What Does Realized Volatility Tell Us About Macroeconomic Fluctuations?*

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Abstract

This paper provides an extensive analysis of the predictive ability to economic activity of several measures of asset realized volatility. We construct monthly measures of aggregated stock market and industry-level stock volatility, and bond market volatility from daily returns. We model log realized volatility as composed of a long-run component that is common across all these series, and a short-run sectoral component. If volatility indeed has components, volatility proxies are characterized by large measurement error, which veils analysis of their fundamental information and relationship with the economy. We find that realized volatility of asset returns helps predict future economic activity. Notably, there are substantial gains from using the long term component of the volatility measures for linearly projecting future economic activity, as well as for forecasting business cycle turning points. We extend the analysis to extract a nonlinear long-run component of the volatility series and evaluate its performance in an out-of-sample real time analysis. Given the unexpected severity of the recent 2007-2009 recession, this period offers an ideal environment to evaluate ex-ante predictive performance. The nonlinear volatility component yields early real time signals of the upcoming recession, concomitant with the first signs of distress in the financial markets due to problems in the housing sector in mid 2007. In addition, the model implied chronology is consistent with the recession timeline and periods of financial distress during the subsequent period.

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1. INTRODUCTION

The countercyclical relation between systematic movements in financial asset returns and volatility with economic activity has been widely documented in the literature. Bear markets, which correspond to periods of generally decreasing asset prices, usually lead economic recessions by a few months and end before the trough, anticipating the economic recovery. These periods are characterized by negative returns and high volatility, whereas bull markets, during which market prices generally increase, are associated with positive returns and lower volatility.[1] In particular, the empirical regularity that stock market volatility is time-varying has led to a vast literature on modeling and forecasting its dynamics. At the business cycle frequency, the empirical literature in this area has mostly focused on whether macroeconomic variables that behave differently over expansion and recession phases can help predict stock volatility.[2]

On the other hand, there is only a small and incipient literature that uses stock market volatility to forecast economic activity. Measures of return volatility may also be useful to predict the future path of the economy as they proxy for the uncertainty surrounding future cash flows and discount rates. In general, this view is supported by the standard present value model of stock prices (e.g., Schwert 1989a, 1989b). Recently, Mele (2007) provides an explicit theoretical analysis of this relation in a continuous time rational valuation framework, using the fact that risk premia are counter-cyclical, i.e. investors require higher returns during relatively bad times. However, the mechanism that leads to counter-cyclical volatility is that changes in risk premia are larger in magnitude in bad times. This can be caused by habit formation in consumption as in Campbell and Cochrane (1999), and by restricted stock market participation as in Basak and Cuoco (1998). Further theoretical underpinnings of the counter-cyclical character of asset return volatility can be found in the financial accelerator framework of Bernanke, Gertler, and Gilchrist (1999) and more recently in Bloom (2009), who investigates the impact of shocks to economic uncertainty under stochastically evolving business conditions. Recently, Fornari and Mele (2009) investigate the predictive power of aggregate stock market volatility constructed as a moving average of past absolute returns, along with other financial

[1] See for example Officer (1973), Fama and French (1989), Schwert (1989b), Ferson and Harvey (1991), Perez-Quiros and Timmermann (1995), Hamilton and Lin (1996), Whitelaw (1994), Chauvet (1998/1999), Chauvet and Potter (2000, 2001), Maheu and McCurdy (2000), and Senyuz (2010), etc.

[2] See for example, Schwert (1989b), Hamilton and Lin (1996), Engle and Rangel (2008), and David and Veronesi (2009), among many others.

variables for U.S. economic activity. Andreou, Osborn, and Sensier (2000) consider interest rate volatility while Andreou, Ghysels, and Kourtellos (2010) use option implied volatility as a predictor of economic activity besides other financial indicators.

In this paper, we analyze the predictive value of various volatility measures for future economic activity. We consider not just the aggregate stock market volatility, but also stock volatility at the industry level, and bond market volatility. Realized volatility offers a natural framework to match the quarterly or monthly frequency of macro series, by aggregating financial data available at higher frequencies.[3] We use daily data to construct realized monthly volatility and treat volatility as an observable variable. This allows us to use a variety of linear and nonlinear methods to assess predictive power of various volatility measures and their relation with the real economy.

Ex-post sample variances that are computed from higher frequency return data as lower frequency volatility measures have been extensively used in empirical finance, see for example the early work of Poterba and Summers (1986), French, Schwert and Stambaugh (1987), Schwert (1989a, 1989b).[4] More recently, Andersen, Bollerslev, Diebold, and Labys (2000), and Andersen, Bollerslev, Diebold, and Ebens (2001) show the empirical success of realized volatility for measuring and modeling underlying return variability. Some of the theoretical justifications for their use can be found, for example, in Merton (1980) who shows that for a continuous time diffusion process, the diffusion coefficient over a fixed horizon can be accurately estimated by using finely sampled data. Based on the theory of quadratic variation Andersen, Bollerslev, Diebold and Labys (2001), and Barndorff-Nielsen and Shephard (2002a, 2002b) provide the theoretical foundation for using realized volatility measures as proxies for the true underlying variability in returns, under general conditions. Subsequently, Andersen, Bollerslev, Diebold and Labys (2003) advance theoretical underpinnings linking the conditional covariance and realized volatility based on the theory of continuous-time arbitrage-free price processes in addition to the theory of quadratic variation. Using realized volatility presents three major advantages, as discussed in Andersen, Bollerslev, Diebold and Labys (2001, 2003). First, it is a fully nonparametric method, i.e. realized volatility is constructed without the limitations of

[3] An alternative approach is to handle various sampling frequencies using the MIDAS regressions as in Andreou, Ghysels, and Kourtellos (2010), which focus on the information content of mostly the first moment of financial return series.

[4] See survey by Andersen, Bollerslev, Diebold, and Wu (2005).

the assumptions of a parametric model. Second, it is an observable ex-post measure of volatility that consistently estimates ex-ante expected volatility. Finally, measurement error due to limitations on sampling frequency within a finite horizon is uncorrelated over time.

In this paper, we model log realized volatility as composed of a long-run component that is common across all series, and a short-run sectoral component. We find that there are substantial advantages in extracting volatility components. If volatility indeed has components, volatility proxies are characterized by large measurement error, which veils analysis of their fundamental information and relationship with the economy. For example, Schwert (1989b) find little evidence of links between asset volatility and economic activity when aggregating daily data into monthly realized volatilities, whereas there is a growing literature that models volatility as composed of several factors and finds substantial evidence of their linkages, such as Ding and Granger (1996), Gallant, Hsu, and Tauchen (1999), Engle and Lee (1999), Alizadeh, Brandt, and Diebold (2002), Bollerslev and Zhou (2002), Chernov, Gallant, Ghysels, and Tauchen (2003), Chacko and Viceira (2003), Adrian and Rosenberg (2008), Engle, Ghysels, and Sohn (2008), among many others. In particular, Adrian and Rosenberg (2008) develop a three-factor ICAPM where factors are total stock market volatility and its long-term and transitory components. They show that this model is successful in modeling the cross section of expected returns and that the long-term component of volatility is strongly related with economic fundamentals.

This paper provides an extensive analysis of the predictive ability to economic activity of several measures of asset volatility, at the aggregate and industry-level, and from the bonds market. We also provide analysis of the gains obtained from using the long term component of the volatility measures for linearly projecting future economic activity, as well as for forecasting business cycle turning points. The analysis is implemented in-sample, out-of-sample, and using real time data. We find that realized volatility of asset returns helps predict future economic activity. We first analyze the predictive power of constructed realized volatility measures using linear predictive regressions for monthly industrial production growth and an economic factor extracted from four coincident macroeconomic series. We extract the long-run component of volatility that is common across all series, motivated by the ICAPM of Adrian and Rosenberg (2008). Combining information in the realized volatility series proves to be very useful in predicting both growth of industrial production and the economic factor as well as turning points of business cycles via probit and nonlinear dynamic factor models. When we allow for nonlinear dynamics in the common factor of volatility and in the common factor of coincident macro variables, we observe that the estimated factors as well as their implied regime classifications are highly correlated with each other.

We also provide an out-of-sample real time analysis of the last five years of the sample using the nonlinear dynamic factor model of volatility. Given the unexpected severity of the recent 2007-2009 recession, this period offers an ideal environment to evaluate ex-ante predictive performance. The nonlinear long run component of volatility gives early signals of the upcoming recession, simultaneously with the first signs of distress in financial markets due to problems in the housing market, which made headlines in mid 2007. In addition, the model implied chronology is consistent with the recession timeline and periods of financial distress in the subsequent period.

The rest of the paper is organized as follows. Next section explains the construction of the realized volatility measures. Section 3 describes the data sets used and provides an analysis of the macroeconomic and asset volatility relations in the context of dynamic factor models. Section 4 contains a comprehensive analysis of the predictive power of various volatility measures for economic activity using linear regressions, probit models, and Markov-switching dynamic factor models in-sample and in an out-of-sample real time analysis. This section also includes the results of the out-of sample forecasting exercise as well as turning point analysis of the nonlinear volatility factor. Section 5 concludes.

2. REALIZED VOLATILITY MEASURES

We construct three measures of realized volatility series: aggregate stock market volatility, aggregated industry level volatility, and bond market volatility. Let r_{ms} denote the daily excess return over the risk free rate for the value-weighted market portfolio, where s denotes the trading days in a given month, indexed by t. Then, the monthly realized market volatility, RVM_t, is defined as follows

$$(1) \qquad RVM_t = \left(\sum_{s\in t}^{n_t} r_{ms}^2\right)^{1/2}, \quad t = 1, \dots, T,$$

where n_t denotes the number of trading days in month t, and T denotes the total number of months in the sample.[5]

Following Campbell, Letteu, Malkiel, and Xu (2001), we also consider a measure of industry level realized volatility, constructed from the difference between industry returns and the market return. Let r_{is} denote the daily value-weighted return of all firms in industry i. Defining $e_{is} = r_{is} - r_{ms}$ and aggregating across industries, we obtain the monthly industry realized volatility measure, RVI_t

$$(2) \qquad RVI_t = \left(\sum_{i=1}^{m_i} w_{it} \sum_{s \in t}^{n_t} e_{is}^2\right)^{1/2}, \qquad t = 1, \dots, T,$$

where w_{it} is the weight of industry i in the market portfolio with respect to market capitalization, and m_i denotes the total number of industries. This definition of volatility stands between the systemic volatility as measured by the volatility of the market portfolio, and the idiosyncratic firm level volatility. Campbell, Letteu, Malkiel, and Xu (2001) document strong correlation between RVI and GDP growth.

Finally, the third realized volatility measure considered is obtained from the Treasury bond market. Let y_s denote the continuously compounded yield of the 10-year zero coupon T-bond. The daily bond return is given by $r_{bs} = 10(y_{s-1} - y_s)$. We then construct the bond market realized volatility measure, RVB_t based on this daily return as follows

$$(3) \qquad RVB_t = \left(\sum_{s \in t}^{n_t} r_{bs}^2\right)^{1/2}, \qquad t = 1, \dots, T.$$

The realized volatility approach provides directly observable return volatility measures that are consistent, and approximately unbiased. Note that this procedure is a convenient nonparametric way of exploring the inherent information in the higher-frequency for lower

[5] A realized volatility measure taking into account the first order autocorrelation in daily returns can be calculated similarly. We consider this alternative in our calculations and find that the results obtained are qualitatively similar across these measures.

frequency volatility movements. We use these properties to understand the extent of the relation between financial return volatility and aggregate economic activity.

3. REALIZED VOLATILITY AND THE BUSINESS CYCLE

We use daily stock market and industry returns to calculate monthly realized volatilities, retrieved from Kenneth French's Data Library. We consider 48 industries in our data set. The bond dataset is obtained from Gurkaynak, Sack and, Wright (2007). [6] The sample is from 1971:9 to 2009:9, mainly determined by the availability of the daily bond yield data. Our first goal is to understand the relation between economic activity and these realized volatility measures, which contain information on changes in the stock and bond markets. We then explore whether these realized volatility series forecast economic activity in the following sections.

Figure 1 plots the natural logarithm of the three realized volatility measures constructed as described in Section 2, with shaded areas representing recessions as dated by the NBER. The volatilities are individually very noisy. However, a slightly similar pattern can be observed, with them being generally higher during recessions and lower during expansions. The aggregated industry level stock volatility moves closely with the market volatility. Notice that both series increased considerably from mid-1990s to early 2000s, reflecting the great uncertainty surrounding the stock market boom and subsequent crash during this period. Interestingly, a subsequent very low volatility period followed since, which lasted until the beginning of the recent financial crisis in 2007-2008. Bond market volatility generally coincides with the dynamics of the stock market volatility, with some exceptions. In terms of its level, the bond market volatility is lower 1970s, compared to the last three decades. Second, contrarily to the stock market, bond market volatility remained relatively low from the mid-1990 to the early 2000s.

The differences in the dynamics of the volatility measures suggest that a combination of the series could contain additional information on their relationship with the economy. However, we face two potential problems in this analysis. First, as observed in Figure 1, the volatility series are very noisy, which veils to some extent their relationship with the economy, and it

[6] Refer to Kennett French's website for a complete list of the industries and classification procedures. Gurkaynak, Sack, and Wright (2007) dataset can be downloaded from the research site at the Board of Governors of the Federal Reserve System.

makes it difficult to discriminate recession and downturn signals. Second, the volatility series are highly correlated with each other in the entire sample, and even more so when the sample is divided into recession or expansion phases. These two features make it difficult to study how the various volatility series are related to the economy. Therefore, to reduce noise and to aggregate information across volatility series in a formal way, we propose a common factor specification. A dynamic factor model is a signal-noise extractor that filters out idiosyncratic noise inherent to each series from common cyclical movement. This framework, thus, enables analysis of the common variation in the three realized volatility series. The proposed model is related to Adrian and Rosenberg's (2008) ICAPM, which decomposes return volatility into a relatively persistent long-term component and a transitory short-term component.

Let Y_{it} denote the log of the i^{th} realized volatility series where $i = 1$ for RVM_t, $i = 2$ for RVI_t, and $i = 3$ for RVB_t. The dynamic factor model of volatility dynamics can be represented as follows:

$$(4) \qquad Y_{it} = \lambda_i VF_t + u_{it}, \quad u_{it} \sim NID\left(0, \sigma_{u_i}^2\right),$$

$$(5) \qquad VF_t = \alpha + \phi VF_{t-1} + \epsilon_t^v, \qquad \epsilon_t^v \sim NID(0, \sigma_v^2),$$

where VF_t is the common volatility factor, u_{it} denotes the idiosyncratic component and λ_i denotes the factor loading for the i^{th} series. The factor loadings show to what extent each realized volatility series is affected by the common factor. The common factor is extracted as a single volatility measure from all three realized volatility series and is assumed to be uncorrelated with idiosyncratic terms at all leads and lags to ensure identification. The model is estimated using the Kalman filter, and the maximum likelihood estimates are reported in Table 1. The extracted volatility factor is highly persistent with an autoregressive coefficient estimate of around 0.92. All factor loadings are positive indicating positive correlation between the realized volatility measures and the extracted factor.

Figure 2 plots the extracted common volatility factor along with the NBER recessions. Notice how the dynamic factor model filters out the noise and yields a smooth variable that summarizes information common to three realized volatility measures. This feature is important in relating financial volatility to macroeconomic dynamics. The common cyclical volatility in the aggregate and industry-level stock market and in the bond market shows a striking business cycle pattern and is closely related to NBER recessions: it starts rising in the middle of economic expansions, reaching a peak around recessions, subsequently falling during the first stages of economy recoveries. It then reaches a trough around the middle of expansions. The low volatility in the bond market in the early 1970s and in the late 1990s, when combined with the information of high uncertainty in the stock market, yields a common volatility factor that is more closely related to business cycle phases and more robust to outliers. The volatility factor still exhibits some spikes in two other periods that were not followed by recessions. The highest such increase takes place during the 1987 stock market crash. There is also an increase in volatility around 1998-1999 during which the U.S. experienced a mild slowdown associated with the effects of the Asian crisis in 1994, the 1998 Russian crisis, and the 1999 Brazilian and Argentinean currency crises. The common volatility in the stock and bond markets rose in 1998 and remained high during the 2001 recession and jobless recovery that lasted until 2003, indicating the high uncertainty surrounding this period.

Next, we compare the relationship of the volatility factor with a comprehensive measure of aggregate economic activity at the monthly frequency. We estimate a dynamic economic factor that summarizes information common to four coincident economic variables, as in Chauvet (1998). The macro variables used are 100 times the log first differences of seasonally adjusted monthly U.S. industrial production index (IP), real personal income less transfer payments ($PILTP$), real manufacturing and trade sales (MTS), and employees on non-agricultural payroll ($PAYROLL$). [7] These are the same four coincident series used in Chauvet (1998), Chauvet and Piger (2008), by the Conference Board to build its coincident indicator, and by the NBER Business Cycle Dating Committee to date recessions.

Let Z_{kt} be 100 times the log first difference of the observable macroeconomic variables where $k = 1$ for IP, $k = 2$ for $PILTP$, $k = 3$ for MTS, and $k = 4$ for $PAYROLL$. Then, the measurement equation, which links the observables variables and the unobservable factor, and the transition equation are given by:

(6) $$Z_{kt} = \lambda_k EF_t + u_{kt},$$

[7] PILTP and MTS are obtained from the Bureau of Economic Analysis, and PAYROLL from the Bureau of Labor Statistics.

$$(7) \qquad EF_t = \alpha + \phi EF_{t-1} + \epsilon_t^e, \qquad \epsilon_t^e \sim NID(0, \sigma_e^2),$$

$$(8) \qquad u_{kt} = \psi_k u_{k,t-1} + \omega_{kt}, \qquad \omega_{kt} \sim NID\left(0, \sigma_{\omega_k}^2\right),$$

where EF_t is the scalar common economic factor and u_{kt} denotes the idiosyncratic component for the k^{th} series of the economic factor model.

Table 2 presents the maximum likelihood estimates of the macroeconomic model. The extracted economic factor is much less persistent, with an autoregressive parameter estimate of 0.57. The underlying economic series are positively correlated with the factor. Parameters estimates of all idiosyncratic components indicate significant idiosyncratic variation in each of the macroeconomic series.

Figure 3 plots the extracted economic factor and the volatility factor obtained from the above specified dynamic factor models. The strong association between the two factors is striking. There is a negative relationship between the two series, with the volatility factor tending to rise when the economic factor falls, especially around NBER recessions. This suggests that the extracted factors that combine information in the individual series may provide useful information to the predictive relationship between financial volatility dynamics and the economy.

4. PREDICTING ECONOMIC ACTIVITY USING FINANCIAL VOLATILITY

We now investigate whether the individual realized volatility series and the extracted common factor representing variation in the stock and bond markets contain useful information to forecast macroeconomic activity at the monthly frequency. First, we examine the marginal predictive content of the individual volatility series and of the volatility factor in predicting industrial production growth and the coincident indicator of the economy. Second, the nonlinear relationship of each of the series is analyzed using probability methods to determine if they anticipate the peaks and troughs of NBER-dated recessions. In particular, we estimate probit models and Markov switching models for each volatility series and for the dynamic factor volatility. The estimated probabilities of high or low states for each series are used in the analysis of the nonlinear lead-lag relationship with NBER recessions.

The analysis is implemented for both full sample and out of sample prediction. The full sample runs from 1971:9 to 2009:9. The out-of-sample analysis is conducted by estimating all models from 1971:9 to 2004:9, and then recursively re-estimating each of them for the remaining 5 years.[8] In both cases, the best specifications are chosen using cross-correlograms, significance tests as well as Akaike and Bayesian model selection criteria. The forecasting performance is evaluated with respect to symmetric mean squared error (MSE) and asymmetric $LINLIN$ functions (Granger, 1969) given by:

$$(9) \qquad MSE_i = \frac{1}{n}\sum_{t=T-n+1}^{T} \hat{\varepsilon}_{it}^2 ,$$

$$(10) \qquad LINLIN_i = \frac{1}{n}\sum_{t=T-n+1}^{T} \mathbf{1}(\hat{\varepsilon}_{ti} \geq 0)|\hat{\varepsilon}_{ti}| + \mathbf{1}(\hat{\varepsilon}_{ti} < 0)2|\hat{\varepsilon}_{ti}|,$$

where $\mathbf{1}(.)$ denotes the standard indicator function. In the case of $LINLIN$, the loss associated with a negative error is twice as much as the loss associated with a positive error of the same magnitude. To assess statistical significance of out-of-sample loss differences, we use the reality check proposed by White (2000). In this framework, a number of alternative models are jointly compared to a benchmark where the null simply states that the best alternative is not better than the benchmark with respect to a selected loss function.

4.1 Predicting Industrial Production Growth

We start with predictive regressions focusing on IP growth. The benchmark model is a simple autoregressive model for IP growth. We then add lags of each realized volatility measures and the extracted volatility factor to this autoregressive model individually to study whether they increase the predictive power of the benchmark model. The benchmark and the alternative specifications can be summarized as follows:

$$(11) \qquad M_1^{IP}: \qquad IP_t^h = \beta_0^1 + \sum_{j=1}^{p} \beta_j^1 IP_{t-jh}^h + \varepsilon_{1t}^h,$$

[8] We have also implemented fixed and rolling schemes as well, and the results are qualitatively similar.

$$(12)-(14) \quad M_i^{IP}: \qquad IP_t^h = \beta_0^i + \sum\nolimits_{j=1}^{p} \beta_j^i IP_{t-hj}^h + \sum\nolimits_{j=1}^{p} \gamma_j^i\, Y_{i-1,t-hj}^h + \varepsilon_{it}^h, \quad i \in \{2,3,4\},$$

$$(15) \qquad M_5^{IP}: \qquad IP_t^h = \beta_0^5 + \sum\nolimits_{j=1}^{p} \beta_j^5 IP_{t-hj}^h + \sum\nolimits_{j=1}^{p} \gamma_j^5\, VF_{t-hj} + \varepsilon_{5t}^h,$$

where IP_t^h is the h-period cumulative growth in IP from $t-h$ to t, $Y_{i,t}^h$ is the arithmetic average of the log of the i^{th} realized volatility series over the same period, and $h \in \{1,3,6,12\}$. Note that the extracted volatility factor is not averaged as it is already much less noisy compared to the raw RV series. The lag structure is set to ensure that there is no information overlap in the cumulative growth rates and averages. Based on the criteria stated above we set $p = 3$ for $h = 1$, $p = 4$ for $h = 3$, $p = 2$ for $h = 6$, and $p = 1$ for $h = 12$. [9]

Table 3 presents the full sample evaluation results. For all horizons the factor based model dominates all others by providing minimum MSE. The p-values from the standard Granger Causality test indicate that the reductions in MSE when we consider the volatility factor as a predictor are highly significant. Table 4 reports the out-of sample forecast comparison results with respect to both loss functions. Minimum MSE is again achieved by the common factor volatility model, M_5^{IP}, over all horizons. The out-of-sample MSE loss associated with M_5^{IP} relative to the benchmark, M_1^{IP}, ranges from 72.8% ($h = 6$) to 90.3% ($h = 12$). These improvements are significant as indicated by the Reality check p-values except for $h = 12$. M_5^{IP} is the best performing model with respect to $LINLIN$ loss as well but the loss differences are not statistically significant. The results from both in-sample and out-of-sample analysis indicate that lags of the volatility factor help predict IP growth with significant gains over the benchmark autoregressive model that does not include information on volatility.

We repeat the above analysis using unrevised data on IP growth to assess the predictive value of volatility in real time. We obtained the unrevised IP data series from the Federal Reserve Bank of Philadelphia real time data archive, described in Croushore and Stark (2001). The realizations, or *vintages*, of this series correspond to their values as they would have

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[9] Note that we present here the results for a common p for all models, but we have undertaken extensive analysis with different lag structures and find that the results are quite robust to different values across models. The results are available upon request.

appeared at the end of each month from October 2004 to September 2009. For each vintage, the sample collected begins in September 1971 and ends with the most recent data available for that vintage.

Table 5 presents the results. Results are qualitatively similar to the case of revised data, but gains in terms of reduction in MSE compared to the benchmark are larger for $h \geq 3$. We also reject the benchmark for all horizons at 10% level. With respect to $LINLIN$ loss, we reject the benchmark for $h = 6$ at 10% level with a loss reduction of around 15% over the benchmark.

4.2 Predicting Economic Growth

Here we repeat the analysis in section 4.1 by replacing IP growth with the coincident economic factor EF, which provides more comprehensive information about the state of the economy at the monthly frequency. The benchmark and the alternative predictive models are given by:

$$(16) \qquad M_1^{EF}: \quad EF_t^h = \beta_0^1 + \sum_{j=1}^{p} \beta_j^1 EF_{t-jh}^h + \varepsilon_{1t}^h,$$

$$(17)-(19) \quad M_i^{EF}: \quad EF_t^h = \beta_0^i + \sum_{j=1}^{p} \beta_j^i EF_{t-hj}^h + \sum_{j=1}^{p} \gamma_j^i Y_{i-1,t-hj}^h + \varepsilon_{it}^h, \quad i \in \{2,3,4\},$$

$$(20) \qquad M_5^{EF}: \quad EF_t^h = \beta_0^5 + \sum_{j=1}^{p} \beta_j^5 EF_{t-hj}^h + \sum_{j=1}^{p} \gamma_j^5 VF_{t-hj} + \varepsilon_{5t}^h,$$

Specification criteria tests for these models lead to the same lag structures stated above. Tables 6 and 7 summarize the results of the full-sample and out-of sample forecast analysis, respectively. In the full sample, the benchmark model is rejected at 5% with respect to MSE. The best performing model for $h = 1$ is the extended model that includes the aggregate stock market volatility. For all other horizons, the model that includes the volatility factor, M_5^{EF}, outperforms the other specifications. In the out-of-sample exercise, the best model is again M_5^{EF} with substantial loss reductions at all considered horizons, e.g. for $h = 6$ relative loss is 73.8%. Furthermore, these reductions are significant at the 10% level for $h = 3,6$. Similar to the case of IP growth, we observe loss reductions with respect to $LINLIN$ as well, but these are not statistically significant.

In summary, the results from both IP and EF predictive regressions highlight the importance of combining information across individual volatility series. Overall, the best performing model is the one that includes the volatility factor.

4.3 Event Timing Analysis

In this sub-section we study the performance of the constructed realized volatility measures and the extracted volatility factor in event timing predictions. The recent financial crisis and economic recession have revived widespread interest in predicting business cycle turning points rather than just focusing on linear point forecasts. We conduct event timing analysis to predict business cycle phases by estimating both probit models and nonlinear Markov switching dynamic factor models. The probit models use as the dependent variable the NBER reference cycle that takes the value 0 for expansions and 1 for recessions. The Markov-switching models produce probabilities of recessions that can be used for regime classification. We compare their ability to predict NBER business cycle turning points. By comparing the frequencies of correctly identified business cycle phases, we assess the usefulness of the information provided by the realized volatility measures.

4.3.1 Probit-based Predictions of Recessions

We consider a benchmark autoregressive model using industrial production growth, and extended specifications that include additionally lags of the realized volatility measures as well as the common realized volatility factor. The recession probability predictions are generated from the following model:

$$(21) \qquad P(NBER_t = 1 \mid I_{t-h}) = \Phi(\beta' X_{t-h}),$$

where $NBER_t$ is the 0/1 dummy that equals to one (zero) during NBER recessions (expansions), I_{t-h} denotes the information set available at time $t-h$, X_{t-h} is the vector of lagged predictive variables (including unity as the first entry), β' is the vector of regression coefficients, and $\Phi(.)$ is the Gaussian cumulative distribution function, and $h \in \{1,3,6,12\}$. Note that since we are predicting a categorical variable, the forecasts are simply h-step ahead instead of being cumulative h-period predictions as in IP and EF analyzed above. The set of models considered are as follows:

$$(22)\qquad M_{IP,1}^{NBER}:\quad P(NBER_t = 1|I_{t-h}) = \Phi\left(\beta_0^1 + \beta_1^1 IP_{t-h}^h\right),$$

$$(23)\qquad M_{IP,i}^{NBER}:\quad P(NBER_t = 1|I_{t-h}) = \Phi\left(\beta_0^i + \beta_1^i IP_{t-h}^h + \beta_2^i Y_{i-1,t-h}^h\right),\quad i \in \{2,3,4\},$$

$$(24)\qquad M_{IP,5}^{NBER}:\quad P(NBER_t = 1|I_{t-h}) = \Phi\left(\beta_0^5 + \beta_1^5 IP_{t-h}^h + \beta_2^5 VF_{t-h}\right).$$

Table 8 presents the full sample results. The model that includes aggregate stock market volatility, $M_{IP,2}^{NBER}$, achieves the largest loss reduction over the benchmark for $h = 1,3$. The volatility factor based model, $M_{IP,5}^{NBER}$, and the bond market volatility based model, $M_{IP,4}^{NBER}$, are the best models for $h = 6$ and $h = 12$, respectively.

Table 9 reports the out-of-sample forecast evaluation statistics.[10] The volatility factor based model, $M_{IP,5}^{NBER}$ exhibits the best result for all horizons. The maximum gain is achieved for $h = 1$ with a relative loss equal to 66.5% with respect to MSE. The benchmark model is rejected for all horizons with the exception of $h = 12$ with respect to both loss functions.

We implement the same forecasting analysis as above to the extracted economic factor, EF. Replacing IP with EF yields the following specifications.

$$(25)\qquad M_{EF,1}^{NBER}:\quad P(NBER_t = 1|I_{t-h}) = \Phi\left(\beta_0^1 + \beta_1^1 EF_{t-h}^h\right),$$

$$(26-28)\qquad M_{EF,i}^{NBER}:\quad P(NBER_t = 1|I_{t-h}) = \Phi\left(\beta_0^i + \beta_1^i EF_{t-h}^h + \beta_2^i Y_{i-1,t-h}^h\right),\quad i \in \{2,3,4\},$$

$$(29)\qquad M_{EF,5}^{NBER}:\quad P(NBER_t = 1|I_{t-h}) = \Phi\left(\beta_0^5 + \beta_1^5 EF_{t-h}^h + \beta_2^5 VF_{t-h}\right).$$

[10] Note that for the probit model evaluation, we are penalizing positive errors twice as much as negative errors instead. This is consistent with the idea of penalizing a model more heavily when it misses a downward movement in the economy.

Tables 10 and 11 present the full sample and out-of-sample results respectively. For the full sample, similarly to the IP based probit models, $M_{IP,2}^{NBER}$ provides the minimum loss for $h = 1{,}3$, $M_{IP,5}^{NBER}$ for $h = 6$, and $M_{IP,4}^{NBER}$for $h = 12$. Out-of-sample results are also qualitatively very similar to the case of IP based models. The benchmark is rejected for all horizons except for $h = 12$ with respect to both loss functions and the best performing model is again $M_{IP,5}^{NBER}$.

Summing up, the probit-based predictive analysis indicates that the realized volatility measures – especially the extracted volatility factor – contain useful information that improves predictions of the NBER-dated recessions in-sample and out-of-sample.

4.3.2 Nonlinear Dynamic Factor Model-Based Predictions of Recessions

This section considers nonlinear versions of the common dynamic factor models specified for financial volatility and economic activity described in section 4.1. In the factor volatility model, we allow both the drift and variance of the common factor to vary across different regimes with switches driven by an unobservable Markov process. This characterization allows for potential time-varying and countercyclical volatility dynamics. We let the drift and variance to switch between phases, without imposing any *a priori* assumption to restrict their values. The transition equation for the factor volatility (5) is now replaced with:

$$(5') \qquad VF_t = \alpha_{S_t^v} + \phi VF_{t-1} + \epsilon_t^v, \qquad \epsilon_t^v \sim NID(0, \sigma_v^2),$$

where $\alpha_{S_t^v} = \alpha_0(1 - S_t^v) + \alpha_1 S_t^v$ and $\sigma_{S_t^v}^2 = \sigma_0^2(1 - S_t^v) + \sigma_1^2 S_t^v$. S_t^v is the state variable that governs the regimes for the volatility factor. This state variable takes values 0 or 1, according to a first order two-state Markov process, with transition probabilities given by $p_{ij}^v = \Pr[S_t^v = j | S_{t-1}^v = i]$ where $i, j = 0, 1$. States 0 and 1 represent low and high volatility periods, respectively. The nonlinear dynamic factor model of the volatility measures is composed of equations (4) and (5').

Similarly, in the context of the economic factor model, we allow the drift of the common factor to switch between recessions and expansions. The transition equation for the economic factor (7) is replaced with:

$$(7') \qquad EF_t = \alpha_{S_t^e} + \phi EF_{t-1} + \epsilon_t^e, \qquad \epsilon_t^e \sim NID(0, \sigma_e^2),$$

where $\alpha_{S_t^e} = \alpha_0(1 - S_t^e) + \alpha_1 S_t^e$, and S_t^e is the state variable that drives dynamics of the economic factor with transition probabilities $p_{ij}^e = \Pr[S_t^e = j | S_{t-1}^e = i]$. States 0 and 1 are associated with low and high values of the economic factor, respectively. The dynamic factor economic model is now composed of the equations (6), (7'), and (8).

The models are estimated by numerical optimization. We first cast them in state space form and then combine a nonlinear discrete version of the Kalman filter with Hamilton's (1989) filter using Kim's (1994) approximate maximum likelihood method. This allows the estimation of the unobserved state vector and the Markov state probabilities using the observable data. A nonlinear optimization procedure is used to maximize the likelihood function, which is based on the probabilities of the Markov states. Predictions of the factors and the Markov probabilities are obtained from the filter.

Table 12 presents the maximum-likelihood estimates of the nonlinear common factor model of realized volatilities. The model distinguishes between two different levels of volatility, producing a classification of high versus low volatility regimes. All regime switching parameters are highly statistically significant. The intercept estimate for the level of volatility is around 0.24 in the high volatility regime, whereas it is around 0.15 in the low volatility regime. The standard deviation of the factor in the high volatility regime is around 0.2, whereas it is close to 0.07 in the low volatility regime. This indicates that the *volatility of volatility* is positively related with the level of volatility. Transition probability estimates reveal that the low volatility regime is more persistent than the high volatility regime, which is in line with the documented dynamics of financial volatility, e.g. Andersen, Bollerslev, Diebold, and Labys (2003). The factor loading of market realized volatility is normalized to 1 to provide a scale for the common factor. Note that this has no effect on the time series properties of the extracted factor. The other two realized volatility series are positively correlated with the common factor with statistically significant factor loadings.

Table 13 presents the maximum likelihood estimates of parameters and standard deviations of Markov-switching dynamic factor models of the real economy. The intercept of the economic factor during recessions is estimated to be around -1.27, whereas the one for expansions is around 0.82. Both parameters are statistically significant, supporting the presence of asymmetry in the mean behavior of the common economic factor. Expansions, characterized by positive growth, are more persistent than recessions, which are shorter and more abrupt. Factor loadings for all series are significant and positive indicating positive correlation with the factor. The autoregressive coefficients in the idiosyncratic components and error variances are also statistically significant for all series, indicating persistent sectoral dynamics.

Given that we are interested in predicting the beginning and end of the Markov phases, we need a decision rule to convert the probabilities produced by the nonlinear dynamic factor model into turning point dates. One approach, used by Hamilton (1989) among others, is to classify a turning point as occurring when the probabilities move from below 50% to above 50% or vice versa. This has an intuitive appeal as it separates times when an expansion state is more likely from those when a recession state is more likely. We apply the same rule to distinguish economic expansions and recessions as well as high volatility versus low volatility states. We then compare the chronology obtained from the volatility factor with that of the economic factor and with the NBER reference dates to analyze the lead-lag relationship between the economic states and the volatility states.

The smoothed probabilities from the economic and volatility models are plotted in Figure 4. The probabilities of recessions from the economic factor closely match the NBER business cycle classification, rising above 50% during recessions, and reaching values close to zero during expansions. Noticeably, the high volatility states obtained from the volatility factor are strongly correlated with NBER recessions and the economic model predictions. Each high volatility period is associated with economic recessions, with the exception of 1987 stock market crash. The volatility factor moves ahead of the economic factor and of most NBER recessions, giving early warning signals.

Table 14 reports the peak signals from the economic and realized volatility factors and the reference business cycle chronology from the NBER Business Cycle Committee.[11] The economic factor, EF, is on average coincident with recessions. On the other hand, the volatility factor, VF, leads all economic recessions, with the exception of the 1990-1991 recession – in this case, the volatility factor rises at, not before, the onset of this recession.

[11] Note that these signals are based on the smoothed probabilities of recession obtained from a sample that excludes recessions in the late 1950s and in 1960s. This explains some differences in the peak dates compared to Chauvet and Hamilton (2006) and in Chauvet and Piger (2008).

Notice that before the severe double-dip recession in 1980-1981 to 1982, the probabilities of high volatility state increase, signaling the recession that started in January 1980 with a five month lead. Before the 1981-1982 recession, the probabilities of high volatility regime rise again four months before the recession started. Noticeably, starting from early 1998, the probabilities of high volatility regime rise above 50% and remain high until after the official ending of the 2001 recession. The increase in volatility is associated with the uncertainty surrounding the currency crises experienced by Russia in 1998, Brazil in 1999, and Argentina from 1999 to 2001. Interestingly, the probabilities of high volatility regime also remained above 50% even after the 2001 recession had ended, reflecting the great uncertainty during the 'jobless recovery' between 2002-2003. In fact, the weak economic activity during this period led most to believe that the recession had not ended. This was reflected on the NBER Business Cycle Dating Committee's decision to delay announcement that the recession had ended in 2001 until mid 2003. The results indicate that the common realized volatility factor has information about future economic activity and is therefore useful in anticipating beginnings of recessions.

We also provide an out-of-sample real time analysis of the last five years of the sample using the nonlinear dynamic factor model of volatility and the nonlinear economic dynamic factor model.[12] Given the unexpected severity of the recent 2007-2009 recession, this period offers an ideal environment to evaluate the performance of the extracted common volatility factor model in signaling the downturn. As shown in Table 14, the nonlinear factor anticipates the beginning of the recession with a 6-month lead. Figure 5 plots the out-of-sample probabilities of high volatility state from 2004:10 to 2009:9. Around mid-2007 there is a steep increase in the probabilities. This is when first signs of distress in the financial market due to housing market problems made headlines. The probabilities remained high until the end of the sample, and their rises closely match periods of financial turmoil in the first and last two quarters of 2008.

5. CONCLUSION

We analyze the predictive value of various volatility measures for economic activity by considering stock and bond market dynamics. Inspired by recent developments in the financial volatility literature, we construct measures of realized volatility from the aggregate stock market,

[12] The real time data for the coincident series underlying the factor has been collected by Chauvet, and the real time probabilities of recession posted monthly at http://sites.google.com/site/marcellechauvet/probabilities-of-recession.

and industry level stocks, and from the bond market. Monthly measures of realized volatility are obtained by aggregating information in the daily series. This method provides observable asset return volatility series, which allows assessment of their predictive power and relationship with the economy.

We model log realized volatility as composed of a long-run component that is common across all series and short-run sectoral components. The dynamic factor framework extracts a long-run component that represents common information in the realized volatility series as a single smoothed factor, and separates out transitory movements inherent to each series. We find that there are substantial advantages in extracting volatility components. The realized volatilities – especially their long run component – help predict industrial production growth and a coincident indicator of the business cycle. Lagged values of the realized volatility measures and of the extracted common volatility factor, when incorporated into predictive regressions for different measures of economic activity significantly improve the model fit in and out-of-sample.

The recent financial crisis and economic recession have revived widespread interest in predicting business cycle turning points rather than just focusing on linear point forecasts. We conduct event timing analysis to predict business cycle phases by estimating both probit models and nonlinear Markov switching dynamic factor models. Thus, we further extend the previous analysis by extracting a nonlinear long run volatility component, which switches between regimes according to the state of financial markets. We find that realized volatility improves the fit of probit regressions to predict NBER recessions. Further, allowing for asymmetric behavior of the long run component of the realized volatility series significantly improves prediction of business cycle peaks. The nonlinear long run volatility factor consistently enters into a high volatility state prior to all economic recessions. The in-sample and out of sample turning point analysis reveals that the volatility factor consistently leads business cycle peaks.

Finally, we implement a real time out-of-sample analysis and find that the nonlinear volatility factor model performs remarkably well in anticipating the recent 2007-2009 recession. In addition, spikes in the probabilities of high volatility state closely match signals of financial distress during this period.

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Table 1: Maximum Likelihood Estimates of the
Dynamic Factor Volatility Model

Parameter	Estimate
α	0.909
	(0.19)
ϕ	0.917
	(0.02)
λ_1	0.127
	(0.01)
λ_2	0.118
	(0.01)
λ_3	0.082
	(0.01)
σ_{u_1}	0.337
	(0.01)
σ_{u_2}	0.144
	(0.01)
σ_{u_3}	0.488
	(0.02)
Log-L	832.01

The monthly sample runs from 1971:9 to 2009:9. Asymptotic standard errors in parentheses correspond to the diagonal elements of the inverse hessian obtained through numerical calculation. The variance of the common factor (σ_v^2) is set to one for identification.

Table 2: Maximum Likelihood Estimates of the Dynamic Economic Factor Model

Parameter	Estimate	Parameter	Estimate
α	0.224	ψ_2	-0.166
	(0.06)		(0.05)
ϕ	0.574	ψ_3	-0.320
	(0.06)		(0.05)
λ_1	0.449	ψ_4	0.915
	(0.03)		(0.05)
λ_2	0.237	σ_{ω_1}	0.519
	(0.02)		(0.02)
λ_3	0.425	σ_{ω_2}	0.561
	(0.03)		(0.02)
λ_4	0.152	σ_{ω_3}	0.839
	(0.01)		(0.03)
ψ_1	-0.194	σ_{ω_4}	0.519
	(0.06)		(0.01)
Log-L	495.89		

The monthly sample runs from 1971:9 to 2009:9. Asymptotic standard errors in parentheses correspond to the diagonal elements of the inverse hessian obtained through numerical calculation. The variance of the common economic factor (σ_e^2) is set to one for identification in each model.

Table 3: Full Sample Evaluation of Predictive Regressions for IP Growth

h	Best Model	Relative MSE Loss	GC p-value
1	M_5^{IP}	94.77%	**0.000**
3	M_5^{IP}	86.09%	**0.000**
6	M_5^{IP}	89.00%	**0.000**
12	M_5^{IP}	92.86%	**0.000**

The monthly sample runs from 1971:9 to 2009:9. M_1^{IP} is the benchmark regression model using lags of IP. Models M_2^{IP} - M_5^{IP} include lags of RV based predictors besides lagged IP growth. GC p-value is the asymptotic p-value from the Granger Causality test. h denotes cumulative forecast horizon in months.

Table 4: Out of Sample Forecast Evaluation of Predictive Regressions for IP Growth

	MSE			$LINLIN$		
h	Best Model	Relative Loss	RC p-value	Best Model	Relative Loss	RC p-value
1	M_5^{IP}	88.29%	**0.096**	M_5^{IP}	94.48%	0.200
3	M_5^{IP}	75.45%	**0.086**	M_5^{IP}	92.10%	0.262
6	M_5^{IP}	72.84%	**0.084**	M_5^{IP}	90.91%	0.258
12	M_5^{IP}	90.32%	0.146	M_1^{IP}	100%	1.000

The estimation period is from 1971:9 to 2004:9. The out of sample period consists of the remaining 5 years in the sample, from 2004:10 to 2009:09. M_1^{IP} is the benchmark regression model using lags of IP. Models M_2^{IP} - M_5^{IP} include lags of RV based predictors besides lagged IP growth. Relative minimum loss and White's reality check (RC) p-value are reported under MSE and $LINLIN$ loss functions. h denotes cumulative forecast horizon in months.

Table 5: Out of Sample Forecast Evaluation of Predictive Regressions for IP Growth with Real-time Data

	MSE			$LINLIN$		
h	Best Model	Relative Loss	RC p-value	Best Model	Relative Loss	RC p-value
1	M_5^{IP}	88.58%	**0.092**	M_5^{IP}	94.10%	0.164
3	M_5^{IP}	71.52%	**0.062**	M_5^{IP}	89.06%	0.144
6	M_5^{IP}	69.53%	**0.062**	M_5^{IP}	85.19%	**0.088**
12	M_5^{IP}	87.98%	**0.092**	M_5^{IP}	98.08%	0.482

The estimation period is from 1971:9 to 2004:9. The real time out of sample period consists of the remaining 5 years in the sample, from 2004:10 to 2009:09. We use *vintages* of IP, corresponding to their values as they would have appeared at the end of each month from October 2004 to September 2009. For each vintage, the sample collected begins in September 1971 and ends with the most recent data available for that vintage. M_1^{IP} is the benchmark regression model using lags of IP. Models M_2^{IP} - M_5^{IP} include lags of RV based predictors besides lagged IP growth. Relative minimum loss and White's reality check (RC) p-value are reported under MSE and $LINLIN$ loss functions. h denotes cumulative forecast horizon in months.

Table 6: Full Sample Evaluation of Predictive Regressions for the Economic Factor

h	Best Model	Relative MSE Loss	GC p-value
1	M_2^{EF}	96.72%	**0.002**
3	M_5^{EF}	88.09%	**0.000**
6	M_5^{EF}	88.20%	**0.000**
12	M_5^{EF}	93.13%	**0.000**

The monthly sample runs from 1971:9 to 2009:9. M_1^{EF} is the benchmark regression model using lags of economic growth. Models M_2^{EF} - M_5^{EF} include lags of RV based predictors besides lagged economic growth. GC p-value is the asymptotic p-value from the Granger Causality test. h denotes cumulative forecast horizon in months.

Table 7: Out of Sample Forecast Evaluation of Predictive Regressions for the Economic Factor

h	MSE			$LINLIN$		
	Best Model	Relative Loss	RC p-value	Best Model	Relative Loss	RC p-value
1	M_5^{EF}	89.68%	0.216	M_5^{EF}	96.03%	0.358
3	M_5^{EF}	73.77%	**0.090**	M_5^{EF}	88.61%	0.160
6	M_5^{EF}	73.76%	**0.094**	M_5^{EF}	91.03%	0.240
12	M_5^{EF}	92.38%	0.164	M_1^{EF}	100%	1.000

The estimation period is from 1971:9 to 2004:9. The out of sample period consists of the remaining 5 years in the sample, from 2004:10 to 2009:09. M_1^{EF} is the benchmark regression model using lags of economic growth. Models M_2^{EF} - M_5^{EF} include lags of RV based predictors besides lagged economic growth. Relative minimum loss and White's reality check (RC) p-value are reported under MSE and $LINLIN$ loss functions. h denotes cumulative forecast horizon in months.

Table 8: Full Sample Evaluation of Probit Predictions for NBER Using IP and Volatility Variables

h	Best Model	Relative MSE Loss
1	$M_{IP,2}^{NBER}$	81.97%
3	$M_{IP,2}^{NBER}$	93.06%
6	$M_{IP,5}^{NBER}$	94.42%
12	$M_{IP,4}^{NBER}$	98.91%

The sample is from 1971:9 to 2009:9. $M_{IP,1}^{NBER}$ is the benchmark probit model using lagged IP growth. Models $M_{IP,2}^{NBER}$ - $M_{IP,5}^{NBER}$ include the RV based predictor besides lagged IP growth. We assess predictive power by comparing probit probabilities with NBER recessions. h denotes forecast horizon in months.

Table 9: Out-of-Sample Evaluation of Probit Predictions for NBER Using IP and Volatility Variables

h	MSE			$LINLIN$		
	Best Model	Relative Loss	RC p-value	Best Model	Relative Loss	RC p-value
1	$M_{IP,5}^{NBER}$	66.55%	**0.002**	$M_{IP,5}^{NBER}$	73.29%	**0.004**
3	$M_{IP,5}^{NBER}$	80.98%	**0.036**	$M_{IP,5}^{NBER}$	80.06%	**0.010**
6	$M_{IP,5}^{NBER}$	87.72%	**0.082**	$M_{IP,5}^{NBER}$	87.75%	**0.016**
12	$M_{IP,5}^{NBER}$	98.74%	0.566	$M_{IP,5}^{NBER}$	99.11%	0.456

The estimation period is from 1971:9 to 2004:9. The out of sample period consists of the remaining 5 years in the sample, from 2004:10 to 2009:09. $M_{IP,1}^{NBER}$ is the benchmark probit model using lagged IP growth. Models $M_{IP,2}^{NBER}$ - $M_{IP,5}^{NBER}$ include the RV based predictor besides lagged IP growth. We assess predictive power by comparing probit probabilities with NBER recessions. Relative minimum loss and White's reality check (RC) p-value are reported under MSE and $LINLIN$ loss functions. h denotes forecast horizon in months.

Table 10: Full Sample Evaluation of Probit Predictions for NBER with using the Economic Factor and Volatility Variables

h	Best Model	Relative MSE Loss
1	$M_{EF,2}^{NBER}$	83.15%
3	$M_{EF,2}^{NBER}$	95.77%
6	$M_{EF,5}^{NBER}$	95.61%
12	$M_{EF,4}^{NBER}$	98.90%

The sample is from 1971:9 to 2009:9. $M_{EF,1}^{NBER}$ is the benchmark probit model using lags of economic growth. Models $M_{EF,2}^{NBER}$ - $M_{EF,5}^{NBER}$ include the RV based predictor besides lagged economic growth. We assess predictive power by comparing probit probabilities with NBER recessions. h denotes forecast horizon in months.

Table 11: Out-of-Sample Evaluation of Probit Forecasts for NBER Using the Economic Factor and Additional Volatility Variables

h	MSE			$LINLIN$		
	Best Model	Relative Loss	RC p-value	Best Model	Relative Loss	RC p-value
1	$M_{EF,5}^{NBER}$	74.21%	**0.012**	$M_{EF,5}^{NBER}$	78.41%	**0.000**
3	$M_{EF,5}^{NBER}$	88.15%	**0.080**	$M_{EF,5}^{NBER}$	84.26%	**0.002**
6	$M_{EF,5}^{NBER}$	90.67%	**0.084**	$M_{EF,5}^{NBER}$	89.10%	**0.018**
12	$M_{EF,4}^{NBER}$	98.70%	0.540	$M_{EF,5}^{NBER}$	99.17%	0.484

The estimation period is from 1971:9 to 2004:9. The out of sample period consists of the remaining 5 years in the sample, from 2004:10 to 2009:09. $M_{EF,1}^{NBER}$ is the benchmark probit model using lagged economic growth. Models $M_{IP,2}^{NBER}$ - $M_{IP,5}^{NBER}$ include the RV based predictor besides lagged economic growth. We assess predictive power by comparing probit probabilities with NBER recessions. Relative minimum loss and White's reality check (RC) p-value are reported under MSE and $LINLIN$ loss functions. h denotes forecast horizon in months.

Table 12: Maximum Likelihood Estimates of the Nonlinear Dynamic Factor Volatility Model

Parameter	Estimate	Parameter	Estimate
α_1	0.239	σ_1	0.191
	(0.06)		(0.03)
α_0	0.146	σ_0	0.072
	(0.04)		(0.01)
p_{11}	0.915	σ_{u_1}	0.332
	(0.04)		(0.01)
p_{00}	0.965	σ_{u_2}	0.145
	(0.02)		(0.01)
ϕ	0.874	σ_{u_3}	0.489
	(0.03)		(0.02)
λ_2	0.925		
	(0.01)		
λ_3	0.642		
	(0.02)		
Log-L	851.36		

The monthly sample runs from 1971:9 to 2009:9. Asymptotic standard errors in parentheses correspond to the diagonal elements of the inverse hessian obtained through numerical calculation. The factor loading of aggregate stock market volatility (λ_1) is normalized to one for identification.

Table 13: Maximum Likelihood Estimates of the Nonlinear Dynamic Economic Factor Model

Parameter	Estimate	Parameter	Estimate
α_1	-1.273	ψ_1	-0.160
	(0.32)		(0.06)
α_0	0.815	ψ_2	-0.168
	(0.14)		(0.05)
p_{11}	0.895	ψ_3	-0.300
	(0.05)		(0.05)
p_{00}	0.981	ψ_4	0.949
	(0.01)		(0.02)
ϕ	0.189	σ_{ω_1}	0.539
	(0.07)		(0.02)
λ_1	0.389	σ_{ω_2}	0.564
	(0.03)		(0.02)
λ_2	0.209	σ_{ω_3}	0.855
	(0.02)		(0.03)
λ_3	0.370	σ_{ω_4}	0.038
	(0.03)		(0.01)
λ_4	0.130		
	(0.01)		
Log-L	517.26		

The sample runs from 1971:9 to 2009:9. Asymptotic standard errors in parentheses correspond to the diagonal elements of the inverse hessian obtained through numerical calculation. The variance of the common factor (σ_e^2) is set to one for identification in each model.

Table 14: Business Cycle Turning Point Signals
of the Volatility Factor

NBER peaks	VF	EF peaks	VF
1973:11	-2	1974:04	-8
1980:01	-5	1980:03	-7
1981:07	-4	1981:09	-6
1990:07	0	1990:07	0
2001:03	-36	2001:01	-34
2007:12*	-6	2007:12	-6

The minus sign refers to the lead in which the models anticipate the recession dates.
(*) For the real time out of sample analysis we use *vintages* of the coincident series, corresponding to their values as they would have appeared at the end of each month from October 2004 to September 2009. For each vintage, the sample collected begins in September 1971 and ends with the most recent data available for that vintage.

Figure 1: Logarithm of Realized Volatility Measures and NBER dated Recessions

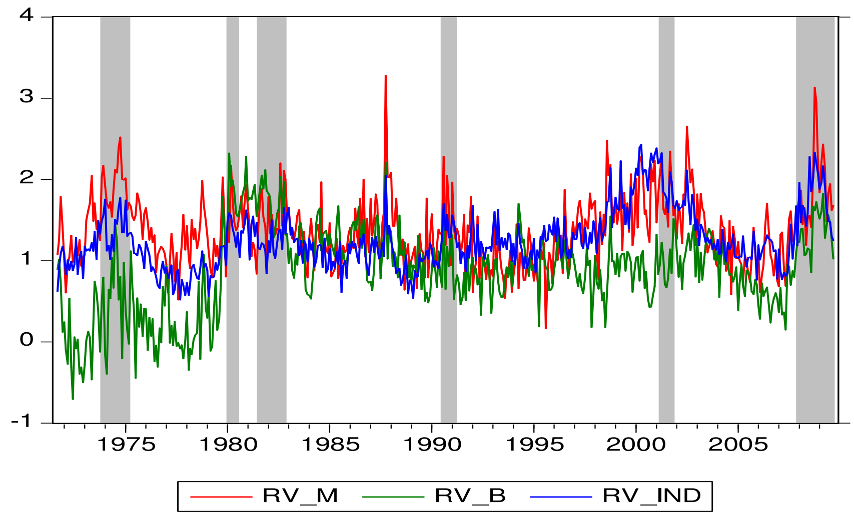

Figure 2: Common Linear Realized Volatility Factor and NBER Recessions

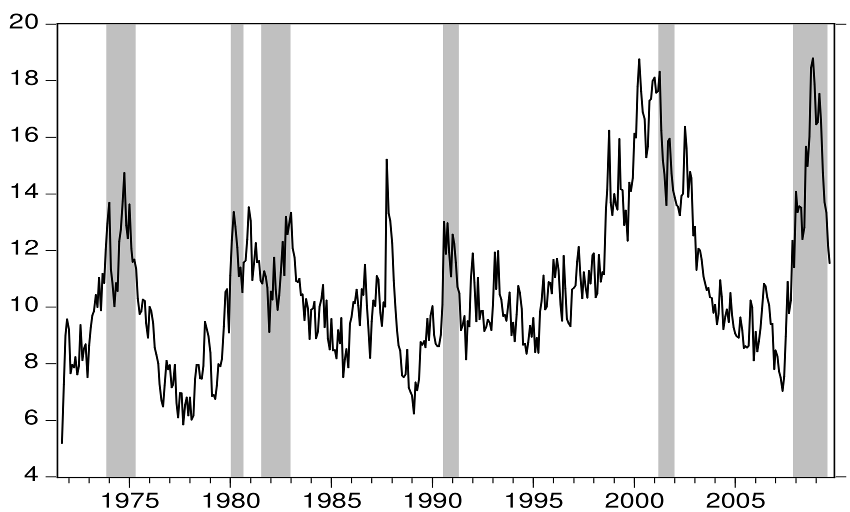

Figure 3: Common Volatility Factor, Economic Factor, and NBER Recessions

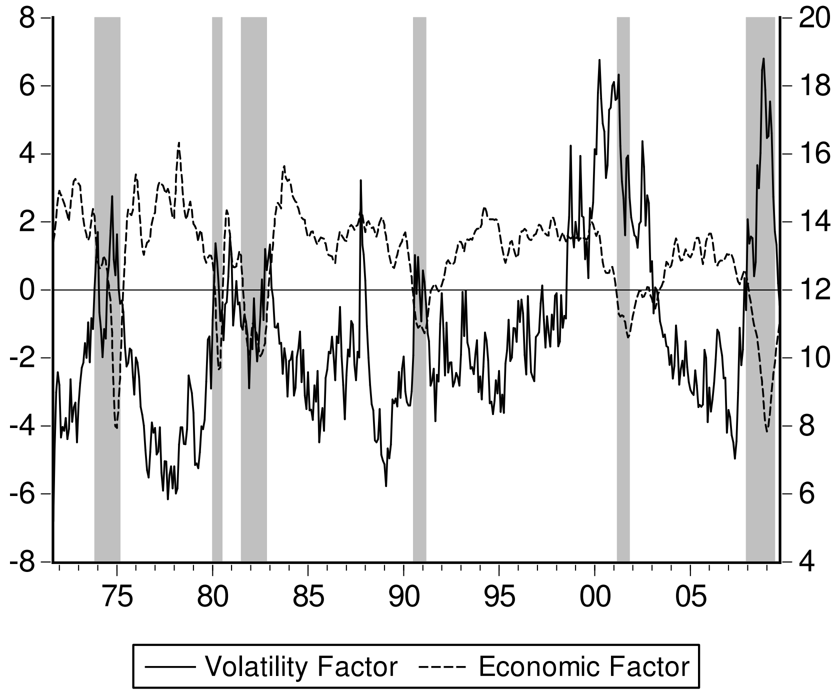

Figure 4: Smoothed Probabilities of the Volatility Factor (---) and of the Economic Factor (—), and NBER Recessions (Shaded Areas)

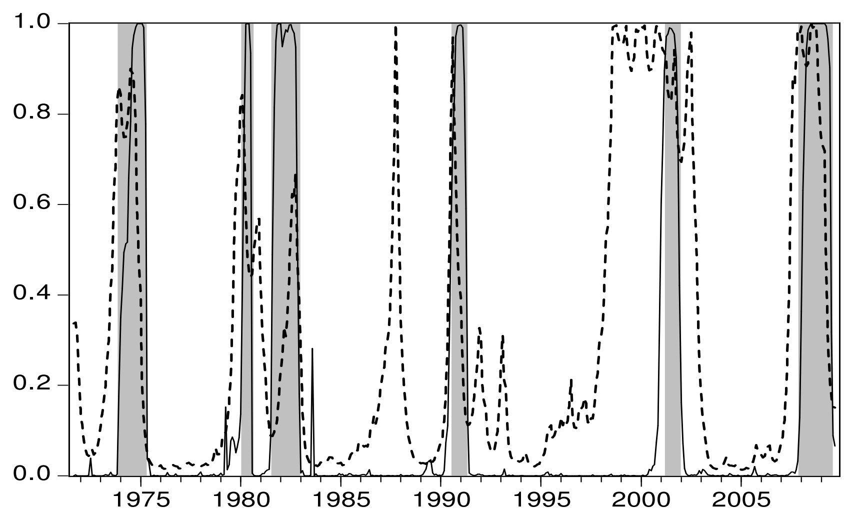

Figure 5: Out of sample Recursive Predictive Probabilities of High Volatility State in the 2007-2009 Recession