Financial Volatility and Economic Activity

Fabio Fornari
Antonio Mele

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Fabio Fornari
European Central Bank

Antonio Mele
London School of Economics

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Abstract

Does capital markets uncertainty affect the business cycle? We find that financial volatility predicts 30% of post-war economic activity in the United States, and that during the Great Moderation, aggregate stock market volatility explains, alone, up to 55% of real growth. In out-of-sample tests, we find that stock volatility helps predict turning points over and above traditional financial variables such as credit or term spreads, and other leading indicators. Combining stock volatility and the term spread leads to a proxy for (i) aggregate risk, (ii) risk-premiums and (iii) monetary policy, which is found to track, and anticipate, the business cycle. At the heart of our analysis is a notion of volatility based on a slowly changing measure of return variability. This volatility is designed to capture long-run uncertainty in capital markets, and is particularly successful at explaining trends in the economic activity at horizons of six months and one year.

1. Introduction

One systematic feature of modern capital markets is the countercyclical behavior of asset prices volatilities, such as those of common stocks, Treasury returns, or corporate bonds. For example, in the last fifty years, the S&P 500 return volatility was 14.18%, on average, annualized. Yet during recessions, this volatility increased to 17.39%, 23 per cent higher than the overall average. During expansions, however, this same volatility attained an average of 13.5%, a modest 4 per cent below the overall average.

That capital markets uncertainty is countercyclical does not naturally imply financial volatility might even anticipate real economic activity. Rather, two key questions arise: Does aggregate stock market volatility affect investment decisions in the real sector of the economy? Does volatility help predict the business cycle? These issues have outstanding policy implications, and are, of course, of immediate concern to corporate decision makers, even in the simple case where a sustained stock volatility merely anticipates, without affecting, the business cycle. Guided from this motivation, this paper aims to provide a systematic summary of the information financial volatility encodes about the development of the business cycle.

We analyze post-war economic activity in the United States, and find that movements in financial volatility are extremely informative about future economic activity. For example, we find that financial volatility explains between about 30% and 40% of the industrial production growth at horizons of one and two years. We successfully control these findings with macroeconomic variables. Some of these variables are standard, and include indexes of real leading indicators, or financial variables such as short-term interest rates, the corporate spread, or stock returns. Other control variables are new, and include indicators of macroeconomic volatility. Together with financial volatility, indicators of macroeconomic volatility explain about 50% of the industrial production growth.

In the most recent sub-samples, stock market volatility explains, *alone*, between about 35% and 55% of future real economic activity, at horizons of one and two years. More generally, we find that the predicting power of stock market volatility has increased in the last twenty-five years, a period that includes a sustained decline in the volatility of real aggregates, notoriously dubbed as the "Great Moderation." Over this period, stock volatility has a predicting power that is quite comparable to that of a traditional leading indicator: the term spread. In fact, we demonstrate that combining the term spread with aggregate stock market volatility leads to a predicting block that anticipates the business cycle reasonably well, delivering quite isolated false signals of economic slowdowns, as summarized by National Bureau of Economic Research (NBER)- dated recessions, and virtually no such signals, over the Great Moderation. We argue that combining the term spread with stock market volatility helps

predict the business cycle, for two reasons: (i) aggregate stock market volatility conveys information about the general macroeconomic risk surrounding the economic environment; and (ii) the term spread subsumes information about risk-premiums and monetary policy. In other words, we suggest that aggregate risk, risk-premiums and monetary policy, provide complementary pieces of information about future movements in real macroeconomic aggregates. Needless to mention, we undertake out-of-sample experiments and submit these findings to reality checks. In these experiments, our combination forecast is able to anticipate all the NBER-dated recessions we could, given the data and estimation constraints our methods allow for, including that occurred during the 2007 subprime crisis.

Relating capital markets uncertainty to future economic fluctuations is an issue that has received little attention in both the empirical and theoretical literature. It was first raised by Schwert (1989a) and, more recently, by Campbell, Lettau, Malkiel and Xu (2001). Schwert concludes that stock market volatility does not anticipate major financial crises and panics, from 1834 to 1987. Rather, he shows, stock volatility rises after the onset of a crisis. Naturally, recessions may develop independently of financial crises and panics. Moreover, financial turmoil might precede recessions, as for example during the 2007 subprime crisis. Campbell, Lettau, Malkiel and Xu (2001) observe indeed that stock volatility might help predict GDP growth, with post-war data. Our paper provides a detailed empirical account of the many issues left unexplored in these two isolated contributions, such as: (i) the relations between financial volatility and both future real aggregates (industrial production growth) and the future general state of the economy (NBER business cycle dates), analyzed both in sample and over reality checks and other out-of-sample experiments; (ii) the information content brought about by a combined use of stock volatility with other predictors, such as, e.g., the term spread; (iii) the control of the findings, obtained through traditional business cycle predictors; (iv) the exploration of the predicting power of a number of financial volatility variables, on top of stock market volatility, such as the volatility of the term spread, the volatility of stock market volatility, the volatility of oil and metals returns or, even, the volatility of real economic aggregates; (v) the analysis of the historical periods, over which the predicting power of stock volatility seems to be the strongest, which we identify in the Great Moderation, as we have explained.

Figure 1 sketches the origins of our results. It depicts our post-war measure of aggregate stock market volatility, designed to smooth transitory episodes of high volatility, which unlikely link with the low frequency nature of the business cycle, as discussed in Section 3. Not only, then, does Figure 1 reveal that stock volatility is countercyclical, in that it raises during all NBER-dated recessions, as originally uncovered in seminal work by Schwert (1989b). Figure 1 also illustrates our findings that stock volatility anticipates NBER-dated recessions, increasing roughly one year ahead of any such recession, with the exception of the 1981-1982 recession, as we further elaborate in Section 4.

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Post hoc ergo propter hoc? Or, does a sustained stock market volatility create the premises for future economic slowdowns? The extant empirical literature mostly focusses on whether business cycle factors might explain stock volatility (e.g., Officer (1973), Schwert (1989b), Hamilton and Lin (1996), Brandt and Kang (2004), Engle and Rangel (2008), Adrian and Rosenberg (2008), Corradi, Distaso and Mele (2009)). Bloom (2009) and Bloom, Floetotto and Jaimovich (2009) are two important pieces our work relates to. Bloom (2009) shows, theoretically and empirically, that uncertainty shocks affect short-run fluctuations in economic activity. Bloom, Floetotto and Jaimovich (2009) show that uncertainty indexes are negatively correlated with future economic activity, in the short-run.

Our paper, and results, while consistent with the hypothesis of volatility spillovers over real aggregates, does not necessarily points in favour of this hypothesis. In Section 2, we provide arguments in support of both the "correlation" and "causation" scenarios. We show, with a simple example, that volatility might merely help predict the business cycle, even when there is not causal link between volatility and future economic activity. The mechanism is the following. If markets process information rationally and quickly, all the variables relating to future production growth and, hence, affecting asset valuation, also impinge upon stock volatility. Therefore, stock volatility helps predict decisions taken in the real sphere of the economy, in the presence of model's misspecification—i.e., when the econometrician's information set does not include the exact asset pricing model the markets use. At the same time, we do not rule out volatility spillovers. These spillovers may occur for reasons related to rational decisions, such as those put forward by Bloom (2009) and Bloom, Floetotto and Jaimovich (2009) in the context of a theory of nonconvex adjustment costs with time-varying uncertainty, as we shall review. Moreover, volatility spillovers might arise due to financial frictions. For instance, we shall explain, financial intermediaries, be they risk-averse or subject to institutional constraints, would scale back their lending activities after a rise in uncertainty, as expected collateral values might be damaged by an increased capital markets volatility. Finally, behavioral biases might channel capital markets uncertainty to macroeconomic slowdowns, an additional hypothesis we shall discuss.

The remainder of the paper is organized as follows. Surveys of the literature related to our paper are in the main text, as we now explain. In Section 2, we discuss hypotheses, and survey the literature, which helps rationalize our empirical findings. Sections 3 describes the data set and measurement methods. Section 4 hinges upon the extant literature about the predicting power of financial variables, and motivates the sets of predictors and controls that we employ in our in-sample and out-of-sample tests. Section 5 provides in-sample evidence. Section 6 contains out-of-sample results. Section 7 concludes. A short appendix gathers a few technical points omitted from the main text.

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2. Financial volatility and real economic activity: theoretical nexus

Why is stock market volatility countercyclical? Why does it help predict the business cycle? This section reviews a few theoretical arguments that attempt to answer these questions. Some of these arguments are new, and others rely on recent explanations of aggregate stock market fluctuations, the presence of financial frictions or nonconvex adjustment costs. In Section 2.1, we develop a simple laboratory model of a production economy, which illustrates why stock volatility can be a valid type of conditioning information to learn about the future state of the economy. Then, we review a number of channels that may lead stock volatility to be countercyclical, or even anticipate economic activity. These channels include time-varying expected returns (Section 2.2), the presence of nonconvex adjustment costs (Section 2.3), procyclicality of capital markets (Section 2.4) and, finally, behavioral biases induced by irrational assessments of economic developments (Section 2.5).

2.1. Production and incomplete information

Consider a two-period production economy with a monopolist firm. In the first period, the firm engages in a production decision. In the second period, the firm sells the output produced in the first period. This firm faces a linear inverse demand,

$$D^{-1}(Q) \equiv a + \tilde{v} - \lambda Q,$$

where a and λ are constants, Q is total demand, and $\tilde{v}$ is a demand shock. We assume that $\tilde{v} \sim N(0, \sigma^2)$, and that prior to production decisions, the firm observes a signal s on $\tilde{v}$, $s = \tilde{v} + \epsilon$, where $\epsilon \sim N(0, \sigma_\epsilon^2)$. Finally, we assume that: (i) the firm faces linear costs, i.e. $C(Q) = zQ$ for some constant $z > 0$; (ii) the firm's managers are risk-neutral, and maximize the value of the firm; and (iii) a safe asset is elastically supplied so as to make the safe interest rate zero. In Appendix A, we show that under these conditions, production takes place only when the signal s takes a sufficiently favorable cutoff value $\hat{s} \equiv -\frac{a-z}{\theta}$, where $\theta = \frac{n-1}{n}$, and n is the signal-to-noise ratio. Accordingly, the value of the firm (the stock price) P, production Q and return volatility Vol (say) are all functions of the current signal s, and equal

$$P(s) = \frac{\theta^2}{4\lambda}(s - \hat{s})^2 \, \mathbb{I}_{s>\hat{s}}, \quad Q(s) = \frac{\theta}{2\lambda}(s - \hat{s}) \, \mathbb{I}_{s>\hat{s}}, \quad \text{Vol}(s) = \frac{2\sigma\sqrt{1-\theta}}{\theta(s-\hat{s})}, \tag{1}$$

where $\mathbb{I}$ is the indicator function, and where return volatility is only defined when economic activity takes place, i.e. when $s > \hat{s}$. According to Eq. (1), production grows linearly with the signal s. The stock price, instead, "overreacts" to this signal in good times, as it increases disproportionately as s

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increases. Finally, volatility is strongly countercyclical, as it increases severely as signals on future demand worsen.

If we knew the structure of this economy, we could predict output by just observing the current stock price. Indeed, by Eq. (1), we could invert the observed stock price $P(s)$ for s, and then plug s in $Q(s)$. In fact, price and volatility would convey the *same* information about output, in this economy. However, consider an econometrician who is not aware of the exact pricing relations in Eq. (1), but who still observes realizations of price and volatility. Conditioning upon the realization of these variables facilitates identifying the state of the economy. Table 2.1 below reports a Monte Carlo experiment in which output is regressed on (i) volatility; (ii) price; and (iii) volatility and price. (See Appendix A for details on this experiment.)

Table 2.1:

Model's misspecification and the predictive ability of asset price and volatility

	const	Vol	R^2	const	Price	R^2	const	Vol	Price	R^2
Avg estim	0.32	-0.17	0.91	0.08	0.55	0.97	0.17	-0.06	0.36	0.99
Avg t-stat	100.88	-53.61		100.16	99.92		153.05	-71.86	14.45	

In this experiment, both prices and volatility help predict output, although none of these variables allows for a perfect prediction. An econometrician who ignores the exact nonlinear relations in Eq. (1), but understands the economics underlying output, asset prices and volatility, would benefit from using data on volatility to estimate the state of the economy.

2.2. *Time-varying expected returns*

Time-varying risk-aversion is perhaps the first channel the literature has identified as conducive to countercyclical volatility. Campbell and Cochrane (1999) consider a model with external habit formation, which predicts that risk-premiums and, hence, expected returns, are high during recessions, i.e. when investors' consumption gets closer to the habit level. Their model explains why risk-premiums are countercyclical, an empirical regularity known since Fama and French (1989) and Ferson and Harvey (1991). Barberis, Huang and Santos (2001) elaborate on prospect theory to generate a similar countercyclical variation in the expected returns.

However, countercyclical risk-premiums do not necessarily lead to countercyclical volatility. Mele (2007) develops a theoretical framework and shows that for stock volatility to be countercyclical, risk-premiums must increase more in bad times than they decrease in good. This condition is satisfied in the Campbell and Cochrane economy, but not necessarily in economies with alternative habit formation mechanisms. The intuition behind this risk-premium channel is that asset prices are discounted risk-adjusted expectations of future dividends. If risk-aversion widens more in bad times than it decreases in good, asset prices fluctuate more in bad times than in good. Naturally, asymmetric movements in risk-premiums can be activated by channels not strictly related to habit formation. For example, Basak and Cuoco (1998) model of restricted stock market participation predicts that risk-premiums are inversely and asymmetrically related to the market participants' consumption share. Danielsson, Shin and Zigrand (2009) consider a model with risk-neutral financial institutions subject to procyclical financial constraints. In their economy, the Sharpe ratio is positive, due to the constraints, and inversely and asymmetrically related to capital, as is stock volatility.

2.3. Uncertainty and irreversible investments

Option pricing theory predicts that uncertainty raises the value to wait. This conclusion often relies upon comparative statics, which track how "exercise boundaries" change with the "uncertainty parameters." Touzi (1999) confirms this general conclusion in the case where uncertainty is a stochastic process—the case of American options with stochastic volatility. Blooms (2009) models time-varying uncertainty of business conditions, assuming that total factor productivity has stochastic volatility. His model, which includes partial irreversible investments and nonconvex adjustment costs, predicts that firms freeze investments during uncertain times, as the value to waiting increases in such periods. Bloom, Floetotto and Jaimovich (2009) reach a similar conclusion within a calibrated real business cycle model: uncertainty shocks are impulses that generate rich propagation mechanisms.

2.4. Procyclicality

The previous models assume asset prices and volatility respond passively to changes in the economic conditions. An alternative assumption is that asset prices have the power to feed back the real economy, an hypothesis known as procyclicality of capital markets. The general idea underlying this hypothesis is that firms' capital structure matters in the presence of capital market frictions. One well-known mechanism is that in bad times, agency frictions make the cost of external funds increase and the availability of funds decrease, which amplifies small shocks occurring in the real sectors of the economy. For example, the financial accelerator hypothesis holds that in bad times,

financial intermediaries reduce their funding activities as the collateral value is also reduced in bad times. Bernanke, Gertler and Gilchrist (1999) present a unified view of how agency problems make funding opportunities depend on firms' collateral. Borio, Furfine and Lowe (2001) explain that the agents' misperception of risk might constitute an additional amplification mechanism. For example, the credit/GDP ratio might be strongly procyclical because financial intermediaries under-estimate risk in good times, and over-estimate risk in bad times, thereby lending too much in good times and too less in bad.

How does financial volatility relate to procyclicality? If financial intermediaries are risk-averse, or subject to institutional constraints, time varying volatility in capital markets might affect lending and investment decisions. Although a formal model of volatility spillovers goes well beyond the scope of this paper, we supply the following informal arguments. In bad times, when financial volatility increases, the value of future collateral becomes more uncertain. In anticipation of this increased uncertainty, the volume of funds financial intermediaries would supply decreases, with a possible cost increase, thereby exacerbating the current economic conditions. This explanation is not inconsistent with the mechanism put forward by Borio, Furfine and Lowe (2001). Indeed, if financial markets are rational and quick processors of information, it might be that financial volatility increases precisely towards the end of the build-up of risk-taking behavior in good times, but just enough before an economic downturn.

2.5.   Behavioral biases

Borio, Furfine and Lowe (2001) develop one behavioral explanation for the misperception of risk by market participants, based on *representativeness heuristic*. (See Shiller (1999) for a survey on behavioral explanations of asset price movements.) Representativeness heuristic is the human tendency to consider some events as being representative of a certain structured class of broader phenomena. For example, financial intermediaries may consider a momentum in economic data as reinforcing the view that the economy will continue to expand.

Representativeness heuristic might be responsible for the predicting power of financial volatility. Market participants might associate two otherwise separate concepts: high volatility in financial markets and slowdown in real economic activity. Thus, a period of high and persistent volatility on Wall Street might reinforce the view that the health of the economy is deteriorating, and this view might transmit to Main Street. *Anchoring* might be a related explanation. In our context, "volatility anchoring" would be an inadequate allowance for the effects financial volatility might really exert on the economic activity, in the counterfactual situation of absence of anchoring biases.

3.   Data and volatility measurement

We investigate the predictive power of financial volatility for the economic activity in the United States. Our data set includes (i) macroeconomic variables such as the seasonally adjusted industrial production index, the consumer price index, the unemployment rate and an index of leading indicators; and (ii) financial variables such as a stock price (total return) index, the price-dividend ratio, the government bond yield (10-year rate), the 3 month rate, the term spread and the corporate spread. We define the term spread as the difference between the 10 year government bond yield and the yield on 3 month Treasury Bills. Our measure of the corporate spread is the difference between the baa yield and the 10-year Government bond yield. Finally, our dataset includes the oil price index and a price index of metals. We make use of monthly observations from January 1957 to September 2008, for a total of 621 observations. All data are collected from the Global Financial Data, available through the ECB electronic library service, with the exception of the industrial production index, which is taken from the IMF Financial Statistics database.

3.1.   Economic activity

We quantify the predicting power of financial volatility on economic activity through two complementary search strategies.

- First, we predict the growth of industrial production at horizons of three, six, twelve and twenty-four months. Accordingly, we define log-changes in the industrial production index,

$$G_{t \to t+k} = \ln \left(\frac{\mathrm{IP}_{t+k}}{\mathrm{IP}_t} \right), \qquad k \in \{3, 6, 12, 24\}, \tag{2}$$

  where IP_t is the industrial production index as of month t.

- Second, we predict probabilities of recessions, by utilizing the NBER-dating series as a recession variable,

$$\mathrm{Rec}_t \equiv \mathbb{I}_{\mathrm{NBER}_t=1}, \tag{3}$$

  which equals one if the US economy is in recession at time t, and zero otherwise. We set the value of this series equal to zero even after the beginning of the last recession, which occurred in December 2007, as this recession was announced by the NBER business cycle dating committee in December 2008, after the end of our sample data.

3.2. Volatility

We use continuously compounded returns to track variations in price indexes. That is, given an asset index and its associated price P_t (such as a bond price index, or a stock price index), we define its return as of time t as,

$$R_t^{tot} \equiv \ln\left(\frac{P_t + D_t}{P_{t-1}}\right),$$

where D_t is the dividend paid off by the asset index. There are two fundamental issues involved in our volatility measurements:

(i) We wish to calculate return volatility induced by *fluctuations in prices*, not by fluctuations in the underlying dividends. Fluctuations in prices convey a better information content about the state of the economy. While dividend volatility is time-varying, this variability may be induced by factors not necessarily related to the business cycle.

(ii) We aim to extract the long-run component of this stock market volatility. Isolated episodes of financial turmoil are not necessarily informative about the future state of the economy. Consequently, they need to be smoothed out.

To address the first issue, we decompose the return R_t^{tot} as,

$$R_t^{tot} = R_t^p + R_t^d \tag{4}$$

where

$$R_t^p \equiv \ln\left(\frac{\mathrm{P/D}_t + 1}{\mathrm{P/D}_{t-1}}\right) \quad \text{and} \quad R_t^d \equiv \ln\left(\frac{D_t}{D_{t-1}}\right), \tag{5}$$

and where $\mathrm{P/D}_t$ is the price-dividend ratio as of time t. The decomposition in Eq. (4) disentangles the return component due to variation in the payoff (dividends) from the returns component due to the reaction of prices to changes in the economic environment. It is the volatility of the R_t^p component that we are mainly interested in.

To address the second issue, we define volatility as a moving average of past absolute returns,

$$\sigma_t^j(\ell) \equiv \sqrt{6\pi} \cdot \frac{1}{\ell} \sum_{i=1}^{\ell} \left| R_{t+1-i}^j \right|, \quad j \in \{p, tot\}, \tag{6}$$

where we use the lag ℓ to create volatility estimates from past returns.[1]

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[1] Fix j and ℓ, and for a given return series R_t, let $\bar{\sigma}_t(\ell) \equiv \frac{1}{\ell} \sum_{i=1}^{\ell} |R_{t+1-i}|$. The measure $\bar{\sigma}_t(\ell)$ is an estimate of the average volatility as of time t in the last ℓ periods, obtained with ℓ lagged absolute returns. To annualize this volatility

The idea to use absolute returns to track volatility goes back at least to Taylor (1986), Schwert (1989a,b) and Ding, Granger and Engle (1993). The advantage is that volatility estimates based on absolute financial returns tend to be more robust to the presence of outliers than volatility estimates based on squared returns, as noted by Davidian and Carroll (1987) in a general context. Instead, our device to use *moving averages* of past absolute returns is related to Officer (1973). While there might be alternative means to measure the long-run component of return volatility, the advantage of the volatility estimator in Eq. (6) lies in its concept simplification and implementation easiness.

While implementing Eq. (6), we used both total return volatility $\sigma_t^{tot}(\cdot)$ and the volatility $\sigma_t^p(\cdot)$ induced by fluctuations in the price-dividend ratio. We also experimented Eq. (6) with different values of the window ℓ. Our empirical results suggest that the choice of ℓ is important. The predictive power of volatility seems to be somewhat limited when ℓ equals 1 or 2 months—volatility is quite noisy with such windows, and unlikely to link with the business cycle. Its predicting power increases dramatically when $\ell = 6$ or $\ell = 12$. However, we shall avoid using lags ℓ larger than twelve or eighteen months as larger windows might possibly induce unit roots in the resulting volatility measures. Finally, Eqs. (4)-(5) rely on the assumption that dividends are paid monthly. Since we use monthly data, and dividends are only paid quarterly, the decomposition in Eqs. (4)-(5) needs to be corrected. In Appendix B, we provide details on how we cope with this complication.

3.3. Alternative volatility measures

Volatility can be estimated through a range of alternative means, as surveyed by Poon and Granger (2003). A classical definition of return volatility is based on the notion of realized volatility, obtained through sums of observed squared returns within a reference period. Following the lead of Merton (1980), this notion has been intensively utilized in recent years (see, e.g., Andersen, Bollerslev and Diebold (2009), for a survey). For example, Schwert (1989b) defines monthly volatility as the standard deviation of the daily returns within a month. Schwert finds that this volatility measure can not be predicted by a similar volatility measure obtained for macroeconomic variables. More recently, Campbell, Lettau, Malkiel and Xu (2001) use this same measure to gauge the impact of stock volatility on GDP growth.

Our focus in this paper differs from Schwert's, in that we do not aim at explaining financial volatil-

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estimate, we multiply $\bar{\sigma}_t(\ell)$ by $\sqrt{12}$. The term $\sqrt{6\pi}$ in Eq. (6) arises for the following reason. If we assume that a given return $R = \sigma u$, where σ is a positive constant and u is a standard unit normal, then $E(|R|) = \sigma\sqrt{\frac{2}{\pi}}$. Eq. (6) follows by multiplying $\sqrt{12}\bar{\sigma}_t(\ell)$ by $\sqrt{\frac{\pi}{2}}$. This correction has been suggested by Schwert (1989) in a related context. Naturally, our results do not depend on this scaling factor.

ity through past macroeconomic volatility. Rather, our target is to predict future macroeconomic activity (i.e. first moments), not macroeconomic volatility (i.e. second moments), through financial volatility, as in Campbell, Lettau, Malkiel and Xu (2001). Moreover, our volatility measures are purposely designed to smooth short-lived information. Our device to include information up to a lag ℓ in Eq. (6) is designed to isolate the long-run component of financial volatility, which is the one that likely relates to the business cycle frequency. In principle, ARCH models might also be used to estimate financial volatility, both short-run and long-run volatility. The advantage of the volatility estimator in Eq. (6) is that it is essentially nonparametric and simple to implement.

4. Predictors

4.1. Stock volatility as a leading indicator: preliminary scrutiny

Figure 1 depicts the time series behavior of two fundamental variables of this paper: (i) aggregate stock market volatility, $\sigma_t^p(\ell)$ in Eq. (6), defined for $\ell = 12$ months, and (ii) industrial production growth at one year, $G_{t \to t+12}$ in Eq. (2). Remarkably, all NBER-dated recessions (the shaded areas in the picture) are associated with an increase in stock market volatility. Moreover, stock volatility is negatively correlated with one year growth, at about -37%. This is the countercyclical property of stock volatility.

Figure 2 compares stock volatility with two traditional financial leading indicators: the term spread and the corporate spread. Stock volatility is negatively correlated with the term spread, at about 10%, and positively correlated with the corporate spread, at about 39%. Figure 3 depicts cross-correlations, and 95% confidence intervals, of one year growth with (i) stock volatility, (ii) the term spread and (iii) the corporate spread. We use as a sampling period, that from January 1983 to September 2008, which includes the Great Moderation. It is over this period that stock volatility exerts its largest predicting power. In particular, high stock volatility predicts low growth, with a correlation of about -18% for a eighteen months lead, and about -40% for a three years lead. These figures are quite comparable, in absolute value, to those for the term spread (see right-top panel). Finally, the right-bottom panel of Figure 3 confirms the coincident nature of the corporate spread, which highly correlates with $G_{t \to t+12}$, but only over the lead period up to twelve months.

We further investigate the leading properties of stock volatility, by performing the following linear regression:

$$\sigma_t = c + \sum_{i \in \{3,12,24,36\}} b_i \sigma_{t-i} + \gamma_1 \mathbb{I}_{t \in \mathcal{O}(\text{NBER}_t=1)} + \gamma_2 \mathbb{I}_{\text{NBER}_t=1} + u_t^\sigma,$$

where: $\sigma_t \equiv \sigma_t^p(12)$; the indicator function $\mathbb{I}_{t \in \mathcal{O}(\text{NBER}_t=1)}$ is always zero, except during the twelve

months preceding any NBER-dated recession; $\mathbb{I}_{\mathrm{NBER}_t=1}$ equals one only during any NBER-dated recession, and is zero otherwise; finally, u_t^σ is a residual term.

Table 4.1 reports the estimates and t-statistics, computed through heteroskedasticity and autocorrelation consistent standard errors, for the parameters c, b_i and γ_i. Over the whole sample, the estimates of γ_1 and γ_2 are positive and highly significant. Over the sampling period from 1957 to 1982, the estimate for γ_1, while positive, is no longer significant, which largely reflects the fact that stock volatility did not raise before the 1981-1982 recession. Over the sample period including the Great Moderation, however, the estimates of γ_1 and γ_2 are positive, and quite comparable both in size and significance. Thus, according to this preliminary evidence, not only is stock volatility countercyclical. It also anticipates economic activity, especially during the period including the Great Moderation.

4.2. Predicting blocks of economic activity, and controls

Financial volatility might be countercyclical, and anticipate the business cycle, because it merely reflects information conveyed by other factors. To assess if financial volatility accounts for additional pieces of information, we need to specify sets of control variables. Table 4.2 lists all the variables that we use in this paper, be they financial volatility variables or other.

First, we include the volatility of three financial variables: stock market returns, the term spread, and the corporate spread. For reasons developed below, we include a fourth financial volatility variable: the volatility of stock market volatility. Stock volatility is computed as outlined in Section 3.2. We use the estimator of the volatility induced by the price-dividend ratio fluctuations, $\sigma_t^p(\ell)$, and smooth realized volatilities with a window lag equal to $\ell = 12$ months (see Eq. (6)). The volatility of the term spread and that of the corporate spread are computed similarly, as follows:

$$\sigma_t^y(\ell) \equiv \sqrt{6\pi} \cdot \frac{1}{\ell} \sum_{i=1}^{\ell} |\Delta y_{t+1-i}|, \tag{7}$$

where Δy_t is the monthly variation of the variable of interest y_t. For the term spread, we take $y_t = \mathrm{term\_spread}_t$ and $y_t = \mathrm{corp\_spread}_t$, with straight forward notation. Finally, we compute the volatility of stock market volatility, as follows:

$$\mathrm{Vol\text{-}Vol}_{t+\ell}^j \equiv \frac{1}{\ell} \sum_{i=1}^{\ell} \left| \sigma_{t+i}^j(\ell) - \hat{\sigma}_{t+i}^j \right|, \quad \hat{\sigma}_{t+\ell}^j \equiv \frac{1}{\ell} \sum_{i=1}^{\ell} \sigma_{t+i}^j(\ell), \quad t = 1, \cdots, T - \ell, \tag{8}$$

where stock market volatility at month t, $\sigma_t^j(\ell)$, is defined as in Eq. (6).

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The second set of variables includes controls, relating to volatility of five macroeconomic variables: the return on the oil price index, the growth of industrial production, inflation, the unemployment rate and metals prices. These volatilities are computed through Eq. (7), as follows. Define the inflation rate $\text{infl}_t = \ln(\frac{\text{CPI}_t}{\text{CPI}_{t-1}})$, where CPI_t is the consumer price index as of month t, and let UR_t and MP_t be the unemployment and metal price index at month t. In Eq. (7), we use $y_t = \ln(\text{OP}_t)$ for the oil price index, $y_t = \ln(\text{IP}_t)$ for industrial production, $y_t = \text{infl}_t$ for inflation, $y_t = \text{UR}_t$ for unemployment and, finally, $y_t = \ln(\text{MP}_t)$ for the metals prices.

The third set of variable is also a set of controls, which include traditional predictors of economic activity: the term spread, the corporate spread, a 12 month moving average of past stock returns, the return on the oil price index, the rate of growth on the index of leading indicators, the 3 month rate, the previously defined inflation rate, the dividend yield and, finally, lagged industrial production growth. The return on the oil price index and the rate of growth on the index of leading indicators have the same horizon as the forecasting horizon of the industrial production growth in Eq. (2).

From the predictors in Table 4.2, we create eight predicting blocks, which are listed in Table 4.3, and discussed below.

Block B1: *Term spread, corporate spread, and 12 month stock market returns.*

Stock market returns are the oldest financial indicator to predict future economic activity, but they are also known to display poor predictive power, as reviewed for example by Stock and Watson (2003a). To enhance the predicting power of stock returns, this block includes variables tracking the market participants risk-appetite, which is widely acknowledged to be procyclical, as discussed in Section 2.2. Naturally, procyclical risk-appetite translates to countercyclical premiums for long-term investments and the risk of default of corporations. For this reason, and because monetary policy is countercyclical, the term spread and the corporate spread contain valuable information about the business cycle. For example, it is well-known since at least Kessel (1965) or, later, Laurent (1988, 1989), Stock and Watson (1989a), Estrella and Hardouvelis (1991) and Harvey (1991, 1993), that inverted yield curves predict recessions with a lead time of about one to two years. Likewise, default risk-premiums are known to contain predictive power since at least Stock and Watson (1989a) and Bernanke and Blinder (1992).

Block B2: *Term spread, short-term rate.*

More recently, Ang, Piazzesi and Wei (2006) argue that the short-term rate has larger marginal predictive power than the term spread. This finding differs from the extant empirical evidence (see, e.g., Plosser and Rouwenhorst (1994)), as it relies on a model that accounts for no-arbitrage relations between the yield curve and the growth of GDP. Such a novel empirical evidence on

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GDP growth motivates this second block, which uses both the term spread and the short-term rate to predict the rate of growth of industrial production and NBER-dated recessions.

Block B3: *Stock market volatility, term spread volatility.*
Before recessions, the yield curve tends to invert, as discussed above. Moreover, near recessions, the term spread literally precipitates (as in Figure 2, top panel), suggesting that the volatility of the term spread might contain information about the pace at which economic conditions deteroriate. This reasoning is corroborated by rigorous evidence that the term spread volatility does increase sharply, before a recession. For space reasons, we do not discuss this evidence further, although we use this term spread volatility, in conjunction with aggregate stock market volatility, to build this block. Stock market volatility, which is the core volatility variable in this paper, is included here, as we wish to consider a parsimonious predicting block entirely relying on financial volatility variables: on the one hand, term spread volatility carries information about the speed at which risk-premiums and monetary policy change in bad times; on the other hand, stock market volatility, through the mechanisms explained in Section 2, links to the business cycle perhaps more broadly, and possibly carries information that is not necessarily captured by the term spread volatility.

Block B4: *Stock market volatility, term spread.*
This predicting block is at the heart of the paper. It differs from the two preceding blocks, in that it replaces the short-term rate in Block B2 with stock volatility, and the term spread volatility in Block B3 with the term spread. By replacing the short-term rate with stock volatility, we aim to test whether stock volatility provides a better predicting power than the short-term rate in Block B2, once the term spread is included. Similarly, we include the term spread to assess whether this variable has better predictive content than the term spread volatility in Block B3, once stock market volatility is included. Note, finally, that this block carries an interesting economic interpretation, as it combines two variables that relate to (i) risk (stock market volatility) and (ii) economic risk-premiums and, monetary policy (the term spread).

Block B5: *Volatility of stock market volatility, short-term rate.*
Not only is stock market volatility countercyclical. As Figure 1 shows, stock market volatility increases sharply as the economy deteroriates. Therefore, the volatility of stock market volatility likely embeds information about the development of the business cycle. Indeed, Corradi, Distaso and Mele (2009) develop a no-arbitrage model that analyzes sources of stock market volatility, and find that: (i) the level of stock market volatility relates to some persistent, unobservable factor; (ii) the bulk of the variation of volatility around this level is explained by business

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cycle factors. Figure 4 informally confirms the second property. The volatility of stock market volatility relates to the business cycle: it increases before and decreases after a recession. The bottom panel of Figure 4 shows that during the Great Moderation, the volatility of stock market volatility is conducive to bad times, displaying a striking correlation of -38% with one year production growth, with a lead time of about two years. All in all, this block replaces the term spread of Block B2 with the volatility of stock market volatility, as it aims to explore whether swings in stock market volatility have a higher predictive power than the term spread.

Naturally, the volatility of stock market volatility also generates false signals, by occasionaly increasing in good times. For example, in 1984 and 1985, stock market volatility precipitated (see Figure 1), as a result of a quite sharp improvement in the business cycle, which led the volatility of volatility to increase. The possibility of occurrence of such false signals calls for controls, which we introduce in the Block B8 discussed below.

Block B6: *Volatility of stock market volatility, term spread.*
This block aims to investigate the same issues discussed for the fifth block, but replaces the short-term rate with the term spread. A comparison between the predicting ability of these two blocks, therefore, leads to assess the relative predicting power of the term spread over the short-term rate, gauged through the additional lenses of the volatility of aggregate stock market volatility.

Block B7: *Volatility of stock market volatility, stock market volatility, term spread.*
This block, and the following, simply expand on Block B6, by adding additional information such as stock market volatility and, as discussed below, an interaction term between stock market volatility and the volatility of stock market volatility.

Block B8: *Volatility of stock market volatility, stock market volatility, interaction term, term spread.*
The interaction term in this block is defined as the product between stock market volatility at time $t - k$, and the volatility of volatility at time t, i.e. $\sigma_{t-k}^{j}(\ell) \cdot \text{Vol-Vol}_{t}^{j}$, where k is fixed, and stock market volatility, $\sigma_{t-k}^{j}(\ell)$, and the volatility of stock market volatility, Vol-Vol_{t}^{j}, are as in Eq. (6) and Eq. (8). This interaction term is needed to cope with the false signals that the volatility of stock market volatility might generate. As we discussed while motivating Block B5, there might be two sorts of "vol-vols": a "good" and a "bad," where the "bad" occurs when economic growth accelerates in such a way to make volatility fall rapidly, thereby inducing the volatility of volatility to increase in very good times. The interaction term has the potential to dampen the issues arising from these events, as it controls for the level of stock volatility occurred around k months earlier. The empirical question is which value of k to use. In our

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tests, we have experimented with a number of trials, and found that the best out-of-sample performance occurs with stock volatility lagged at about one year. Therefore, the empirical results in Sections 5 and 6 below, are obtained with a value of k set equal to twelve months.

Further to the these eight blocks, we consider the predicting ability of a simple model including lagged values of the industrial production growth, which we label Block B0. Finally, the two blocks B9 and B10 displayed in Table 4.3, are needed to control out-of-sample results, and are discussed in Section 6.2.

5. In-sample evidence

5.1. Linear predictions of economic activity

Given a monthly predicting horizon $k \in \{3, 6, 12, 24\}$, we regress industrial production growth $G_{t \to t+k}$ on to the predictors listed on Table 4.2 and the predicting blocks in Table 4.3. For every single regressor or predicting block, we include five lags: the current period plus four additional lags l_i^k, $i = 1, 2, 3, 4$, where the lag structure l_i^k is initially selected according to the highest R^2 criterion.

The regressions on to the predictors in Table 4.2 take the following form:

$$G_{t \to t+k} = \alpha^k + \sum_{j=1}^{P_i} \sum_{\text{lag} \in \left\{0, l_1^k, \cdots, l_4^k\right\}} \beta_j^k (\text{lag}) \cdot \text{Regressor}_j (t - \text{lag}) + \text{Error}(t+k), \quad k \in \{3, 6, 12, 24\}, \quad (9)$$

where, for $i = 1, \cdots, 18$, P_i is the number of regressors, and $\alpha^k, \{\beta_j^k (\text{lag})\}_{\text{lag} \in \left\{0, l_1^k, \cdots, l_4^k\right\}}$ are the parameters to be estimated. For the only purpose of simplifying the presentation, we report results arising from the use of a uniform lag structure, where each regression in Eq. (9) is performed against predictors lagged at 3, 12, 18, 24 and 36 months. The predictability pattern of our financial volatility indicators is quite robust to the choice of these lags.

The first of these linear regressions includes stock market volatility as a regressor, which is Predictor P1 in Table 4.2. The second regression includes stock market volatility and the volatility of the term spread, which are Predictors P1 and P2. The last regression has all the eighteen regressors listed on Table 4.2. Table 5.1, Panel A, reports cumulative R^2 for these regressions, along with information about Granger causality test statistics, summarized by the F-statistics for the null hypothesis that the loadings on stock market volatility are all zero, at the 5% confidence level. Panels B and C in Table 5.1 report cumulative R^2 for regressions performed on two sub-samples: a first sub-sample, spanning the period from January 1957 to December 1981, which includes 300 observations; and a

second, from January 1982 to September 2008, which has 321 observations. We choose these two sub-samples because they have approximately the same size, and because the year 1982 likely marks the beginning of structural changes, ranging from the inauguration of the Federal Reserve monetary policy turning point, to the lower volatility of real macroeconomic variables (e.g., Blanchard and Simon (2001))—the Great Moderation (e.g., Bernanke (2004)).

Our results are easily summarized. We find that for the whole sample, the first four predictors, based on financial volatility, explain about 30% of industrial production growth, at one year forecasting horizon, and about 40% at two year forecasting horizon. The predicting power of stock market volatility over the Great Moderation is striking: it explains, alone, from 35% to 55% of growth, at horizons of one year and two years. In contrast, the same volatility explains 4% of growth, at one year horizon, in the first sub-sample. Naturally, these R^2 need to be interpreted cautiously, as the ordering of regressors does obviously matter. To address this issue, we check the significance of the coefficient estimates on stock market volatility, and look at the F-tests that these coefficients are all zero. In both cases, we use heteroskedasticity and autocorrelation consistent standard errors, which are needed to deal with the serial dependence of the regressands.

For space reasons, we do not report all coefficients estimates. Instead, Figure 5 reports point estimates and confidence intervals of the loadings for stock market volatility only, when *all* the regressors in Table 4.2 are used. At a forecasting horizon of six months or more, volatility is negatively related to future economic activity, especially at recent and distant lags. This pattern seems to be consistent across all predicting horizons and, also, the sampling periods, although the most significant estimates occur over the Great Moderation period. The F-tests suggest that stock market volatility is not picking up information already conveyed by other predictors, at horizons ranging from six months to two years. Again, the F-tests confirm that stock volatility is a robust predictor of growth, over the Great Moderation: only at three month horizon, do these tests reject the null of Granger causality, at the conventional 95% level.

Next, we perform the regression in Eq. (9), using the first nine predicting blocks of Table 4.3. Table 5.2 reports R^2 for all the separate regressions of industrial production growth on to these blocks, for the selected forecasting horizons. The most remarkable explanatory power is that of (i) Block B2, which contains the term spread and the short-term rate, and (ii) Block B4, which includes aggregate stock market volatility and the term spread. For example, Block B4 explains about 50% of one-year growth in the first sub-sample, and 57% of one-year growth during the Great Moderation. In the first sub-sample, Block B2 explains more than Block B4, while in the second sample, it is Block B4 that explains more than Block B2.

The two blocks, B1 and B5, provide the highest explanatory power, for the whole sample. Block

B1, which includes the term spread, corporate spread and stock returns, is, however, less parsimonious than blocks B2 and B4. Moreover, it explains less than B2 and B4, over each separate sub-sample. Block B5, which has the volatility of stock market volatility and the short-term rate, seems to perform quite well in the first sub-sample, explaining about 64% of real growth at one year horizon, more than blocks B2 and B4 do. The same figure, however, drops to 12% in the sub-sample spanning the Great Moderation. Finally, the two blocks B7 and B8, which contain the term spread and volatility of volatility variables, explain a large proportion of growth, especially during the Great Moderation. At the same time, these blocks lack parsimony, as they have three (B7) or four (B8) regressors.

To summarize, our preliminary, in-sample, findings suggest that the two predicting blocks B2 and B4, are those providing both an important explanatory power and relatively stable links with future growth. The term spread is in common in these two blocks. The difference between B2 and B4 stems from the additional conditioning information: the short-term rate (block B2), and aggregate stock market volatility (block B4). The evidence in this section does not lead to neat conclusions about which block is more promising, although such a task is even more appropriate while discussing out-of-sample predictions, in Section 6.

5.2. Probabilities of recessions

We estimate probabilities of recessions using Probit models fed by the first nine predicting blocks in Table 4.2. As in Estrella and Hardouvelis (1991), we model recessions in Eq. (3) by setting $\text{Rec}_t = 1$, if some latent variable $\text{Rec}_t^* \geq 0$, and $\text{Rec}_t = 0$, otherwise. For each predicting horizon k, we model the predictive part of Rec_t^* as a linear combination of the variables included in the blocks of Table 4.3, as follows:

$$\text{Rec}_t^* = B_{t-k}^i + u_t, \quad k \in \{3, 6, 12, 24\},$$

where $i = 0, 1, \cdots, 8$, u_t is independent and identically distributed as a standard normal variable, and B_t^i is a linear combination of the variables included in any Block Bi of Table 4.3, with each regressor lagged as in Eq. (9). Thus, B_{t-k}^i includes predictors observed or measured at time $t - (3 + k)$, $t - (12 + k)$, $t - (18 + k)$, $t - (24 + k)$ and $t - (36 + k)$ months.

The weights of the linear combinations B_t^i are estimated via maximum likelihood, where the log-likelihood of a single observation is given by $\text{Rec}_t \ln \Phi(B_{t-k}^i) + (1 - \text{Rec}_t) \ln \left(1 - \Phi(B_{t-k}^i)\right)$, and Φ is the standard cumulative normal distribution. Thus, the probability of a NBER recession at time t, predicted by any block Bi, at horizon k, is:

$$\text{Probit}_t\left(\text{Rec}_t | \, \text{B}i\right) \equiv \Phi(\hat{B}_{t-k}^i), \quad k \in \{3, 6, 12, 24\}, \tag{10}$$

where $\hat{B}_t^i$ denotes the linear combination B_t^i, evaluated at the estimated parameters. Naturally, the probabilities in Eq. (10) are computed conditionally upon the entire sample. Out-of-sample forecasts of recession probabilities are discussed, and computed, in Section 6.

Table 5.3 reports pseudo R^2, along with frequencies of correctly identified recessions and expansions, for each block in Table 4.3. We define a recession to be correctly identified if the probability in Eq. (10) predicted by any block, over the said recession event, exceeds 16.22%, which is the fraction of time the US spent in recession over the entire sample period. Figure 6 depicts the probabilities of NBER-recessions predicted by blocks B1 through B8, obtained setting $k = 12$ months in Eq. (10).

Probit analysis is quite consistent with our previous findings about growth. Blocks B7 and B8, which include the term spread, stock market volatility and volatility of volatility variables, deliver the highest R^2. These R^2, however, might be attributable to the large number of regressors in these blocks. Blocks B2 (term spread and short-term rate) and B4 (stock market volatility and term spread) are, instead, more parsimonious, and yet they explain NBER-dated recessions reasonably well, with R^2 equal to approximately 40% (six month horizon) and 30% (one year horizon).

Block B1 (term spread, corporate spread and stock returns) has also explanatory power, comparable to that of B2 and B4. However, it is less parsimonious and seems to generate wrong recession signals more frequently than B2 and B4, for example around the two years 1983 and 1998 (see Figure 6). Quantitatively, Table 5.3 confirms that at horizons of six months or longer, the frequency of correctly identified expansions is lower for B1 than for B2 and B4: B1 produces too many wrong signals in good times, compared to B2 and B4. The performances of B2 and B4 seem to be quite comparable, in terms of the statistics in Table 5.3. At the same time, Figure 6 reveals that block B2 produces one wrong and sizeable recession signal (a predicted recession probability of almost 50%), just after the Monetary experiment of the early 1980s, which Block B4 does not predict. These two different predictions are due to the effects the new monetary policy regime had on interest rates and stock market volatility. On the one hand, soon after the FOMC meeting on October 5th, 1982, when Federal Reserve Chairman Volcker concluded that money supply could be increased more rapidly than in the previous three years, capital markets expectations stabilized, and led to an extraordinary low aggregate stock market volatility (see Figures 1 and 2). On the other hand, the short-term rate did continue to raise, after the Monetary experiment. These two circumstances explain why block B2 (which includes the short-term rate) produces a recession signal in the mid 1980s, while block B4 (which includes stock market volatility) does not. Naturally, this is a particular episode of financial history, but it does illustrate in an exemplary manner the role stock volatility could play in informing about the development of the business cycle.

Except perhaps block B1, no block really helps predict the last recession in the sample, which

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started in December 2007. It is an important failure, as the latest predictions produced by these models may be safely interpreted as coincident recession forecasts, due to our assumption that $\text{Rec}_t = 0$ in Eq. (3) after December 2007 (see Section 3.1). The explanation for this failure is that our in-sample analysis averages out complex and temporally heterogeneous relations: arguably, the links between capital markets volatility and the business cycle over the 2007 recession might be distinct, at least quantitatively, from those occurred half a century earlier. For example, our findings in Section 5.1 suggest that these links are much stronger over the Great Moderation. Estimating Probit models using data for the whole sample may simply dilute the strength of these links. We address this issue while implementing our out-of-sample analysis, discussed in the next section.

6.   Out-of-sample predictions

This section assesses the relative accuracy of the predicting blocks in Table 4.3. We consider both linear predictions of industrial production growth and predictions of recession probabilities, at horizons of 3 months, 6 months, 1 year and 2 years.

6.1.   Assessing predictive accuracy

For both the linear predictions of industrial production growth and recession probabilities, we implement rolling estimates and real-time multi-step ahead predictions. We utilize a lag structure with a span larger than that we used over the in-sample analysis, with predictors lagged at 3, 6, 12, 36 and 48 months.[2] The use of a larger span is needed, as multi-step ahead predictions inevitably lead to dissipation of long-term information, as we explain below.

Instead, the rationale behind the use of rolling regressions is that the relations linking the capital markets to the general state of the economy may undergo structural shifts. To illustrate, the legal system, the state of technology or the monetary regime are all inherently heterogeneous, over time. For example, as acknowledged in Section 5.1, the volatility of macroeconomic aggregates has substantially decreased during the Great Moderation. At the same time, the spectacular drop in the economic activity occurred after the 2007 subprime crisis may point to reversals in this macroeconomic volatility. A second example of a possible structural shift relates to our preliminary in-sample analysis of Section 5.1, where we uncover evidence of substantial changes in the way how financial volatility links to future economic conditions. The models we use, hinge upon the simple predicting blocks in Table 4.3, and do

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[2]We experimented with lag structures aiming at maximizing the out-of-sample performance of the blocks, according to the criteria explained below, and obtained results quite close to those we report here.

not necessarily account for these sources of heterogeneity. In fact, many authors suggest that the use of predicting variables with limited memory do help handle the nonstationary nature of economic data (e.g., Clements and Hendry (1999), Giacomini and White (2006)). Rolling regressions, introduced by Fama and MacBeth (1973) in a different context, easily address these delicate issues.

We use rolling estimates that comprise M observations, with $M = 120$ and 90 months. Consider, for example, Block B1, and a predicting target of the industrial production growth one year ahead, $G_{t-12 \to t}$ in Eq. (2). We use the first M observations in the sample to estimate a linear regression of $G_{t-12 \to t}$ on to the three variables in Block B1, $G_{t-12 \to t} = \mathcal{B}^1_{t-12} + z_t$, where $\mathcal{B}^1_t$ is a linear combination of the three variables, lagged at 3, 6, 12, 36 and 48 months, and z_t is a residual term. The twelve-month ahead forecast as of time M, is $\hat{G}^1_{M \to M+12} \equiv \hat{\mathcal{B}}^1_M$, where $\hat{\mathcal{B}}^1_M$ is the linear combination $\mathcal{B}^1_M$, evaluated at the estimated parameters. Then, we roll-over one observation ahead, run a second regression with M observations, perform a second twelve-month ahead forecast, and compute $\hat{G}^1_{M+1 \to M+13}$. We continue in this way and compute forecasts until the end of the sample. We implement this procedure to obtain nine series of forecasts $\hat{G}^i_{t \to t+k}$, $i = 0$ (for Block B0), and $i = 1, \cdots, 8$ (for Block B1 through Block B8), for $t = M, \cdots, N - k$, where N is the sample size, and for all the predicting horizons k: 3 months, 6 months, 1 year and 2 years. The forecast errors are,

$$\epsilon^i_{t,k} \equiv G_{t \to t+k} - \hat{G}^i_{t \to t+k}, \quad i = 0, 1, \cdots, 8, \quad t = M, \cdots, N - k, \quad k \in \{3, 6, 12, 24\}. \tag{11}$$

Prediction errors arising in the context of Probit models are defined in a similar way. To save on notation, they are denoted as the previous forecasting errors, viz

$$\epsilon^i_{t,k} \equiv \mathbb{I}_{\mathrm{NBER}_{t+k}=1} - \mathrm{Probit}_t \left(\mathrm{Rec}_{t+k} | \, \mathrm{B}i \right), \quad i = 0, 1, \cdots, 8, \quad t = M, \cdots, N - k, \quad k \in \{3, 6, 12, 24\}, \tag{12}$$

where $\mathbb{I}_{\mathrm{NBER}_t=1}$ is defined as we explained after Eq. (3), and $\mathrm{Probit}_t \left(\mathrm{Rec}_{t+k} | \, \mathrm{B}i \right)$ is the probability of a NBER-dated recession at time $t + k$, predicted by a Probit model, given all available information provided by a given Block Bi from time $t - M$ to time t: $\mathrm{Probit}_t \left(\mathrm{Rec}_{t+k} | \, \mathrm{B}i \right) = \Phi(\hat{\mathbb{B}}^i_t)$, where $\hat{\mathbb{B}}^i_t$ is defined as $\hat{B}^i_t$ in Eq. (10), with the difference that the parameters in $\hat{\mathbb{B}}^i_t$ are estimated using sample data from $t - M$ to t, not the entire sample data.

Decisions about NBER-dating are taken later than recessions actually occur. A piece of information of considerable interest is an estimate of the probability of being in a recession around recession periods, which we estimate as a one-month ahead prediction of any Probit model, as follows:

$$\mathrm{Probit}^k_t \left(\mathrm{Rec}_{t+1} | \, \mathrm{B}i \right) \equiv \Phi(\hat{\mathbb{B}}^i_{t-k+1}), \quad k \in \{3, 6, 12, 24\}. \tag{13}$$

Note that although the regressors in Eq. (13) are shifted away by the forecasting horizon, k, the parameter estimates in $\hat{\mathbb{B}}^i_{t-k+1}$ are obtained with sample data from $t - M$ to t, thus providing fresh

information about the nature of the links between any predicting block and the business cycle. Instead, the prediction $\mathrm{Probit}_t \left(\mathrm{Rec}_{t+k} | \mathrm{B}i \right)$ in (12) utilizes parameter estimates that are k months "stale." Finally, in this context, forecasting errors are defined similarly as in Eqs. (11)-(12).

To measure the loss induced by all these forecast errors, we use an absolute error loss function, $|\epsilon_{t,k}^i|$, and implement two testing procedures: (i) an unconditional procedure, which aims to assess the relative merits of our predicting blocks, on average, as described in Section 6.1.1; and (ii) a conditional procedure, which compares the predictive ability of these blocks in different points in time and, presumably, states of the economy, as explained in Section 6.1.2.

6.1.1. Unconditional predictive ability

We test whether the predictive accuracy of a given block i is, unconditionally, higher than that of another block j, through the Diebold and Mariano (1995) (DM, henceforth) test statistic. Let

$$\bar{d}_{T,k}^{i,j} = \frac{1}{T} \sum_{t=1}^{T} \left(\left| \epsilon_{t,k}^i \right| - | \epsilon_{t,k}^j | \right),$$

where $T = N - M - 1$ is the number of available forecasts. We test the null hypothesis that the forecasting block i has unconditionally lower expected loss than the forecasting block j through the standardized test statistics $\sqrt{T} \bar{d}_{T,k}^{i,j} / V_{T,k}^{i,j}$, where $V_{T,k}^{i,j}$ is a consistent estimate of the long-variance of $\bar{d}_{T,k}^{i,j}$, obtained through the usual Newey-West estimator, with a truncation lag equal to the predicting horizon, k.

6.1.2. Conditional predictive ability

We utilize the testing strategy devised by Giacomini and White (2006) (GW, henceforth) to assess the relative predicting accuracy of the blocks in Table 4.3. This strategy is similar in spirit to that of DM, in that it relates to rolling predictive regressions for the forecasting target.[3] The novelty of the GW test is that it allows us to investigate whether one predicting block performs better over the remaining ones, under any particular circumstances such as say, the future business cycle conditions, or the monetary policy regime.

Define the difference in the loss functions generated by any two blocks i and j at time t, for the predicting horizon k, as $\Delta \epsilon_{t,k}^{i,j} \equiv |\epsilon_{t,k}^i| - |\epsilon_{t,k}^j|$. The GW test is based on the regression of $\Delta \epsilon_{t+1,k}^{i,j}$ on some vector of variables $h_{t,k}^{i,j}$, deemed to explain the failure of equal conditional predictive ability

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[3]Note that the DM test can be applied to forecasts obtained with both rolling and expanding windows. By contrast, the GW test described below only applies to predictors with limited memory, such as those we consider in this section.

stemming from any two blocks:

$$\Delta\epsilon_{t+1,k}^{i,j} = \delta_k^{i,j} \cdot h_{t,k}^{i,j} + u_{t+1,k}^{i,j}, \quad t = M-1, \cdots, N-k, \tag{14}$$

where for any two predicting blocks i and j, and predicting horizon k, $\delta_k^{i,j}$ is a vector of constants, and, finally, $u_{t+1,k}^{i,j}$ is a residual term. Under standard regularity conditions, the null of equal conditional predictive ability of any two blocks is rejected whenever $T \cdot R^2 > \chi_{q,1-\alpha}^2$, where: (i) R^2 is the uncentered R^2 of the regression in Eq. (14), and (ii) $\chi_{q,1-\alpha}^2$ is the $(1-\alpha)$ quantile of a chi-square with q degrees of freedom, where q is the dimension of the test function $h_{t,k}^{i,j}$. Naturally, the GW test is asymptotically equivalent to DM, once $h_{t,k}^{i,j}$ is chosen to be a vector of constants.

A crucial choice relates to the type of conditioning information to include in the vector $h_{t,k}^{i,j}$. In Monte Carlo experiments, Giacomini and White (2006) show that the test has both reasonable size and power, once $h_{t,k}^{i,j} = [1 \ \Delta\epsilon_{t,k}^{i,j}]^\top$. This choice is appealing, in our context, as it connects failure of equal predictive ability with persistence and size of previous forecasting errors. Indeed, some blocks in Table 4.3 might perform better than others at predicting turning points, but can produce rather disappointing outcomes over periods of, say, prolonged expansions of the economy. The GW test can be used to implement an adaptive decision rule for selecting a predictive block over the others, thus exploiting the best conditional predictive power of any block.

This rule comprises two steps. In step one, one checks whether the null of equal conditional predictive ability is rejected. In case of rejection, one proceeds to step two, where one computes $E_N(\Delta\epsilon_{N+1,k}^{i,j}) \approx \hat{\delta}_k^{i,j} \cdot h_{N,k}^{i,j}$, with $E_N(\cdot)$ denoting the expectation conditional on the information set as of time N, and $\hat{\delta}_k^{i,j}$ denoting the estimate of $\delta_k^{i,j}$ in Eq. (14). Then, the rule is to select Block Bj if $E_N(\Delta\epsilon_{N+1,k}^{i,j}) > 0$, and to select Block B$i$ otherwise. A useful summary statistics is the frequency at which this rule selects any one of two predicting blocks, over the out-of-sample period, $(N - M - 1)^{-1} \sum_{t=M-1}^{N-1} \mathbb{I}(\hat{\delta}_k^{i,j} \cdot h_{t,k}^{i,j} > 0)$, where $\mathbb{I}$ is the indicator function.

6.2. Results

6.2.1. Linear predictions

Table 6.1 reports out-of-sample tests of predictive accuracy, based on the DM statistics and the GW reality check of conditional predictive ability. Panel A reports the value of this test, when the rolling estimation window is $M = 120$ months; panel B displays the results for $M = 90$ months. In both cases, the naïve Block B0 (comprising lagged values of growth) is the one that performs best, at a predicting horizon of 3 months. Its performance, however, is comparable to those of Blocks B2 (term spread and short-term rate) and B4 (stock market volatility and term spread), with Block B4

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performing marginally better than B2. For example, the GW decision rule would have led us to choose B4 against B2 54% of the time, when $M = 120$, but only 51% of the time, when $M = 90$. At horizons of 6 and 12 months, the performances of the three blocks, B0, B2, and B4, are, again, comparable and the best. At the horizon of 24 months, B2 and B4 display the best relative performance, with the volatility-term spread block B4 performing better than the yield curve block B2, at least when $M = 120$ months. In this case, for example, the GW rule tells us we would have chosen B4 over B2 65% of the time. When $M = 90$, however, B2 and B4 perform roughly as B0, with B4 prevailing, but not significantly, over B2 (and other blocks). Finally, the volatility block B8 seems to perform quite poorly, at any horizon, and for any considered rolling window. Overall, it is only better than block B3. Equally disappointing is the volatility block B7, with the exception of 24 months. Thus, this first battery of tests suggests that among the best predicting blocks alternative to the naïve Block B0, the best are the yield curve block B2 and the volatility-term spread block B4.

Figure 7, top panel, reports graphical evidence of how all the volatility blocks in Table 4.3, B3 through B8, help predict growth at six months horizon. For each point in time, we calculate the 5% and the 95% percentiles of the cross-section of the growth forecasts produced by these blocks, thus avoiding over-parametrization.[4] This cross-sectional range seems to track growth reasonably well, from the mid of the 1980s on. Its performance is almost identical, once we include B2 in the pool of predicting blocks, with the exception of the period immediately following the 2001 recession.

Next, we consider an experiment where we create two combination forecasts, which include: (i) B0, B1 and B2, denoted as Block B-0,1,2, and (ii) B1, B2, B4, denoted as Block B-1,2,4. The predictions of these two combinations are obtained as the arithmetic mean of the forecasts produced by each of the three blocks they are built upon, and as such, they are not plagued by over-parametrization issues. The motivation underlying these two combination forecasts is to investigate whether the information provided by Block B4 is better than that provided by the naïve block B0, once we condition on the two blocks B1 (which includes the term spread, corporate spread and stock returns) and B2. The reason for including B1, is that although this block is clearly outperformed by others, it does seem to provide some useful information at horizons of six months and one year. At a horizon of one year, and for $M = 90$, it is even better than B4, although still worse than B2.

Table 6.1, Panel C, reports DM statistics and GW decision rules for these two combination forecasts. Overall, both blocks outperform the remaining ones, at all horizons and rolling estimation windows, although their relative performance is the best at six months and one year. There are, however, interesting exceptions: the performance of Block B-0,1,2 is only marginally better than B4

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[4]This range does not rely on a single set of rolling regressions including all the variables in the six volatility blocks, B3 through B8. Rather, it relies on parameter estimates obtained by fitting six separate sets of rolling regressions.

at six months, one year and two years horizons. For example, at two years, the GW decision rule says we would have chosen B-0,1,2 against B4 only 37% of the time, with $M = 120$. Likewise, the performance of Block B-0,1,2 is only marginally better than B2, at horizons of one and two years. The performance of Block B-1,2,4 is, instead, quite better than every single block, at horizons of six months and one year, and for all rolling windows, M. It is only at a three months horizon that Block B-1,2,4 performs only marginally better than the naïve B0, but still much better than blocks B2 or B4. At two years horizon, Block B-1,2,4 performs better than every single blocks, although its performance seems to deteriorate somehow for $M = 120$. Finally, Block B-0,1,2 is better than Block B-1,2,4 at three months, and worse than B-1,2,4 at six months. The two blocks are comparable at one and two years horizon, B-1,2,4 is the best when $M = 120$.

To summarize, stock market volatility does help predict growth, especially at six months and one year, and when used in conjunction with other financial variables such as the term spread and the corporate spread. At shorter predicting horizons, stock market volatility does not seem to add important pieces of information on top of those already conveyed by traditional leading indicators.

6.2.2. Probabilities of recessions, coincident and leading

Table 6.2 reports tests of predictive accuracy for Probit models of NBER-dated recessions, obtained with a rolling estimation window equal to $M = 360$ months. Panel A reports results for coincident probabilities, computed as one-month ahead predictions, i.e. $\mathrm{Probit}_t^k\left(\mathrm{Rec}_{t+1}|\,\mathrm{B}i\right)$ in Eq. (13), with $k \in \{3, 6, 12, 24\}$. At horizons of three and six months, the volatility Block B8 performs the best, although only marginally better than Block B1, at three months. (Block B1, however, does not perform much better than the remaining blocks at this, or other, horizons.) At one year horizon, the performance of the volatility-term spread block B4 is quite comparable to that of B8, and both B4 and B8 significantly outperform the yield curve Block B2. At one year horizon, the volatility block B7 does also perform well, in comparison to all the other blocks except B4 and B8. At two years horizon, all blocks do not appear to perform significantly better than the naïve Block B0.

Figure 8 depicts coincident probabilities predicted by all blocks from B1 through B8, at the twelve months horizon, i.e. $\mathrm{Probit}_t^k\left(\mathrm{Rec}_{t+1}|\,\mathrm{B}i\right)$ in Eq. (13), with $k = 12$, along with the horizontal line drawn at 16.22%, which is the fraction of time the US spent in recession over the entire sample period. The picture confirms, qualitatively, the general message emerging from the previous discussion: the volatility-term spread block B4 and the volatility block B8 would have performed quite well at signaling the last three recessions. At the same time, B8 does produce a sizeable and wrong warning flag of a recession in 2003, which the volatility-term spread block B4 does not. The 2001 recession deserves additional discussion. As documented by Stock and Watson (2003b), this recession took

forecasters by surprise. The predicting block B4 would have helped signal this downturn: the coincident probability of an imminent recession predicted by Block B4 was larger than 16.22%, even before the 2001 recession. Note that the two volatility blocks, B7 and B8, also point to a recession, in 2001, but they both deliver one false recession signal in 2003. Finally, on top of B4, the additional volatility blocks, B5 through B8, would have signaled the 2007 recession. Block B4 would also have signaled the 1990-1991 recession, which the yield curve block B2 could not really, a difficulty shared by many recession forecasts of the time, as documented for example by Stock and Watson (1993). Useless to mention, the block comprising stock returns, Block B1, is literally able to "forecast five of the last three recessions," as in the old adage.

Panel B of Table 6.2 reports results for the more challenging exercise of multi-step ahead predictions, computed as $\text{Probit}_t\left(\text{Rec}_{t+k}|\,\text{B}i\right)$ in Eq. (12). In this exercise, the only recession we can cover is the 2001 recession. Therefore, our tests are simply gauging the ability of the predicting blocks to anticipate expansion periods. Overall, it is Block B2 which does better, at all horizons except two years. (At two year horizon, however, all blocks perform similarly as the naïve Block B0.) This conclusion is corroborated by panel C of Table 6.2, which shows the frequency of correctly identified recessions and expansions, for both coincident and multi-step ahead probabilities. According to panel C, B2 does indeed roughly produce the highest frequencies of correctly identified expansion, among all blocks.

Figure 9 reports multi-step probability predictions, computed as $\text{Probit}_t\left(\text{Rec}_{t+k}|\,\text{B}i\right)$ in Eq. (12), for $k = 6$ months. Once again, predicting blocks with volatility variables would have produced significant warning flags for the 2007 recession, with the exception of blocks B3 and B5. Particularly informative is the volatility-term spread block B4, which also helps anticipate the 2001 recession. Figure 10 complements Figure 9, in that it reports the average probability forecasts the nine blocks in Table 4.3 would have produced, for the two recessions occurred in 2001 and in 2007. We consider (i) the average probability for the first six months of any such recession, which would necessarily have produced up to six months before the two recessions actually occurred, and (ii) the average probability over the whole recessions, assuming September 2008 is still part of a NBER recession event. Figure 10 reveals that as regards the 2007 recession, the yield curve block B2 simply does not work, as it fails to predict a probability of recession larger than the threshold 16.22%. Instead, all volatility blocks (excluding B3 and B5) seem to perform reasonably well. In particular, Block B4 is the one that best anticipates the 2007 recession, six months ahead. Over the whole recession, the average probability is the highest for the volatility Block B6 (comprising the volatility of stock market volatility and the term spread), although statistically not significantly better than that produced by Block B4. (Standard errors for the average probabilities are available upon request.)

The 2001 recession would have been harder to predict. For any predicting block, the average recession probability for the 2001 recession is approximately half that the blocks deliver for the 2007 recession. The block that best anticipates this recession six months ahead is the Block B1, with an average probability of only about 27%. This same block produces the highest average probability over the entire recession episode (48%), and it is followed by Block B4 (32%). With the exception of Block B5, the remaining volatility blocks would also have produced significant warning flags of a recession, a few months after its inception, as Figure 10 reveals. Instead, the yield curve block B2 would have been uninformative about this recession episode.

6.2.3. Controls

We control the previous results with two blocks.

Block B9: *Volatilities of: oil return, industrial production growth, inflation, metal return.*
This block contains indicators of volatility related to macroeconomic variables, which does spike around recessions. (Results are available upon request.) This block is, thus, a natural alternative to the financial volatility blocks analyzed throughout the paper.

The last block we consider contains standard indexes of leading indicators:

Block B10: *Oil return, index of leading indicators (growth), inflation, dividend yield.*

Table 6.3 reports results related to linear predictions. At three months horizon, Blocks B9 and B10 are outperformed by all the other blocks, for all rolling estimation windows M, although the outperformance is only quite marginal for block B8. At longer horizons (six months and one year), Block B9 (but not Block B10) seems to be quite comparable to Block B2 and all the volatility blocks, and both Blocks B9 and B10 are worse than B4 at a one year horizon.

Table 6.4 reports, instead, results for multi-step probabilities generated by probit models. Again, the main difficulty here is that these tests only cover a single recession episode, that occurred in 2001. Overall, the two blocks B2 and B4 seem to perform better than both B9 and B10, altough their best relative performance occurs at the horizons of six months and one year. At two year horizon, Block B9 outperforms all the remaining blocks.

7. Conclusion

The key idea underlying this paper is simple: if financial volatility is countercyclical, it might encode information about the development of the business cycle. Our conclusion, based on an array of measurement methods, is that stock volatility does indeed help predict the business cycle. We rely on predictions of both industrial production growth and NBER-dated recessions, utilizing in-sample models and submitting our findings to reality checks and other out-of-sample experiments. We control the significance of these predicting relations, by looking at alternative predicting blocks of economic activity, which include (i) traditional leading indicators, (ii) financial variables such as the term spread or the corporate spread, (iii) additional volatility variables, such as the volatility of the term spread, the volatility of stock market volatility or the volatility of real aggregates. In fact, we find that combining stock volatility with the term spread leads to a predicting block of economic activity, which tracks, and anticipates, the business cycle reasonably well. For instance, this predicting block would have considerably helped predict at least the last three recessions, with no "false positive" signals.

While we have outlined a few theoretical explanations for these findings, we still lack a systematic explanation of them. Bloom (2009) and Bloom, Floetotto and Jaimovich (2009) certainly constitute important advances into the issue of how uncertainty shocks stand as a valid propagation mechanism. The next and intriguing step is to integrate financial volatility into a plausible propagation mechanism, within a context of realistically calibrated asset prices.

Appendix

A.

Derivation of Eqs. (1). Since managers maximize the value of the firm, the share price of the firm is the firm's maximized value, viz

$$P(s) = \max_{Q \geq 0} E\left(D^{-1}(Q)Q - C(Q)\middle| s\right). \tag{A.1}$$

The production chosen by the firm equals,

$$Q(s) = \arg\max_{Q \geq 0} E\left((a + \tilde{v} - \lambda Q)Q - zQ\middle| s\right) = \max\left\{\frac{a - z + E(\tilde{v}|s)}{2\lambda}, 0\right\},$$

where $E(\tilde{v}|s) = \theta s$ (by the Projection Theorem), with $\theta = \frac{\sigma^2}{\sigma^2 + \sigma_\epsilon^2}$, as in the main text. By replacing this solution back into Eq. (A.1), we find the price function in Eq. (1). Finally, the expression for return volatility in Eq. (1) follows by computing the right hand side of the following definition,

$$\mathrm{Vol}(s) \equiv \sqrt{E\left[\left(\frac{D^{-1}(Q(s))Q(s) - C(Q(s))}{P(s)} - 1\right)^2\middle| s\right]},$$

holding for all $s : a - z + E(\tilde{v}|s) > 0$, i.e. for all $s > \hat{s}$, where $\hat{s} = -\frac{a-z}{\theta}$, as in the main text. ∎

Details on the Monte Carlo experiment in Table 2.1. We set $\sigma = \sigma_\epsilon = a - z = 1$, and $\lambda = 5$. We draw 500 values from the signals distribution. For each draw, we compute prices, production and volatility from Eqs. (1). We only retain prices, production and return volatility when economic activity takes place, i.e. when $s > \hat{s}$. Return volatility blows up as s approaches $\hat{s}$, and we only consider signal realizations that are 5% larger than the cutoff $\hat{s}$. For each Monte Carlo repetition, we compute the values of constants, regression slopes and centered R^2. Table 2.1 reports OLS estimates, t-stats, and R^2 averaged over all the Monte Carlo repetitions.

B.

Dividend correction for the volatility of the price-dividend ratio. We have,

$$E\left(R_t^{tot}\right) = E\left(\ln\left(\frac{P_t + x_t}{P_{t-1}}\right)\right),$$

where E is the unconditional expectation, and $x_t = D_t$ every four months, and zero elsewhere. Therefore,

$$E\left(R_t^{tot}\right) = \frac{1}{4}E\left(\ln\left(\frac{\mathrm{P/D}_t + 1}{\mathrm{P/D}_{t-1}}\right)\right) + \frac{3}{4}E\left(\ln\left(\frac{\mathrm{P/D}_t}{\mathrm{P/D}_{t-1}}\right)\right) + \frac{1}{4}E\left(\ln\left(\frac{D_t}{D_{t-1}}\right)\right) + \frac{3}{4}\ln 1. \tag{B.1}$$

For each sampling period we consider, we search numerically for the real number $\bar{x}$ such that

$$\hat{E}\left(\ln\left(\frac{P_t + \bar{x}}{P_{t-1}}\right)\right) = \frac{1}{4}\hat{E}\left(\ln\left(\frac{\mathrm{P/D}_t + 1}{\mathrm{P/D}_{t-1}}\right)\right) + \frac{3}{4}\hat{E}\left(\ln\left(\frac{\mathrm{P/D}_t}{\mathrm{P/D}_{t-1}}\right)\right)$$

where $\hat{E}$ denotes the sample average counterpart to the expectation operator E. By the same arguments leading to Eq. (B.1), this $\bar{x}$ can also be found as the solution to the following equation,

$$\hat{E}\left(\ln\left(\frac{P_t + \bar{x}}{P_{t-1}}\right)\right) = \hat{E}\left(R_t^{tot}\right) - \frac{1}{4}\hat{E}\left(\ln\left(\frac{D_t}{D_{t-1}}\right)\right).$$

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Tables

Table 4.1: Stock market volatility before and during NBER-dated recessions

This table report parameter estimates and t-statistics computed through heteroskedasticity and autocorrelation consistent standard errors for the linear regression:

$$\sigma_t = c + \sum_{i \in \{3,12,24,36\}} b_i \sigma_{t-i} + \gamma_1 \mathbb{I}_{t \in \mathcal{O}(\mathrm{NBER}_t=1)} + \gamma_2 \mathbb{I}_{\mathrm{NBER}_t=1} + u_t^{\sigma},$$

where σ_t is the aggregate stock market volatility as of month t, estimated as the annualized moving average of the absolute monthly returns in the previous year, $\sigma_t \equiv \frac{\kappa}{\sqrt{12}} \sum_{i=1}^{12} |R_{t+1-i}|$, R_t is the per cent return on a stock price (total return) index at month t, κ is a scaling factor defined in the main text, and u_t^{σ} is a residual term. The indicator function $\mathbb{I}_{t \in \mathcal{O}(\mathrm{NBER}_t=1)}$ equals one, in the twelve months preceding any NBER-dated recession, and zero otherwise. The indicator function $\mathbb{I}_{\mathrm{NBER}_t=1}$ equals one, during any NBER-dated recession, and zero otherwise. The sample covers monthly data from January 1957 to September 2008.

Panel A: Full sample, 1957-2008

	c	b_3	b_{12}	b_{24}	b_{36}	γ_1	γ_2
estimate	3.11	0.94	-0.15	-0.01	-0.01	0.48	1.51
t-stat	7.18	40.10	-6.48	-0.65	-0.98	2.52	5.80

Panel B: 1957-1982

	c	b_3	b_{12}	b_{24}	b_{36}	γ_1	γ_2
estimate	3.60	0.98	-0.24	0.02	-0.04	0.34	1.87
t-stat	6.19	27.83	-8.85	1.07	-1.91	1.41	5.50

Panel C: 1983-2008

	c	b_3	b_{12}	b_{24}	b_{36}	γ_1	γ_2
estimate	2.88	0.94	-0.09	-0.05	-0.01	1.01	1.22
t-stat	4.76	32.56	-2.28	-1.86	-0.41	3.35	3.36

Table 4.2: Predictors of economic activity

Financial Volatility
  P1 = stock market volatility
  P2 = volatility of the term spread
  P3 = volatility of the corporate spread
  P4 = volatility of stock market volatility

Macroeconomic Volatility
  P5 = volatility of oil return
  P6 = volatility of industrial production growth
  P7 = volatility of inflation
  P8 = volatility of unemployment rate
  P9 = volatility of metal return

Traditional Predictors
P10 = term spread
P11 = corporate spread
P12 = stock returns
P13 = oil return
P14 = index of leading indicators, growth
P15 = 3 month interest rate
P16 = inflation
P17 = dividend yield
P18 = lagged industrial production growth

Table 4.3: Predicting blocks of economic activity

B0 = lagged industrial production
B1 = term spread, corporate spread, 12 month stock market returns
B2 = term spread, short-term rate
B3 = stock market volatility, term spread volatility
B4 = stock market volatility, term spread
B5 = volatility of stock market volatility, short-term rate
B6 = volatility of stock market volatility, term spread
B7 = volatility of stock market volatility, stock market volatility, term spread
B8 = volatility of stock market volatility, stock market volatility, interaction term, term spread

Macroeconomic controls
B9 = volatilities of: oil return, industrial production growth, inflation, metal return
B10 = oil return, index of leading indicators (growth), inflation, dividend yield

Table 5.1: R^2 for in-sample regressions on predictors of economic activity

This table provides cumulative R^2 for in-sample forecasts of industrial production growth at horizons of 3 months, 6 months, 1 year and 2 years, obtained through the predictors in Table 4.2. The sample covers monthly data for the period from January 1957 to September 2008. Shaded figures indicate marginal significance levels for F-stats greater than 95%, against the null hypothesis that the stock market volatility coefficients are all zero.

Panel A: Full sample, 1957-2008

Predictors	3m	6m	1Y	2Y
P1 = stock market volatility	0.01	0.02	0.06	0.11
P2 = volatility of the term spread	0.06	0.09	0.14	0.17
P3 = volatility of the corporate spread	0.09	0.14	0.21	0.28
P4 = volatility of stock market volatility	0.14	0.21	0.29	0.37
P5 = volatility of oil return	0.22	0.31	0.34	0.43
P6 = volatility of industrial production index	0.27	0.36	0.38	0.47
P7 = volatility of inflation	0.33	0.43	0.45	0.68
P8 = volatility of unemployment rate	0.38	0.50	0.53	0.80
P9 = volatility of metal return	0.39	0.51	0.57	0.83
P10 through P18	0.61	0.75	0.85	0.92

Panel B: 1957-1982

Predictors	3m	6m	1Y	2Y
P1 = stock market volatility	0.01	0.01	0.04	0.09
P2 = volatility of the term spread	0.05	0.08	0.14	0.18
P3 = volatility of the corporate spread	0.09	0.15	0.24	0.32
P4 = volatility of stock market volatility	0.26	0.42	0.55	0.63
P5 = volatility of oil return	0.51	0.63	0.70	0.74
P6 = volatility of industrial production index	0.55	0.70	0.73	0.75
P7 = volatility of inflation	0.61	0.76	0.78	0.89
P8 = volatility of unemployment rate	0.60	0.77	0.81	0.92
P9 = volatility of metal return	0.62	0.78	0.85	0.92
P10 through P18	0.72	0.86	0.94	0.97

Panel C: 1983-2008

Predictors	3m	6m	1Y	2Y
P1 = stock market volatility	0.12	0.23	0.35	0.55
P2 = volatility of the term spread	0.23	0.37	0.50	0.70
P3 = volatility of the corporate spread	0.26	0.40	0.55	0.75
P4 = volatility of stock market volatility	0.33	0.49	0.60	0.79
P5 = volatility of oil return	0.44	0.59	0.70	0.84
P6 = volatility of industrial production index	0.43	0.59	0.71	0.86
P7 = volatility of inflation	0.46	0.64	0.73	0.87
P8 = volatility of unemployment rate	0.49	0.71	0.85	0.92
P9 = volatility of metal return	0.50	0.73	0.88	0.94
P10 through P18	0.60	0.86	0.95	0.97

Table 5.2: R^2 for in-sample regressions on predicting blocks of economic activity

This table provides R^2 for in-sample forecasts of industrial production growth at horizons of 3 months, 6 months, 1 year and 2 years, obtained through the first nine predicting blocks in Table 4.3. The sample covers monthly data for the period from January 1957 to September 2008. Keys: **B0**: Lagged industrial production; **B1**: Term spread, Corp. spread, Stock mkt returns; **B2**: Term spread, short rate; **B3**: Stock mkt volatility, Term spread volatility; **B4**: Stock mkt volatility, Term spread; **B5**: Vol of stock mkt vol, Short-rate; **B6**: Vol of stock mkt vol, Term spread; **B7**: Vol of stock mkt vol, Stock mkt vol, Term spread; **B8**: Vol of stock mkt vol, Stock mkt vol, Interaction, Term spread.

Panel A: Full sample, 1957-2008

Predicting block	3m	6m	1Y	2Y
B0	0.18	0.09	0.04	0.03
B1	0.27	0.28	0.38	0.41
B2	0.17	0.27	0.38	0.39
B3	0.17	0.09	0.13	0.18
B4	0.12	0.15	0.24	0.32
B5	0.18	0.28	0.39	0.38
B6	0.10	0.15	0.17	0.15
B7	0.15	0.19	0.28	0.38
B8	0.23	0.29	0.37	0.40

Panel B: 1957-1982

Predicting block	3m	6m	1Y	2Y
B0	0.17	0.09	0.05	0.11
B1	0.32	0.40	0.56	0.49
B2	0.27	0.43	0.61	0.66
B3	0.18	0.18	0.22	0.25
B4	0.21	0.35	0.50	0.38
B5	0.29	0.46	0.64	0.74
B6	0.25	0.35	0.47	0.47
B7	0.28	0.45	0.60	0.53
B8	0.41	0.50	0.65	0.55

Panel C: 1983-2008

Predicting block	3m	6m	1Y	2Y
B0	0.18	0.08	0.05	0.06
B1	0.41	0.31	0.40	0.47
B2	0.25	0.33	0.42	0.46
B3	0.25	0.40	0.54	0.72
B4	0.26	0.47	0.57	0.68
B5	0.11	0.10	0.12	0.12
B6	0.15	0.21	0.26	0.27
B7	0.26	0.48	0.63	0.78
B8	0.26	0.48	0.63	0.79

Table 5.3: R² for in-sample Probit-based predictions of recessions, and frequencies of correctly identified business cycle conditions

This table provides pseudo R², and the frequencies of correctly identified NBER recessions and expansions, for in-sample forecasts of probabilities of NBER recessions, obtained through Probit models fed by the first nine predicting blocks in Table 4.3. The sample covers monthly data from January 1957 to September 2008. A correctly identified recession (resp., expansion) occurs when the probability of recession (resp., expansion) predicted by a given block exceeds (resp., does not exceed) 16.22%, which is the fraction of time the US economy spent in recession in the sample, according to NBER dating. For each predicting horizon (3 and 6 months, 1 Year and 2 Years), the column labeled R² reports pseudo R², and the columns labeled Rec and Exp report frequencies of correctly identified recessions and expansions. Keys: **B0**: Lagged industrial production; **B1**: Term spread, Corp. spread, Stock mkt returns; **B2**: Term spread, short rate; **B3**: Stock mkt volatility, Term spread volatility; **B4**: Stock mkt volatility, Term spread; **B5**: Vol of stock mkt vol, Short-rate; **B6**: Vol of stock mkt vol, Term spread; **B7**: Vol of stock mkt vol, Stock mkt vol, Term spread; **B8**: Vol of stock mkt vol, Stock mkt vol, Interaction, Term spread.

Predicting block	3 months			6 months			1 Year			2 Years		
	R²	Rec	Exp	R²	Rec	Exp	R²	Rec	Exp	R²	Rec	Exp
B0	0.10	0.73	0.76	0.02	0.57	0.67	0.02	0.51	0.68	0.03	0.67	0.68
B1	0.36	0.90	0.79	0.36	0.89	0.80	0.29	0.89	0.78	0.04	0.62	0.69
B2	0.32	0.84	0.81	0.39	0.87	0.85	0.28	0.89	0.83	0.05	0.66	0.74
B3	0.25	0.87	0.77	0.23	0.71	0.76	0.13	0.71	0.73	0.16	0.83	0.73
B4	0.30	0.83	0.76	0.41	0.91	0.84	0.28	0.90	0.81	0.08	0.67	0.72
B5	0.32	0.85	0.79	0.34	0.95	0.83	0.07	0.73	0.73	0.07	0.67	0.74
B6	0.29	0.89	0.76	0.35	0.90	0.82	0.20	0.88	0.75	0.05	0.67	0.70
B7	0.37	0.91	0.83	0.46	0.94	0.85	0.34	0.93	0.86	0.05	0.67	0.70
B8	0.48	0.96	0.89	0.60	0.94	0.91	0.38	0.89	0.88	0.12	0.80	0.69

Table 6.1: Out-of-sample tests of predictive accuracy for linear models

This table reports Diebold and Mariano (1995) (DM) test statistics for relative predictive accuracy of industrial production growth, obtained through the first nine predicting blocks in Table 4.3, or two selected combinations of them, and the fraction of time the Giacomini and White (2006) (GW) test of conditional predictive ability would have led to choose any one of these blocks, or the two selected combinations of them, against the others. The sample covers monthly data for the period from January 1957 to September 2008. The rolling estimation window, M, is set equal to 120 (Panel A) and 90 (Panel B), and forecasting horizons are 3 months, 6 months, 1 year and 2 years. Panel C reports DM statistics and GW frequencies for average forecasts of two selected combinations of blocks (Blocks B0, B1, B2, and Blocks B1, B2, B4), against all blocks, with rolling estimation window $M = 120$ and 90 months, and forecasting horizons of 3 months, 6 months, 1 year and 2 years. A positive value for the DM test statistic indicates that the predicting block on the column has lower expected loss than the predicting block on the row. For GW, each figure indicates the frequency each predicting block on the column would be chosen against each predicting block on the row.

Table continued on the next pages

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Table 6.1, Panel A: Rolling estimation window = 120 months

Predicting horizon = 3 months

Diebold-Mariano statistics

	B1	B2	B3	B4	B5	B6	B7	B8
B0	-0.78	-1.09	-2.46	-0.50	-1.53	-2.17	-2.31	-3.21
B1		-0.44	-1.66	0.30	-0.89	-1.19	-1.50	-2.68
B2			-1.21	0.71	-0.47	-0.78	-1.05	-2.38
B3				1.96	0.76	0.55	0.24	-0.84
B4					-1.11	-1.48	-2.65	-3.34
B5						-0.40	-0.75	-2.03
B6							-0.42	-1.61
B7								-1.63

Giacomini-White conditional choices (frequencies)

	B1	B2	B3	B4	B5	B6	B7	B8
B0	0.45	0.46	0.39	0.48	0.43	0.43	0.40	0.36
B1		0.49	0.40	0.54	0.44	0.48	0.45	0.36
B2			0.44	0.51	0.46	0.44	0.45	0.36
B3				0.57	0.55	0.52	0.51	0.45
B4					0.42	0.45	0.35	0.39
B5						0.46	0.48	0.40
B6							0.45	0.43
B7								0.42

Predicting horizon = 6 months

Diebold-Mariano statistics

	B1	B2	B3	B4	B5	B6	B7	B8
B0	0.10	-0.18	-3.08	0.63	-1.69	-0.91	-0.92	-2.34
B1		-0.28	-2.80	0.55	-1.67	-0.89	-1.01	-2.48
B2			-3.12	0.78	-1.62	-0.55	-0.71	-2.44
B3				3.31	1.47	2.33	2.33	0.91
B4					-2.12	-1.37	-2.42	-3.88
B5						1.11	0.82	-0.86
B6							-0.13	-1.77
B7								-2.33

Giacomini-White conditional choices (frequencies)

	B1	B2	B3	B4	B5	B6	B7	B8
B0	0.49	0.49	0.37	0.54	0.41	0.51	0.48	0.41
B1		0.52	0.38	0.53	0.48	0.46	0.45	0.41
B2			0.34	0.51	0.38	0.46	0.41	0.36
B3				0.63	0.55	0.59	0.57	0.52
B4					0.39	0.47	0.41	0.32
B5						0.54	0.52	0.44
B6							0.52	0.42
B7								0.43

Predicting horizon = 1 year

Diebold-Mariano statistics

	B1	B2	B3	B4	B5	B6	B7	B8
B0	-0.81	0.17	-2.42	-0.36	-0.83	-0.38	-1.01	-2.40
B1		0.92	-1.85	0.43	-0.38	0.41	-0.32	-2.07
B2			-2.32	-0.55	-1.50	-0.56	-1.14	-2.55
B3				2.32	1.48	2.41	1.72	-0.07
B4					-0.65	0.01	-0.88	-2.96
B5						0.82	0.05	-1.99
B6							-0.97	-2.90
B7								-3.50

Giacomini-White conditional choices (frequencies)

	B1	B2	B3	B4	B5	B6	B7	B8
B0	0.41	0.52	0.40	0.50	0.46	0.49	0.48	0.41
B1		0.58	0.43	0.55	0.50	0.54	0.51	0.44
B2			0.42	0.46	0.38	0.42	0.41	0.34
B3				0.59	0.60	0.61	0.59	0.48
B4					0.48	0.48	0.44	0.36
B5						0.49	0.46	0.37
B6							0.44	0.38
B7								0.36

Predicting horizon = 2 years

Diebold-Mariano statistics

	B1	B2	B3	B4	B5	B6	B7	B8
B0	0.40	-0.37	-1.15	3.30	0.50	2.05	0.99	-0.45
B1		-0.60	-1.32	1.75	0.27	1.79	0.87	-0.78
B2			-1.12	1.71	1.04	1.89	1.13	-0.11
B3				2.04	2.01	2.54	1.88	0.77
B4					-0.74	0.14	-0.61	-2.04
B5						1.13	0.33	-0.77
B6							-0.97	-2.48
B7								-3.14

Giacomini-White conditional choices (frequencies)

	B1	B2	B3	B4	B5	B6	B7	B8
B0	0.48	0.45	0.42	0.74	0.52	0.63	0.59	0.53
B1		0.48	0.42	0.67	0.54	0.62	0.56	0.46
B2			0.44	0.65	0.54	0.63	0.60	0.53
B3				0.64	0.59	0.62	0.63	0.57
B4					0.41	0.47	0.47	0.38
B5						0.55	0.54	0.48
B6							0.47	0.36
B7								0.36

Keys — **B0**: Autoregressive; **B1**: Term spread, Corp. spread, Stock mkt returns; **B2**: Term spread, short rate; **B3**: Stock mkt volatility, Term spread volatility; **B4**: Stock mkt volatility, Term spread; **B5**: Vol of stock mkt vol, Short-rate; **B6**: Vol of stock mkt vol, Term spread; **B7**: Vol of stock mkt vol, Stock mkt vol, Term spread; **B8**: Vol of stock mkt vol, Stock mkt vol, Interaction, Term spread.

Table 6.1, Panel B: Rolling estimation window = 90 months

Predicting horizon = 3 months

Diebold-Mariano statistics

	B1	B2	B3	B4	B5	B6	B7	B8
B0	-0.83	-1.40	-3.74	-0.54	-2.29	-3.06	-3.91	-5.87
B1		-0.87	-2.50	0.38	-1.88	-2.24	-3.36	-5.91
B2			-1.75	1.14	-1.04	-1.29	-2.25	-4.47
B3				2.84	0.85	0.77	-0.18	-2.63
B4					-2.15	-2.73	-4.18	-6.10
B5						-0.27	-1.49	-4.30
B6							-1.42	-4.07
B7								-4.23

Giacomini-White conditional choices (frequencies)

	B1	B2	B3	B4	B5	B6	B7	B8
B0	0.47	0.45	0.33	0.48	0.42	0.35	0.32	0.21
B1		0.46	0.37	0.52	0.43	0.39	0.32	0.21
B2			0.39	0.51	0.47	0.43	0.39	0.29
B3				0.61	0.54	0.51	0.48	0.37
B4					0.40	0.39	0.33	0.23
B5						0.46	0.45	0.29
B6							0.42	0.32
B7								0.31

Predicting horizon = 6 months

Diebold-Mariano statistics

	B1	B2	B3	B4	B5	B6	B7	B8
B0	1.51	0.46	-3.63	1.07	-1.28	-1.73	-2.61	-4.72
B1		-0.98	-4.14	-0.66	-2.95	-3.24	-3.96	-6.33
B2			-3.50	0.45	-1.85	-1.93	-2.42	-4.51
B3				4.09	1.95	2.16	1.83	-0.38
B4					-2.19	-2.84	-3.96	-6.14
B5						-0.20	-0.85	-2.87
B6							-0.75	-3.02
B7								-3.25

Giacomini-White conditional choices (frequencies)

	B1	B2	B3	B4	B5	B6	B7	B8
B0	0.54	0.58	0.37	0.52	0.46	0.42	0.43	0.29
B1		0.52	0.34	0.46	0.40	0.33	0.33	0.18
B2			0.34	0.45	0.40	0.36	0.34	0.25
B3				0.64	0.56	0.54	0.55	0.47
B4					0.42	0.36	0.37	0.23
B5						0.46	0.48	0.34
B6							0.48	0.36
B7								0.35

Predicting horizon = 1 year

Diebold-Mariano statistics

	B1	B2	B3	B4	B5	B6	B7	B8
B0	2.38	1.18	-2.05	0.55	-0.09	0.43	-0.78	-2.42
B1		-0.91	-3.66	-2.54	-2.49	-2.41	-2.81	-3.77
B2			-2.90	-0.84	-1.66	-0.89	-1.76	-3.06
B3				2.60	1.81	2.49	1.54	-1.03
B4					-0.64	-0.19	-1.61	-3.14
B5						0.56	-0.56	-2.35
B6							-1.74	-3.07
B7								-2.72

Giacomini-White conditional choices (frequencies)

	B1	B2	B3	B4	B5	B6	B7	B8
B0	0.61	0.58	0.41	0.54	0.51	0.49	0.51	0.35
B1		0.48	0.34	0.37	0.42	0.41	0.37	0.25
B2			0.35	0.39	0.38	0.39	0.37	0.23
B3				0.62	0.58	0.57	0.58	0.45
B4					0.51	0.46	0.43	0.28
B5						0.48	0.49	0.34
B6							0.45	0.28
B7								0.28

Predicting horizon = 2 years

Diebold-Mariano statistics

	B1	B2	B3	B4	B5	B6	B7	B8
B0	-0.04	0.20	-0.41	0.67	0.11	1.09	-0.48	-1.72
B1		0.24	-0.38	0.79	0.15	1.44	-0.43	-1.65
B2			-0.58	0.41	-0.11	0.92	-0.64	-1.69
B3				0.92	0.52	1.41	0.09	-1.54
B4					-0.53	0.55	-1.25	-2.18
B5						1.12	-0.65	-1.88
B6							-2.39	-2.57
B7								-2.24

Giacomini-White conditional choices (frequencies)

	B1	B2	B3	B4	B5	B6	B7	B8
B0	0.51	0.54	0.53	0.49	0.54	0.57	0.51	0.45
B1		0.55	0.52	0.55	0.55	0.56	0.49	0.43
B2			0.51	0.51	0.51	0.52	0.45	0.42
B3				0.51	0.49	0.53	0.47	0.42
B4					0.46	0.53	0.42	0.39
B5						0.52	0.45	0.38
B6							0.41	0.35
B7								0.41

Keys — **B0**: Autoregressive; **B1**: Term spread, Corp. spread, Stock mkt returns; **B2**: Term spread, short rate; **B3**: Stock mkt volatility, Term spread volatility; **B4**: Stock mkt volatility, Term spread; **B5**: Vol of stock mkt vol, Short-rate; **B6**: Vol of stock mkt vol, Term spread; **B7**: Vol of stock mkt vol, Stock mkt vol, Term spread; **B8**: Vol of stock mkt vol, Stock mkt vol, Interaction, Term spread.

Table 6.1, Panel C: Combination forecasts

Predicting horizon = 3 months

| | *Diebold-Mariano statistics* | | | | | *Giacomini-White conditional choices (frequencies)* | | | |
| | $M = 120$ months | | $M = 90$ months | | | $M = 120$ months | | $M = 90$ months | |
	B-0,1,2	**B-1,2,4**	**B-0,1,2**	**B-1,2,4**		**B-0,1,2**	**B-1,2,4**	**B-0,1,2**	**B-1,2,4**
B0	2.25	1.43	2.28	1.37	**B0**	0.59	0.57	0.63	0.60
B1	3.72	3.24	4.05	3.41	**B1**	0.68	0.57	0.73	0.69
B2	3.89	3.71	4.51	4.15	**B2**	0.68	0.66	0.72	0.67
B3	4.06	3.65	4.89	4.22	**B3**	0.69	0.66	0.75	0.71
B4	2.64	3.03	3.11	3.32	**B4**	0.60	0.66	0.69	0.70
B5	3.64	3.45	4.32	4.16	**B5**	0.65	0.65	0.67	0.67
B6	4.46	3.82	5.43	4.99	**B6**	0.68	0.66	0.71	0.67
B7	4.42	4.63	6.05	5.92	**B7**	0.72	0.74	0.77	0.77
B8	5.47	5.53	7.54	7.54	**B8**	0.73	0.74	0.84	0.85
B-0,1,2		-0.71		-1.17	**B-0,1,2**		0.48		0.46

Predicting horizon = 6 months

| | *Diebold-Mariano statistics* | | | | | *Giacomini-White conditional choices (frequencies)* | | | |
| | $M = 120$ months | | $M = 90$ months | | | $M = 120$ months | | $M = 90$ months | |
	B-0,1,2	**B-1,2,4**	**B-0,1,2**	**B-1,2,4**		**B-0,1,2**	**B-1,2,4**	**B-0,1,2**	**B-1,2,4**
B0	2.78	2.80	3.89	3.54	**B0**	0.63	0.64	0.67	0.67
B1	2.46	3.67	2.01	3.56	**B1**	0.61	0.69	0.59	0.68
B2	2.55	3.16	2.77	3.72	**B2**	0.55	0.60	0.57	0.62
B3	4.61	4.85	5.37	5.46	**B3**	0.68	0.73	0.73	0.73
B4	1.48	2.79	2.40	4.03	**B4**	0.55	0.62	0.59	0.71
B5	3.77	4.49	4.32	4.93	**B5**	0.62	0.70	0.66	0.70
B6	3.48	4.05	5.17	5.78	**B6**	0.63	0.64	0.68	0.73
B7	3.51	4.68	5.49	5.82	**B7**	0.62	0.70	0.72	0.76
B8	4.56	5.37	7.42	7.85	**B8**	0.71	0.75	0.86	0.91
B-0,1,2		1.76		1.96	**B-0,1,2**		0.63		0.61

Predicting horizon = 1 year

| | *Diebold-Mariano statistics* | | | | | *Giacomini-White conditional choices (frequencies)* | | | |
| | $M = 120$ months | | $M = 90$ months | | | $M = 120$ months | | $M = 90$ months | |
	B-0,1,2	**B-1,2,4**	**B-0,1,2**	**B-1,2,4**		**B-0,1,2**	**B-1,2,4**	**B-0,1,2**	**B-1,2,4**
B0	1.86	1.41	3.84	3.04	**B0**	0.57	0.55	0.71	0.65
B1	3.09	3.24	0.31	1.16	**B1**	0.68	0.71	0.54	0.57
B2	1.16	1.42	1.41	2.03	**B2**	0.53	0.53	0.55	0.57
B3	3.02	3.30	4.36	4.74	**B3**	0.62	0.64	0.69	0.73
B4	1.74	2.77	2.84	4.55	**B4**	0.53	0.61	0.66	0.70
B5	2.06	2.51	2.73	3.63	**B5**	0.58	0.61	0.60	0.61
B6	1.76	2.26	2.76	3.84	**B6**	0.52	0.56	0.63	0.67
B7	2.14	2.58	3.54	4.02	**B7**	0.55	0.59	0.63	0.68
B8	3.25	3.72	3.95	4.46	**B8**	0.64	0.68	0.81	0.85
B-0,1,2		0.35		1.07	**B-0,1,2**		0.54		0.54

Predicting horizon = 2 years

| | *Diebold-Mariano statistics* | | | | | *Giacomini-White conditional choices (frequencies)* | | | |
| | $M = 120$ months | | $M = 90$ months | | | $M = 120$ months | | $M = 90$ months | |
	B-0,1,2	**B-1,2,4**	**B-0,1,2**	**B-1,2,4**		**B-0,1,2**	**B-1,2,4**	**B-0,1,2**	**B-1,2,4**
B0	2.39	3.32	2.29	2.09	**B0**	0.62	0.72	0.62	0.59
B1	1.86	2.91	2.71	3.24	**B1**	0.58	0.68	0.63	0.65
B2	1.47	2.12	1.51	1.99	**B2**	0.57	0.65	0.57	0.58
B3	1.91	2.28	1.53	1.84	**B3**	0.62	0.64	0.54	0.57
B4	-0.90	0.25	0.91	1.72	**B4**	0.37	0.47	0.54	0.55
B5	0.47	0.93	1.34	1.83	**B5**	0.47	0.53	0.56	0.57
B6	-0.82	-0.02	0.56	1.29	**B6**	0.41	0.48	0.55	0.51
B7	0.11	0.83	2.10	2.60	**B7**	0.45	0.49	0.60	0.61
B8	1.57	2.18	2.54	2.84	**B8**	0.57	0.62	0.63	0.65
B-0,1,2		2.91		0.79	**B-0,1,2**		0.76		0.54

Keys — **B0**: Autoregressive; **B1**: Term spread, Corp. spread, Stock mkt returns; **B2**: Term spread, short rate; **B3**: Stock mkt volatility, Term spread volatility; **B4**: Stock mkt volatility, Term spread; **B5**: Vol of stock mkt vol, Short-rate; **B6**: Vol of stock mkt vol, Term spread; **B7**: Vol of stock mkt vol, Stock mkt vol, Term spread; **B8**: Vol of stock mkt vol, Stock mkt vol, Interaction, Term spread; **B-0,1,2**: Average of forecasts from Blocks B0, B1 and B2; **B-1,2,4**: Average of forecasts from Blocks B1, B2 and B4.

Table 6.2: Out-of-sample tests of predictive accuracy for Probit-based models of recessions

Panel A of this table reports Diebold and Mariano (1995) (DM) test statistics for relative predictive accuracy of the first nine predicting blocks in Table 4.3 about probabilities of NBER recessions, and the fraction of time the Giacomini and White (2006) (GW) test of conditional predictive ability would have led to choose any one of these blocks against the others. The sample covers monthly data for the period from January 1957 to September 2008. The rolling estimation window, M, is set equal to 360 months. Panel A reports DM statistics and GW frequencies related to "coincident" probability estimates, defined as one-month ahead projections of Probit models estimated at forecasting horizons of 3 months, 6 months, 1 year and 2 years. Panel B reports DM statistics and GW frequencies related to "multi-step ahead" probability estimates, defined as projections of Probit models 3 months, 6 months, 1 year and 2 years ahead. A positive value for the DM test statistic indicates that the predicting block on the column has lower expected loss than the predicting block on the row. For GW, each figure indicates the frequency each predicting block on the column would be chosen against each predicting block on the row. Panel C reports the frequencies of correctly identified NBER recessions and expansions, for out-of-sample forecasts of probabilities of NBER expansions and recessions, both "coincident" and "multi-step ahead." A correctly identified recession (resp., expansion) occurs when the probability of recession (resp., expansion) predicted by a given block exceeds (resp., does not exceed) 16.22%, which is the fraction of time the US economy spent in recession in the sample, according to NBER dating. For each predicting horizon (3 and 6 months, 1 Year and 2 Years), the columns labeled Rec and Exp report frequencies of correctly identified recessions and expansions.

Table continued on the next pages

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Table 6.2, Panel A: Tests of predictive ability, coincident probabilities

Predicting horizon = 3 months

Diebold-Mariano statistics

	B1	B2	B3	B4	B5	B6	B7	B8
B0	3.87	4.20	3.01	3.67	5.53	2.13	4.27	6.98
B1		-1.40	-1.57	-1.03	-0.58	-1.95	-0.49	1.03
B2			-0.19	0.70	1.59	-0.45	1.43	3.32
B3				0.84	1.22	-0.17	1.32	3.40
B4					0.50	-0.96	0.82	2.69
B5						-1.22	0.18	3.06
B6							1.83	3.05
B7								3.24

Giacomini-White conditional choices (frequencies)

	B1	B2	B3	B4	B5	B6	B7	B8
B0	0.86	0.73	0.79	0.80	0.79	0.75	0.83	0.95
B1		0.21	0.32	0.43	0.34	0.22	0.50	0.58
B2			0.46	0.61	0.73	0.61	0.79	0.87
B3				0.70	0.51	0.64	0.73	0.87
B4					0.55	0.37	0.66	0.75
B5						0.50	0.65	0.79
B6							0.63	0.80
B7								0.86

Predicting horizon = 6 months

Diebold-Mariano statistics

	B1	B2	B3	B4	B5	B6	B7	B8
B0	1.66	5.89	1.71	3.79	6.87	2.07	6.05	7.73
B1		2.45	-0.07	2.42	1.62	1.00	3.20	3.85
B2			-1.72	0.65	0.43	-1.33	2.55	3.84
B3				1.96	2.43	0.60	2.92	4.02
B4					-0.16	-1.65	1.05	1.99
B5						-1.00	0.94	1.88
B6							2.58	3.04
B7								2.62

Giacomini-White conditional choices (frequencies)

	B1	B2	B3	B4	B5	B6	B7	B8
B0	0.75	0.87	0.70	0.85	0.87	0.82	0.95	0.97
B1		0.82	0.38	0.85	0.51	0.70	0.95	0.97
B2			0.33	0.75	0.41	0.46	0.86	0.85
B3				0.78	0.67	0.67	0.90	0.94
B4					0.24	0.19	0.34	0.61
B5						0.53	0.80	0.84
B6							0.86	0.90
B7								0.82

Predicting horizon = 1 year

Diebold-Mariano statistics

	B1	B2	B3	B4	B5	B6	B7	B8
B0	1.40	2.30	-0.14	3.39	-0.41	0.74	3.13	3.34
B1		0.50	-0.94	1.78	-2.20	-0.80	1.39	1.48
B2			-1.37	2.31	-2.98	-1.73	1.71	1.93
B3				2.76	-0.12	0.58	2.68	2.86
B4					-3.74	-2.56	-0.29	0.05
B5						2.09	3.85	3.89
B6							2.42	2.54
B7								1.02

Giacomini-White conditional choices (frequencies)

	B1	B2	B3	B4	B5	B6	B7	B8
B0	0.75	0.74	0.54	0.83	0.47	0.77	0.86	0.86
B1		0.49	0.42	0.63	0.19	0.30	0.55	0.57
B2			0.43	0.80	0.23	0.23	0.67	0.65
B3				0.77	0.47	0.61	0.92	0.91
B4					0.14	0.22	0.43	0.54
B5						0.74	0.85	0.84
B6							0.70	0.76
B7								0.74

Predicting horizon = 2 years

Diebold-Mariano statistics

	B1	B2	B3	B4	B5	B6	B7	B8
B0	1.23	-1.23	0.06	0.51	-0.68	-0.84	-0.84	-0.77
B1		-2.22	-0.37	-0.41	-1.38	-1.46	-1.46	-1.34
B2			0.76	1.50	0.44	0.06	0.06	-0.01
B3				0.29	-0.42	-0.58	-0.58	-0.60
B4					-0.83	-0.97	-0.97	-0.92
B5						-0.47	-0.47	-0.30
B6							0.01	-0.09
B7								-0.09

Giacomini-White conditional choices (frequencies)

	B1	B2	B3	B4	B5	B6	B7	B8
B0	0.81	0.33	0.58	0.53	0.44	0.39	0.39	0.39
B1		0.18	0.46	0.37	0.23	0.16	0.16	0.29
B2			0.67	0.78	0.59	0.57	0.57	0.62
B3				0.35	0.37	0.33	0.33	0.43
B4					0.39	0.36	0.36	0.52
B5						0.46	0.46	0.54
B6							0.01	0.46
B7								0.46

Keys — **B0**: Autoregressive; **B1**: Term spread, Corp. spread, Stock mkt returns; **B2**: Term spread, short rate; **B3**: Stock mkt volatility, Term spread volatility; **B4**: Stock mkt volatility, Term spread; **B5**: Vol of stock mkt vol, Short-rate; **B6**: Vol of stock mkt vol, Term spread; **B7**: Vol of stock mkt vol, Stock mkt vol, Term spread; **B8**: Vol of stock mkt vol, Stock mkt vol, Interaction, Term spread.

Table 6.2, Panel B: Tests of predictive ability, multi-step ahead probabilities

Predicting horizon = 3 months

Diebold-Mariano statistics

	B1	B2	B3	B4	B5	B6	B7	B8
B0	2.69	6.71	0.43	2.43	3.22	0.59	2.56	2.81
B1		1.11	-1.61	-0.11	-0.10	-2.11	-0.05	0.19
B2			-2.52	-1.52	-1.50	-2.86	-1.51	-0.96
B3				1.34	1.49	0.15	1.52	1.73
B4					-0.02	-1.54	0.13	0.47
B5						-1.27	0.08	0.30
B6							1.98	1.62
B7								0.38

Giacomini-White conditional choices (frequencies)

	B1	B2	B3	B4	B5	B6	B7	B8
B0	0.71	0.83	0.75	0.72	0.77	0.69	0.75	0.74
B1		0.66	0.43	0.69	0.65	0.48	0.76	0.65
B2			0.46	0.41	0.71	0.25	0.36	0.42
B3				0.61	0.47	0.51	0.59	0.68
B4					0.57	0.30	0.42	0.37
B5						0.30	0.37	0.47
B6							0.65	0.58
B7								0.34

Predicting horizon = 6 months

Diebold-Mariano statistics

	B1	B2	B3	B4	B5	B6	B7	B8
B0	1.01	6.03	-0.02	1.62	4.97	0.55	2.07	2.20
B1		2.52	-0.79	0.90	1.32	-0.76	1.19	1.21
B2			-3.05	-1.46	-0.35	-3.27	-1.48	-1.08
B3				1.37	2.79	0.44	1.78	1.86
B4					0.81	-1.25	0.74	0.87
B5						-1.72	-0.68	-0.54
B6							1.68	1.45
B7								0.41

Giacomini-White conditional choices (frequencies)

	B1	B2	B3	B4	B5	B6	B7	B8
B0	0.66	0.85	0.65	0.77	0.85	0.67	0.81	0.80
B1		0.88	0.37	0.74	0.69	0.39	0.73	0.72
B2			0.33	0.44	0.65	0.11	0.47	0.46
B3				0.71	0.68	0.58	0.73	0.78
B4					0.64	0.18	0.37	0.46
B5						0.26	0.38	0.48
B6							0.70	0.66
B7								0.57

Predicting horizon = 1 year

Diebold-Mariano statistics

	B1	B2	B3	B4	B5	B6	B7	B8
B0	0.57	2.04	-1.36	1.12	-0.62	0.92	1.51	1.56
B1		2.02	-1.58	0.96	-0.84	0.33	1.21	1.21
B2			-2.58	-0.46	-2.12	-1.42	0.07	0.20
B3				2.48	1.11	1.81	3.17	3.31
B4					-1.22	-0.62	0.75	0.79
B5						1.18	1.60	1.61
B6							0.99	1.10
B7								0.37

Giacomini-White conditional choices (frequencies)

	B1	B2	B3	B4	B5	B6	B7	B8
B0	0.61	0.69	0.45	0.74	0.43	0.64	0.73	0.77
B1		0.58	0.44	0.60	0.35	0.42	0.62	0.63
B2			0.36	0.62	0.29	0.34	0.63	0.65
B3				0.69	0.51	0.61	0.84	0.83
B4					0.28	0.39	0.45	0.56
B5						0.76	0.74	0.86
B6							0.63	0.66
B7								0.61

Predicting horizon = 2 years

Diebold-Mariano statistics

	B1	B2	B3	B4	B5	B6	B7	B8
B0	1.74	-0.74	-1.48	-0.78	0.23	-0.52	-0.51	-1.43
B1		-2.33	-1.71	-1.69	-1.22	-1.65	-1.65	-2.74
B2			-0.86	2.01	1.35	-0.09	-0.07	-1.36
B3				1.43	1.09	0.58	0.61	0.03
B4					0.54	-0.05	-0.03	-0.81
B5						-1.42	-1.02	-2.31
B6							0.11	-2.28
B7								-2.28

Giacomini-White conditional choices (frequencies)

	B1	B2	B3	B4	B5	B6	B7	B8
B0	0.78	0.39	0.52	0.54	0.47	0.41	0.41	0.39
B1		0.16	0.34	0.35	0.18	0.12	0.13	0.08
B2			0.55	0.55	0.45	0.42	0.40	0.41
B3				0.42	0.44	0.42	0.41	0.45
B4					0.48	0.45	0.45	0.45
B5						0.37	0.35	0.33
B6							0.51	0.38
B7								0.39

Keys — **B0**: Autoregressive; **B1**: Term spread, Corp. spread, Stock mkt returns; **B2**: Term spread, short rate; **B3**: Stock mkt volatility, Term spread volatility; **B4**: Stock mkt volatility, Term spread; **B5**: Vol of stock mkt vol, Short-rate; **B6**: Vol of stock mkt vol, Term spread; **B7**: Vol of stock mkt vol, Stock mkt vol, Term spread; **B8**: Vol of stock mkt vol, Stock mkt vol, Interaction, Term spread.

Table 6.2, Panel C: Frequencies of correctly identified NBER recessions and expansions

Coincident probabilities

Predicting block	3 months		6 months		1 Year		2 Years	
	Rec	Exp	Rec	Exp	Rec	Exp	Rec	Exp
B0	0.61	0.78	0.39	0.64	0.50	0.70	0.28	0.66
B1	0.94	0.86	0.89	0.73	0.72	0.80	0.00	0.76
B2	0.28	0.87	0.50	0.91	0.67	0.82	0.56	0.54
B3	0.83	0.88	0.83	0.76	0.94	0.63	0.94	0.72
B4	0.78	0.85	1.00	0.85	1.00	0.87	0.89	0.77
B5	0.50	0.95	0.44	0.97	0.22	0.68	0.50	0.64
B6	0.78	0.81	0.50	0.83	0.56	0.79	0.61	0.57
B7	0.61	0.89	0.56	0.96	0.72	0.93	0.61	0.57
B8	0.56	0.96	0.67	0.98	0.61	0.94	0.44	0.58

Multi-step ahead probabilities

Predicting block	3 months		6 months		1 Year		2 Years	
	Rec	Exp	Rec	Exp	Rec	Exp	Rec	Exp
B0	1.00	0.74	0.88	0.72	1.00	0.62	0.88	0.53
B1	0.66	0.80	0.89	0.74	0.00	0.77	0.00	0.77
B2	0.55	0.88	0.44	0.91	0.00	0.85	0.11	0.57
B3	0.44	0.78	0.22	0.69	0.66	0.54	0.00	0.59
B4	0.66	0.79	0.55	0.82	0.22	0.83	0.00	0.65
B5	0.44	0.83	0.00	0.88	0.00	0.61	1.00	0.55
B6	1.00	0.77	0.33	0.76	0.33	0.80	1.00	0.47
B7	0.66	0.83	0.22	0.88	0.00	0.87	1.00	0.47
B8	0.55	0.83	0.22	0.88	0.33	0.88	0.44	0.43

Keys — **B0**: Autoregressive; **B1**: Term spread, Corp. spread, Stock mkt returns; **B2**: Term spread, short rate; **B3**: Stock mkt volatility, Term spread volatility; **B4**: Stock mkt volatility, Term spread; **B5**: Vol of stock mkt vol, Short-rate; **B6**: Vol of stock mkt vol, Term spread; **B7**: Vol of stock mkt vol, Stock mkt vol, Term spread; **B8**: Vol of stock mkt vol, Stock mkt vol, Interaction, Term spread.

Table 6.3: Out-of-sample tests of predictive accuracy for control predictors, linear models

This table reports Diebold and Mariano (1995) (DM) test statistics for relative predictive accuracy of industrial production growth, obtained through the last two predicting blocks in Table 4.3 (Blocks B9 and B10), and the fraction of time the Giacomini and White (2006) (GW) test of conditional predictive ability would have led to choose any one of these two blocks, against all the remaining blocks. The sample covers monthly data for the period from January 1957 to September 2008. The rolling estimation window, M, is set equal to 120 and 90, and forecasting horizons are 3 months, 6 months, 1 year and 2 years. A negative value for the DM test statistic indicates that the predicting block on the column has lower expected loss than the predicting block on the row. For GW, each figure indicates the frequency each predicting block on the row would be chosen against each predicting block on the column.

Table continued on the next pages

Predicting horizon = 3 months

Diebold-Mariano statistics

		B0	B1	B2	B3	B4	B5	B6	B7	B8	B9
M=120	B9	-3.33	-3.56	-3.59	-1.36	-3.72	-2.96	-2.26	-2.50	-1.51	
	B10	-2.28	-2.61	-2.24	-0.39	-2.48	-1.67	-1.10	-1.26	-0.30	1.17
M=90	B9	-3.99	-3.77	-3.56	-3.57	-3.79	-3.54	-3.54	-2.38	-1.05	
	B10	-3.50	-2.66	-2.69	-2.41	-2.42	-2.43	-2.21	-1.01	0.12	1.11

Giacomini-White conditional choices (frequencies)

		B0	B1	B2	B3	B4	B5	B6	B7	B8	B9
M=120	B9	0.37	0.36	0.33	0.40	0.31	0.39	0.42	0.38	0.45	
	B10	0.25	0.29	0.33	0.44	0.30	0.38	0.46	0.40	0.46	0.52
M=90	B9	0.26	0.31	0.30	0.25	0.24	0.34	0.30	0.34	0.46	
	B10	0.33	0.31	0.31	0.36	0.30	0.35	0.32	0.42	0.47	0.58

Predicting horizon = 6 months

Diebold-Mariano statistics

		B0	B1	B2	B3	B4	B5	B6	B7	B8	B9
M=120	B9	-0.78	-1.79	-1.45	0.95	-1.52	-1.35	-0.81	-0.54	-0.21	
	B10	-2.07	-2.90	-2.65	-0.01	-2.84	-2.39	-1.91	-1.93	-1.64	-1.27
M=90	B9	-0.91	-2.71	-2.97	-0.69	-1.24	-1.84	-1.81	-0.27	-0.01	
	B10	-1.77	-3.37	-3.76	-1.71	-2.13	-2.59	-2.37	-1.11	-0.94	-0.93

Giacomini-White conditional choices (frequencies)

		B0	B1	B2	B3	B4	B5	B6	B7	B8	B9
M=120	B9	0.49	0.39	0.45	0.47	0.40	0.40	0.50	0.49	0.50	
	B10	0.37	0.30	0.33	0.49	0.30	0.43	0.46	0.42	0.40	0.38
M=90	B9	0.46	0.34	0.33	0.42	0.42	0.37	0.39	0.41	0.44	
	B10	0.41	0.32	0.27	0.38	0.35	0.37	0.38	0.42	0.39	0.47

Predicting horizon = 1 year

Diebold-Mariano statistics

		B0	B1	B2	B3	B4	B5	B6	B7	B8	B9
M=120	B9	-1.42	-1.44	-1.57	-0.66	-1.57	-1.68	-1.88	-1.51	-0.69	
	B10	-3.49	-4.17	-4.41	-2.66	-3.25	-5.09	-5.05	-4.81	-3.48	-2.20
M=90	B9	-1.01	-1.88	-2.50	-0.63	0.37	-2.44	-1.78	-0.47	-0.64	
	B10	-1.44	-2.76	-3.66	-1.34	-0.08	-3.76	-2.70	-1.33	-1.51	-0.95

Giacomini-White conditional choices (frequencies)

		B0	B1	B2	B3	B4	B5	B6	B7	B8	B9
M=120	B9	0.43	0.44	0.41	0.43	0.38	0.37	0.38	0.37	0.41	
	B10	0.28	0.26	0.24	0.35	0.26	0.20	0.21	0.20	0.21	0.34
M=90	B9	0.48	0.41	0.36	0.37	0.57	0.33	0.36	0.43	0.43	
	B10	0.46	0.36	0.26	0.32	0.51	0.30	0.33	0.39	0.36	0.38

Predicting horizon = 2 years

Diebold-Mariano statistics

		B0	B1	B2	B3	B4	B5	B6	B7	B8	B9
M=120	B9	-2.04	-1.15	-0.90	-0.44	-2.64	-1.06	-2.90	-1.65	-0.61	
	B10	-2.70	-1.50	-1.04	-0.64	-2.29	-1.01	-1.99	-1.29	-0.61	-0.27
M=90	B9	-1.37	-1.11	-2.01	-1.44	-2.32	-2.47	-1.13	-1.17	-0.51	
	B10	-1.22	-0.59	-0.91	-0.73	-1.25	-1.05	-0.45	-0.37	0.05	0.33

Giacomini-White conditional choices (frequencies)

		B0	B1	B2	B3	B4	B5	B6	B7	B8	B9
M=120	B9	0.39	0.50	0.42	0.48	0.34	0.41	0.29	0.34	0.41	
	B10	0.26	0.40	0.40	0.38	0.30	0.40	0.33	0.36	0.39	0.43
M=90	B9	0.43	0.42	0.39	0.39	0.36	0.36	0.42	0.41	0.45	
	B10	0.40	0.46	0.41	0.46	0.45	0.41	0.42	0.45	0.51	0.52

Keys — **B0**: Autoregressive; **B1**: Term spread, Corp. spread, Stock mkt returns; **B2**: Term spread, short rate; **B3**: Stock mkt volatility, Term spread volatility; **B4**: Stock mkt volatility, Term spread; **B5**: Vol of stock mkt vol, Short-rate; **B6**: Vol of stock mkt vol, Term spread; **B7**: Vol of stock mkt vol, Stock mkt vol, Term spread; **B8**: Vol of stock mkt vol, Stock mkt vol, Interaction, Term spread; **B9**: volatilities of: oil return, industrial production growth, inflation, metal return; **B10**: oil return, index of leading indicators (growth), inflation, dividend yield.

Table 6.4: Out-of-sample tests of predictive accuracy for control predictors, Probit-based recessions models

Panel A of this table reports Diebold and Mariano (1995) (DM) test statistics for relative predictive accuracy of the last two predicting blocks in Table 4.3 (Blocks B9 and B10) in Table 4.3 about probabilities of NBER recessions, and the fraction of time the Giacomini and White (2006) (GW) test of conditional predictive ability would have led to choose any one of these two blocks against the other blocks. Probabilities are "multi-step ahead" probability estimates, defined as projections of Probit models 3 months, 6 months, 1 year and 2 years ahead. The sample covers monthly data for the period from January 1957 to September 2008. The rolling estimation window, M, is set equal to 360 months. A negative value for the DM test statistic indicates that the predicting block on the column has lower expected loss than the predicting block on the row. For GW, each figure indicates the frequency each predicting block on the row would be chosen against each predicting block on the column. Panel B reports the frequencies of correctly identified NBER recessions and expansions, for out-of-sample "multi-step ahead" forecasts of probabilities of NBER expansions and recessions. A correctly identified recession (resp., expansion) occurs when the probability of recession (resp., expansion) predicted by a given block exceeds (resp., does not exceed) 16.22%, which is the fraction of time the US economy spent in recession in the sample, according to NBER dating. For each predicting horizon (3 and 6 months, 1 Year and 2 Years), the columns labeled Rec and Exp report frequencies of correctly identified recessions and expansions.

Table continued on the next pages

Table 6.4, Panel A: Tests of predictive ability

Predicting horizon = 3 months

Diebold-Mariano statistics

	B0	B1	B2	B3	B4	B5	B6	B7	B8	B9
B9	1.29	-0.53	-1.32	0.80	-0.48	-0.46	0.54	-0.52	-0.65	
B10	3.94	-0.29	-2.17	1.82	-0.14	-0.14	1.32	-0.23	-0.49	0.42

Giacomini-White conditional choices (frequencies)

	B0	B1	B2	B3	B4	B5	B6	B7	B8	B9
B9	0.86	0.63	0.58	0.75	0.60	0.59	0.68	0.65	0.57	
B10	0.79	0.41	0.34	0.55	0.31	0.39	0.58	0.31	0.30	0.23

Predicting horizon = 6 months

Diebold-Mariano statistics

	B0	B1	B2	B3	B4	B5	B6	B7	B8	B9
B9	-0.14	-0.69	-2.29	-0.12	-1.18	-2.03	-0.44	-1.42	-1.50	
B10	-0.30	-1.15	-4.27	-0.23	-1.81	-3.42	-0.72	-2.36	-2.52	-0.02

Giacomini-White conditional choices (frequencies)

	B0	B1	B2	B3	B4	B5	B6	B7	B8	B9
B9	0.81	0.58	0.42	0.59	0.42	0.34	0.68	0.42	0.40	
B10	0.62	0.31	0.17	0.44	0.21	0.11	0.30	0.14	0.15	0.19

Predicting horizon = 1 year

Diebold-Mariano statistics

	B0	B1	B2	B3	B4	B5	B6	B7	B8	B9
B9	-0.98	-0.99	-1.66	0.28	-1.42	-0.67	-1.17	-1.67	-1.74	
B10	-0.10	-0.72	-2.52	1.41	-1.75	0.16	-1.29	-2.04	-2.04	0.66

Giacomini-White conditional choices (frequencies)

	B0	B1	B2	B3	B4	B5	B6	B7	B8	B9
B9	0.73	0.60	0.58	0.56	0.58	0.75	0.66	0.50	0.52	
B10	0.55	0.41	0.33	0.62	0.27	0.67	0.44	0.29	0.26	0.34

Predicting horizon = 2 years

Diebold-Mariano statistics

	B0	B1	B2	B3	B4	B5	B6	B7	B8	B9
B9	2.60	1.01	2.27	2.06	2.21	1.67	1.84	1.84	2.49	
B10	-0.14	-0.97	0.32	1.78	0.42	-0.23	0.24	0.24	0.88	-1.43

Giacomini-White conditional choices (frequencies)

	B0	B1	B2	B3	B4	B5	B6	B7	B8	B9
B9	0.84	0.71	0.81	0.79	0.84	0.84	0.84	0.84	0.85	
B10	0.65	0.55	0.73	0.67	0.67	0.68	0.65	0.65	0.68	0.46

Table 6.4, Panel B: Frequencies of correctly identified NBER recessions and expansions

Predicting block	3 months		6 months		1 Year		2 Years	
	Rec	Exp	Rec	Exp	Rec	Exp	Rec	Exp
B9	0.55	0.81	0.33	0.77	0.11	0.71	0.00	0.84
B10	0.33	0.87	0.00	0.71	0.00	0.76	0.00	0.76

Keys — **B0**: Autoregressive; **B1**: Term spread, Corp. spread, Stock mkt returns; **B2**: Term spread, short rate; **B3**: Stock mkt volatility, Term spread volatility; **B4**: Stock mkt volatility, Term spread; **B5**: Vol of stock mkt vol, Short-rate; **B6**: Vol of stock mkt vol, Term spread; **B7**: Vol of stock mkt vol, Stock mkt vol, Term spread; **B8**: Vol of stock mkt vol, Stock mkt vol, Interaction, Term spread; **B9**: volatilities of: oil return, industrial production growth, inflation, metal return; **B10**: oil return, index of leading indicators (growth), inflation, dividend yield.
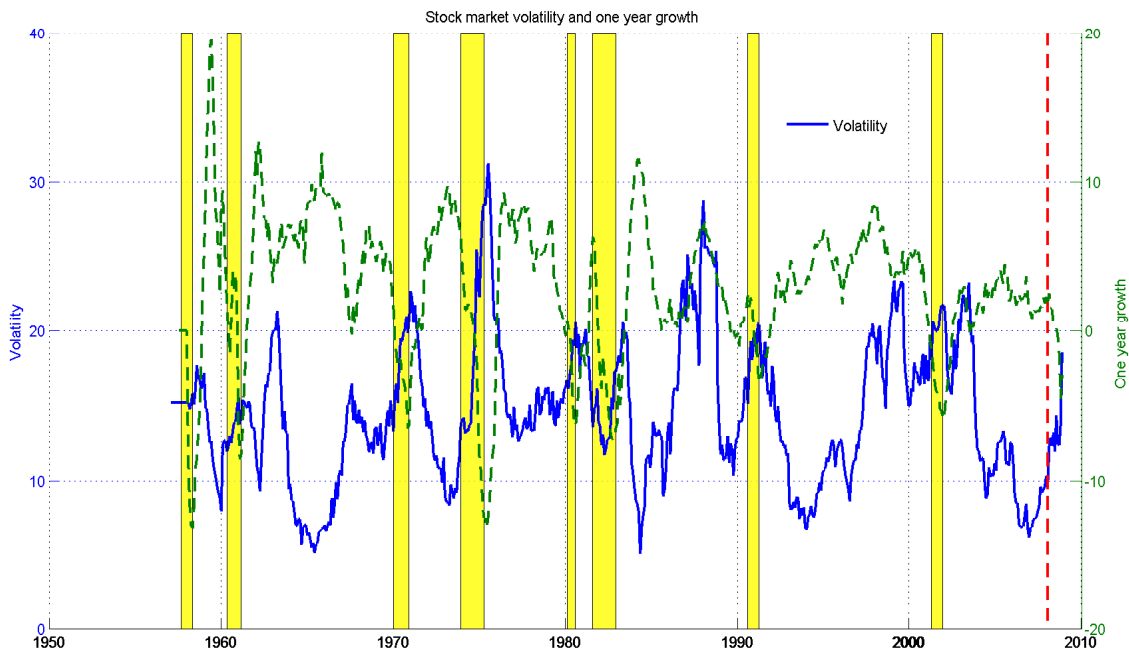
Figures

Figure 1 – Aggregate stock market volatility and industrial production growth. This figure plots aggregate stock market volatility against one year industrial production growth in the United States. Volatility as of month t is defined as the annualized moving average of the absolute monthly returns in the previous year, $\frac{\kappa}{\sqrt{12}} \sum_{i=1}^{12} |R_{t+1-i}|$, where R_t is the return on a stock price (total return) index at month t, and κ is a scaling factor defined in the main text. One year industrial production growth as of month t is defined as $\ln(\text{IP}_t/\text{IP}_{t-12})$, where IP_t is the seasonally adjusted industrial production index at month t. The sample covers monthly data for the period from January 1957 to September 2008. Shaded areas (in yellow) track NBER-dated recessions, and the vertical dashed line (in red) indicates the beginning of the latest NBER-dated recession.

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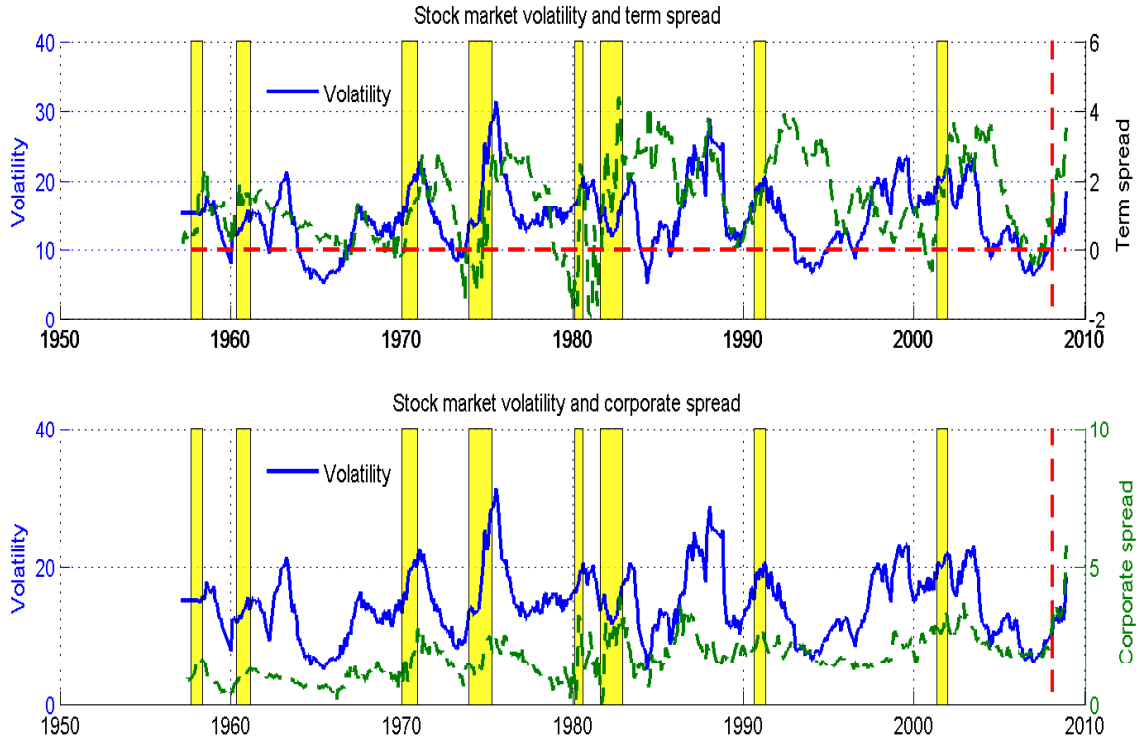
Figure 2 – Aggregate stock market volatility, the term spread and the corporate spread. This figure plots aggregate stock market volatility against two traditional financial predictors of economic activity in the United States: the term spread (top panel) and the corporate spread (bottom panel). Volatility as of month t is defined as the annualized moving average of the absolute monthly returns in the previous year, $\frac{\kappa}{\sqrt{12}} \sum_{i=1}^{12} |R_{t+1-i}|$, where R_t is the return on a stock price (total return) index at month t, and κ is a scaling factor defined in the main text. The term spread is obtained as the difference between the 10 year government bond yield and the yield on 3-month Treasury Bills. The corporate spread is the difference between the baa yield and the 10 year Government bond yield. The sample covers monthly data for the period from January 1957 to September 2008. Shaded areas (in yellow) track NBER-dated recessions, and the vertical dashed line (in red) indicates the beginning of the latest NBER-dated recession.

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Figure 3 – Sample cross-correlation between industrial production growth and aggregate stock volatility, the term and the corporate spread. This figure plots the sample cross-correlations between one year industrial production growth and (i) aggregate stock market volatility (left panel), (ii) the term spread (right-top panel), and (iii) the corporate spread (right-bottom panel). One year industrial production growth as of month t is defined as $\ln\left(\text{IP}_t/\text{IP}_{t-12}\right)$, where IP_t is the seasonally adjusted industrial production index at month t. Volatility as of month t is defined as the annualized moving average of the absolute monthly returns in the previous year, $\frac{\kappa}{\sqrt{12}}\sum_{i=1}^{12}|R_{t+1-i}|$, where R_t is the return on a stock price (total return) index at month t, and κ is a scaling factor defined in the main text. The term spread is obtained as the difference between the 10 year government bond yield and the yield on 3-month Treasury Bills. The corporate spread is the difference between the baa yield and the 10 year Government bond yield. The sample covers monthly data including the "Great Moderation," from January 1983 to September 2008.
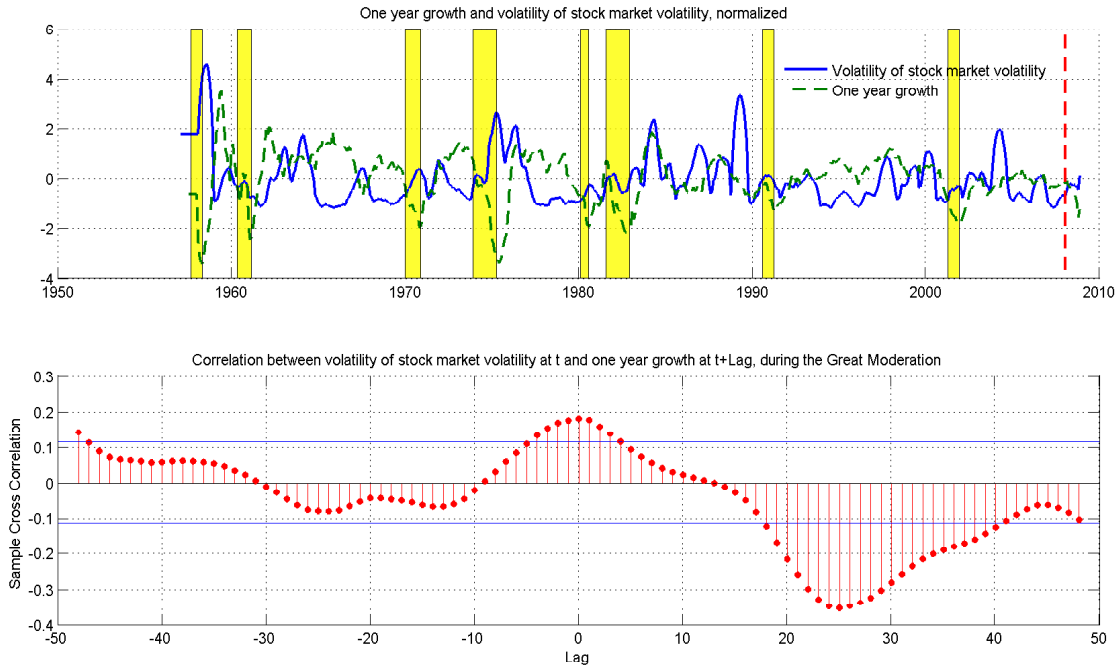
Figure 4 − Volatility of aggregate stock market volatility and industrial production growth. The top panel plots the volatility of aggregate stock market volatility against one year industrial production growth in the United States. Volatility of volatility as of month t is defined as the moving average of the absolute deviations of stock volatility from its average in the previous year, $\frac{1}{12}\sum_{i=1}^{12}|\sigma_{t+1+i}-\hat{\sigma}_{t+1-i}|$, where $\hat{\sigma}_t \equiv \frac{1}{12}\sum_{i=1}^{12}\sigma_{t+1-i}$ and σ_t is the aggregate stock market volatility depicted in in Figures 1 and 2. One year industrial production growth as of month t is defined as $\ln(\text{IP}_t/\text{IP}_{t-12})$, where IP_t is the seasonally adjusted industrial production index at month t. Both series are normalized so that they have the same sample mean and standard deviation, equal to zero and one. The sample covers monthly data for the period from January 1957 to September 2008. Shaded areas (in yellow) track NBER-dated recessions, and the vertical dashed line (in red) indicates the beginning of the latest NBER-dated recession. The bottom panel plots the sample cross correlations between the volatility of aggregate stock market volatility and one year industrial production growth, over the sample including the "Great Moderation," from January 1983 to September 2008.

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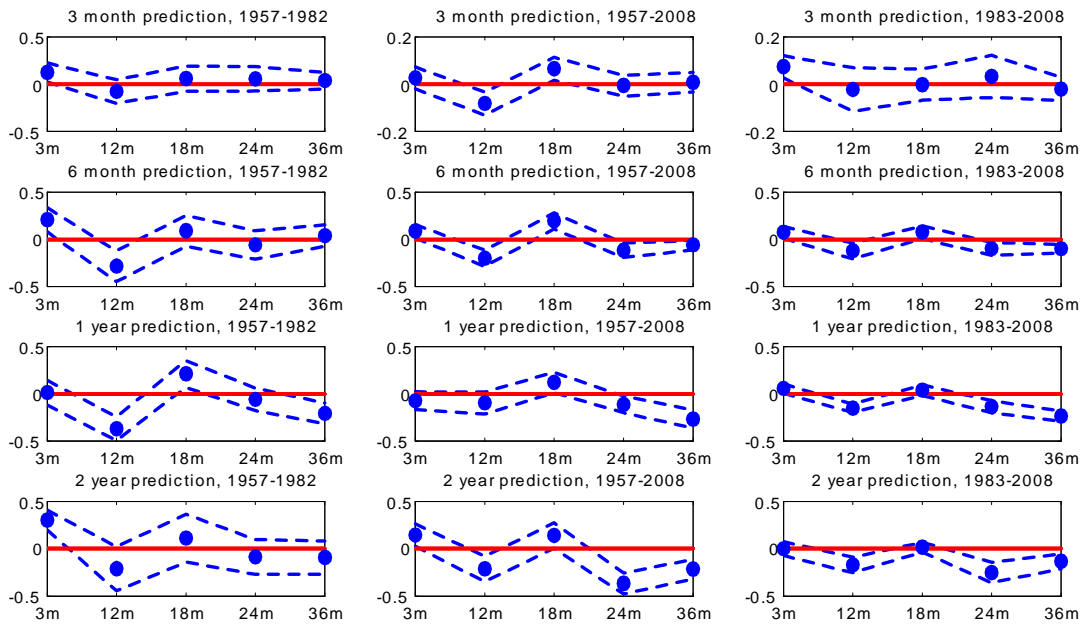
Figure 5 – Estimates of volatility loading on industrial production growth. Point estimates and 95% confidence bands for the loadings on stock market volatility lagged at 3, 12, 18, 24 and 36 months, in regressions of 3 month, 6 month, 1 year and 2 year industrial production growth on stock market volatility and the additional predictors listed on Table 4.2. Confidence bands are obtained with heteroskedasticity and autocorrelation consistent standard errors.
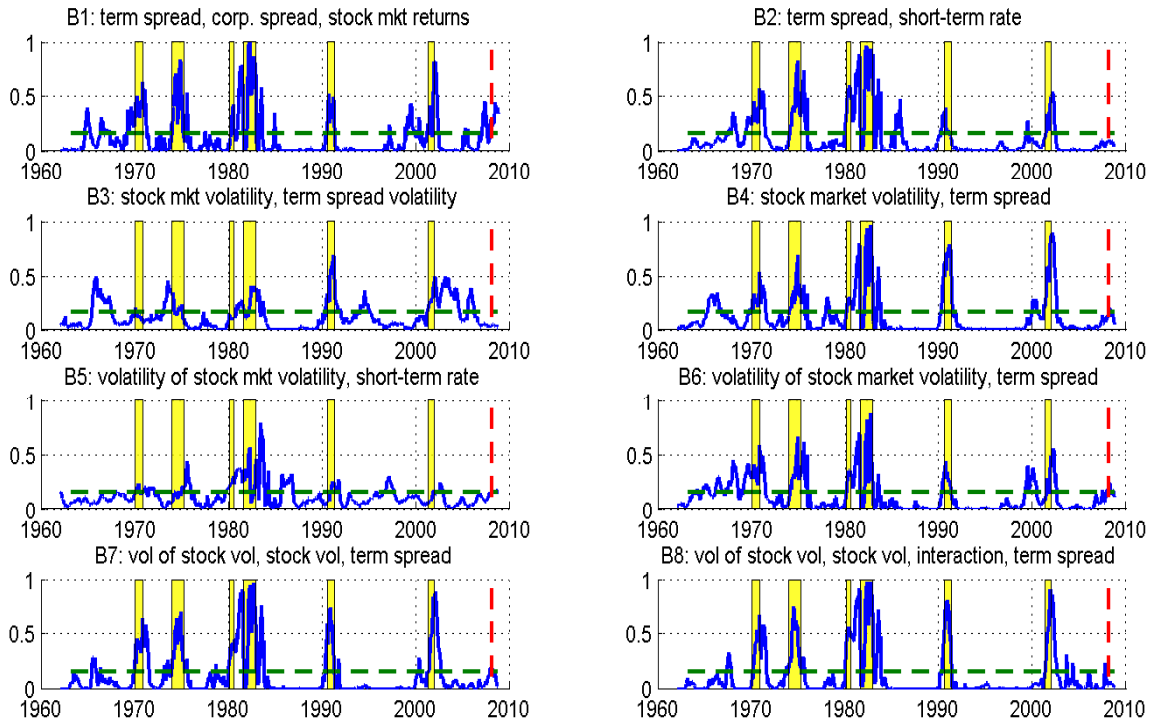
Figure 6 – Probabilities of recession predicted by in-sample estimates of Probit models. In-sample forecasts of recession probabilities one year ahead, obtained through the predicting blocks in Table 4.3, B1 through B8. The horizontal dashed line (in green) is drawn at a value equal to 16.22%, which is the fraction of time the US economy spent in recession in the sample, according to NBER dating. The sample covers monthly data for the period from January 1957 to September 2008. Shaded areas (in yellow) track NBER-dated recessions, and the vertical dashed line (in red) indicates the beginning of the latest NBER-dated recession.

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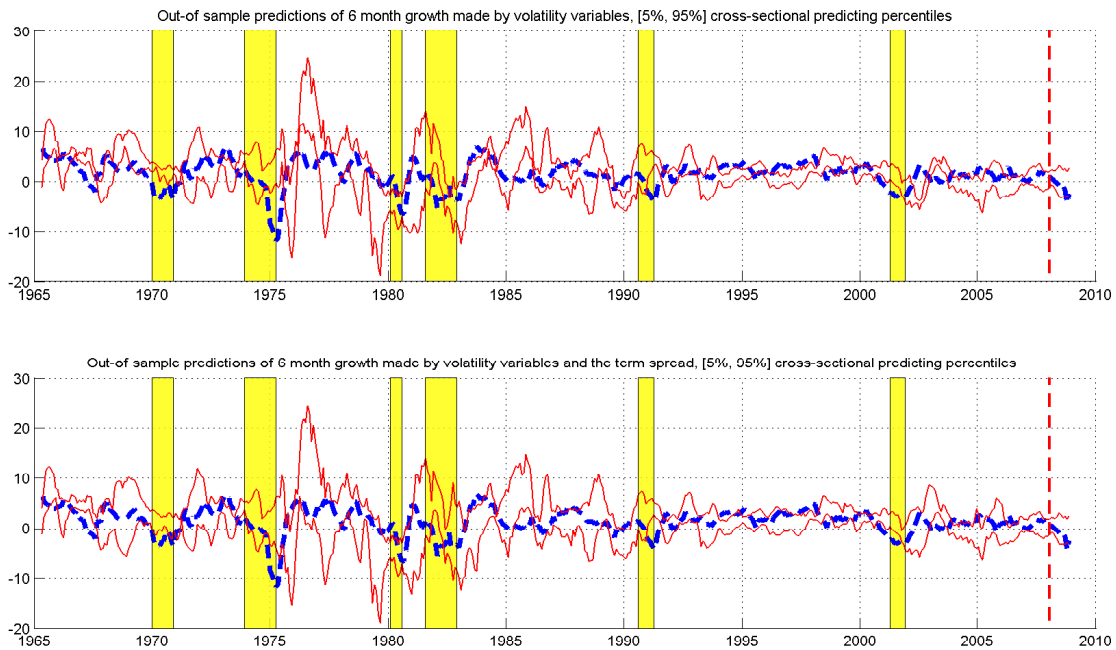
Figure 7 – Linear predictions of economic activity. Out-of sample forecasts of the six month industrial production growth. This figure depicts realized values for the six month industrial production growth, along with forecasts obtained through: (i) the predicting blocks B3 through B8 in Table 4.3, based on financial volatility variables such as the volatility of the term spread, stock market volatility, volatility of stock market volatility, an interaction term between stock volatility and volatility of stock volatility (top panel); and (ii) the predicting blocks B2 through B8 in Table 4.3, where the block B2 includes the short term rate and the term spread (bottom panel). The dashed line (in blue) is the realized value of six month industrial production growth. The solid lines are 5% and 95% percentiles of the cross sectional distribution of the predicting blocks. Predictions are obtained on rolling samples with size equal to 90 monthly observations. The sample covers monthly data for the period from January 1957 to September 2008. Shaded areas (in yellow) track NBER-dated recessions, and the vertical dashed line (in red) indicates the beginning of the latest NBER-dated recession.

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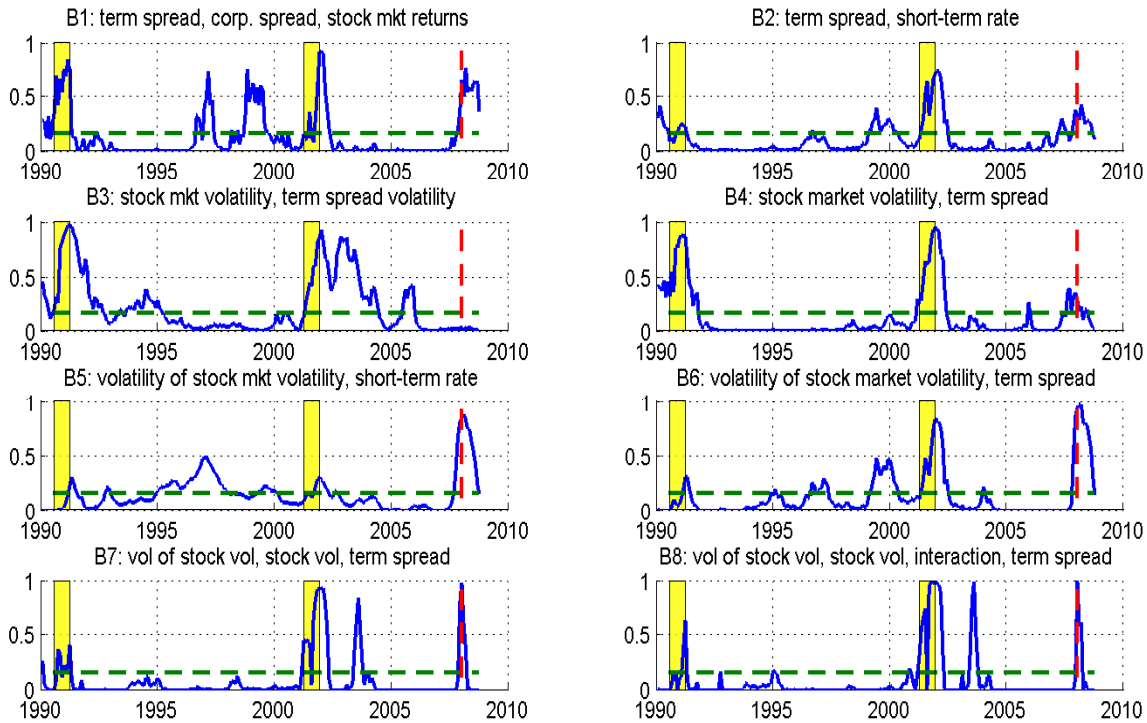
Figure 8 – Probabilities of recession predicted by Probit models: out-of-sample, coincident projections. Out-of sample forecasts of NBER-recession probabilities one-month ahead, obtained through Probit models estimated on rolling samples with size equal to 360 monthly observations, using the predicting blocks in Table 4.3, B1 through B8, and estimation window equal to twelve months. The horizontal dashed line (in green) is drawn at a value equal to 16.22%, which is the fraction of time the US economy spent in recession in the sample, according to NBER dating. The sample covers monthly data for the period from January 1957 to September 2008. Shaded areas (in yellow) track NBER-dated recessions, and the vertical dashed line (in red) indicates the beginning of the latest NBER-dated recession.
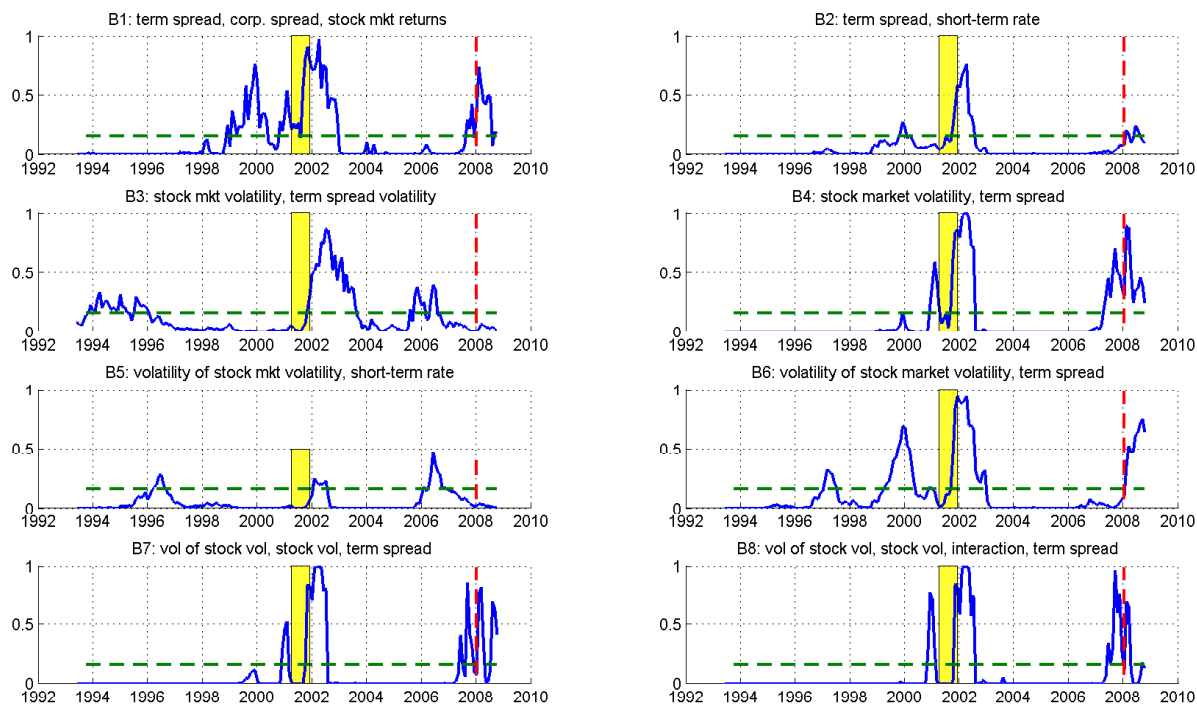
Figure 9 – Probabilities of recession predicted by Probit models: out-of-sample, six month projections. Out-of sample forecasts of NBER-recession probabilities six-month ahead, obtained through Probit models estimated on rolling samples with size equal to 360 monthly observations, using the first nine predicting blocks in Table 4.3, and estimation window equal to six months. The horizontal dashed line (in green) is drawn at a value equal to 16.22%, which is the fraction of time the US economy spent in recession in the sample, according to NBER dating. The sample covers monthly data for the period from January 1957 to September 2008. Shaded areas (in yellow) track NBER-dated recessions, and the vertical dashed line (in red) indicates the beginning of the latest NBER-dated recession.
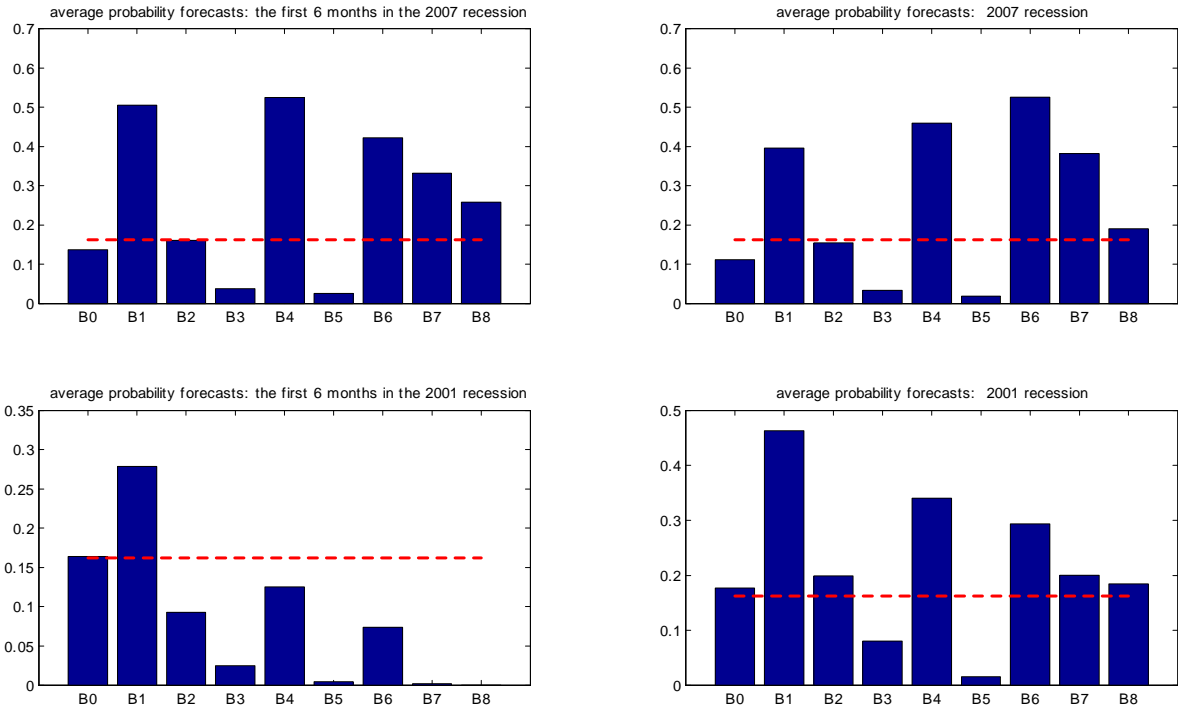
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Figure 10 – A tale of two recessions, 2001 and 2007: **average probabilities of recessions predicted by Probit models, out-of-sample, six month projections**. This figure reports out-of-sample, average probability forecasts produced by the nine blocks of Table 4.3 six months earlier, and related to the two recession episodes occurred in 2001 and in 2007. The graphs on the first column report the average projections for the first six months since the inception of each recession. The graphs on the second column report the average projections for the whole recession episodes. Keys: **B0**: Past six month industrial production growth; **B1**: Term spread, Corp. spread, Stock mkt returns; **B2**: Term spread, short rate; **B3**: Stock mkt volatility, Term spread volatility; **B4**: Stock mkt volatility, Term spread; **B5**: Vol of stock mkt vol, Short-rate; **B6**: Vol of stock mkt vol, Term spread; **B7**: Vol of stock mkt vol, Stock mkt vol, Term spread; **B8**: Vol of stock mkt vol, Stock mkt vol, Interaction, Term spread.