# Distilling the Macroeconomic News Flow[*]

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May 2014

**Abstract**

We propose a simple cross-sectional technique to extract daily factors from economic news released at different times and frequencies. Our approach can effectively handle the large number of different announcements that are relevant for tracking current economic conditions. We apply the technique to extract real-time measures of inflation, output, employment, and macroeconomic sentiment, as well as corresponding measures of disagreement among economists about these indices. We find that our procedure provides more timely and accurate forecasts of future changes in economic conditions than other real-time forecasting approaches.

**Keywords:** macroeconomic news, forecasting, nowcasting, disagreement

**JEL classification:** G12

[*]We thank an anonymous referee, Daryl Caldwell, Robert Darwin, Fabio Fornari, Amit Goyal, Ana-Maria Tenekedjieva, and seminar participants at BlackRock, City University, the 2012 Asset Pricing Retreat at Cass Business School, the Fall 2012 Inquire UK Conference in Bath, the Imperial College Hedge Fund Conference, the Stockholm School of Economics, and the University of York, for their comments and suggestions. We are indebted to Inquire UK for financial support.

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## 1 Introduction

Timely measurement of the state of the economy relies traditionally on low-frequency observations of a few economic aggregates referring to previous weeks, months, or even quarters. A prominent example is the advance estimate of GDP released quarterly about a month after the end of the quarter. The low frequency and delayed observation of any such economic aggregate considered in isolation stands in sharp contrast with the rich macroeconomic news flow that market participants observe almost daily. This news flow contains information that agents use to learn about the economy in the absence of private information. In particular, the finance literature has identified a large cross-section of dozens of different news releases that have significant and immediate effects on financial markets (e.g., Andersen et al., 2003).

We distill the economic news flow observed by market participants into a small set of indicators describing four distinct aspects of the economy: inflation, output, employment, and macroeconomic sentiment. Specifically, we propose a simple cross-sectional technique to extract daily principal components from economic news releases associated with a given information type and observed at different times and frequencies. Our approach is simple, robust (no numerical optimization is required), and can effectively handle the large number of announcements that are relevant for tracking the evolution of economic conditions in real-time. At the same time, our empirical analysis shows that the output of our approach is more timely and informative than more sophisticated but also more difficult to implement statistical techniques. Intuitively, the potential disadvantage of a simpler modeling approach is more than compensated for by the sheer quantity of data our approach can effectively incorporate.

Our paper relates to the literature on measuring the state of the economy in a time-series setting based only on fundamental economic data (see Banbura et al., 2012, for a survey), commonly referred to as "nowcasting." There are two general approaches to this problem. The first approach is to use a balanced panel regression, along the lines of the seminal paper of Stock and Watson (1989). The purpose of this first approach is to construct a coincident index of economic activity using factor models on a large set of macroeconomic releases, which basically amounts to constructing a weighted average of several monthly or quarterly indicators. The advantage of this technique is that the resulting index is based on many macroeconomic variables. However, this advantage also results in a relatively low measurement frequency, because the econometrician has to wait for the panel to be complete before the index can be constructed. A second general approach is to model macroeconomic data using a state-space model (e.g., Evans, 2005). The advantage of this second approach is to produce an indicator at a higher frequency, since a state-space model can effectively handle the sparse and delayed reporting of economic data and missing information on non-release days. However, this technique is impractical for large cross-sections of macroeconomic releases. For example, Evans (2005) only considers the set of different (preliminary, advance, and final) GDP releases. Arouba et al. (2009) propose a business condition index, called the ADS index, constructed using four indicators at different frequencies, including a continuously observable financial markets variable, . Finally, Giannone et al. (2008) combine the two approaches by modeling factors extracted from a balanced panel of monthly releases in a state-space setting.

Our goal is to measure the state of the economy with a methodology that broadly retains the advantages of both approaches without their respective limitations. Specifically, we consider a large universe of macroeconomic announcements. This is a crucial aspect of our methodology, given the evidence of many influential releases from the macroeconomic announcement literature. At the same time, our approach can handle data released at different frequencies and missing observations to produce a real-time high-frequency measurement of the state of the economy.

Our methodology has several other differentiating features relative to the literature. First, we do not aim to estimate a real-time series of GDP, for example, but we rather leave the macroeconomic factor(s) truly latent and unspecified. In this sense, we do not impose any structure on the estimation and thus do not take a stand on what is the appropriate metric of the state of the economy. We simply let the data speak for itself. Second, our focus on a large cross-section of economic news releases allows us to extract factors from four subsets of macroeconomic news (e.g., inflation, output, employment, and macroeconomic sentiment). We use these subset indicators to learn about the relations between different driving forces of the economy. Third, we utilize news flow data that is truly real-time and unrestated, as opposed to approximately dated historical data that is often restated (e.g., Koening et al., 2003; see also Ghysels et al., 2012, for an illustration of the issues arising from restated macroeconomic data). Fourth, we refrain from using any financial market based data, as our aim is to objectively measure the macroeconomic news flow absent any market's interpretation of the same. Finally, we also apply our methodology to the dispersion of economic forecasts as a new way to obtain a high-frequency measure of macroeconomic uncertainty based on the disagreement of a cross-section of economic experts. In summary, our fairly simple and data-driven method delivers a real-time, daily, unbiased, and objective reading of the state of the macroeconomy, which can be used for a number of purposes, most notably to study the relation between financial market and economic dynamics.

We find that an economic activity factor (which combines output and employment information, as they are highly correlated) as well as a macroeconomic sentiment factor, both extracted from the large cross-section of macroeconomic news, have sensible dynamics. The greatest dips in both series are well aligned with the ex-post defined NBER recession periods. The macroeconomic sentiment factor, obtained from consumer and business confidence releases, is highly correlated with economic activity, but appears to lead fundamentals especially around important turning points. Finally, our inflation factor exhibits dynamics that seem only weakly correlated with growth, with much more erratic variation, and has an unclear pattern in expansions versus recessions.

Our empirical proxy of economic uncertainty based on economic expert disagreement is interesting for at least two reasons. First, it shows little correlation with the estimates of the latent economic activity, macroeconomic sentiment, and inflation factors, suggesting that they are likely to contain different information. Second, and more importantly, macroeconomic uncertainty exhibits intriguing asymmetric dynamics. The peaks of disagreement correspond to the final stages of recession periods, while uncertainty is relatively subdued at the end of economic expansions. This evidence suggests that economists tend to disagree mostly on recoveries from prior contractions, whereas everyone seems to see the end of an economic expansion coming.

We formally relate a real-time factor of economic growth (which further aggregates the information relative to economic activity by combining information relating to output, employment and macroeconomic sentiment) to vintages of the Chicago Fed National Activity Index (CFNAI), constructed by the Chicago Federal Reserve Board based on Stock and Watson (1989), on CFNAI release dates at the monthly frequency and to the vintage version of the ADS index of Arouba et al. (2009) at the weekly frequency. We find that our latent growth factor is strongly correlated to both of these alternative approaches. However, since our factor is constructed using information from either a larger cross-section of news or in a more timely manner, it turns out to have significant forecasting power for both CFNAI and the ADS index beyond their own lags. We also find that our growth factor has predictive power for future actual GDP releases and is highly correlated with the quarterly GDP expectations in the Survey of Professional Forecasters (SPF). This is a remarkable feature given that, unlike the ADS index, our growth factor is not optimally weighted to forecast GDP. The large correlation with the quarterly releases of the SPF offers an intuitive interpretation of our growth factor as the high-frequency daily reading of economist expectations about macroeconomic fundamentals.

We extend this empirical analysis to the real-time inflation factor extracted from inflation-related announcements. This is a novel aspect of our analysis, as the extant approaches generally ignore these releases to optimally forecast GDP and growth.[1] Our real-time inflation factor generally seems to lead the pattern of CPI actual releases and the inflation forecast contained in the SPF, albeit in a relatively noisy fashion. More specifically, we find that our inflation factor observed on quarterly SPF release dates has predictive power for the upcoming actual CPI announcement, beyond CPI own lags and the median SPF inflation forecast.

Another intriguing finding is that our latent factors obtained exclusively from macroeconomic information are highly correlated with financial indicators, such as the default spread and the implied stock return volatility index VIX. More specifically, we find that the combination of our latent growth factor and its dispersion can explain almost one third of VIX levels. This is an important finding in light of the documented difficulties for macroeconomic quantities to explain

[1] For example, the 85 macroeconomic indicators used to construct the CFNAI are drawn from production, employment, consumption, and sales categories, but none of them is drawn from a nominal inflation-related category.

financial market volatility (see, for example, the seminal paper of Schwert, 1989).

Finally, we combine the information of the growth indicator and its dispersion extracted from economist disagreement, and document very strong predictability for future growth, from 5 days and up to six months ahead. Given the illustrated relation of our macroeconomic indicator with financial variables and its extremely timely nature, this result suggests that our quantitative measure of the news flow could have predictive power for future financial market dynamics.

The remainder of the paper proceeds as follows. In Section 2, we describe the macroeconomic news and we carry out some preliminary analysis on macroeconomic announcements. Section 3 explains our methodology for estimating in real-time the state of the economy and its uncertainty. We present our empirical results in Section 4. Section 5 concludes with a summary of our findings.

# 2 Data and Preliminaries

## 2.1 Macroeconomic news and forecasts

We obtain data on the dates, release times, and actual released figures for 43 *distinct* U.S. macroeconomic announcements covering the period from January 1997 through December 2011, for a total of more than 8,000 announcements over about 3,800 business days. This data is obtained from Bloomberg through the Economic Calendar screen, which provides precisely time-stamped and unrestated announcement data.[2,3] We also collect data on economist forecasts for each announcement. Bloomberg surveys economists during the weeks prior to the release of each indicator to obtain a consensus estimate. We work with the individual economist level forecasts, rather than the aggregated consensus forecasts, in order to construct cross-sectional measures of disagreement for each news release.

Bloomberg contains data for many of our series prior to 1997, but those data are stored in historical fields which (a) are not associated with clear announcement dates and times (rather they are dated according to the period they reference) and (b) are restated over time.[4] We collect this more problematic data for January 1985 through 1996 for two reasons. First, we use this historical data to construct an initial correlation matrix estimate, which is required by our methodology

[2]We emphasize the fact that we work with distinct announcements because there are a lot more than 43 statistics if we included multiple versions of essentially the same data released in the same economic report. For example, the CFNAI uses 13 industrial production statistics, resulting in 20 percent of the index being determined by a single release. In contrast, we include in our analysis only the headline month-over-month figure.

[3]The importance of using real-time versus final data in macroeconomic forecasting has been discussed extensively in the literature (e.g., Koenig et al., 2003). In our real-time framework, revisions and restatements could be used as new information that becomes available on the date of the restatement release. However, since restatements are typically announced contemporaneously with new initial releases, we focus exclusively on the latter.

[4]For example, there are monthly releases of quarterly GDP labeled "advance," "preliminary" and "final" all referring to the same quarter. Bloomberg's historical field for GDP is dated according to the referenced quarter, so that the advance release gets overwritten by the preliminary release, which in turn gets overwritten by the final release. Historically only the final releases are stored.

(see Section 3). Second, we use this data for a robustness check with a longer sample period (see Section 4.5). In order to date the releases prior to 1997, we compute for each news series the *median* time between the reference period and the announcement. For example, the employment report is traditionally released four days after the end of the month to which the report refers. We then apply this median reporting lag to the reference period of the older data in order to obtain an approximate announcement date.

Since economist-level forecasts are not available prior to 1997, we instead collect data from the Survey of Professional Forecasters (SPF). The SPF is the oldest quarterly survey of macroeconomic forecasts in the United States. The survey began in 1968 and was conducted by the American Statistical Association and the National Bureau of Economic Research. The Federal Reserve Bank of Philadelphia took over the survey in 1990. The SPF's web page offers the actual releases, documentation, mean and median forecasts of all the respondents as well as the individual responses from each economist. The individual responses are kept confidential by using identification numbers.

Most macroeconomic indicators are released on different days and at different frequencies, making it difficult to process the flow of information in a systematic and consistent way. Figure 1 shows that actual news releases occur with a variety of different lags with respect to the month they are referencing. Furthermore, news on different indicators are frequently released simultaneously.[5] For example, the employment report traditionally announced on the first Friday of the month contains four different indicators: nonfarm payrolls, nonfarm payrolls in the manufacturing sector, the unemployment rate, and average weekly hours. Finally, the release frequency varies across different economic aggregates. Data releases of different economic indicators are usually observed at different frequency; e.g., GDP data are sampled quarterly, the nonfarm payrolls are released monthly, initial jobless claims are sampled weekly, etc. These features of our large cross-section of macroeconomic news releases generate a sparse matrix of data that our methodology will have to take up. The Appendix describes in detail the set of macroeconomic news in our sample, including their frequency, source, and units of measurement.

### 2.2 Categorizing the macroeconomic news flow

Our aim is to extract a set of factors describing the state of the economy. Rather than relying on a statistical procedure to obtain orthogonalized factors that are increasingly difficult to interpret with the order of the factor, we impose a specific economically motivated structure on the macroeconomic news flow. Based on both empirical evidence and economic rationale, we first separate the aggregate

[5] On approximately 80 percent of days, there was at least one data release. Multiple data releases occurred much less frequently, on approximately 60 percent of the days in the sample.

economy into two broad dimensions: the nominal and the real side.[6] In practice, we split the set of announcements into nominal inflation-related announcements and news that relates to real growth. Growth data, in turn, come in two flavors – objective realizations of past economic activity and subjective often forward-looking views derived from surveys which we label "macro sentiment."[7] Finally, economic activity can be split one last time into information relating to output versus employment.

Through this structure, we obtain two (inflation and growth), three (inflation, economic activity, and macro sentiment), or four (inflation, output, employment, and macro sentiment) factors:

- Inflation
- Growth
  - Economic Activity
    - Output
    - Employment
  - Macro Sentiment

where, for example, the economic activity factor is obtained from the combined information relating to output and employment. In that sense, the information is nested from right to left.

More specifically, the inflation factor is extracted from the news flow of nine inflation-related releases: consumer price index, CPI ex food and energy, employment cost index, GDP price index, import price index, nonfarm productivity, personal consumption expenditure core price index, producer price index, and PPI ex food and energy. For the output factor, we utilize information from both the supply and demand side of the economy in the form of news about advance retail sales, business inventories, capacity utilization, consumer credit, domestic vehicle sales, durable goods orders, durables ex-transportation, factory orders, GDP, industrial production, ISM manufacturing, ISM non-manufacturing composite, personal consumption, personal income, personal spending, retail sales less autos, and wholesale inventories. Employment news is captured by releases of ADP payrolls, manufacturing payrolls, non-farm payrolls, continuing claims, initial jobless claims, and the unemployment rate. Finally, we extract the macro sentiment factor from the information in 10 macroeconomic surveys: ABC consumer confidence, Chicago purchasing manager, consumer confidence, Dallas Fed manufacturing activity, Empire manufacturing survey, leading indicators index, NAPM-Milwaukee, Philadelphia Fed business outlook survey, Richmond Fed manufacturing index, and the University of Michigan confidence index. The Appendix summarizes the assignment of announcements to the four categories: inflation, output, employment, and macro sentiment.

[6] The economy is often separated into nominal and real sides because shocks to the two should be treated differently from a policy perspective. For example, many argue, from the perspective of monetary policy, that nominal shocks should be minimized, whereas real shocks should not be intervened upon. Other studies also suggest that a nominal and a real factor can jointly account for much of the observed variation in major economic aggregates.

[7] The behavioral finance and economics literature tends to associate the term *sentiment* with emotions that in a rational framework should not affect decisions. We take a broader perspective and use the term sentiment to encompass agents subjective forward-looking interpretation of the data as revealed through surveys.

It is worth reiterating at this point that we do not include any market-based data (such as stock prices, interest rates, credit spreads, or VIX) in our analysis, unlike, for example, Arouba et al. (2009) and Giannone et al. (2008). While such data are very timely and undoubtedly informative about the state of the economy, they represent already the market's *interpretation* of the macroeconomic news flow. Our aim is to objectively summarize and describe the macroeconomic news flow itself.

### 2.3 Transformation and temporal alignment

We examine the stationarity of each data series in two ways. First, we conduct a Dickey-Fuller test on each series. Second, we read the definition and description of each statistic to determine from an economic perspective whether it is a non-stationary index or a stationary quarterly growth rate, for example. In a few cases where the conclusions from the two approaches differ, usually because the available data is too short to examining statistically, we rely more on the description to determine whether the series is stationary. All series that are deemed non-stationary are first-differenced in news release time. The Appendix contains more details.

The final data management task is to align the data temporally by moving from announcement time to calendar time. We do this by populating the news releases in a $T \times N$ matrix where $T$ denotes the total number of week days in our sample and $N$ refers to the 43 announcement types. The data at this stage looks like the top panel of Figure 2.

There are two important aspects of the data to discuss. First, there are a vast number of missing values, as we can think of each news series as a continuously evolving statistic that is observed only once per month or quarter. Second, not all announcements have a complete history. Some announcements are initiated in the middle of the sample and/or are terminated before the end of the sample. To solve the missing data problem, we simply forward fill the last observed release until the next announcement. Forward filling can be rationalized as replacing missing values with expected values under a simple independent random walk assumption for each news series. Of course, both independence in the cross-section and random walk dynamics through time are simplifying assumptions that are rejected by the data (in fact, the motivation for our methodology described below is the cross-sectional correlation structure within news category). A more sophisticated approach for filling in missing data would be to compute the expectation of the missing values given the full cross-section of previous releases as well as the cross-sectional and intertemporal correlation structure of the data. An optimal solution would also allow for sampling error, which is the case in Kalman filter or Bayesian data augmentation algorithms. However, there is a clear trade-off between statistical complexity and ability to process a large cross-section of news series. Since the goal of our approach is to utilize the entire cross-section of news, we choose a very simple statistical model for filling in missing observations. After forward filling, the data looks like the bottom plot of Figure 2.[8]

Note that the second data issue, the fact that some series do not span the entire sample period, cannot be solved with missing values imputation. It is instead explicitly addressed in our methodology below.

# 3 Methodology

## 3.1 Subset principal component analysis

Our goal is to extract from the cross-section of macroeconomic news releases a set of factors that capture in real-time the state of inflation, output, employment, and macro sentiment, as well as the two more overarching factors measuring economic activity and growth. The most obvious ways of accomplishing this, full data principal components analysis (PCA) and forecasting regressions, do not appeal to us. First, with full data PCA we obtain factors that are mechanically orthogonal, whereas the dimensions of the economic news flow we want to capture are likely correlated (e.g., output and employment are both high at the peak and low at the trough of an economic cycle). This orthogonalization makes it practically impossible to assign an economic meaning to higher order factors. Second, trying to identify the factors through predictive regressions on a candidate variables in each category, such as final GDP for output, would require us being able to identify a single series that represents each category. While this is a common approach in the nowcasting literature, it relies on ex-ante knowledge of the key statistic to track and assumes that there is only one such statistic that does not change over time (see also Stock and Watson, 1989).

Instead, we rely on our ex-ante categorization of the news and, within each category subset, let the data speak for itself by extracting the first principal component of that subset of data. Specifically, on each day of our sample $t$, we obtain for each news category $i$ the first principal component from the correlation matrix $\Omega_{t,i}$ of the stationary news series in category $i$. We work with the correlation matrix to abstract from arbitrary scaling of data. Moreover, in order to obtain a real-time measure, we use a telescoping (with a common historical start date and rolling end dates) correlation matrix starting in 1980.[9] We denote the $N_i \times 1$ principal component weights by $c_{t,i}$, where $N_i$ is the number of news series in category $i$. Consistent with extracting principal components from a telescoping correlation matrix, we standardize the news series using telescoping estimates of their means and standard deviations.

[8] The forward-filling could potentially accommodate data revisions or restatements on the day they occur, if the restatements are not contemporaneous with subsequent initial releases.

[9] We also experimented with fixed window size rolling correlation matrices for 5, 10, 15, and 20 years. The results are qualitatively similar, particularly for the longer data windows.

### 3.2 Economic new series correlation matrix

The key inputs to our methodology are the within news category correlation matrices $\Omega_{t,i}$. Specifically, we need to calculate from historical data up through date $t$ the correlation of all news series of category $i$ that are "active" on that date, where active means that the news series was previously initiated and has not yet been terminated. There are two issues that need to be addressed in computing these correlation matrices. First, the data is in the form of an unbalanced panel due to some of the series being initiated after the start date of the estimation window (e.g., series $j = 5$ in Figure 2). Second, the data is naturally persistent, partly due to autocorrelation of the data in announcement time, partly due to the cross-sectional misalignment of the news in calendar time, and largely due to the forward filling of missing data.

We address the first unbalanced panel issue by using a correlation matrix estimator along the lines of Stambaugh (1997), who shows how to adjust first and second moments estimates for unequal sample lengths. The intuition of his approach is to use the observed data on the longer series, along with a projection of the shorter series onto the longer ones estimated when both are observed, to adjust the moments of the shorter time series.

To correct for the persistence, we could use the standard approach of Newey-West (1987), where due to the nature of the data we would account for up to one quarter of autocorrelation and cross-autocorrelation. Unfortunately, the kind of persistence in our data is not ideally captured by the non-parametric Newey-West approach for two reasons. First, we have daily data, so adjusting for up to a quarter of autocorrelation would involve approximately 60 cross-autocorrelation matrices. Second, the (cross-) autocorrelations are not exponentially decaying as a typical ARMA model might predict. Instead, the data is locally constant, due to the forward filling, and over longer intervals only moderately (cross-) autocorrelated due to the statistical nature of the news series.

This peculiar correlation structure of economic news forward filled onto a daily calendar is actually identical to that found in high-frequency asset prices, where asynchronous and infrequent trading creates a misaligned and locally constant panel of observations. In that literature, Ait-Sahalia, Mykland, and Zhang (2005) propose a "two-scales realized volatility" estimator to handle this specific structure of short-term constancy versus long-horizon weak dependence. Specifically, their estimator subsamples the data at a sufficiently low frequency that overcomes the local constancy and then averages over the set of all possible estimators that start the subsampling schemes at different times.

We adopt exactly the same approach, except of course our application is very different. Specifically, at date $t$ we subsample the forward filled news series backward at a monthly frequency and then compute a Newey-West estimate of the correlation matrix using four lags. We repeat the same for monthly sampling starting at dates $\{t-1, t-2, ..., t-d+1\}$ (assuming $d$ days per month) and then average the resulting $d$ correlation matrix estimates.

### 3.3 Level versus disagreement factors

Given the vector of principal component weights $c_{t,i}$ obtained with our methodology, we then construct for each news category two time series. First, we sum at each date the product of the weights multiplied by the most recent releases to obtain our real-time *level* factors. Second, we sum the product of the same weights multiplied this time by the cross-sectional standard deviations of the economist forecasts for the most recent releases to obtain our real-time *disagreement* factors. Throughout our sample not every news series has economist level forecasts data available. We therefore construct the disagreement factor using the available data, re-normalizing first the principal component weights to account for the proportion of missing data.

## 4 Results

We first describe empirically the dynamics of the real-time macroeconomic factors. To get a sense for how our methodology compares to other approaches, we then relate our growth factor to the vintage releases of the CFNAI and ADS index. We analyze whether our real-time growth factor actually predicts subsequent GDP releases, comparing it to the predictability by the corresponding SPF forecasts. Along the same lines, we examine our real-time inflation factor and analyze whether it predicts subsequent CPI releases relative to the SPF forecasts. We then examine the relation between the growth factor and its dispersion with volatility in financial markets. This latter analysis is motivated by the apparent lack of a strong relation between real activity and financial market volatility (e.g., Schwert, 1989). Finally, we examine the joint dynamics of our real-time growth index, growth dispersion, inflation index, and inflation dispersion, and we also extend the sample backward using a pseudo real-time approach as a robustness check.

### 4.1 Preliminaries

In panel A of Table 1, we present correlations between the seven real-time macroeconomic indices and their respective economist forecast dispersions, which we interpret as proxies for macroeconomic uncertainty. There are a number of interesting observations. First, inflation is relatively uncorrelated with the other macroeconomic indices. Its highest correlation is 0.36 with output. In contrast, output, employment, and sentiment are highly correlated with each other (correlations ranging from 0.75 to 0.84) and are each even more highly correlated with the composite indices for economic activity and growth. The correlations with the growth index, in particular, range from 0.92 to 0.95. We conclude from these high correlations that the growth index contains most of the information revealed by output, employment, and sentiment, and we therefore focus on examining the aggregated growth index and its dispersion going forward.

Second, the correlations between macroeconomic uncertainty mimics the general patterns we observe in the indices, but at somewhat lower levels, particularly for sentiment. For example, the correlations between output dispersion, employment dispersion, and sentiment dispersion with growth dispersion are 0.96, 0.68, and 0.54, respectively.

Finally, we observe an interesting negative correlation between the levels and dispersions of our real-time macroeconomic factors. The correlations are generally small in magnitude, except for inflation uncertainty, which is -0.5 and more highly correlated with the level of growth and its components (output, employment, and macro sentiment). This suggests that at times of strong (weak) growth, the uncertainty about inflation is low (high). In contrast, the state of inflation seems irrelevant for the uncertainty about the other real-time macroeconomic indices.

In panel B, we compute contemporaneous correlations between excess stock market returns, the growth factor, the dispersion of growth forecasts, and a number of financial market variables associated in the literature with the state of the economy or macroeconomic uncertainty.[10] There is no meaningful contemporaneous correlation between our real-time macroeconomic factor and stock market returns. In contrast, there are significant contemporaneous correlations between the growth factor and a number of financial variables, most notably the correlation with VIX (-0.51), the dividend yield (-0.71), and the default premium (-0.84). Growth dispersion has a weaker relation with the financial variables, but it still retains a significant correlation with VIX (0.25) and with the price-earnings ratio (0.19). These descriptive results foreshadow the link between our real-time growth factor and financial market volatility, proxied here by VIX, that we investigate more thoroughly in Section 4.3.[11]

Figures 3, 4, 5, and 6 provide graphical descriptions of our real-time macroeconomic indices. The upper panel of Figure 3 starts by plotting the estimated real-time output and employment factors. The gray areas in the plots represent NBER recessions. Output seems to anticipate employment somewhat, especially around business cycle turns, but the two factors are very highly correlated. For this specific comparison, we extend the sample to the end of 2013 to study more closely the recovery out of the most recent recession. The lower panel of Figure 3 shows that the employment factor lagged behind output during the recovery until the end of 2011, suggesting that growth was occurring without a comparable improvement in jobs. Since then, however, employment caught up with the output factor in 2013. While it might be worthwhile to tease apart the marginal information contained in these two series for these kind of analyses, for the purposes of this paper we collapse them into a single factor, labeled economic activity.

In the upper plot of Figure 4, we relate this aggregated economic activity index to our macroeconomic sentiment factor. As in the previous figure, we observe a large correlation between

[10]We obtain daily data on S&P 500 returns, the VIX index, the dividend yield, the price earning ratio, the default premium (as the difference between Moody's BAA and AAA rated bond yields), and the term premium (as the difference between 10-year and 3-mo Treasury yields) from Bloomberg and Datastream.

[11]Our inflation index is only significantly correlated with VIX (-0.30). Inflation dispersion is related to VIX (0.26), the dividend yield (0.61), and the price-earnings ratio (-0.33). These results, which we report for completeness but do not return to in later analyses, are not tabulated to preserve space.

the two series, with macro sentiment clearly anticipating economic activity around turning points. Following the same reasoning as above, we therefore further aggregate the information into a single growth factor (comprised now of the information contained in output, employment, and macro sentiment). Finally, in the lower panel of Figure 4, we compare this aggregate growth factor with our real-time inflation index. While these two series are also somewhat positively correlated, the strength of correlation is far weaker, with the inflation series behaving much more erratically. For the remainder of the paper we therefore keep the real-time growth factor separate from the inflation factor.

### 4.1.1 Economist Disagreement

We conclude this preliminary analysis with two figures showing growth and inflation factors and economist disagreement. Specifically, in Figure 5 we plot the real-time growth factor in the top chart and the economist disagreement about growth in the bottom chart. Not surprisingly, the growth index dips through the recession periods of 2001 and 2008-2009. More interestingly, though, the forecast dispersion appears relatively low at the beginning and extremely high toward the end of recessions, suggesting that economists tend to agree on downturns but cannot foresee recoveries as clearly.

We further investigate this intriguing pattern of economist disagreement in several ways. First, we find that the growth index and its volatility tend to have a stable and significantly negative correlation of -0.35 over all our sample period, suggesting that growth tends to be more volatile and difficult to predict during economic contractions (when the growth index is negative). Second, we select periods identified as NBER-dated recessions and find that the volatility of growth is 63 percent higher in these periods than it is in expansions. Along similar lines, we try to identify more precisely the last part of recession phases by selecting periods when the growth index level is negative, but the growth index first difference is positive (using either a daily or monthly first difference). In these late recession periods, the volatility of the growth index tends to be about 20 percent higher than in the other business cycle phases. In summary, this empirical evidence suggests that the cyclicality of macroeconomic disagreement seems to be also a result of the growth index becoming more volatile in recessions. In these periods, macroeconomic announcements generate larger innovations in the growth index and this contributes to larger macroeconomic dispersion.

Note that the dispersion of growth forecasts is also relatively large and noisy at the beginning of our sample. While there might have been indeed a higher degree of macroeconomic uncertainty at that time, it is more likely that this pattern is due to the small number of macroeconomic news releases for which economist forecasts were available in the first year of our sample. Out of the 34 variables used to construct the growth index, only 11 had forecasts reported on Bloomberg in 1997 and for those releases only an average of four economists were providing their forecasts.

In Figure 6 we show the real-time inflation factor in the top plot and the economist disagreement about inflation in the bottom plot. The inflation index is more erratic than the growth index, but it still dips through the recession periods, especially in 2008-2009. The inflation forecast dispersion is extremely volatile and the only pattern to stand out is the very large disagreement characterizing the end of the last recession.

#### 4.1.2 Comparison with the CFNAI

The CFNAI published monthly by the Chicago Federal Reserve Bank of Chicago is a commonly used real-time indicator of economic conditions in the finance and economics literature (e.g., Beber et al., 2011). The index, which evolved from the Stock and Watson (1989) coincident indicator, is generally preferred to NBER expansion and recession dates because it is timely (though at a monthly frequency) and continuous, as opposed to the discrete peak and trough NBER dates. Given its popularity, as well as because it utilizes a broad cross-section of economic indicators like our approach, the CFNAI is an obvious first benchmark for evaluating the performance of our approach. Before we dive into the quantitative comparison, though, it is worthwhile highlighting the differences between the CFNAI and our approach. First, the CFNAI is a weighted average of currently 85 monthly indicators that is formed monthly once about two-third of the indicators have been updated (the remaining one-third are projected). Second, the weights are determined by PCA using a simple unadjusted monthly correlation matrix. In contrast, our index is formed daily, based on the most recent observations of only a subset of growth-related data series, and the weights are determined by PCA using an auto-correlation adjusted daily correlation matrix.

There are two important details in setting up a fair comparison between our approach and the CFNAI. First, at any release date, the CFNAI is constructed for the whole history given the most recent PCA weights, restated figures, and subsequently realized (for the one-third projected series) economic data, as opposed to keeping track of a sequence of point-in-time measures. We therefore obtain a panel of CFNAI vintages from the Chicago Fed's website. This allows us to construct a point in time version of the CFNAI that reflects not only unrestated or unobservable data, but also the relative weighting based on changing correlation structure. The second detail is the timing of the monthly releases. The CFNAI is normally released toward the end of each calendar month. Based on the last available publication dates, the data is on average released on the 23rd day of the month. We thus match each monthly CFNAI release with our real-time growth index on either the actual release dates, when available, or estimated release dates based on this average timing.

Figure 7 plots the monthly CFNAI with matching monthly observations of our real-time growth factor. To ease the comparison over the subsample for which both series are available, we re-standardize them to have mean zero and standard deviation one in-sample. As is immediately apparent, the two series are very similar with a correlation of 0.94. More importantly, though, notice that the real-time growth index seems to anticipate the turning points of the CFNAI.

The high correlation between the two indices is not surprising given the similarities in methodology. The second observation, that our real-time growth index seems to lead the CFNAI, however, deserves closer inspection. For this, we set up a vector auto-regression (VAR) model for the CFNAI, the real-time growth factor, and their respective previous month's lags. In panel A of Table 2 the model is constrained to be diagonal, whereas in panel B it is unconstrained. The real-time growth index has significant predictive power for the CFNAI, beyond the lagged CFNAI. However, the opposite is not true, as the CFNAI is not a significant predictor of the real-time growth index beyond its own lag. In other words, there is fairly strong evidence of Granger causality from our Growth index to the CFNAI (with a $t$-statistic of 4.25), but not in the opposite direction.

The forecasting power of the real-time growth index for the CFNAI can potentially be explained by a number of features. First, as we noted in footnote 2, our growth index is constructed from a cross-section of distinct statistics, whereas the CFNAI uses multiple variations of the same information. Second, some of the releases used in the construction of CFNAI (e.g., the six statistics on housing) are not directly related to growth and could potentially introduce a pattern with different cyclicality or persistence. Third, the CFNAI release includes projected monthly values for one-third of the series. Clearly, this can be an important source of index predictability. Finally, the weighting factor for each of the CFNAI underlying series is re-estimated monthly, whereas it is updated daily in our real-time growth index, even if we sample our index monthly for comparison purposes in the VAR estimation. For these reasons, even if the CFNAI and our growth index both rely on a large cross-section of news, the information content of the resulting index can still differ substantially with the use of different methods. This is true even when we constrain our growth index to be observed with the same monthly frequency of the CFNAI.

### 4.1.3 Comparison with the ADS index

The CFNAI is an obvious benchmark because like our approach it utilizes a large cross-section of data series. The ADS index, developed by Arouba et al. (2009) and now published by the Philadelphia Fed, is an equally worthy candidate for comparison because, being based on a state-space model, it can be updated daily like our approach (though in practice the ADS index is updated weekly). For the ADS index it is even more critical to use vintage data, as for a given release the index time-series is full-sample smoothed, using the Kalman filter algorithm, and therefore contains forward looking information (in addition to using restated or subsequently released data like the CFNAI does). Only the end-point of the index series is therefore a valid point-in-time measure. Weekly vintage releases of the ADS business conditions index are available starting at the end of 2008, resulting in a relatively short sample of 283 observations. We match each weekly release with our daily real-time growth factor observed on the release date.

Figure 8 plots the ADS index and our growth factor, where again we re-standardize both for this subsample. The two series are also very similar with a correlation of 0.91. This observation is a little more surprising. On one hand, the ADS index is based on only six indicators as opposed to our 34, which likely explains why the ADS index is considerably more noisy. On the other hand, through the state-space model used to construct the ADS index, the weighting of data is optimized to forecast GDP. The weights of our real-time growth index are instead optimized to explain the correlation structure of the cross-section of news releases. The figure suggests that the principal component of growth-related news is highly correlated with the best predictor for future GDP formed from a subset of the data series. We will return to the question of how well our real-time growth factor forecasts future growth in the next section.

Table 3 repeats the Granger causality analysis for the ADS index and our real-time growth factor. In panel A the VAR model is constrained and in panel B it is unconstrained. Similar to our findings for the CFNAI, we find a statistically significant Granger causal relation from our growth factor to the ADS index, meaning that the growth factor predicts future realizations of the ADS index beyond the lagged ADS index (with a $t$-statistic of 4.9). The opposite causal relation, from the ADS index to our growth factor is insignificant, and of the wrong sign.

To better understand the reasons for the forecasting power of our real-time growth factor for the ADS index, we construct an ADS replica using our method on the same macroeconomic announcement series used in the original ADS construction, namely weekly initial jobless claims; monthly payroll employment, industrial production, personal income less transfer payments, manufacturing and trade sales, and quarterly real GDP. The ADS index and its replica have a 0.95 correlation, suggesting that the different methodologies alter the output only modestly. We then replace the original ADS index with our replica and re-estimate the VAR model of Table 3. We find very similar results (not reported, for brevity), that is, a statistically significant Granger causal relation from our growth factor to the ADS replica index, meaning that the growth factor predicts future realizations of the ADS replica index beyond the lagged ADS replica index. These findings suggest that the forecasting power of the real-time growth index originates mainly from the large cross-section of macroeconomic releases, rather than from the different methodology. Obviously, our method can easily deal with an arbitrarily large cross-section, whereas the ADS methodology is constrained in this dimension.

## 4.2 Forecasting future GDP and CPI releases

The last two subsections showed that our methodology of extracting daily factors from economic news released at different times and frequencies delivers a real-time growth factor that is highly correlated with existing nowcasting indices, but provides potentially more timely and certainly more frequent information. We specifically found a high correlation with the ADS index for which the data is weighted to best forecast future GDP growth. This finding begs the question of how well our real-time factors, which are not explicitly constructed to forecast, can nevertheless be used for forecasting future fundamentals (both growth and inflation).

Since the CFNAI and ADS index focus exclusively on growth and their vintage histories are limited, especially for the more forecasting oriented ADS index, we instead use as forecasting benchmarks the much longer histories of quarterly growth and inflation forecasts from the Survey of Professional Forecasters (SPF) carried out by the Philadelphia Fed. More specifically, we use the average forecasts of the annualized nominal GDP growth rate for the next quarter as well as of the annualized percent change in the CPI over the next year. The survey results are released around the end of the second month of the quarter, and we match the timing of our real-time growth and inflation factors to the survey release dates. Our focus on *release* dates, as opposed to *survey* dates, allows us to preserve the real-time nature of the comparison. Since our methodology does not involve a collection and dissemination lag, it can potentially use a larger information set than the SPF survey. For the actual statistics to be forecasted, we use advance GDP growth, which is announced about one month after the end of the quarter, and headline CPI change, which is typically released two weeks after the end of the quarter. For example, we forecast the 1997 first quarter GDP and CPI using the SPF mean forecasts of 4.90 percent and 3.01 percent, respectively, released on February 26, 1997 and the real-time growth and inflation factors of 0.79 and -0.45, respectively, obtained on the same day. The actual release of CPI came out about three weeks later on March 19, 1997 at 3.00 percent and GDP was announced two months after the survey on April 30, 1997 at 5.60 percent.

Table 4 shows the results for growth forecasting. We find that the mean forecasts of the SPF and our real-time growth factor contain about equally useful information for predicting subsequent GDP releases beyond lagged GDP. The model $R^2$ are large at 45 and 41 percent and the more informative marginal $R^2$ (measuring the incremental forecasting ability of the additional regressor relative to a simpler autoregressive model) are 20 and 15 percent, respectively. Furthermore, the correlation between the real-time growth factor and quarterly SPF forecasts is very high at 0.89. This suggests that the real-time growth index can be interpreted as a higher frequency reading of economic growth expectations with the same properties as the lower frequency SPF forecasts. Alternatively, perhaps the professional forecasters deploy nowcasting models, either explicitly or, more likely for the historical data, implicitly. This observation is consistent with Liebermann (2010), who finds that (a different approach to) nowcasting is comparable to the SPF at the date of release but superior prior (when no SPF is available) and shortly after, as it updates.

Figure 9 illustrates these points graphically. The high correlation between our growth factor, SPF consensus, and subsequent GDP releases, is immediately apparent from the plot. This is particularly the case around the shaded NBER recession periods.

Table 5 shows the results for inflation forecasting. Again we find that both the mean forecasts of the SPF and the real-time inflation factor contain about equally useful information to predict the subsequent CPI releases, beyond lagged CPI. The model $R^2$ are even higher at 70 and 69 percent, respectively, but a larger fraction of this predictability comes simply from the higher persistence of inflation. The marginal $R^2$ relative to the autoregressive benchmark model is ten percent for the SPF forecasts and eight percent for the real-time inflation factor. By that metric, the forecasting ability of both predictors is weaker compared to GDP forecasting. Moreover, the correlation between the predictors is also significantly weaker at only 0.21. It appears from these results that it is relatively more difficult to predict inflation from the intra-quarter news flow, which may partly be attributed to the fact that there is less inflation relevant news (only nine distinct releases on seven days).

Figure 10 presents these results graphically. Although our real-time inflation factor and the SPF consensus forecasts are clearly correlated and seem to anticipate actual CPI releases, particularly around the NBER recession periods, the real-time inflation factor exhibits a more erratic behavior. This reflects again the relatively sparse inflation news flow.

The results in tables 4 and 5 demonstrate not only the ability of our real-time factors to predict subsequent realizations of economic fundamentals but, equally interestingly, how similar these factors are to the SPF consensus forecasts. This is consistent with the findings of Liebermann (2010) and by no means diminishes the relevance of our real-time factors, since they have the distinct advantage of being available daily for weeks before and incorporating new information daily for months after the quarterly SPF is released. To complete the comparison of our real-time factors with the SPF, however, we can also relate their respective second moments. Specifically, we compare our measures of uncertainty surrounding growth and inflation, which capture the disagreement of economists about the various components that make up our real-time factors, with the dispersions of SPF forecasts, which capture the disagreement among economists about future growth and inflation directly. It is reasonable to expect that when economists disagree on recent economic data, the same or similar economists will also disagree about the future path of the economy. Consistent with this intuition, we find that our measure of uncertainty about growth and the dispersion of SPF growth forecasts has a correlation of 0.55. The corresponding correlation for inflation is 0.39. Although these correlations for the second moments are not as strong as for the first, we still conclude that our proxies for macroeconomic uncertainty capture, at a daily frequency, similar uncertainty as that reflected in the dispersion of SPF forecasts.

## 4.3 Macroeconomic conditions and financial market volatility

One of the differentiating aspects of our methodology is that it produces a daily reading of the state of the economy that does not rely on information from financial markets, unlike the approaches of Giannone et al. (2008) and Aruoba et al. (2009), for example. We can therefore use our real-time factors to investigate the link between macroeconomic conditions and financial market dynamics, particularly stock market volatility. We focus on stock market volatility for two reasons. First, volatility is easier to measure than expected returns. Second, but related, the apparent disconnect between stock market volatility, which is easily measured, and economic fundamentals, the improved measurement of which is the purpose of our methodology, is one of the longest standing puzzles in finance. In a seminal paper, Schwert (1989) finds that the standard deviations of a host of macroeconomic variables and a recession dummy explain only a small fraction of stock market volatility. More recently, Engle and Rangel (2008) refer to the relation between the macro economy and stock market volatility as the central unsolved problem of 25 years of volatility research.

We measure stock market volatility using the forward looking option implied volatility index VIX, rather than a measure of backward looking realized volatility. Realized volatility could be mechanically correlated with our real-time factors because large economic surprises invoke large stock market responses. The empirical question is not whether the stock market responds contemporaneously to economic data, there is plenty of evidence it does (e.g., Flannery and Protopapadakis, 2002), but rather whether business cycle related changes in economic conditions lead to persistent changes in future stock market volatility.

We first provide some graphical evidence of the relation between the VIX index, our real-time growth factor, and growth dispersion. Specifically, we plot the VIX index along with the growth factor in Figure 11, where we invert the axis for the growth factor to highlight the strong negative correlation (-0.51 from Table 1) between the two series. We plot the VIX index along with growth dispersion in Figure 12. The correlation between these two series is lower (0.25 from Table 1), but increases somewhat to 0.31 when we start the sample in 2000 when growth dispersion is less noisy (recall the discussion surrounding Figure 5).

We extend this bivariate analysis in Table 6, where we regress the VIX index contemporaneously on our real-time growth factor and/or growth dispersion. Panel A shows the results for the full sample, and Panel B is for the less noisy 2000 onward subsample. We will focus the discussion on panel B. In the first two model specifications both regressors are by themselves strongly statistically significant. Our real-time growth factor explains 41 percent of the variation in the VIX index, and growth dispersion explains about ten percent stand-alone. Combined, in the third model specification, the adjusted $R^2$ increases to 42 percent with the growth factor being highly significant and growth dispersion being borderline significant. Beyond statistical significance, though, the economic effects implied by the coefficient estimates are large. A one standard deviation deterioration in growth results in more than a five percentage point increase in the VIX index, which is about a quarter increase relative to a base level of 23 percent. A one standard deviation increase in growth dispersion is associated with a four percent point increase in VIX.

In summary, contrary to Schwert (1989) and much of the subsequent literature, we present evidence of a strong link between macroeconomic conditions and stock market volatility. We find that the level of growth, i.e., business cycles, are more important than the uncertainty about growth, though the latter still plays a significant role, both statistically and economically in magnitude. This suggests that better real-time measurement of economic fundamentals may help resolve the long-standard disconnect between the macro economy and financial stock market volatility.

### 4.4 Real-time growth and inflation dynamics

Table 7 describes the joint dynamics of the real-time growth index, growth dispersion, the real-time inflation index, and inflation dispersion. We estimate three first-order vector autoregression (VAR) models with one-period lag lengths of five, 20, or 60 business days, respectively. The estimates are based on the sample starting in 2000 (when dispersion measures are less noisy), using overlapping daily observations, and the standard errors used to compute the $t$-statistics are autocorrelation adjusted. Since the results are fairly consistent across specifications, we mainly focus our discussion on the intermediate 20 day horizon.[12]

All four series are persistent, especially at shorter horizons, as evidenced by the magnitude and statistical significance of the own lag terms, as well as by the differences between the $R^2$ and the marginal $R^2$ that exclude the impact of the own lag terms. Growth is highly persistent at all three horizons, whereas the autocorrelation of the other three series drops sharply as the lag length increases. This finding is visually consistent with the behavior of the series in figures 5 and 6.

We also observe an interesting lead-lag interaction between the growth index and growth dispersion. Higher growth dispersion is associated with higher future growth whereas, in the opposite direction, higher growth is associated with subsequently lower growth dispersion. Figure 13 illustrates graphically the first cross-autocorrelation, from growth dispersion to the growth level. It shows the median change in growth at different horizons unconditionally and following realizations of growth dispersion above or below median and in the top or bottom quartile. Periods of high dispersion, and especially those in the top quartile, are clearly followed by acceleration in growth over the subsequent weeks and months. The second cross-autocorrelation in Table 7, from the growth level to growth dispersion, is even stronger both in magnitude (recall the data is standardized so coefficients can be directly interpreted) and statistical significance ($t$-statistics around six and marginal $R^2$ of almost 20 percent). This result is consistent with our prior observation that economists seem to agree on the end of an economic expansion (following high growth, dispersion is low), but not on the end of an economic contraction (following low growth, dispersion is high).

[12] We also estimate the VAR model in subsamples corresponding to four distinct business cycle phases: early expansion (positive growth index and positive growth index monthly first difference), late expansion (positive growth index and negative growth index monthly first difference), early recession (negative growth index and negative growth index monthly first difference), and late recession (negative growth index and positive growth index monthly first difference). The results are largely similar in all four subsamples.

The cross-autocorrelations between the inflation index and inflation uncertainty are largely small and insignificant. However, higher growth seems to lead lower uncertainty about inflation, with strongest results at longer horizons. This finding is consistent with Figure 6, where the uncertainty about inflation appears relatively larger at the end of the recessions in our sample.

### 4.5 Extending the sample backwards

Our sample is limited by the availability of precisely dated and unrestated economic news releases. In this section, we extend our sample backward to the beginning of 1985 using the median reporting lag for each release type and inferring the release date.[13] While the use of potentially misdated and restated data weakens the real-time interpretation of our macroeconomic indices, the longer sample period that spans one more business cycle serves as a useful robustness check.

In Figure 14 we plot our "real-time" growth index together with NBER ex-post determined recession dates and the expectations for current quarter GDP growth in the SPF. The growth index behaves the same during the 1990-1991 recession as it does for the other two recessions that are covered by our original sample. We observe the sudden drop in the growth index and the subsequent gradual recovery. Moreover, in the new 1985 to 1997 period, the growth index tracks the low-frequency growth expectations of the SPF even more closely, suggesting again that our approach captures the same information but at a daily frequency.

For our measure of macroeconomic uncertainty, the sample cannot be extended back because the panel of economist forecasts we use to construct the disagreement about growth measure are not available before 1997. Nevertheless, to see what a longer growth dispersion series might look like, we apply our methodology to the five disagreement measures about growth that can be obtained from the SPF (namely disagreement about GDP, corporate profits, employment, unemployment, and productivity growth) . Figure 15 shows the results. We first notice a large correlation between our daily measure of macroeconomic uncertainty and the quarterly measure of disagreement from the SPF over the original sample period. More interestingly, the backdated SPF based measure of uncertainty corroborates our earlier observation that uncertainty peaks toward the end of recessions and is more subdued at the end of expansions.

## 5 Conclusions

We proposed a simple cross-sectional technique to extract daily factors from economic news released at different times and frequencies. Our approach can effectively handle the large number of

[13] To get a sense for the accuracy of our procedure of dating the announcements based on reporting lags, we partially cross-check our inferred release dates with a database of Reuters news. More specifically, for a subsample of 15 announcements on the total of 43 considered news items and for a shorter sample period going back to 1990, we find that 91 percent of the estimated release days are less than two days off from the actual release days.

different announcements that are relevant for tracking current economic conditions. We applied the technique to extract real-time measures of inflation, output, employment, and macroeconomic sentiment, as well as corresponding measures of disagreement among economists about these indices. Our procedure provides more timely and accurate forecasts of future changes in economic conditions than other real-time forecasting approaches. At the same time, both the level and dispersion measures are highly correlated with corresponding statistics from the SPF, suggesting they capture the same information except our approach does so at a daily instead of quarterly frequency. Finally, in contrast to much of the extant literature, our real-time growth factor and corresponding disagreement measure, both constructed entirely from macroeconomic data, explain a remarkable fraction of financial volatility dynamics.

The purpose of our method is to obtain a real-time, daily, unbiased, and objective reading of the state of the macroeconomy, using an approach that lets the data speak as much as possible. Our forecasting results demonstrate that a fairly simple and unstructured method still delivers a very sensible and timely measurement of the state of the economy. A real-time daily reading of macroeconomic fundamentals that is reliable can be used for a number of purposes, most notably to study the relation between financial market and economic dynamics.

# A Macroeconomic News

The following table summarizes the main features of the macroeconomic news releases we work with. The news Category is either inflation (Inf), employment (Emp), output (Out), or sentiment (Sen). If the sample series is stationary in our sample, we make no adjustment (Adj=0), otherwise we use first differences with respect to the previous period (Adj=1). We also indicate Units, Frequency (M for monthly, W for weekly, Q for quarterly), and the Source of the release.

| Category | Release Name | Adj | Units | Freq | Source |
|---|---|---|---|---|---|
| Inf | US Import Price Index by End Use All MoM | 0 | Rate | M | Bureau Labor Statistics |
| Inf | US PPI Finished Goods Total MoM | 0 | Rate | M | Bureau Labor Statistics |
| Inf | US PPI Finished Goods Except Foods Energy | 0 | Rate | M | Bureau Labor Statistics |
| Inf | US CPI Urban Consumers MoM | 0 | Rate | M | Bureau Labor Statistics |
| Inf | US CPI Urban Consumers Less Food Energy | 0 | Rate | M | Bureau Labor Statistics |
| Inf | BLS Employment Cost Civilian Workers QoQ | 0 | Rate | Q | Bureau Labor Statistics |
| Inf | US GDP Price Index QoQ SAAR | 0 | Rate | Q | Bureau Economic Analysis |
| Inf | US Personal Cons. Expenditure Core Price Index MoM | 0 | Rate | M | Bureau Economic Analysis |
| Inf | US Output Per Hour Nonfarm Business Sector QoQ | 0 | Rate | Q | Bureau Labor Statistics |
| Emp | ADP National Employment Report Private Nonfarm Change | 0 | Volume | M | Automatic Data Processing |
| Emp | US Initial Jobless Claims | 1 | Volume | W | Department of Labor |
| Emp | US Continuing Jobless Claims | 1 | Volume | W | Department of Labor |
| Emp | US Employees on Nonfarm Payrolls Total Net Change | 0 | Value | M | Bureau Labor Statistics |
| Emp | US Employees on Nonfarm Payrolls Manufact Net Change | 0 | Value | M | Bureau Labor Statistics |
| Emp | US Unemployment Rate Total in Labor Force | 1 | Rate | M | Bureau Labor Statistics |
| Emp | US Average Weekly Hours All Total Private | 1 | Volume | M | Bureau Labor Statistics |
| Out | ISM Manufacturing PMI | 0 | Value | M | Institute Supply Management |
| Out | US Manufacturers New Orders Total MoM | 0 | Rate | M | U.S. Census Bureau |
| Out | US Auto Sales Domestic Vehicles | 1 | Volume | M | Bloomberg |
| Out | ISM Non-Manufacturing NMI NSA | 0 | Value | M | Institute Supply Management |
| Out | Federal Reserve Consumer Credit Net Change | 1 | Value | M | Federal Reserve |
| Out | Merchant Wholesalers Inventories Change | 0 | Rate | M | U.S. Census Bureau |
| Out | Adjusted Retail Food Services Sales Change | 0 | Rate | M | U.S. Census Bureau |
| Out | Adjusted Retail Sales Less Autos Change | 0 | Rate | M | U.S. Census Bureau |
| Out | US Industrial Production MoM 2007=100 SA | 0 | Rate | M | Federal Reserve |
| Out | US Capacity Utilization of Total Capacity | 0 | Rate | M | Federal Reserve |
| Out | US Manufacturing Trade Inventories Total | 0 | Rate | M | U.S. Census Bureau |
| Out | US Durable Goods New Orders Industries | 0 | Rate | M | U.S. Census Bureau |
| Out | US Durable Goods New Orders Ex Transp. | 0 | Rate | M | U.S. Census Bureau |
| Out | GDP US Chained 2005 Dollars QoQ SAAR | 0 | Rate | Q | Bureau Economic Analysis |
| Out | GDP US Personal Consumption Chained Change | 0 | Rate | Q | Bureau Economic Analysis |
| Out | US Personal Income MoM | 0 | Rate | M | Bureau Economic Analysis |
| Out | US Personal Consumption Expend. Nominal Dollars | 0 | Rate | M | Bureau Economic Analysis |
| Sen | Bloomberg US Weekly Consumer Comfort Index | 1 | Price | W | Bloomberg |
| Sen | University Michigan Survey Consumer Confidence | 1 | Price | M | U. of Michigan Survey Research |
| Sen | Empire State Manufact. Survey Business Conditions | 1 | Value | M | Federal Reserve |
| Sen | Conference Board US Leading Index MoM | 0 | Rate | M | Conference Board |
| Sen | Philadelphia Fed Business Outlook General Conditions | 1 | Price | M | Philadelphia Fed |
| Sen | Conference Board Consumer Confidence SA 1985=100 | 1 | Rate | M | Conference Board |
| Sen | Richmond Fed Reserve Manufacturing Survey | 0 | Rate | M | Richmond Fed |
| Sen | US Chicago Purchasing Managers Index SA | 1 | Price | M | Kingsbury Intern. |
| Sen | ISM Milwaukee Purchasers Manufacturing Index | 1 | Rate | M | NAPM - Milwaukee |
| Sen | Dallas Fed Manufact. Outlook Business Activity | 1 | Rate | M | Dallas Fed |

## Table 1: Summary Statistics

Panel A shows correlations between daily observations of six real-times macroeconomic indices and their respective economist forecast dispersions. Panel B reports additional summary statistics and correlations between the growth index, growth dispersion, and a set of financial variables. Specifically, $R_{mt} - R_{ft}$ denotes the log return on the S&P 500 index in excess of the 3-month Treasury-bill rate, VIX is the CBOE option implied volatility index, $\ln(P/E)$ and $\ln(D/P)$ are the log price-earning ratio and log dividend yield, Def is the default spread (Moody's BAA minus AAA corporate bond yields), Term is the term spread (10-year minus 3-month Treasury yields). The sample period is January 1997 to December 2011.

Panel A:

| | | Index | | | | | | Dispersion | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Inflation | Output | Employment | Sentiment | Economic Activity | Growth | Inflation | Output | Employment | Sentiment | Economic Activity | Growth |
| Index | Inflation | 1.00 | 0.36 | 0.13 | 0.14 | 0.25 | 0.22 | -0.08 | -0.18 | -0.16 | -0.18 | -0.19 | -0.20 |
| | Output | | 1.00 | 0.84 | 0.82 | 0.96 | 0.95 | -0.53 | -0.22 | -0.34 | -0.19 | -0.26 | -0.26 |
| | Employment | | | 1.00 | 0.75 | 0.96 | 0.92 | -0.53 | -0.12 | -0.30 | -0.15 | -0.16 | -0.16 |
| | Sentiment | | | | 1.00 | 0.82 | 0.93 | -0.50 | 0.07 | -0.05 | -0.07 | 0.06 | 0.05 |
| | Economic Activity | | | | | 1.00 | 0.97 | -0.55 | -0.18 | -0.34 | -0.18 | -0.23 | -0.23 |
| | Growth | | | | | | 1.00 | -0.56 | -0.10 | -0.25 | -0.15 | -0.13 | -0.14 |
| Dispersion | Inflation | | | | | | | 1.00 | 0.26 | 0.15 | 0.14 | 0.25 | 0.25 |
| | Output | | | | | | | | 1.00 | 0.52 | 0.40 | 0.98 | 0.96 |
| | Employment | | | | | | | | | 1.00 | 0.35 | 0.68 | 0.68 |
| | Sentiment | | | | | | | | | | 1.00 | 0.42 | 0.54 |
| | Econonmic Activity | | | | | | | | | | | 1.00 | 0.99 |
| | Growth | | | | | | | | | | | | 1.00 |

Panel B:

| | | $R_{mt} - R_{ft}$ | Growth Index | Growth Dispersion | VIX | $\ln(\frac{P}{E})$ | $\ln(\frac{D}{P})$ | Def | Term |
|---|---|---|---|---|---|---|---|---|---|
| Summary Statistics | Mean | 0.63 | -0.04 | -0.00 | 0.23 | 2.98 | 0.55 | 1.03 | 1.68 |
| | Std Deviation | 21.42 | 1.15 | 0.99 | 0.09 | 0.23 | 0.25 | 0.48 | 1.30 |
| | Skewness | -0.20 | -1.30 | 1.40 | 1.78 | 0.05 | 0.48 | 2.82 | -0.06 |
| | Kurtosis | 9.77 | 4.97 | 4.19 | 8.85 | 2.19 | 3.56 | 12.25 | 1.66 |
| Correlation Matrix | $R_{mt} - R_{ft}$ | 1.00 | 0.01 | 0.01 | -0.13 | 0.04 | -0.03 | -0.01 | 0.01 |
| | Growth Index | | 1.00 | -0.14 | -0.51 | 0.55 | -0.71 | -0.84 | -0.51 |
| | Growth Dispersion | | | 1.00 | 0.25 | 0.19 | 0.09 | 0.14 | 0.02 |
| | VIX | | | | 1.00 | -0.14 | 0.31 | 0.63 | 0.22 |
| | $\ln(P/E)$ | | | | | 1.00 | -0.85 | -0.52 | -0.28 |
| | $\ln(D/P)$ | | | | | | 1.00 | 0.69 | 0.42 |
| | Def | | | | | | | 1.00 | 0.40 |
| | Term | | | | | | | | 1.00 |

## Table 2: CFNAI versus Growth Index

This table shows estimates of the following vector auto-regression:

$$\begin{bmatrix} Y_t \\ X_t \end{bmatrix} = A + B \begin{bmatrix} Y_{t-1} \\ X_{t-1} \end{bmatrix} + \epsilon_t,$$

where $Y_t$ is the CFNAI and $X_t$ is the real-time growth index. We use the value of the real-time growth index observed on the day of the monthly release of the CFNAI. The sample is monthly observations from February 2001 (first available vintage value of the CFNAI) to December 2011. In panel A the model is constrained to be diagonal, whereas in panel B it is unconstrained. The $R^2$ statistic is adjusted and in parentheses are robust Newey-West $t$-statistics.

| | | Independent | | |
|---|---|---|---|---|
| Dependent | Constant | $\text{CFNAI}_{t-1}$ | $\text{Growth}_{t-1}$ | $R^2$(%) |
| | | Panel A: Constrained | | |
| $\text{CFNAI}_t$ | -0.03 | 0.91 | | 83.56 |
| | (1.89) | (17.30) | | |
| $\text{Growth}_t$ | -0.01 | | 0.96 | 91.77 |
| | (-0.74) | | (24.79) | |
| | | Panel B: Unconstrained | | |
| $\text{CFNAI}_t$ | -0.08 | 0.41 | 0.39 | 86.86 |
| | (-2.08) | (3.68) | (4.25) | |
| $\text{Growth}_t$ | -0.01 | 0.05 | 0.93 | 91.72 |
| | (-0.48) | (0.52) | (13.31) | |

## Table 3: ADS Index versus Growth Index

This table shows estimates of the following vector auto-regression:

$$\begin{bmatrix} Y_t \\ X_t \end{bmatrix} = A + B \begin{bmatrix} Y_{t-1} \\ X_{t-1} \end{bmatrix} + \epsilon_t,$$

where $Y_t$ is the ADS index and $X_t$ is the real-time growth index. We use the value of the real-time growth index observed on the day of the weekly release of the ADS index. The sample is weekly observations from December 2008 (first available vintage value of the ADS index) through December 2011. In panel A the model is constrained to be diagonal whereas in panel B it is unconstrained. The $R^2$ statistic is adjusted and in parentheses are robust Newey-West $t$-statistics.

| | | Independent | | |
|---|---|---|---|---|
| Dependent | Constant | $\text{ADS}_{t-1}$ | $\text{Growth}_{t-1}$ | $R^2(\%)$ |
| | | Panel A: Constrained | | |
| $\text{ADS}_t$ | -0.02 | 0.95 | | 91.43 |
| | (-1.78) | (52.98) | | |
| $\text{Growth}_t$ | 0.01 | | 0.99 | 99.61 |
| | (0.41) | | (165.45) | |
| | | Panel B: Unconstrained | | |
| $\text{ADS}_t$ | 0.04 | 0.76 | 0.12 | 92.18 |
| | (2.11) | (21.98) | (4.90) | |
| $\text{Growth}_t$ | 0.01 | -0.02 | 1.01 | 99.61 |
| | (0.78) | (-1.18) | (68.46) | |

**Table 4: Predicting Quarterly GDP Releases**

This table shows estimates of the following predictive regression:

$$\text{GDP}_t = \alpha + \beta_1 \text{GDP}_{t-1Q} + \beta_2 X_{t-2M} + \epsilon_t,$$

where $\text{GDP}_t$ is a quarterly GDP release, $\text{GDP}_{t-1Q}$ is the previous quarter's GDP release, and $X_{t-2M}$ is the average forecast of quarterly GDP by the Survey of Professional Forecasters (SPF) and/or our real-time growth index, both observed on the same day about two months before the GDP release (when the SPF is released). The sample is quarterly observations from the beginning of 1997 to the end of 2011. The $R^2$ statistic is adjusted and in parentheses are robust Newey-West $t$-statistics.

| | Model Specification | | | |
|---|---|---|---|---|
| | 1 | 2 | 3 | 4 |
| Constant | -0.61 | -0.15 | -0.11 | -0.08 |
| | (-2.75) | (-0.99) | (-0.60) | (-0.53) |
| $\text{GDP}_{t-1Q}$ | 0.22 | 0.06 | 0.04 | 0.03 |
| | (4.14) | (1.10) | (0.68) | (0.57) |
| $\text{SPF}_{t-2M}$ | | 0.57 | | 0.44 |
| | | (3.25) | | (1.68) |
| $\text{Growth}_{t-2M}$ | | | 0.58 | 0.20 |
| | | | (2.73) | (0.75) |
| $R^2(\%)$ | 30.28 | 44.60 | 41.18 | 44.25 |
| Maginal $R^2(\%)$ of $X_{t-2M}$ | | 20.54 | 15.63 | 20.04 |

**Table 5: Predicting Monthly CPI Releases**

This table shows estimates of the following predictive regression:

$$\text{CPI}_t = \alpha + \beta_1 \text{CPI}_{t-1M} + \beta_2 X_{t-1M} + \epsilon_t,$$

where $\text{CPI}_t$ is the monthly CPI release, $\text{CPI}_{t-1M}$ is the previous month's CPI release, and $X_{t-1M}$ is the average forecast of year-on-year CPI by the Survey of Professional Forecasters (SPF) and/or our real-time inflation index, both observed quarterly on the same day about one month before the CPI release (when the SPF is released in the second month of each quarter). The sample is quarterly observations from the beginning of 1997 to the end of 2011. The $R^2$ statistic is adjusted and in parentheses are robust Newey-West $t$-statistics.

| | Model Specification | | | |
|---|---|---|---|---|
| | 1 | 2 | 3 | 4 |
| Constant | 0.57 | -0.04 | 0.63 | 0.08 |
| | (3.54) | (-0.18) | (3.90) | (0.47) |
| $\text{CPI}_{t-1M}$ | 0.77 | 0.48 | 0.75 | 0.50 |
| | (11.11) | (3.03) | (10.45) | (3.98) |
| $\text{SPF}_{t-1M}$ | | 0.54 | | 0.47 |
| | | (2.55) | | (3.12) |
| $\text{Inflation}_{t-1M}$ | | | 0.21 | 0.17 |
| | | | (1.69) | (1.96) |
| $R^2(\%)$ | 66.48 | 69.84 | 69.04 | 71.48 |
| Maginal $R^2(\%)$ of $X_{t-1M}$ | | 10.02 | 7.64 | 14.92 |

**Table 6: Explaining Financial Market Volatility**

This table shows estimates of the following contemporaneous regression:

$$\mathrm{VIX}_t = \alpha + \beta X_t + \epsilon_t,$$

where $X_t$ is our real time growth index and/or dispersion of economist forecasts about growth news. The sample is daily observations from January 1997 through December 2011 in Panel A and January 2000 through December 2011 in Panel B. Robust Newey-West t-statistics are reported in parentheses.

| | Model Specification | | |
|---|---|---|---|
| | 1 | 2 | 3 |
| Panel A: 1997-2011 | | | |
| Constant | 0.23 | 0.23 | 0.23 |
| | (34.46) | (39.45) | (40.79) |
| Growth Index | -0.0387 | | -0.0368 |
| | (-5.79) | | (-5.42) |
| Growth Dispersion | | 0.0217 | 0.0159 |
| | | (3.50) | (3.40) |
| $R^2(\%)$ | 25.70 | 5.98 | 28.85 |
| Panel B: 2000-2011 | | | |
| Constant | 0.23 | 0.21 | 0.20 |
| | (27.41) | (34.64) | (30.26) |
| Growth Index | -0.0534 | | -0.0622 |
| | (-7.37) | | (-6.04) |
| Growth Dispersion | | 0.0402 | -0.0212 |
| | | (3.84) | (-1.93) |
| $R^2(\%)$ | 40.83 | 9.68 | 42.41 |

## Table 7: Growth and Inflation Dynamics

This table shows estimates of the following vector auto-regression:

$$Y_t = A + BY_{t-L} + \epsilon_{t-L},$$

where $Y_t$ is a vector containing our real-time growth index, growth dispersion, inflation index, and inflation dispersion. $L$ represents the lag in the VAR. The sample is daily observations from January 2000 to December 2011. The $R^2$ statistic is adjusted, and in parentheses are robust Newey-West $t$-statistics. The marginal $R^2$ represents the proportion of variance explained beyond the first lag of the dependent variable.

| | Independent $Y_{t-L}$ | | | | | |
|---|---|---|---|---|---|---|
| Dependent $Y_t$ | Growth Index | Growth Dispersion | Inflation Index | Inflation Dispersion | $R^2$(%) | Marginal $R^2$(%) |
| Growth Factor | | | | | | |
| $L = 5$ | 1.0033 | 0.0348 | 0.0193 | -0.0089 | 98.75 | 2.80 |
| | (169.46) | (3.68) | (2.32) | (-2.13) | | |
| $L = 20$ | 1.0006 | 0.1269 | 0.0563 | -0.0233 | 93.42 | 6.38 |
| | (46.40) | (3.95) | (1.69) | (-1.38) | | |
| $L = 60$ | 0.9198 | 0.2349 | 0.1001 | -0.0309 | 74.48 | 5.91 |
| | (14.12) | (2.47) | (0.96) | (-0.53) | | |
| Growth Dispersion | | | | | | |
| $L = 5$ | -0.0475 | 0.8949 | 0.0315 | 0.0066 | 91.10 | 4.33 |
| | (-5.10) | (55.11) | (1.95) | (0.77) | | |
| $L = 20$ | -0.2149 | 0.5270 | 0.1268 | 0.0143 | 67.16 | 18.97 |
| | (-6.10) | (9.43) | (2.16) | (0.50) | | |
| $L = 60$ | -0.4366 | -0.0005 | 0.1208 | 0.0258 | 51.82 | 37.79 |
| | (-6.05) | (-0.01) | (1.31) | (0.61) | | |
| Inflation Factor | | | | | | |
| $L = 5$ | -0.0182 | -0.0026 | 0.8459 | -0.0001 | 73.02 | 0.61 |
| | (-1.79) | (-0.17) | (38.40) | (-0.00) | | |
| $L = 20$ | -0.0677 | 0.0481 | 0.3232 | -0.0497 | 15.66 | 3.25 |
| | (-2.13) | (1.07) | (5.75) | (-1.98) | | |
| $L = 60$ | -0.0990 | 0.0696 | 0.0949 | -0.0489 | 8.94 | 6.79 |
| | (-2.24) | (1.12) | (1.41) | (-1.16) | | |
| Inflation Dispersion | | | | | | |
| $L = 5$ | -0.0477 | 0.0559 | 0.0167 | 0.8656 | 84.87 | 2.70 |
| | (-3.05) | (2.00) | (0.51) | (37.98) | | |
| $L = 20$ | -0.2501 | 0.0813 | 0.0940 | 0.4555 | 48.38 | 11.28 |
| | (-4.73) | (0.90) | (0.90) | (9.29) | | |
| $L = 60$ | -0.6148 | -0.3779 | 0.0507 | 0.0835 | 33.26 | 26.44 |
| | (-4.74) | (-2.32) | (0.33) | (0.86) | | |

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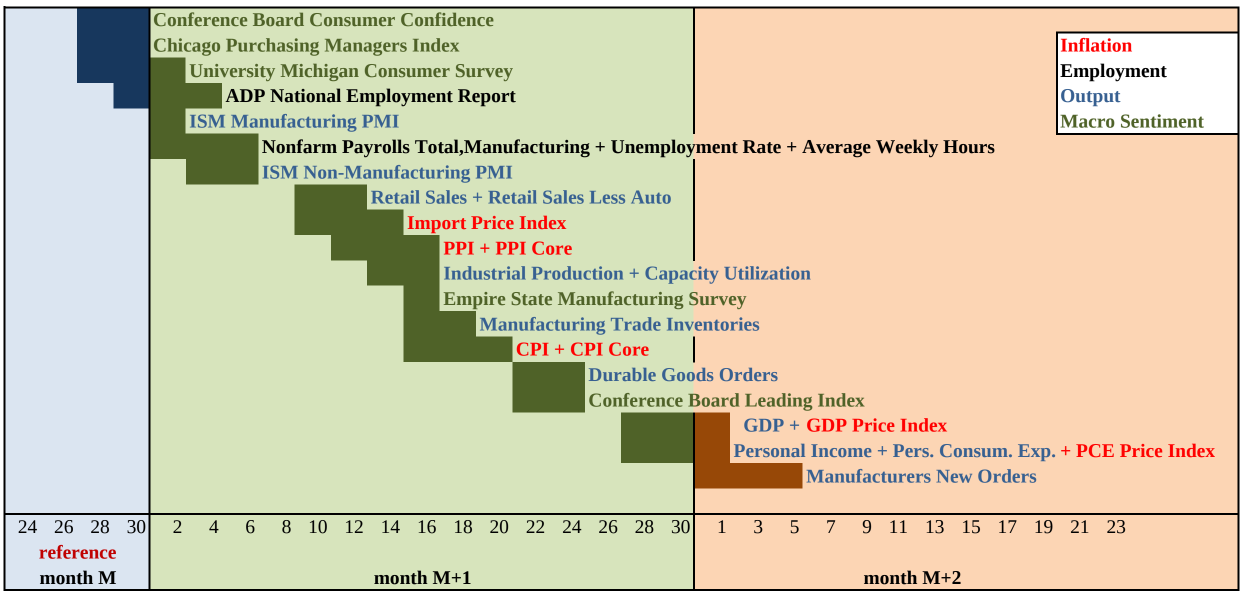
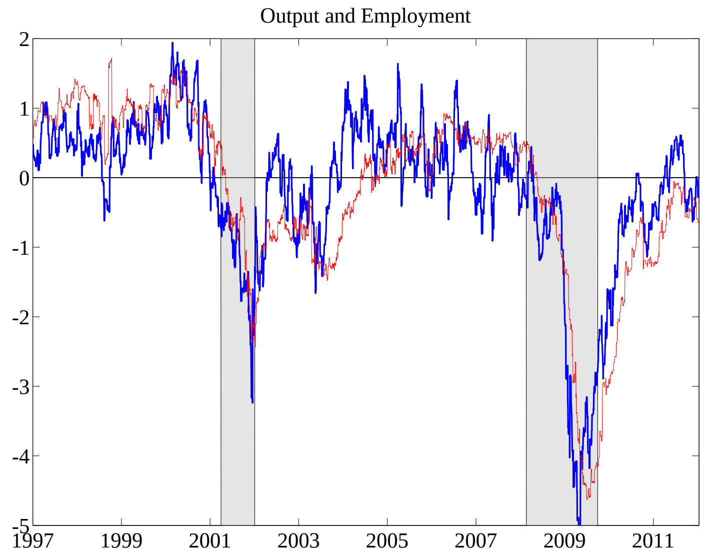



Figure 1: This figure shows the typical reporting structure for a large cross-section of U.S. macroeconomic announcements. On the horizontal axis, we represent the days of the reference month $M$ and the subsequent two months. On the vertical axis, we list the macroeconomic releases in order of reporting, highlighting in bold the typical reporting period. The macroeconomic announcements are color-coded in the four aggregates of inflation news, employment news, output news, and macro-sentiment news.

| | j=1 | j=2 | … | j=5 | j=6 | … | j=N |
|---|---|---|---|---|---|---|---|
| **1** | ... | ... | ... | *missing* | ... | ... | ... |
| **…** | ... | ... | ... | *missing* | ... | ... | ... |
| **…** | ... | ... | ... | *missing* | ... | ... | ... |
| **t-22** | $\mathbf{A_{t-22,1}}$ | not released | ... | *missing* | not released | ... | ... |
| **t-21** | not released | $\mathbf{A_{t-21,2}}$ | ... | *missing* | $\mathbf{A_{t-21,6}}$ | ... | ... |
| **…** | not released | not released | ... | *missing* | not released | ... | ... |
| ***t*** | $\mathbf{A_{t,1}}$ | not released | ... | $\mathbf{A_{t,5}}$ | not released | ... | ... |
| **t+1** | not released | $\mathbf{A_{t+1,2}}$ | ... | not released | $\mathbf{A_{t+1,6}}$ | ... | ... |
| **…** | not released | not released | ... | not released | *discontinued* | ... | ... |
| **…** | ... | ... | ... | ... | *discontinued* | ... | ... |
| ***T*** | ... | ... | ... | ... | *discontinued* | ... | ... |

| | j=1 | j=2 | … | j=5 | j=6 | … | j=N |
|---|---|---|---|---|---|---|---|
| **1** | ... | ... | ... | *missing* | ... | ... | ... |
| **…** | ... | ... | ... | *missing* | ... | ... | ... |
| **…** | ... | ... | ... | *missing* | ... | ... | ... |
| **t-22** | $\mathbf{A_{t-22,1}}$ | $E[A_{t-22,2}]=A_{t-43,2}$ | ... | *missing* | $E[A_{t-22,6}]=A_{t-43,6}$ | ... | ... |
| **t-21** | $E[A_{t-21,1}]=A_{t-22,1}$ | $\mathbf{A_{t-21,2}}$ | ... | *missing* | $\mathbf{A_{t-21,6}}$ | ... | ... |
| **…** | $E[A_{...,1}]=A_{t-22,1}$ | $E[A_{...,2}]=A_{t-21,2}$ | ... | *missing* | $E[A_{...,2}]=A_{t-21,6}$ | ... | ... |
| ***t*** | $\mathbf{A_{t,1}}$ | $E[A_{t,2}]=A_{t-21,2}$ | ... | $\mathbf{A_{t,5}}$ | $E[A_{t,2}]=A_{t-21,6}$ | ... | ... |
| **t+1** | $E[A_{t+1,1}]=A_{t,1}$ | $\mathbf{A_{t+1,2}}$ | ... | $E[A_{t+1,5}]=A_{t,5}$ | $\mathbf{A_{t+1,6}}$ | ... | ... |
| **…** | $E[A_{...,1}]=A_{t,1}$ | $E[A_{...,2}]=A_{t+1,2}$ | ... | $E[A_{...,5}]=A_{t,5}$ | *discontinued* | ... | ... |
| **…** | ... | ... | ... | ... | *discontinued* | ... | ... |
| ***T*** | ... | ... | ... | ... | *discontinued* | ... | ... |

Figure 2: This figure shows a stylized example of the actual macroeconomic announcement data, for $N$ announcement types over a daily sample period between 1 and $T$. The releases $j = 1$ and $j = 2$ are monthly indicators released on two different days of the month. The macroeconomic indicator $j = 5$ is a news release that did not exist at the beginning of the sample, but was included in the sample from day $t$ onwards. The macroeconomic indicator $j = 6$ did exist at the beginning of the sample, but was subsequently discontinued. The top panel represents the matrix of the actual macroeconomic releases in real-time as it is constructed from the data. The bottom panel shows how our simple forward filling algorithm is used to fill in the expectation of the indicator when it is not released.



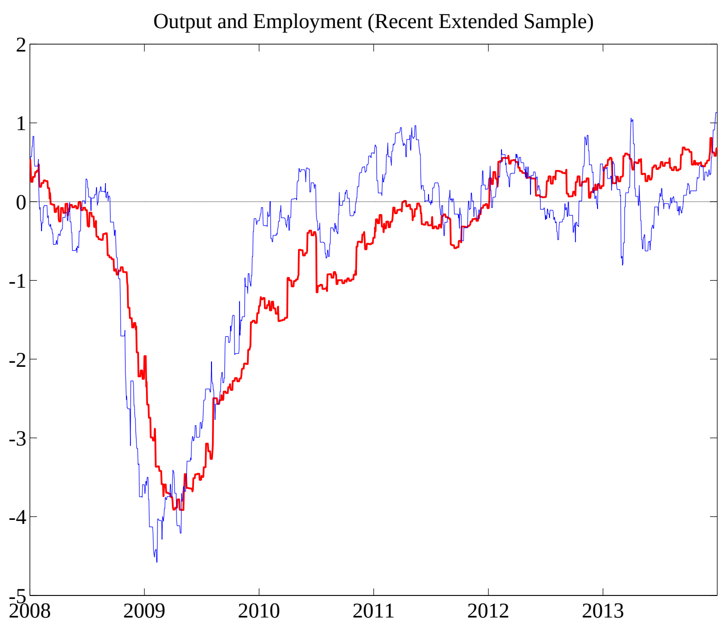
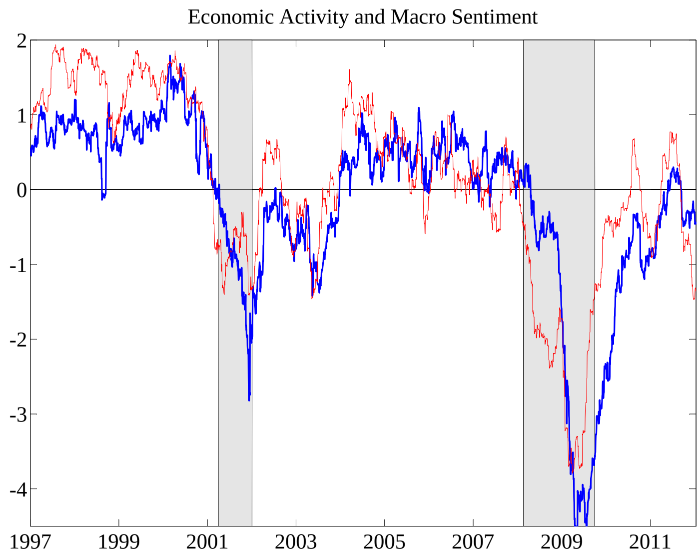




Figure 3: The upper panel shows the real-time output (blue line) and employment factor (red line) from 1997 to 2011. Grey areas denote NBER recessions. The lower panel plots again the real-time output (blue line) and employment factor (red line) for the recent extended subsample 2008 to 2013.



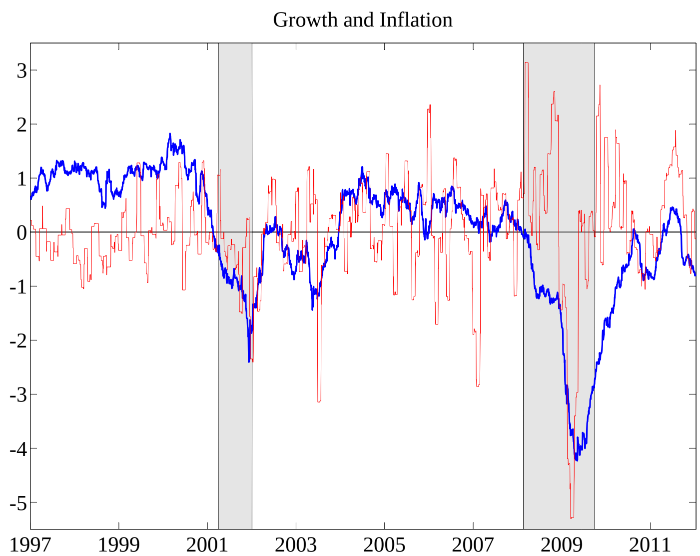




Figure 4: The upper panel shows the real-time economic activity (blue line) and macro sentiment (red line) factors. The lower panel plots the real-time growth (blue line) and inflation (red line) factors. Grey areas denote NBER recessions.

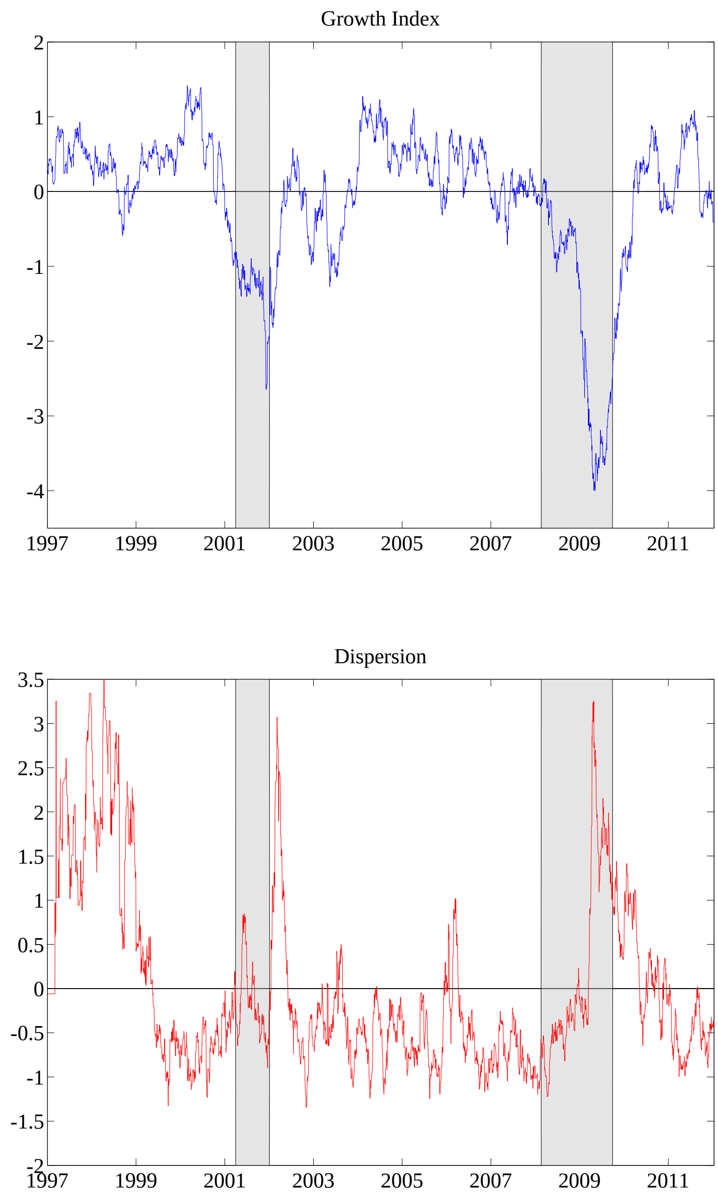



Figure 5: The upper panel shows the real-time growth factor. The lower panel is the dispersion of economist forecasts about upcoming growth news releases. Grey areas denote NBER recessions.

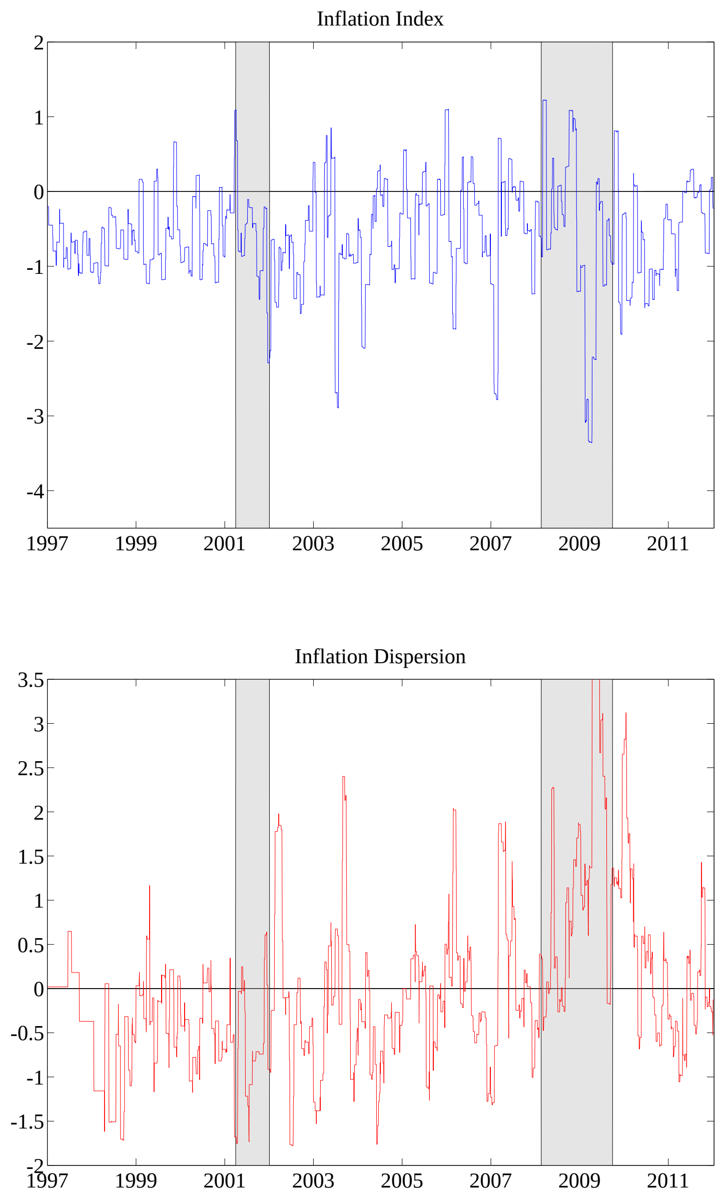



Figure 6: The upper panel shows the real-time inflation factor. The lower panel is the dispersion of economist forecasts about upcoming inflation news releases. Grey areas denote NBER recessions.

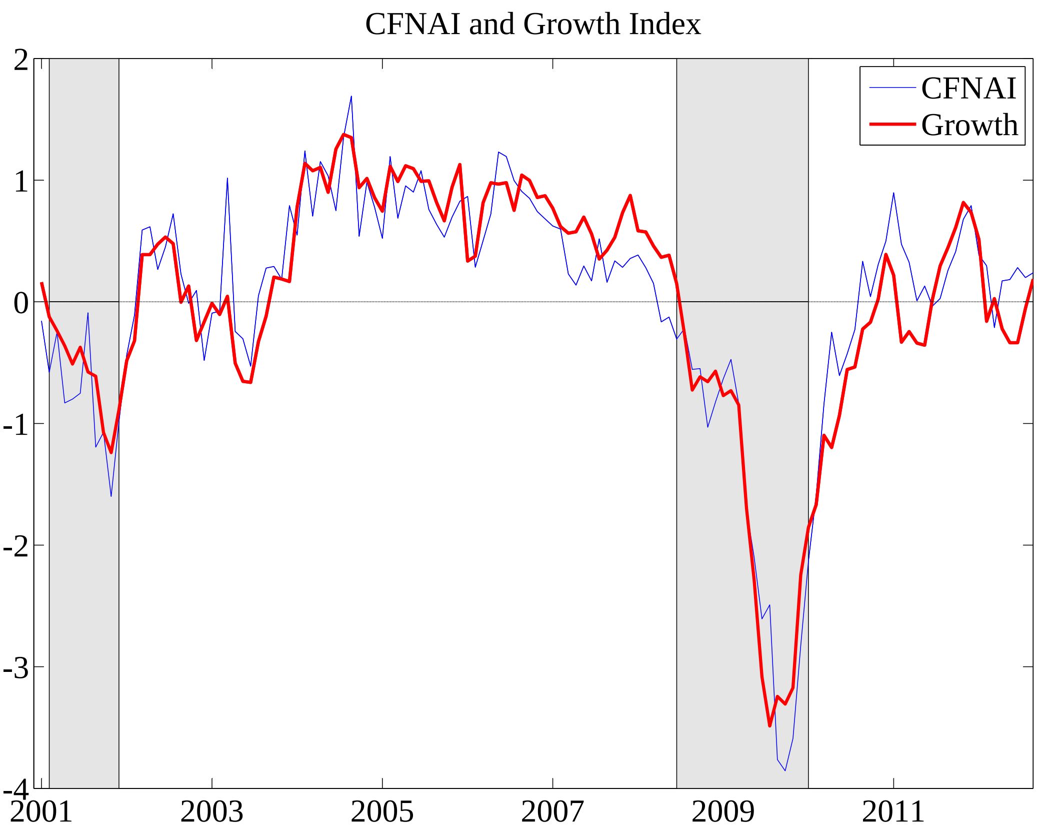



Figure 7: This figure shows the real-time growth factor and the CFNAI, both observed at the monthly frequency on the same day during the sample period Feb-2001 to Dec-2011.

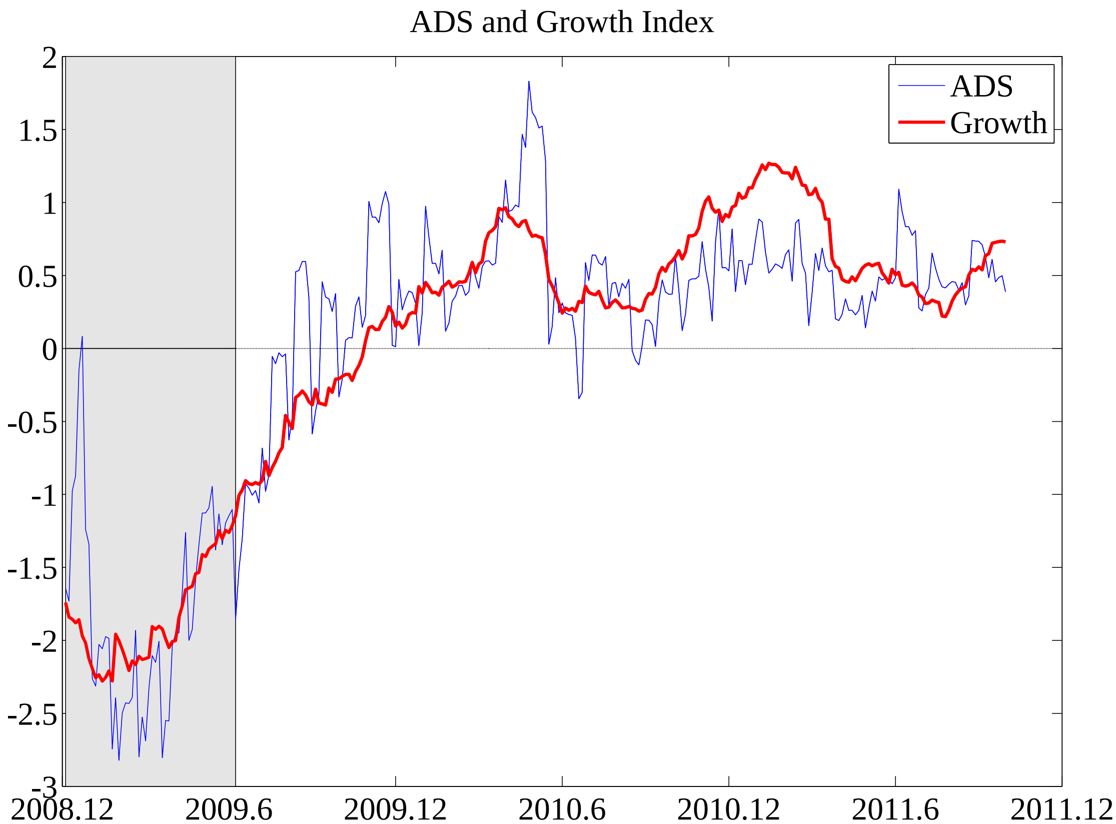



Figure 8: This figure shows the real-time growth factor and the corresponding vintages of the ADS index during the sample period Dec-2008 to Dec-2011.

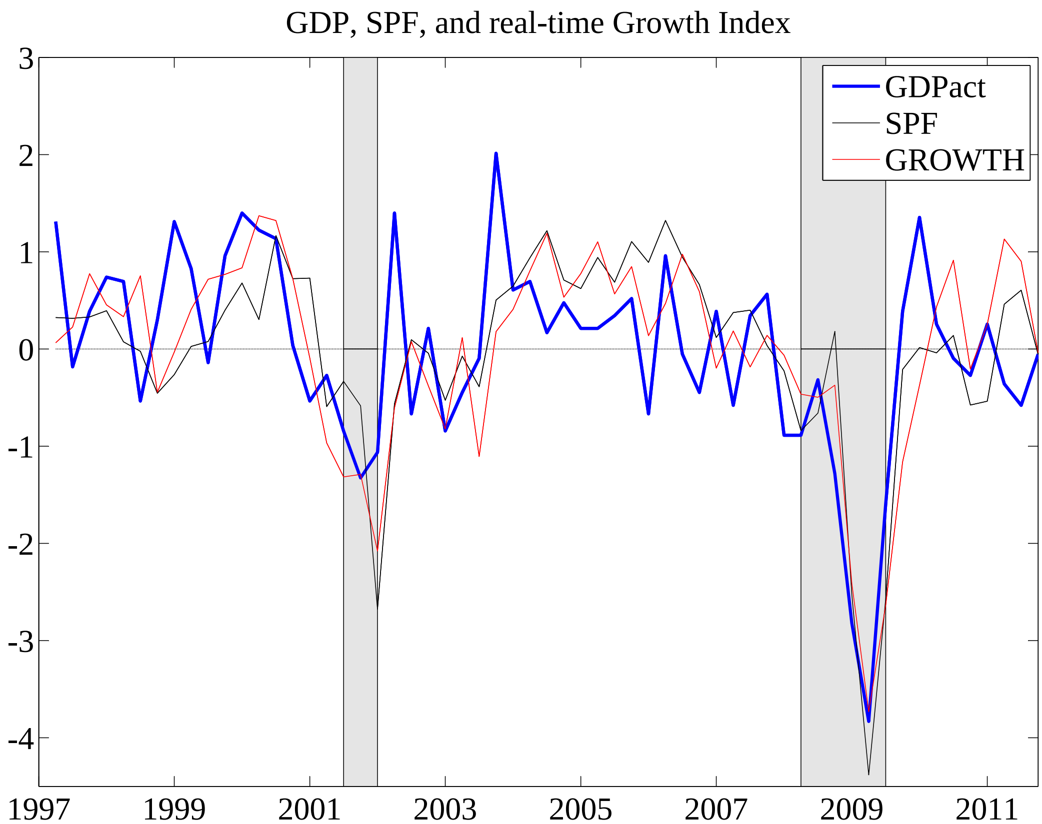



Figure 9: This figure shows the real-time growth factor, the median projection of nominal GDP growth rate from the Survey of Professional Forecasters (SPF) on the same dates, and the actual GDP release for the same quarter, at quarterly frequency during the sample Jan-1997 to Dec-2011.

CPI, SPF, and Real-time Inflation Index

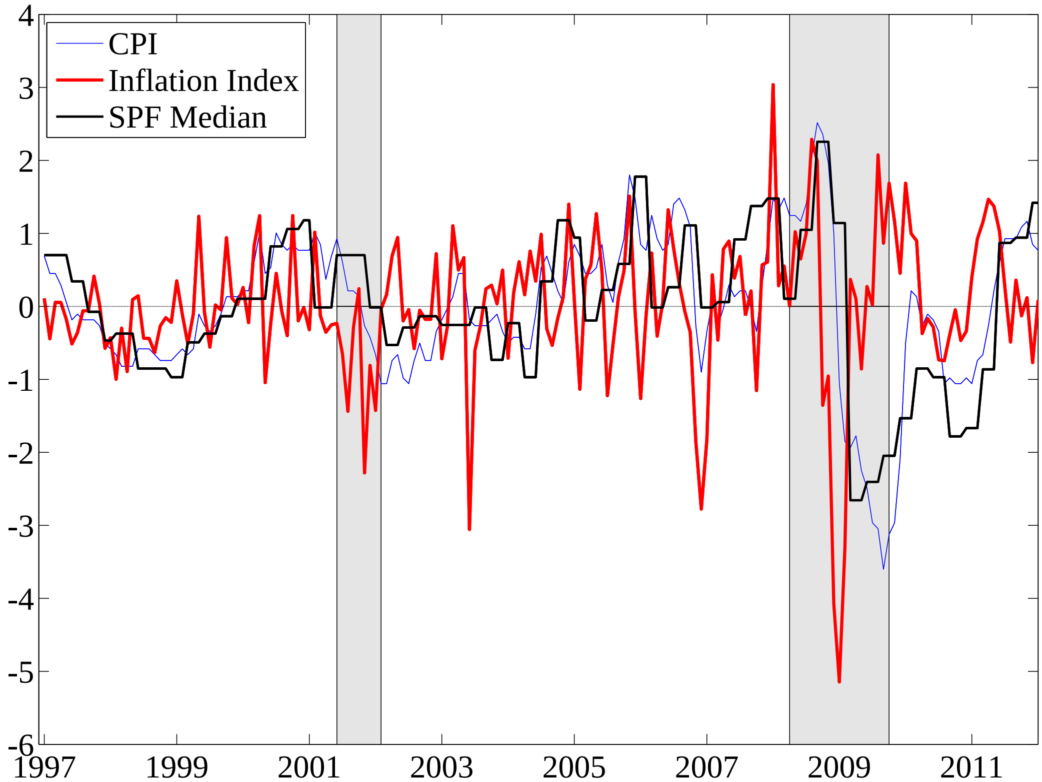



Figure 10: This figure shows the real-time inflation factor, the median projection of CPI from the Survey of Professional Forecasters (SPF) on the same dates, and the actual CPI release of the following month, at quarterly frequency during the sample Jan-1997 to Dec-2011.

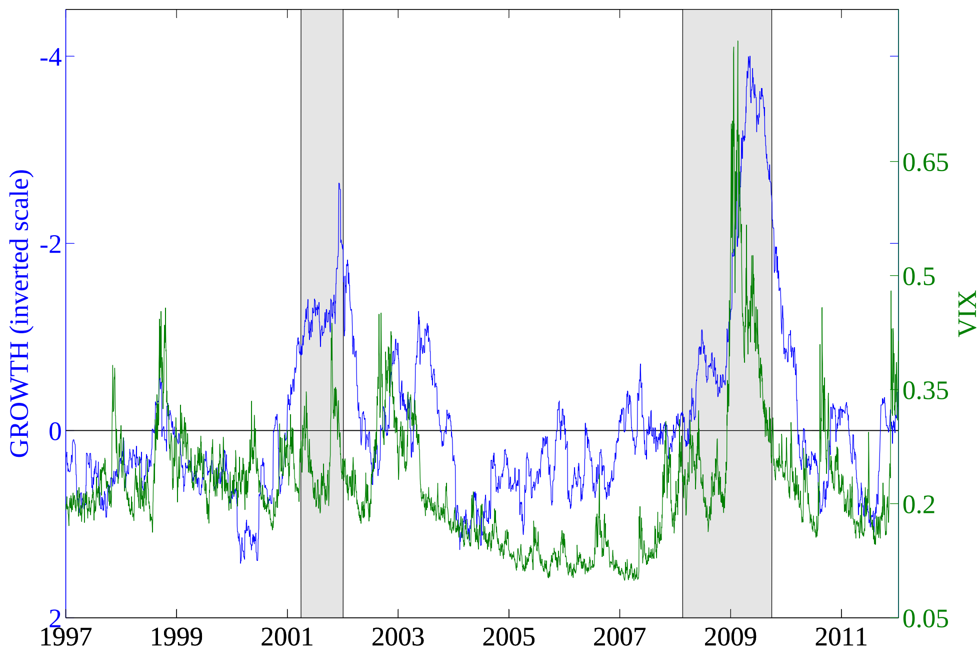



Figure 11: This figure shows the real-time growth factor (inverted left-scale) and VIX (right-scale) during our sample period.

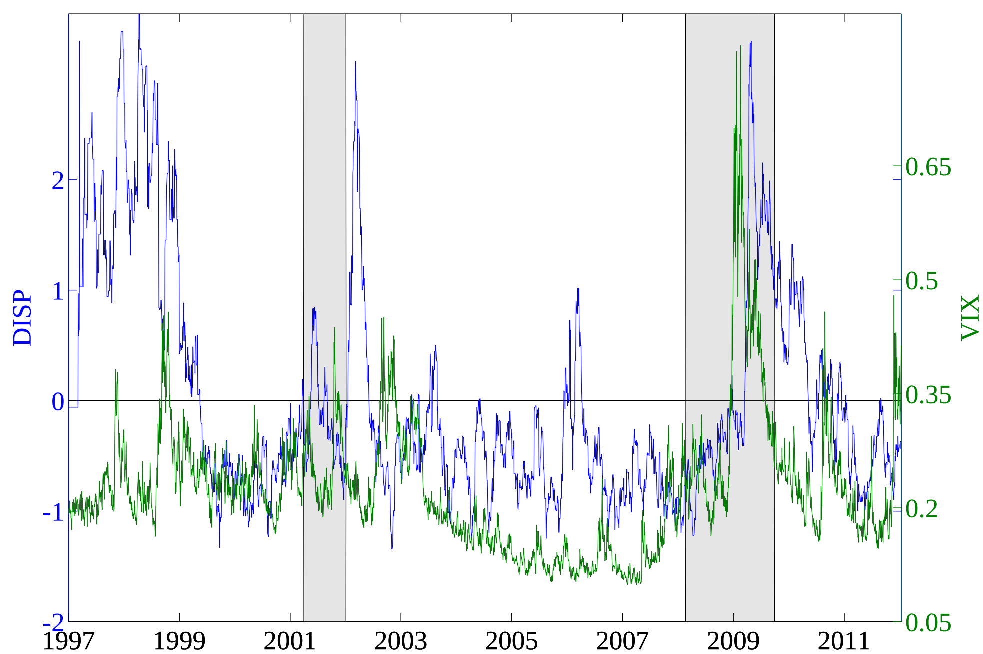



Figure 12: This figure shows the dispersion of economist forecasts about growth news (left-scale) and VIX (right-scale) during our sample period.

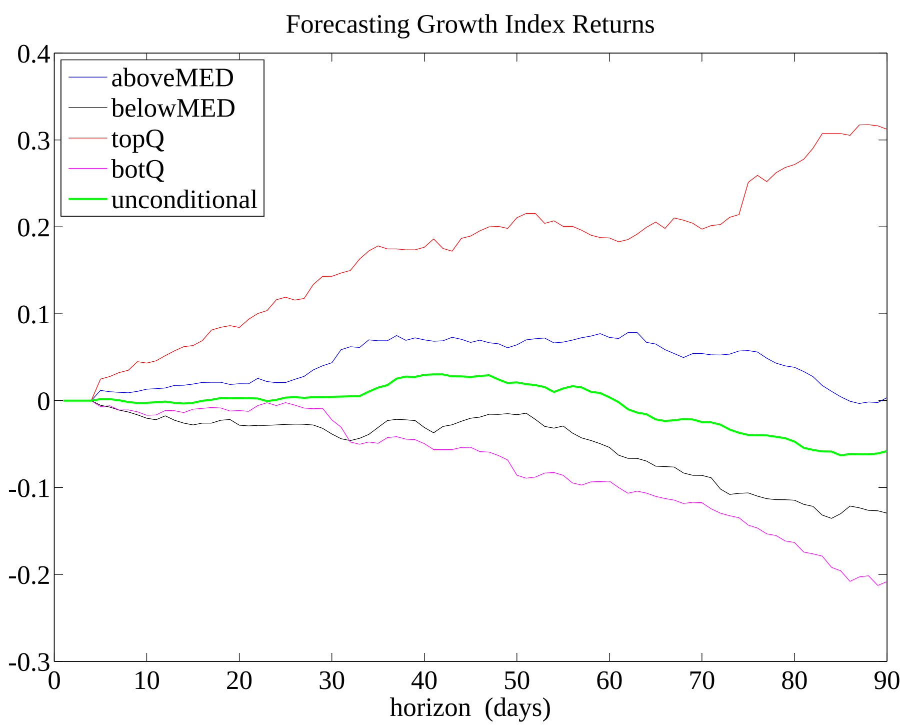



Figure 13: This figure shows the median first difference in the growth index for different horizons (in days), unconditionally and conditionally on current dispersion about growth news being above (below) the sample median and in the top (bottom) quartile.

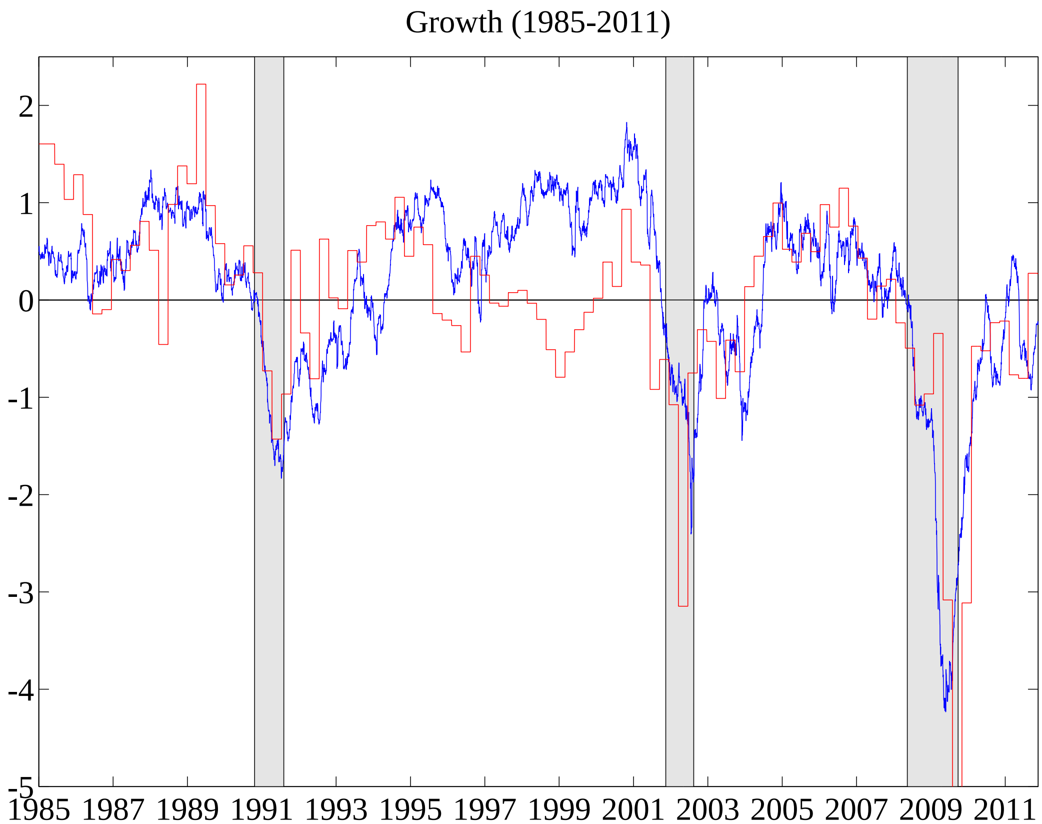



Figure 14: This figure shows our real-time growth index constructed from economic releases backfilled to January 1985. The red line indicates the quarterly expectation of GDP growth for the current quarter contained in the Survey of Professional Forecasters. Grey areas denote NBER recessions.

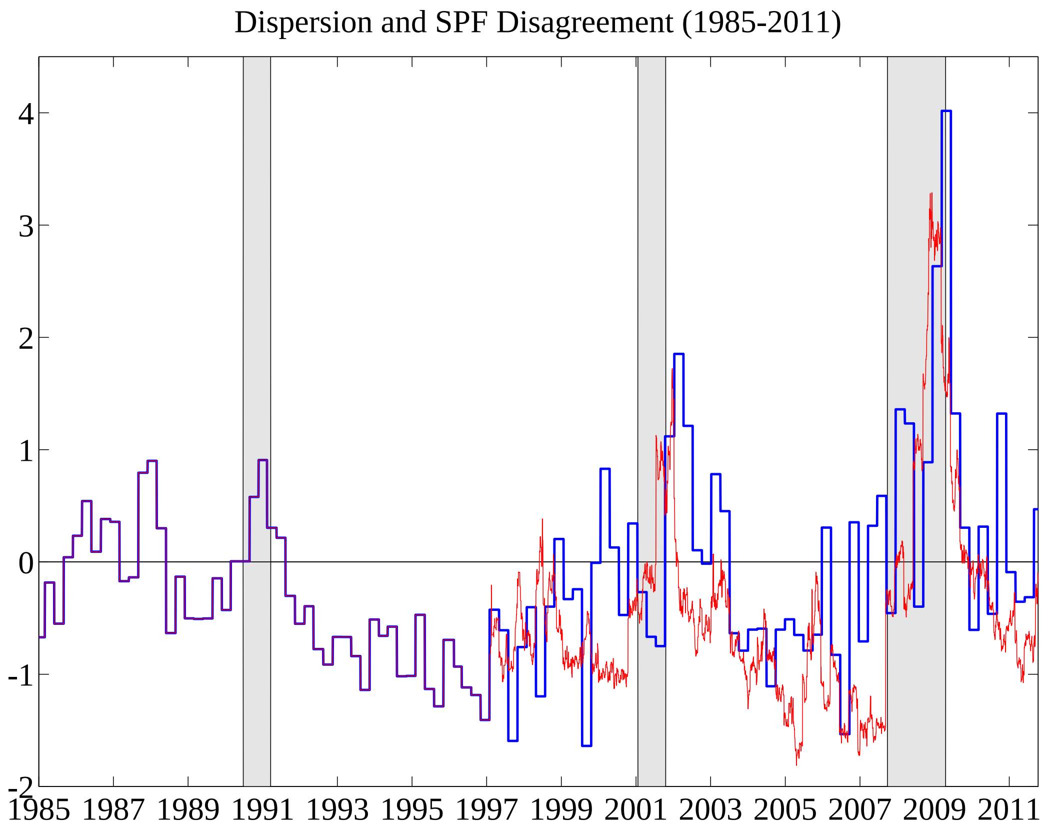



Figure 15: This figure shows our daily factor for the dispersion of economist forecasts about growth news (in red) and the disagreement measure in the quarterly Survey of Professional Forecasters (SPF) (in blue). Grey areas denote NBER recessions.