,h}} & \sum_{h=-1}^{0}\sigma^2_{u_{s,h}} & \sum_{h=-1}^{-1}\sigma^2_{u_{s,h}} & 0 \\ \sum_{h=-1}^{3}\sigma^2_{u_{s,h}} & \sum_{h=-1}^{2}\sigma^2_{u_{s,h}} & \sum_{h=-1}^{1}\sigma^2_{u_{s,h}} & \sum_{h=-1}^{0}\sigma^2_{u_{s,h}} & \sum_{h=-1}^{-1}\sigma^2_{u_{s,h}} & 0 \\ \sum_{h=-1}^{2}\sigma^2_{u_{s,h}} & \sum_{h=-1}^{2}\sigma^2_{u_{s,h}} & \sum_{h=-1}^{1}\sigma^2_{u_{s,h}} & \sum_{h=-1}^{0}\sigma^2_{u_{s,h}} & \sum_{h=-1}^{-1}\sigma^2_{u_{s,h}} & 0 \\ \sum_{h=-1}^{1}\sigma^2_{u_{s,h}} & \sum_{h=-1}^{1}\sigma^2_{u_{s,h}} & \sum_{h=-1}^{1}\sigma^2_{u_{s,h}} & \sum_{h=-1}^{0}\sigma^2_{u_{s,h}} & \sum_{h=-1}^{-1}\sigma^2_{u_{s,h}} & 0 \\ \sum_{h=-1}^{0}\sigma^2_{u_{s,h}} & \sum_{h=-1}^{0}\sigma^2_{u_{s,h}} & \sum_{h=-1}^{0}\sigma^2_{u_{s,h}} & \sum_{h=-1}^{0}\sigma^2_{u_{s,h}} & \sum_{h=-1}^{-1}\sigma^2_{u_{s,h}} & 0 \\ \sum_{h=-1}^{-1}\sigma^2_{u_{s,h}} & \sum_{h=-1}^{-1}\sigma^2_{u_{s,h}} & \sum_{h=-1}^{-1}\sigma^2_{u_{s,h}} & \sum_{h=-1}^{-1}\sigma^2_{u_{s,h}} & \sum_{h=-1}^{-1}\sigma^2_{u_{s,h}} & 0 \end{bmatrix}, \; s=\min\left(t_1,t_2\right)-1 \tag{1.29}$$

$$\mathbf{d}_{t_1,t_2} = \begin{bmatrix} \sum_{h=-1}^{2}\sigma_{u_{s,h}}^2 & \sum_{h=-1}^{1}\sigma_{u_{s,h}}^2 & \sum_{h=-1}^{0}\sigma_{u_{s,h}}^2 & \sum_{h=-1}^{-1}\sigma_{u_{s,h}}^2 & 0 & 0 \\ \sum_{h=-1}^{2}\sigma_{u_{s,h}}^2 & \sum_{h=-1}^{1}\sigma_{u_{s,h}}^2 & \sum_{h=-1}^{0}\sigma_{u_{s,h}}^2 & \sum_{h=-1}^{-1}\sigma_{u_{s,h}}^2 & 0 & 0 \\ \sum_{h=-1}^{2}\sigma_{u_{s,h}}^2 & \sum_{h=-1}^{1}\sigma_{u_{s,h}}^2 & \sum_{h=-1}^{0}\sigma_{u_{s,h}}^2 & \sum_{h=-1}^{-1}\sigma_{u_{s,h}}^2 & 0 & 0 \\ \sum_{h=-1}^{1}\sigma_{u_{s,h}}^2 & \sum_{h=-1}^{1}\sigma_{u_{s,h}}^2 & \sum_{h=-1}^{0}\sigma_{u_{s,h}}^2 & \sum_{h=-1}^{-1}\sigma_{u_{s,h}}^2 & 0 & 0 \\ \sum_{h=-1}^{0}\sigma_{u_{s,h}}^2 & \sum_{h=-1}^{0}\sigma_{u_{s,h}}^2 & \sum_{h=-1}^{0}\sigma_{u_{s,h}}^2 & \sum_{h=-1}^{-1}\sigma_{u_{s,h}}^2 & 0 & 0 \\ \sum_{h=-1}^{-1}\sigma_{u_{s,h}}^2 & \sum_{h=-1}^{-1}\sigma_{u_{s,h}}^2 & \sum_{h=-1}^{-1}\sigma_{u_{s,h}}^2 & \sum_{h=-1}^{-1}\sigma_{u_{s,h}}^2 & 0 & 0 \end{bmatrix}, \ s = \min(t_1, t_2) - 1 \qquad (1.30)$$

$$\mathbf{e}_{t_1,t_2} = \begin{bmatrix} \sum_{h=-1}^{1}\sigma_{u_{s,h}}^2 & \sum_{h=-1}^{0}\sigma_{u_{s,h}}^2 & \sum_{h=-1}^{-1}\sigma_{u_{s,h}}^2 & 0 & 0 & 0 \\ \sum_{h=-1}^{1}\sigma_{u_{s,h}}^2 & \sum_{h=-1}^{0}\sigma_{u_{s,h}}^2 & \sum_{h=-1}^{-1}\sigma_{u_{s,h}}^2 & 0 & 0 & 0 \\ \sum_{h=-1}^{1}\sigma_{u_{s,h}}^2 & \sum_{h=-1}^{0}\sigma_{u_{s,h}}^2 & \sum_{h=-1}^{-1}\sigma_{u_{s,h}}^2 & 0 & 0 & 0 \\ \sum_{h=-1}^{1}\sigma_{u_{s,h}}^2 & \sum_{h=-1}^{0}\sigma_{u_{s,h}}^2 & \sum_{h=-1}^{-1}\sigma_{u_{s,h}}^2 & 0 & 0 & 0 \\ \sum_{h=-1}^{0}\sigma_{u_{s,h}}^2 & \sum_{h=-1}^{0}\sigma_{u_{s,h}}^2 & \sum_{h=-1}^{-1}\sigma_{u_{s,h}}^2 & 0 & 0 & 0 \\ \sum_{h=-1}^{-1}\sigma_{u_{s,h}}^2 & \sum_{h=-1}^{-1}\sigma_{u_{s,h}}^2 & \sum_{h=-1}^{-1}\sigma_{u_{s,h}}^2 & 0 & 0 & 0 \end{bmatrix}, \ s = \min(t_1, t_2) - 1 \qquad (1.31)$$

$$\mathbf{f}_{t_1,t_2} = \begin{bmatrix} \sum_{h=-1}^{0} \sigma^2_{u_{s,h}} & \sum_{h=-1}^{-1} \sigma^2_{u_{s,h}} & 0 & 0 & 0 & 0 \\ \sum_{h=-1}^{0} \sigma^2_{u_{s,h}} & \sum_{h=-1}^{-1} \sigma^2_{u_{s,h}} & 0 & 0 & 0 & 0 \\ \sum_{h=-1}^{0} \sigma^2_{u_{s,h}} & \sum_{h=-1}^{-1} \sigma^2_{u_{s,h}} & 0 & 0 & 0 & 0 \\ \sum_{h=-1}^{0} \sigma^2_{u_{s,h}} & \sum_{h=-1}^{-1} \sigma^2_{u_{s,h}} & 0 & 0 & 0 & 0 \\ \sum_{h=-1}^{0} \sigma^2_{u_{s,h}} & \sum_{h=-1}^{-1} \sigma^2_{u_{s,h}} & 0 & 0 & 0 & 0 \\ \sum_{h=-1}^{-1} \sigma^2_{u_{s,h}} & \sum_{h=-1}^{-1} \sigma^2_{u_{s,h}} & 0 & 0 & 0 & 0 \end{bmatrix}, \ s = \min\left(t_1, t_2\right) - 1 \tag{1.32}$$

$$\mathbf{g}_{t_1,t_2} = \begin{bmatrix} \sum_{h=-1}^{-1} \sigma^2_{u_{s,h}} & 0 & 0 & 0 & 0 & 0 \\ \sum_{h=-1}^{-1} \sigma^2_{u_{s,h}} & 0 & 0 & 0 & 0 & 0 \\ \sum_{h=-1}^{-1} \sigma^2_{u_{s,h}} & 0 & 0 & 0 & 0 & 0 \\ \sum_{h=-1}^{-1} \sigma^2_{u_{s,h}} & 0 & 0 & 0 & 0 & 0 \\ \sum_{h=-1}^{-1} \sigma^2_{u_{s,h}} & 0 & 0 & 0 & 0 & 0 \\ \sum_{h=-1}^{-1} \sigma^2_{u_{s,h}} & 0 & 0 & 0 & 0 & 0 \end{bmatrix}, \ s = \min\left(t_1, t_2\right) - 1 \tag{1.33}$$

I estimate the cross-sectional variances, $s^2_{u_{th}}$, by taking the variance of (1.13) across individuals:

$$s^2_{u_{th}} = \frac{1}{N-2} \sum_{i=1}^{N} \left(-F_{ith} + F_{i,t,h-1} + \hat{\phi}_{ih} - \hat{\phi}_{i,h-1} - \hat{u}_{th} \right)^2 \tag{1.34}$$

The estimation of the idiosyncratic error variances, $s^2_{\varepsilon_i}$, follows naturally from (1.11). We have:

$$
\begin{aligned}
&A_t - F_{ith} = \lambda_{th} - \phi_{ih} - \varepsilon_{ith} \\
&\hat{\phi}_{ih} = -\frac{1}{T}\sum_{t=1}^{T}\left(A_t - F_{ith}\right) \\
&\hat{\lambda}_{th} = \frac{1}{N}\sum_{i=1}^{N}\left(A_t - F_{ith} + \hat{\phi}_{ih}\right) \\
&\hat{\varepsilon}_{ith} = -\left(A_t - F_{ith} + \hat{\phi}_{ih} - \hat{\lambda}_{th}\right) \\
&s_{\varepsilon_i}^2 = \frac{1}{TH-3}\sum_{i=1}^{N}\sum_{t=1}^{T}\left(A_t - F_{ith} + \hat{\phi}_{ih} - \hat{\lambda}_{th} + \hat{\varepsilon}_{ith}\right)^2
\end{aligned}
\tag{1.35}
$$

Inserting the estimated variances in (1.34) and (1.35) into the matrix construct shown in (1.24), (1.25), and (1.28) through (1.33) yields the error covariance matrix **Σ**. I then employ GMM estimation to obtain the standard errors as the square roots of the diagonal of $\left(\mathbf{X'X}\right)^{-1}\mathbf{X\Sigma X}\left(\mathbf{X'X}\right)^{-1}$ where **X** is an *NTH* x *NH* matrix of individual- and horizon-specific dummies. A diagram of the estimated biases is shown in Figure 13. The white vertical lines separate forecasters whose ASA-NBER identification numbers are shown on the horizontal axis. Dark vertical bars indicate the individual- and horizon-specific biases where horizons decline as one moves to the right in the figure. Note the general trend of a decrease in bias as the horizon declines (the average bias at horizon 4 is –0.00087 vs. –0.00061 at horizon 1).

[Figure 13]

Figure 14 shows the ratio of the forecasters' estimated biases to the GMM standard errors of the estimated biases. Again, white vertical lines separate forecasters whose ID numbers appear on the horizontal axis, and horizons decline as one moves to the right. For example, all vertical bars greater than (approximately) 2 represent individual- and horizon-specific biases that are significant at the 5% level. Of the 52 forecasters, 26 show statistically insignificant biases at all four forecast horizons.[13] Nine show statistically significant biases at horizon 4, 14 at horizon 3, 13 at horizon 2, and 24 at horizon 1. The average standard error is 0.0022 at horizon 4 vs. 0.0009 at horizon 1. Combined with the trend of declining biases shown in Figure 13, it appears that, as the forecasters biases decline the biases become less consistent.

[Figure 14]

These results are consistent with Davies and Lahiri's (1999) findings. They found that 12 out of 45 forecasters showed statistically significant biases when the biases were restricted to be individual specific only (i.e. $\phi_{ih} = \phi_i \;\forall\; h$). As a rough approximation to their restrictions, we can look at the ratio of the average bias for each forecaster across horizons to the average standard error (across horizons) of the forecaster biases (i.e. $\sum_{h=1}^{4} \phi_{ih} / \sum_{h=1}^{4} s_{\phi_{ih}}$). Taking this rough approximation as a proxy for the test statistic, we find 12 out of the 52 to be "statistically significant" at the 5% level.[14]

7. Conclusion

The development of panel data analysis techniques enabled researchers to extract more information from a data set than could be extracted from a simple pooling of the data. Similarly, three-dimensional panel data present even more information than simple (two dimensional) panel data. To extract this additional information, however, requires the use of new methodologies. This paper builds on the analytical frameworks set forth by Davies and Lahiri (1995, 1999) and demonstrates that their frameworks imply the existence of new and richer measures of shocks and volatilities than those heretofore

[13] Recall that, due to data differencing, we have lost horizons 0 and –1.

employed in the literature. This paper also relaxes restrictions imposed in the Davies-Lahiri frameworks to achieve a more general framework, and employs the more general framework in tests of forecaster bias. In addition to providing a more general framework for testing rationality, an immediate implication of this work is that researchers must make careful distinctions between the timing of the occurrence of shocks and the timing of the impacts of those shocks on the target. Suggestions for future research include using these new shock measures to explore the relationships between volatility and business cycle turning points, between shocks and volatility, among shocks, volatility, and forecast variance, and the propagation of volatility over time.

[14] A formal comparison would require imposing the restriction $\phi_{ih} = \phi_i \ \forall \ h$ and re-running the GMM tests.

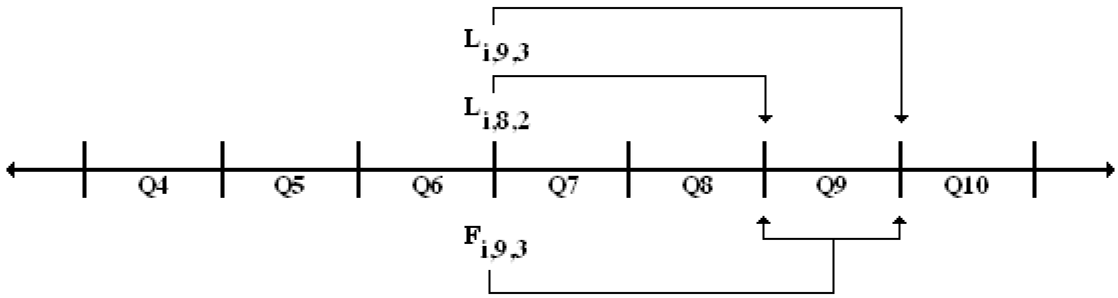


Figure 1. Construction of the Implied Inflation Forecasts

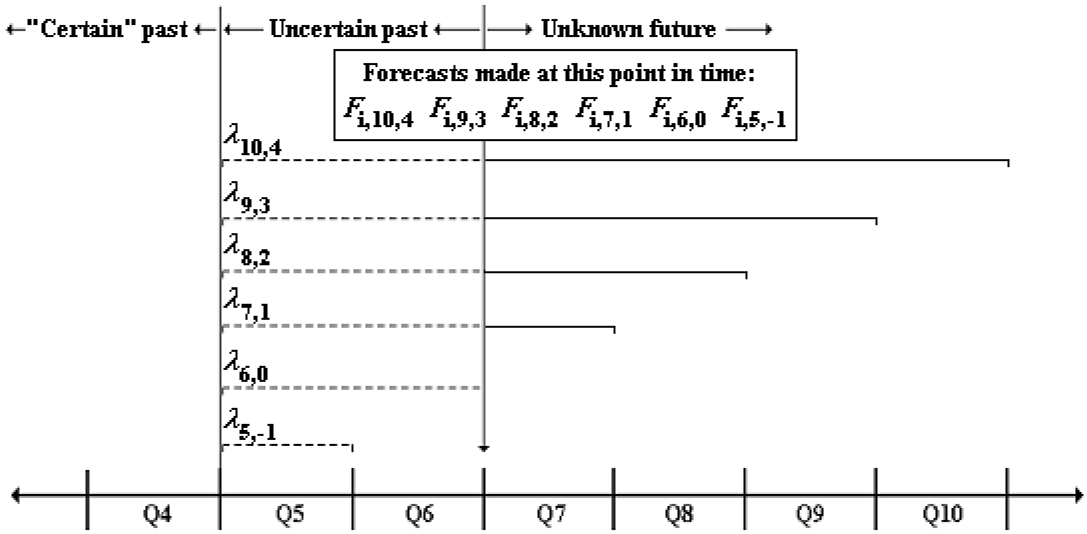


Figure 2. Schematic of Forecasts and Cumulative Shocks

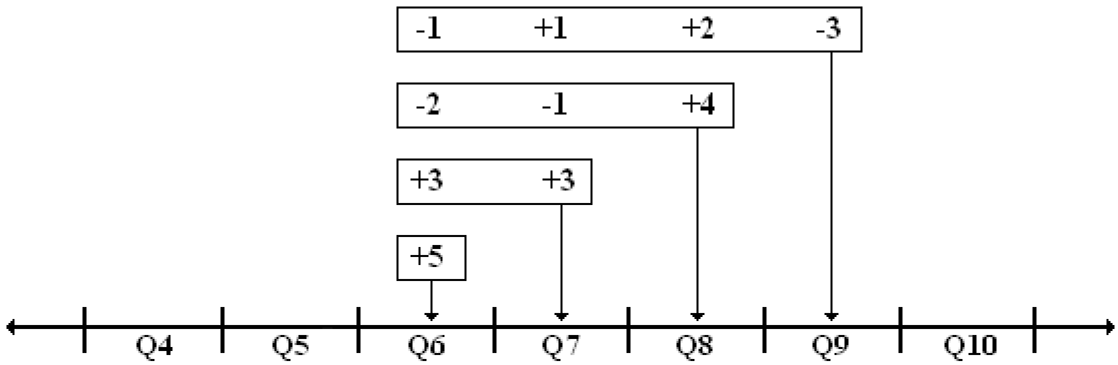


Figure 3. Occurrence versus Impact of Shocks

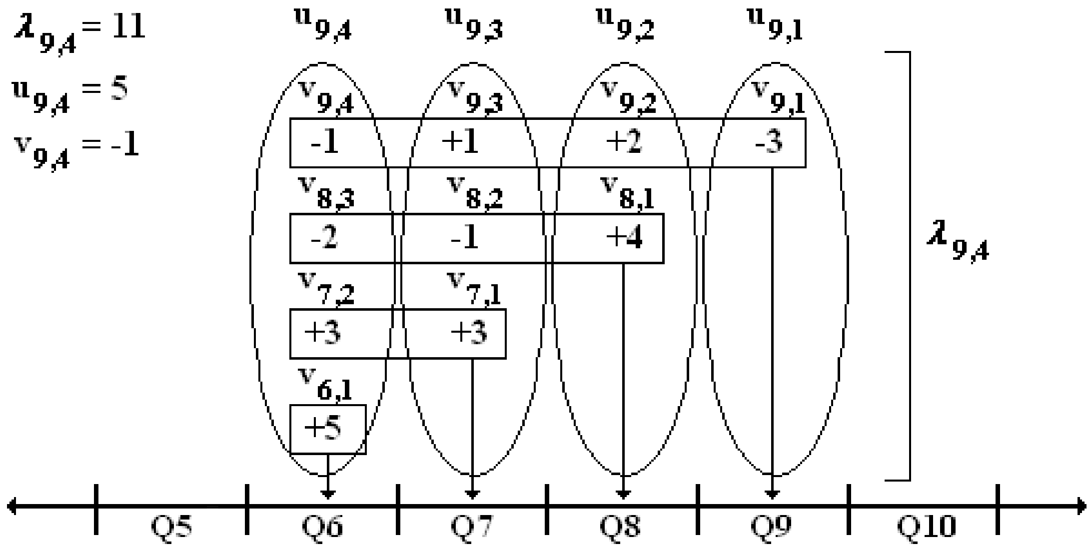


Figure 4. Cumulative, Cross-Sectional, and Discrete Shocks

Shock Measure	Shocks Occur From	Shocks Impact Inflation From
Cumulative shocks λ_{th}	Beginning of quarter $t-h$ to the end of quarter t.	Beginning of quarter $t-h$ to the end of quarter t.
Cross-sectional shocks u_{th}	Beginning of quarter $t-h$ to the end of quarter $t-h$.	Beginning of quarter $t-h$ to the end of quarter t.
Discrete shocks v_{th}	Beginning of quarter $t-h$ to the end of quarter $t-h$.	Beginning of quarter t to the end of quarter t.

Table 1. Cumulative, Cross-Sectional, and Discrete Shocks

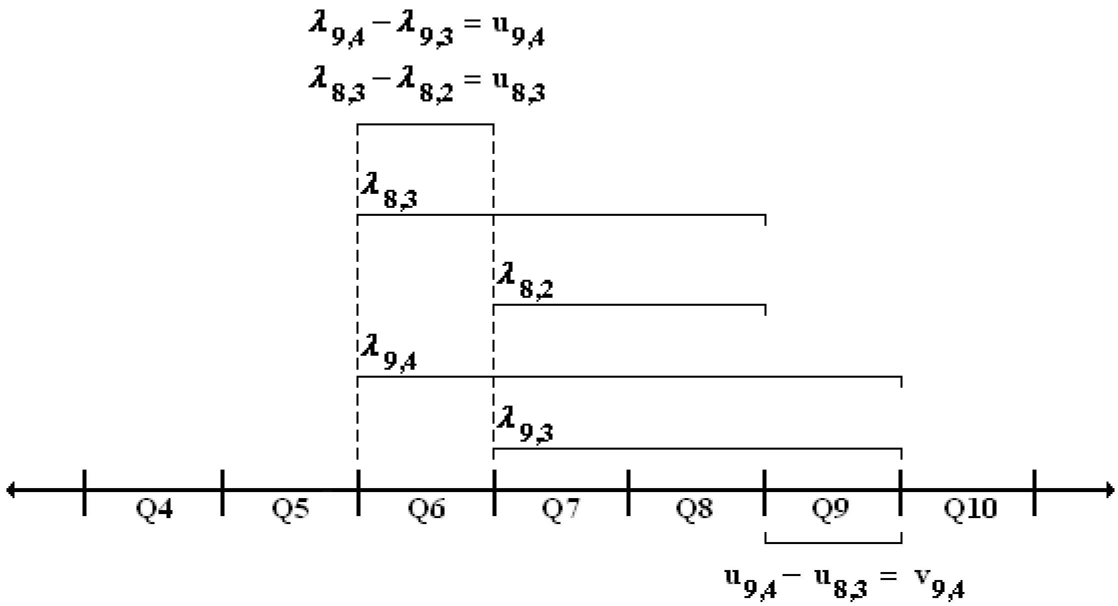


Figure 5. Derivations of Shocks

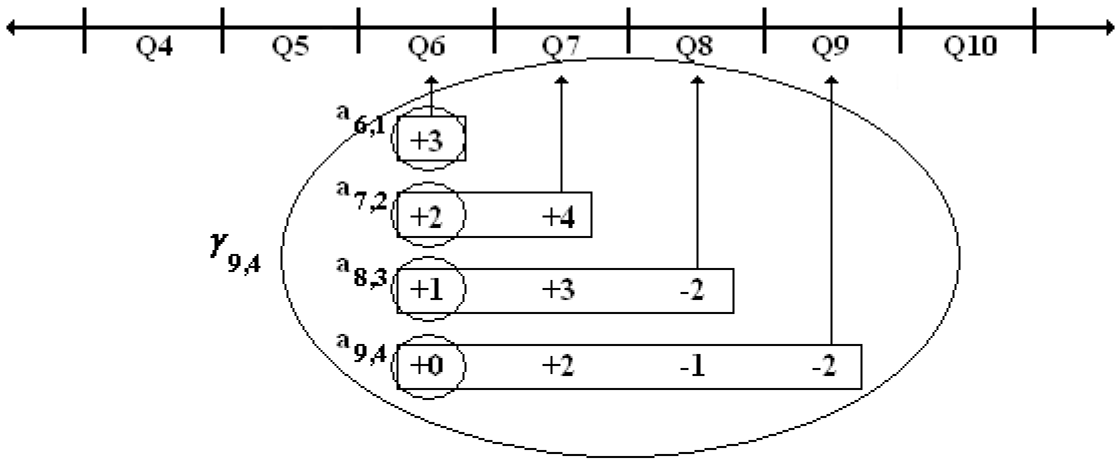


Figure 6. Cumulative and Discrete Anticipated Changes

Anticipated Change Measure	**Anticipated Change is Conceived From**	**Anticipated Change is Expected to Impact Inflation From**
Cumulative anticipated changes γ_{th}	Beginning of quarter $t - h$ to the end of quarter $t - h$.	Beginning of quarter $t - h$ to the end of quarter t.
Discrete anticipated changes a_{th}	Beginning of quarter $t - h$ to the end of quarter $t - h$.	Beginning of quarter t to the end of quarter t.

Table 2. Cumulative and Discrete Anticipated Changes

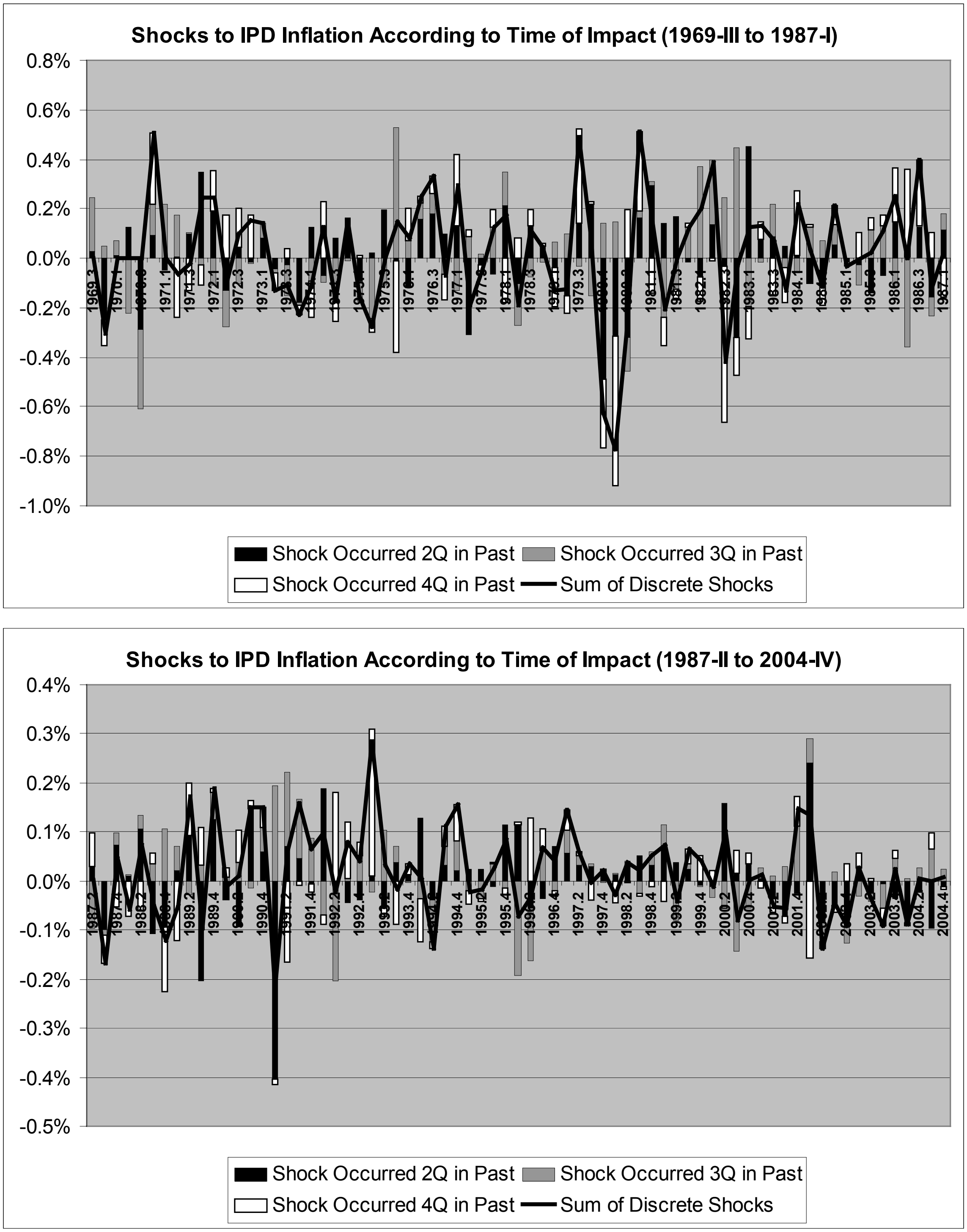
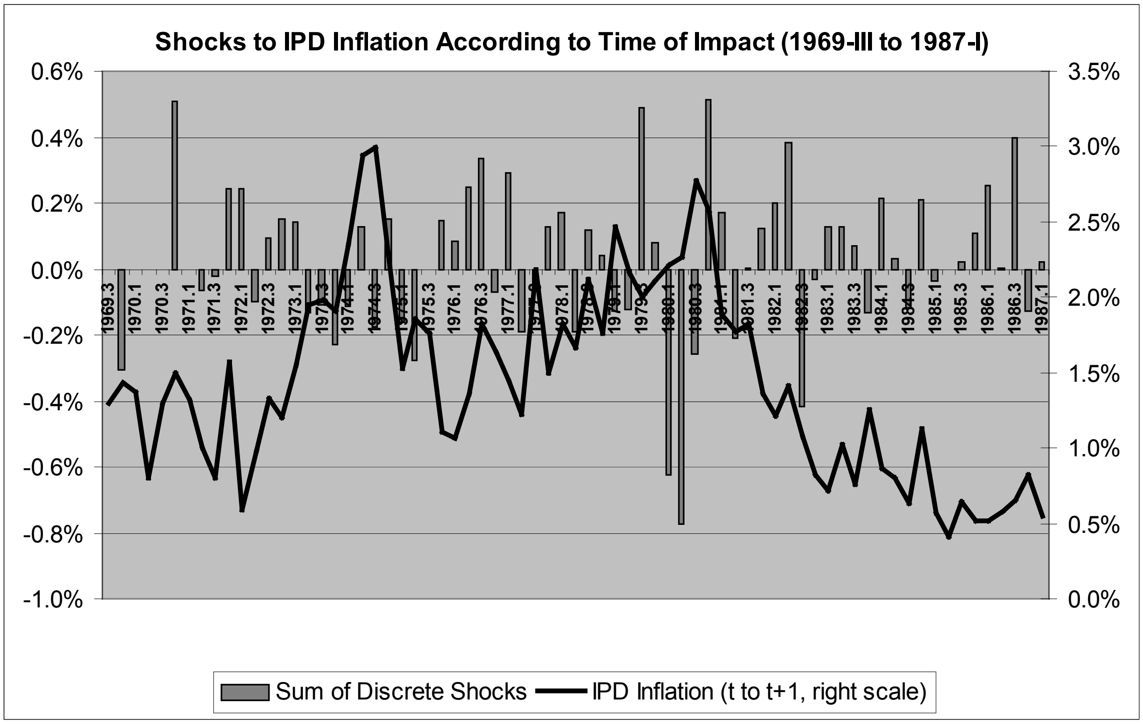


Figure 7. Discrete Shocks to IPD Inflation According to Time of Impact



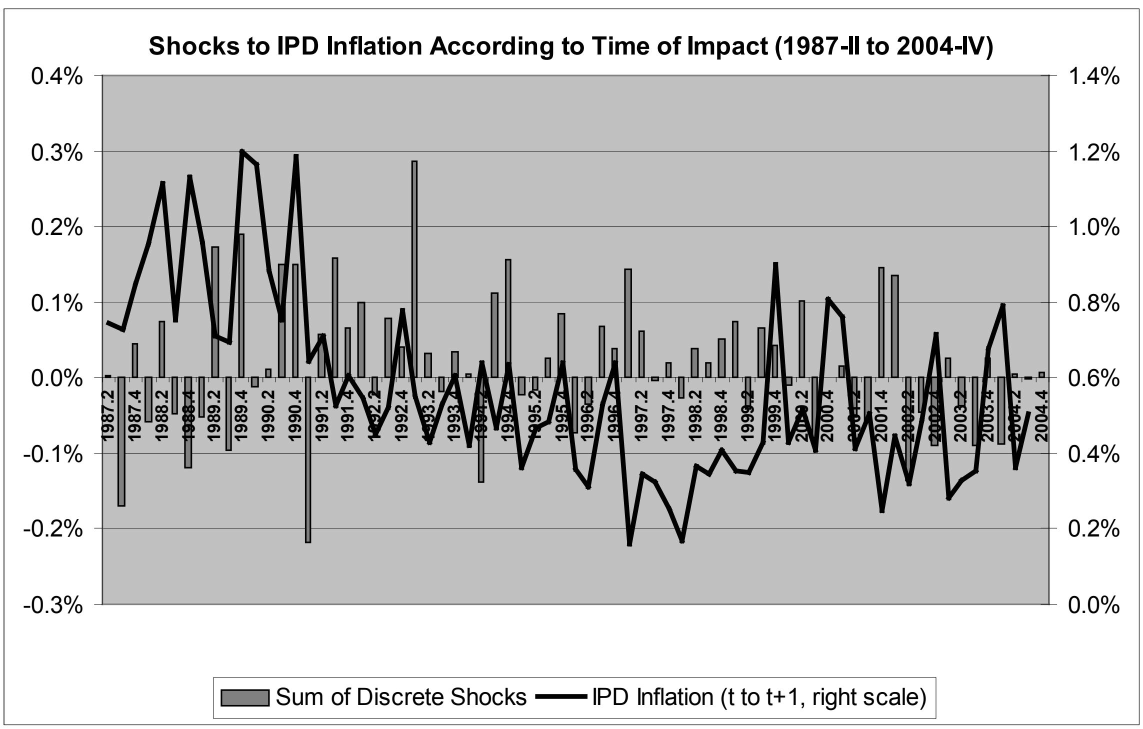


Figure 8. Summed Discrete Shocks and IPD Inflation

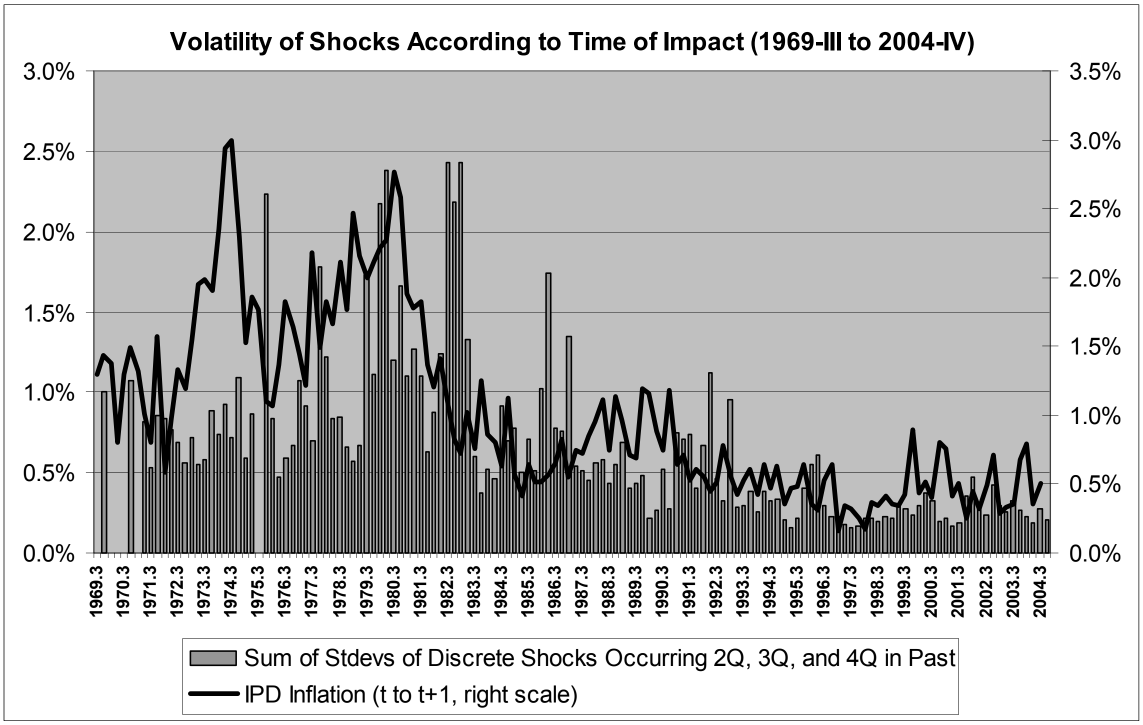
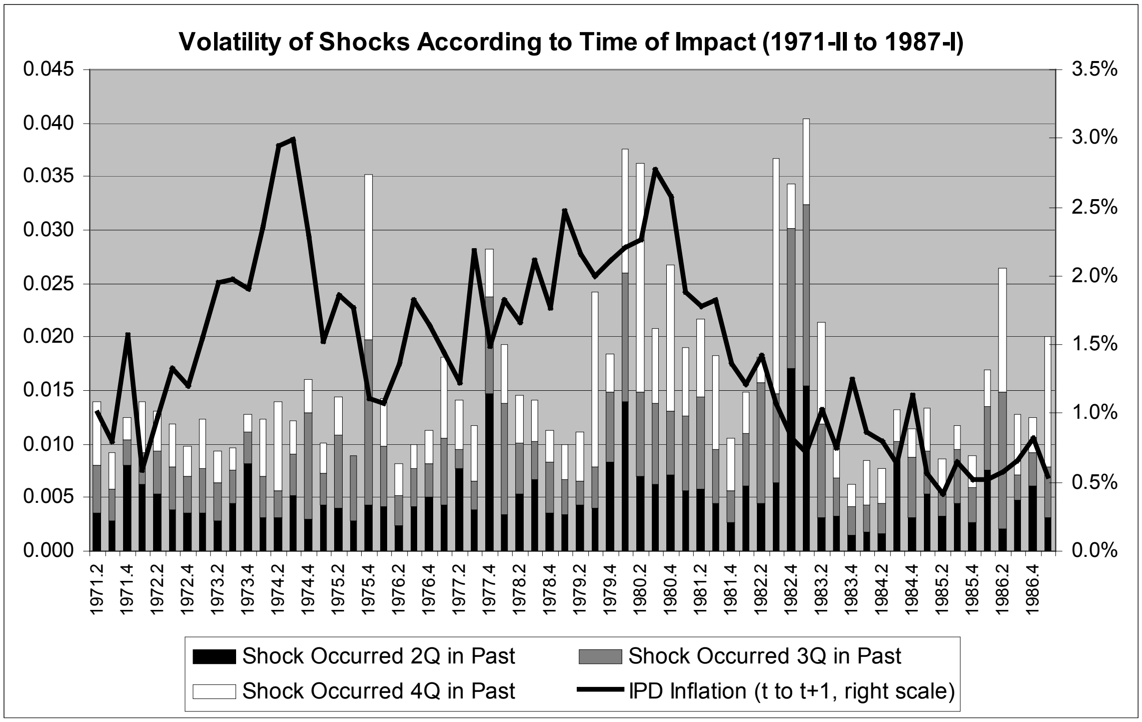


Figure 9. Volatility of Discrete Shocks and IPD Inflation



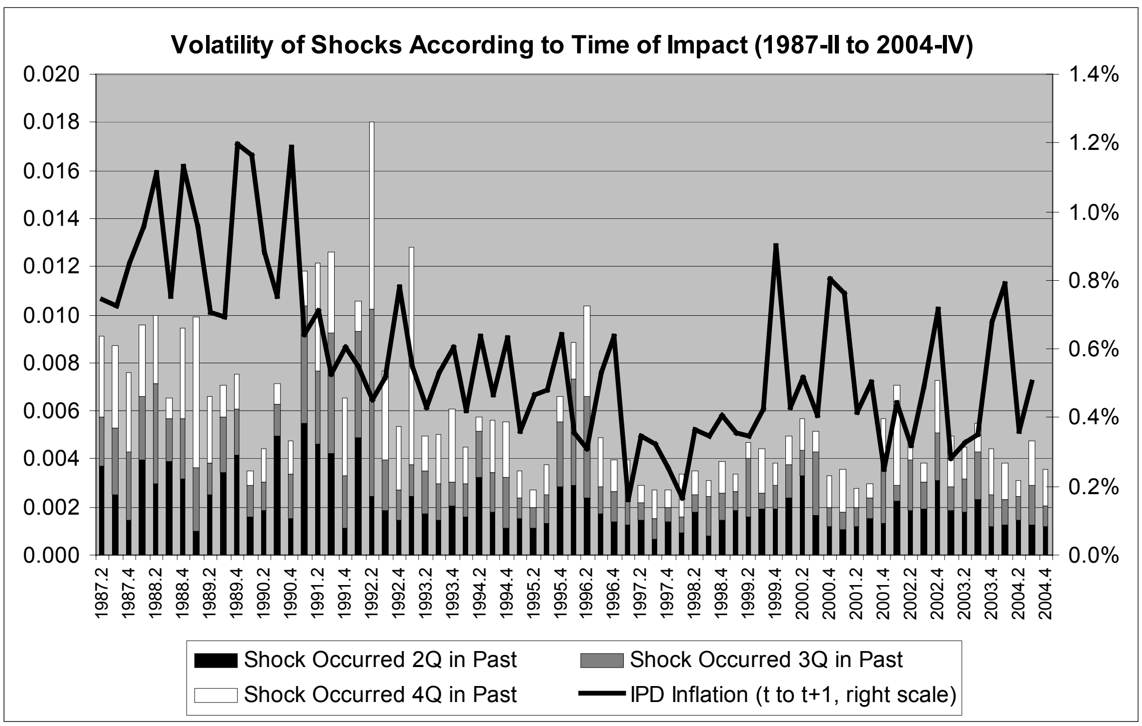


Figure 10. Discrete Volatilities According to Time of Impact

Matrix	Covariance of errors across:
$\mathbf{\Sigma}$	All targets, all horizons, and all individuals.
$\mathbf{A}_i$	All targets, all horizons, individual *i*.
$\mathbf{B}$	All targets, all horizons, and any two individuals.
$\mathbf{b}_t$	Target *t* and all horizons.
$\mathbf{c}_t$	Targets *t* and $t - 1$, and all horizons.
$\mathbf{d}_t$	Targets *t* and $t - 2$, and all horizons.
$\mathbf{e}_t$	Targets *t* and $t - 3$, and all horizons.
$\mathbf{f}_t$	Targets *t* and $t - 4$, and all horizons.
$\mathbf{g}_t$	Targets *t* and $t - 5$, and all horizons.

Table 3. Components of the Error Covariance Matrix

	$\lambda_{10,4}$	$\lambda_{10,3}$	$\lambda_{10,2}$	$\lambda_{10,1}$	$\lambda_{10,0}$	$\lambda_{10,-1}$
$\lambda_{9,4}$	$u_{8,-1}, u_{8,0}, u_{8,1}, u_{8,2}, u_{8,3}$	$u_{8,-1}, u_{8,0}, u_{8,1}, u_{8,2}$	$u_{8,-1}, u_{8,0}, u_{8,1}$	$u_{8,-1}, u_{8,0}$	$u_{8,-1}$	$\varnothing$
$\lambda_{9,3}$	$u_{8,-1}, u_{8,0}, u_{8,1}, u_{8,2}, u_{8,3}$	$u_{8,-1}, u_{8,0}, u_{8,1}, u_{8,2}$	$u_{8,-1}, u_{8,0}, u_{8,1}$	$u_{8,-1}, u_{8,0}$	$u_{8,-1}$	$\varnothing$
$\lambda_{9,2}$	$u_{8,-1}, u_{8,0}, u_{8,1}, u_{8,2}$	$u_{8,-1}, u_{8,0}, u_{8,1}, u_{8,2}$	$u_{8,-1}, u_{8,0}, u_{8,1}$	$u_{8,-1}, u_{8,0}$	$u_{8,-1}$	$\varnothing$
$\lambda_{9,1}$	$u_{8,-1}, u_{8,0}, u_{8,1}$	$u_{8,-1}, u_{8,0}, u_{8,1}$	$u_{8,-1}, u_{8,0}, u_{8,1}$	$u_{8,-1}, u_{8,0}$	$u_{8,-1}$	$\varnothing$
$\lambda_{9,0}$	$u_{8,-1}, u_{8,0}$	$u_{8,-1}, u_{8,0}$	$u_{8,-1}, u_{8,0}$	$u_{8,-1}, u_{8,0}$	$u_{8,-1}$	$\varnothing$
$\lambda_{9,-1}$	$u_{8,-1}$	$u_{8,-1}$	$u_{8,-1}$	$u_{8,-1}$	$u_{8,-1}$	$\varnothing$

Table 4. Cross-Sectional Shocks Common to Cumulative Shocks for Targets 9 and 10

	$\lambda_{10,4}$	$\lambda_{10,3}$	$\lambda_{10,2}$	$\lambda_{10,1}$	$\lambda_{10,0}$	$\lambda_{10,-1}$
$\lambda_{8,4}$	$u_{7,-1}, u_{7,0}, u_{7,1}, u_{7,2}$	$u_{7,-1}, u_{7,0}, u_{7,1}$	$u_{7,-1}, u_{7,0}$	$u_{7,-1}$	$\varnothing$	$\varnothing$
$\lambda_{8,3}$	$u_{7,-1}, u_{7,0}, u_{7,1}, u_{7,2}$	$u_{7,-1}, u_{7,0}, u_{7,1}$	$u_{7,-1}, u_{7,0}$	$u_{7,-1}$	$\varnothing$	$\varnothing$
$\lambda_{8,2}$	$u_{7,-1}, u_{7,0}, u_{7,1}, u_{7,2}$	$u_{7,-1}, u_{7,0}, u_{7,1}$	$u_{7,-1}, u_{7,0}$	$u_{7,-1}$	$\varnothing$	$\varnothing$
$\lambda_{8,1}$	$u_{7,-1}, u_{7,0}, u_{7,1}$	$u_{7,-1}, u_{7,0}, u_{7,1}$	$u_{7,-1}, u_{7,0}$	$u_{7,-1}$	$\varnothing$	$\varnothing$
$\lambda_{8,0}$	$u_{7,-1}, u_{7,0}$	$u_{7,-1}, u_{7,0}$	$u_{7,-1}, u_{7,0}$	$u_{7,-1}$	$\varnothing$	$\varnothing$
$\lambda_{8,-1}$	$u_{7,-1}$	$u_{7,-1}$	$u_{7,-1}$	$u_{7,-1}$	$\varnothing$	$\varnothing$

Table 5. Cross-Sectional Shocks Common to Cumulative Shocks for Targets 8 and 10

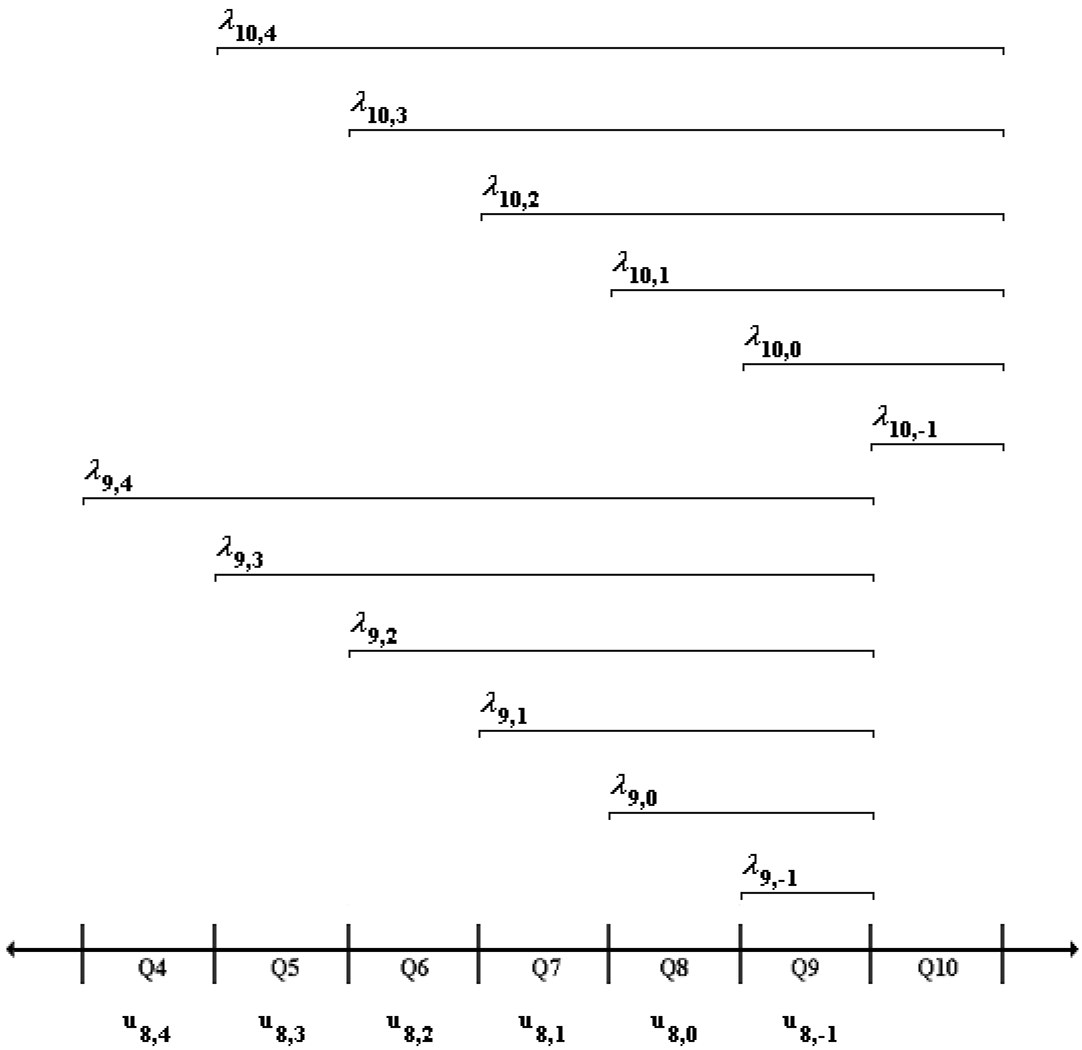


Figure 11. Correlations of cumulative shocks across horizons and for one-quarter separated targets.

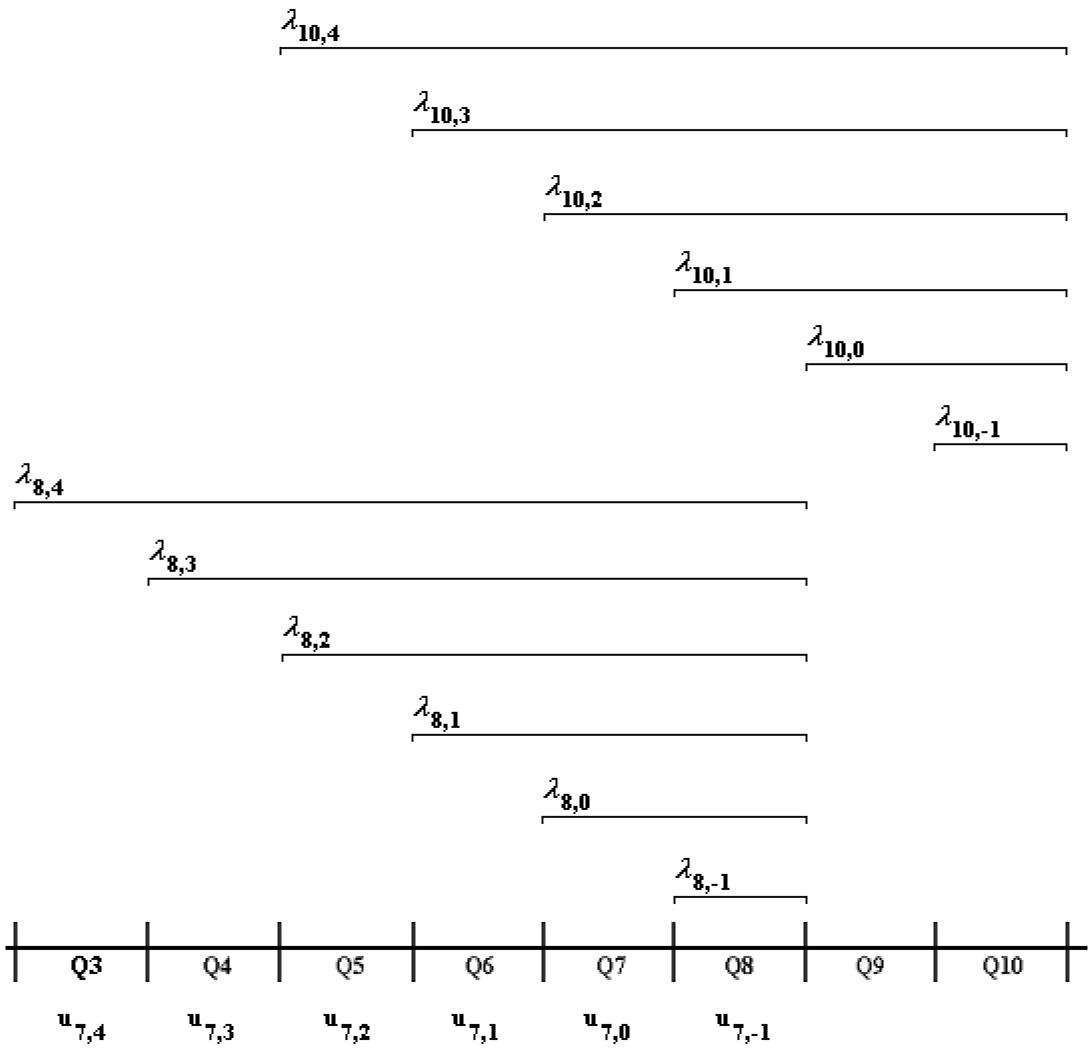


Figure 12. Correlations of cumulative shocks across horizons and for two-quarter separated targets

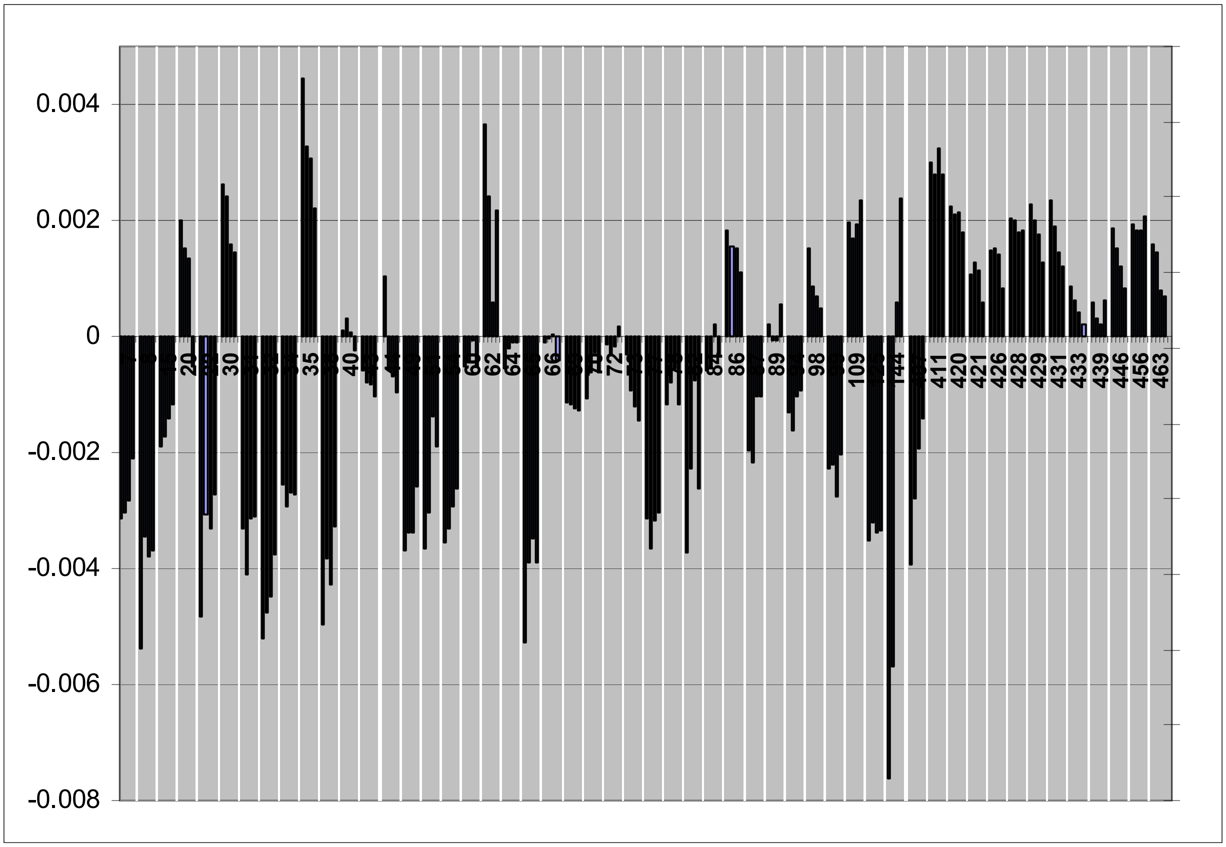


Figure 13. Forecaster biases

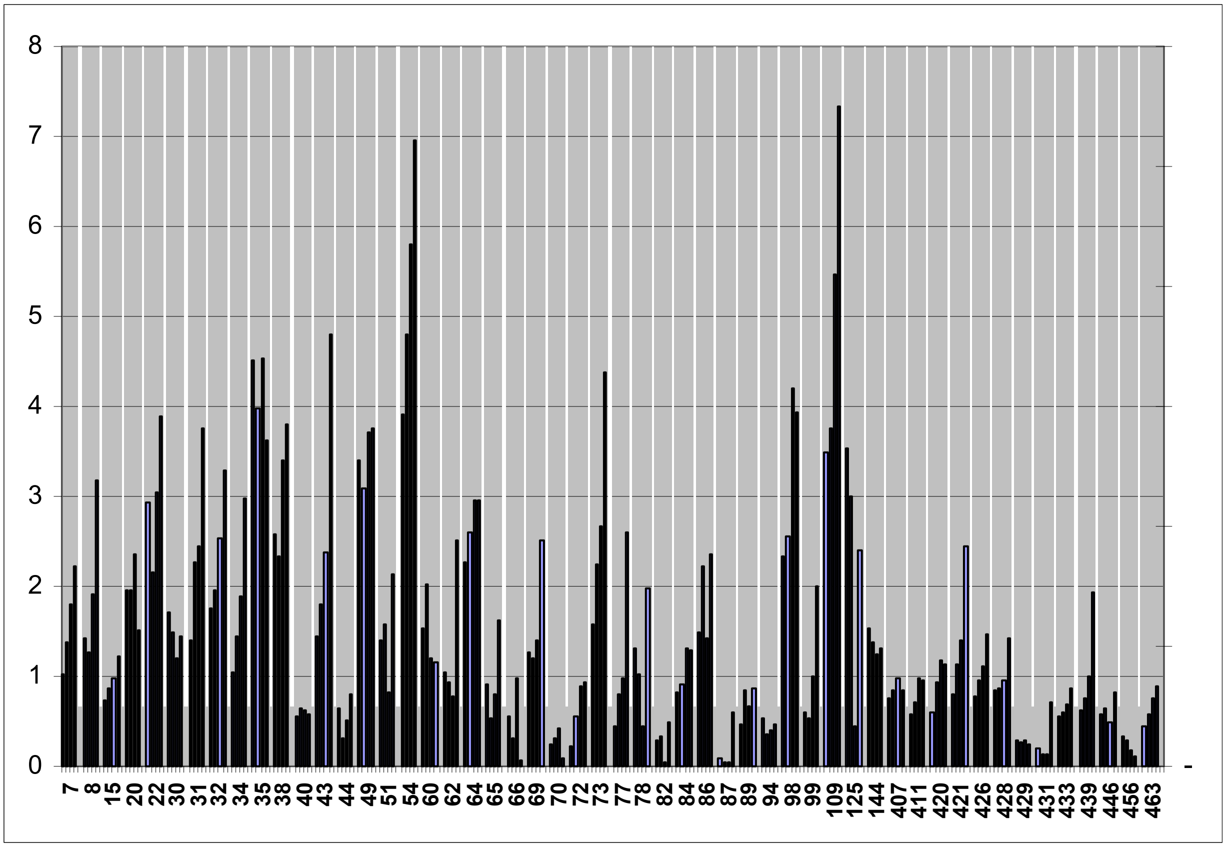


Figure 14. Statistical significance of forecaster biases

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