Sorting Stocks, Volatility Bounds, and Real Activity Prediction

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Abstract

This paper analyzes the capacity of the Hansen–Jagannathan volatility bound to predict future economic growth. Our results show that the portfolio sorting procedure employed to construct the data used to estimate the volatility bound is the key issue in the bound being able to predict real activity. We find that the volatility bound estimated with 10 size-sorted portfolios is a powerful in-sample and out-of-sample predictor of future industrial production growth.

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1. Introduction

Does financial uncertainty predict future real activity? The answer to this question is particularly relevant after the recent turmoil experienced by industrial economies over the world. This paper shows that changes in the uncertainty embedded in stock prices are a powerful indicator of future economic growth.[1] However, it is also the case that the information contained in stock return co movements is the key issue for optimally detecting the impact of financial uncertainty in future real activity.

It has been recognized for a long time that the stock market is a leading economic indicator. The original papers by Fama (1981, 1990), and Schwert (1990) argue that stock returns at monthly, quarterly and annual frequencies are highly correlated with future output growth rates and this predicting ability increases with the length of the horizon. Similarly, Stock and Watson (2003) provide a comprehensive analysis of the forecasting capacity of different variables related to financial markets in forecasting production and inflation. They find that short and long interest rates, the term spread and the stock market index improve the forecast of real gross domestic product (GDP) growth, although they also point out non-trivial instability problems inherent in the predictive relations.

Additionally, direct measures of uncertainty in financial markets seem to have relevant information about macroeconomic variables in the future. Schwert (1989) suggests that market volatility reflects uncertainty about future cash flows and discount rates. However, he does not find evidence supporting his argument since during his sample period volatility rises after the beginning of recessions. Campbell et al. (2001) find that stock volatility at a market, industry, and firm level helps to predict GDP

[1] Bloom (2009) argues that uncertainty shocks, approximated by stock market volatility, cause firms with non-convex labor and capital adjustment costs to delay hiring and investment since higher uncertainty increases the real option value of waiting. Aggregate growth productivity then falls after the uncertainty shock because the adverse effects in employment and investment slow down the reallocation from low- to high-productivity firms, which explains the real activity growth rate in the economy.

growth during the post-war period. More recently, Fornari and Mele (2011) show that a slowly changing measure of stock market volatility that captures the long run uncertainty in the financial market explains future trends of economic activity.[2] Moreover, this measure of stock market volatility, together with the term structure spread, anticipate all National Bureau of Economic Research recession episodes, including the recent financial and credit crisis. In addition, Chauvet, Senyuz, and Yoldas (2011) report that the long-run component of financial volatility, in the sense of Adrian and Rosenberg (2008) but extracted from the realized volatility of market, industry, and 10-year zero coupon Treasury bond returns, helps in predicting economic activity.[3]

Finally, Nieto and Rubio (2011), using a consumption-based parametric approach for measuring the uncertainty embedded in financial prices, also predict real activity.[4] Specifically, they use the volatility of alternative consumption-based stochastic discount factor specifications as a measure of uncertainty. Working with contemporaneous and long-run recursive preferences, they argue that the significant predictability of this volatility relies mainly on the joint effect of their components, that is, the volatility of consumption growth, stock market volatility, and the covariance between consumption growth and market returns.[5]

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[2] Fornari and Mele (2011) justify their findings following the theoretical framework of Mele (2007, 2008), who shows the countercyclical and asymmetric nature of volatility in recessions and expansions.

[3] In related literature, Andreou, Ghysels, and Kourtellos (2010) employ implied volatility as a predictor of economic activity and Backus, Chernov, and Martin (2011) employ equity index options to quantify the distribution of consumption growth disasters. These authors show that options suggest smaller probabilities of extreme outcomes than have been estimated from macroeconomic data. It is important to point out that not only lagged market returns and volatility have been employed as leading indicators of economic activity. Naes, Skleltorp, and Arne-Odegaard (2011) report a strong relation between stock market liquidity and the business cycle.

[4] The authors also show some power in predicting stock market returns at relatively long horizons. Although they show some predicting capacity at short horizons, the predictability of stock market returns is much weaker than at long horizons. Our current paper does not address the issue of predicting stock returns. For recent literature on predicting future stock market excess returns, see, among many others, Campbell and Yogo (2006), Cochrane (2008), Goyal and Welch (2008), Brennan and Taylor (2010), Ferreira and Santa-Clara (2011), and Cochrane (2011).

[5] The authors also find similar effects using non-separable durable and nondurable preferences.

This paper employs a much simpler approach to investigate the predictability of real activity. In particular, we use the Hansen–Jagannathan (HJ hereafter, 1991) volatility bound from a model-free perspective rather than a marginal rate of substitution approach. Given a set of portfolio returns and the average risk-free rate for the corresponding sample, we obtain the volatility bound using the expression proposed by HJ and a rolling window of five years of past data. We show how the model-free volatility bound is a powerful predictor of future economic growth for both in-sample and out-of-sample contexts. In the end, the HJ bound is the maximum Sharpe ratio; thus our measure includes not only excess market returns but also information about correlation or exposure to common shocks and market volatility. However, the paper's main finding is that the predictability of the bound depends on the sorting procedure used to construct the equity portfolios employed in the bound's estimation. Hence, the dynamic interaction effects between individual stocks seem to be a key issue in extracting the information contained in the stock markets about future real activity.

This paper is organized as follows. Section 2 describes our data and Section 3 presents the main in-sample predictability results, using size-sorted portfolios. Section 4 discusses the forecasting evidence using alternative sorting procedures and Section 5 compares the predicting ability of the HJ measure with respect to standard state variable predictors. Section 6 performs the out-of-sample analysis and Section 7 further investigates the reasons underlying the forecasting capacity throughout the principal components of the variance–covariance matrices of the alternative equity portfolios employed in the paper. Section 8 concludes with a summary and final remarks.

2. Data

Most stock market data are from Kenneth French´s website. We obtain monthly data from January 1927 to December 2010 for the market return (R_m), the risk-free rate (R_f), the small-minus-big (*SMB*) and high-minus-low (*HML*) Fama and French (1993) risk factors, and 10 value-weighted size-, book-to-market-, momentum-, and dividend yield-sorted equity portfolios. Table 1 contains descriptive statistics on these portfolios. We observe the well-known size and value premia. On an annualized basis, small firms earn, on average, 7.4% more than large firms, while value firms earn 6.3% more than growth firms. Similarly, high-momentum companies obtain a 14.4% higher average return than low-momentum firms, while high dividend yield stocks achieve a 1.9% higher return, on average, than low dividend payment stocks. As expected, we observe more dispersion in average returns in size-, book-to-market-, and momentum-sorted portfolios than in dividend yield-sorted stocks. At the same time, small, growth, and low-momentum stocks present higher volatility than large, value, and high-momentum firms. Extreme dividend yield stocks are more volatile than intermediate dividend yield firms, but the high and low dividend yield portfolio volatilities are very similar. Finally, the correlations between small and large companies, value and growth firms, high- and low-momentum stocks, and high and low dividend yield assets are found to be the smallest within a given sorting category: 0.698, 0.714, 0.594, and 0.667 for size-, book-to-market-, momentum-, and dividend yield-sorted portfolios, respectively.

The price-dividend ratio in logs (*PD*) is computed from the original series on Robert Shiller’s website. Additionally, yields for the 10-year government bond, the one-month T-bill, and Moody’s Baa Corporate Bond series are obtained from the Federal Reserve Statistical Release. We then compute two state variables based on these interest rates: a term structure slope (*Term*), computed as the difference between the 10-year government bond and one-month T-bill yields, and a default premium (*Default*) that is the difference between Moody´s yield on Baa Corporate Bonds and the 10-year government bond yields.

Given the real activity forecasting evidence from aggregate illiquidity reported by Naes, Skjeltorp, and Arne-Odegaard (2011), we also use a market-wide illiquidity indicator (*Illiq*) based on the aggregate illiquidity ratio proposed by Amihud (2002).[6] This is the ratio of the absolute daily return over the dollar volume for a given stock, which is closely related to the notion of price impact. This measure is averaged monthly and across all available stocks to obtain the market-wide illiquidity measure for each month in the sample. As in Naes, Skjeltorp, and Arne-Odegaard (2011), we demean the series relative to a two-year moving average of the series.

We also obtain nominal consumption expenditures on nondurable goods and services from the Table 2.8.5 of the National Institute of Pension Administrators (NIPA). Population data are from NIPA's Table 2.6 and the price deflator is computed using prices from NIPA's Table 2.8.4 with the year 2000 as its basis. All this information is used to construct monthly seasonally adjusted real per capita consumption expenditures on nondurable goods and services (ΔC). Finally, monthly data of the industrial production index (*IPI*) are downloaded from the Federal Reserve, with series identifier G17, IP Mayor Industry Groups.[7]

[6] The main advantage of Amihud's illiquidity ratio is that it can be easily computed using daily data during long periods. Moreover, Hasbrouck (2009) shows that, at least for US data, Amihud´s ratio better approximates Kyle´s lambda relative to competing measures of illiquidity.

[7] With the exception of market-wide illiquidity, monthly data for all these state variables are available from January 1965 to July 2010. The illiquidity variable is available from January 1965 to December 2008.

3. In-Sample Predictability of Real Activity with the Volatility of the HJ Bound

We first estimate the monthly HJ volatility bound of the model-free stochastic discount factor with overlapping sub-periods of five years of monthly data from the 10 size-sorted portfolios, using

$$\sigma(M) \geq \left[(1_N - E(M)E(R))' V^{-1}(1_N - E(M)E(R))\right]^{1/2}, \tag{1}$$

where *M* is the stochastic discount factor satisfying the first-order pricing equations,

$$1 = E_t\left[M_{t+1}R_{jt+1}\right],$$

$$E_t\left[M_{t+1}\right] = 1/R_{ft+1},$$

where 1_N and $E(R)$ are the *N*-vectors of ones and average gross returns, respectively; V^{-1} is the inverse of the variance–covariance matrix of returns; and R_f is the gross risk-free rate. The monthly estimated volatility corresponds to the average level of the risk-free interest rate for each of the five-year sub-periods. Unlike the work by Nieto and Rubio (2011), this procedure does not depend on any particular consumption-based stochastic discount factor specification, so the potential predictive relation does not depend on any given consumption dynamics.

Figure 1 shows this rolling-window HJ volatility bound and the National Bureau of Economic Research's recession bars for the period from 1931 to 2010. It shows how the bound tends to increase before macroeconomic recessions, reaching its historical peak well before and during the recent financial turmoil. Although the peaks of the bound tend to occur during the corresponding recession months, the volatility of the stochastic discount factor always increases before the start of a recession.

Panel A of Table 2 contains the results from the following predictive ordinary least squares (OLS) autocorrelation-robust standard error regressions:

$$\Delta IPI_{t,t+\tau} = \alpha + \beta\,\sigma_t(M) + \varepsilon_{t+\tau}, \tag{2}$$

where $\Delta IPI_{t,t+\tau}$ is the growth of industrial production at horizons of one, three, six, 12, and 24 months calculated as $\Delta IPI_{t,t+\tau} = ln(IPI_{t+\tau}/IPI_t)$, and $\sigma_t(M)$ is the volatility of the stochastic discount factor available at month *t* that is estimated with five years of monthly data up to month *t*. Given data restrictions on some of the state variables used later, we run these predictive regressions between January 1965 and July 2010.

The regression in expression (2) is estimated with $\sigma_t(M)$ from the use of 10 size-sorted portfolios, as well as with the five smallest and five largest portfolios. This separation allows one to analyze whether the forecasting relation is especially strong when the uncertainty measure tracks the higher degree of sensitivity of small companies to economic shocks. The first block of Panel A of Table 2 reports the key results of the paper. There is a negative and significant relationship between the volatility of the stochastic discount factor and future industrial production growth. Both the magnitude of (the absolute value of) the coefficients and the R^2 value increase considerably with the time horizon, with R^2 as high as (approximately) 20 percent at the 24-month horizon. If we interpret $\sigma_t(M)$ as a measure of the financial uncertainty embedded in stock prices, these results show that higher uncertainty has a negative and significant impact on future real activity. Therefore, our measure of uncertainty conveys information about future economic growth.[8]

The results using the smallest or largest set of size-sorted portfolios separately also tend to show a negative relationship between $\sigma_t(M)$ and future real activity. Once

[8] Because the HJ volatility bound is very persistent, we also calculate the bias-corrected estimator and the corresponding bias-corrected *t*-statistic proposed by Amihud and Hurvich (2004). These authors suggest a regression method for hypothesis testing in predictive regressions in which the independent variable is persistent and its innovations are correlated with the dependent variable. This produces biased estimates and biased *t*-statistics. The authors' simulations show that their adjustment outperforms other bias correction methods, such as those suggested by Stambaugh (1999) and Lewellen (2004). Consequently, we replicate the forecasting regressions with their procedure. The results are qualitatively the same as those reported in Table 2, and the predicting capacity of the bound remains statistically significant. The results are available upon request.

again, the longer the horizon in the regression, the stronger the predicting results. However, for the one-, three-, six-, and 12-month horizons, both the magnitudes of the coefficients and the R^2 are smaller for both sets of five portfolios than for the original 10 size-sorted portfolios. For the longest horizon, the R^2 value for the original set and the five largest portfolios are 19.6 and 18.1 percent, respectively. It is somehow surprising that the R^2 value when $\sigma_t(M)$ is calculated for the five smallest portfolios is relatively lower and equal to 12.6 percent, although the magnitude of the negative slope coefficients are almost the same in all three cases. Generally speaking, we can conclude that forecasting capacity seems to be stronger using all assets in the stock market, as represented by the 10 size-sorted portfolios, rather than employing either the sets of largest or smallest stocks. Therefore, these initial results do not allow us to associate the forecasting ability reported with the potentially greater or lesser sensitivity of alternative equity portfolios to economic shocks.

To further investigate this finding, Panel B of Table 2 reports the results of the following forecasting regressions:

$$\begin{aligned} \Delta IPI_{t,t+\tau} &= \alpha + \beta_1\, \sigma_t^{10}(M) + \beta_2 \sigma_t^{Small}(M) + \varepsilon_{t+\tau}, \\ \Delta IPI_{t,t+\tau} &= \alpha + \beta_1\, \sigma_t^{10}(M) + \beta_2 \sigma_t^{Big}(M) + \varepsilon_{t+\tau}, \end{aligned} \tag{3}$$

where $\sigma_t^{Small}(M)$ and $\sigma_t^{Big}(M)$ are the volatility of the HJ bound estimated by expression (1) for the five smallest and five largest portfolios, respectively, and $\sigma_t^{10}(M)$ is the bound for the 10 size-sorted portfolios. The time series of these three HJ bounds are displayed in Figure 2. Although the series of $\sigma_t^{Small}(M)$ and $\sigma_t^{Big}(M)$ cross each other in several points in time, depending on the particular state of the economy, the series of $\sigma_t^{10}(M)$ is practically always above the other two estimations of the HJ bound.

The results provided in Panel B of Table 2 show that the regression coefficients associated with $\sigma_t^{10}(M)$ and R^2 are practically the same as in Panel A. The inclusion of $\sigma_t^{Small}(M)$ and $\sigma_t^{Big}(M)$ does not add any significant explanatory power of future economic growth once we control for the behavior of the HJ bound under all 10 size-sorted portfolios. The only exception occurs when we also employ $\sigma_t^{Big}(M)$ at the longest horizon. Even in this case, the coefficient associated with $\sigma_t^{Big}(M)$ is estimated with much less precession than the coefficient related to $\sigma_t^{10}(M)$, and the magnitude of the $\sigma_t^{Big}(M)$ coefficient is (in absolute value) approximately half the $\sigma_t^{10}(M)$ slope coefficient.

We conclude that the forecasting ability of the volatility of the stochastic discount factor as characterized by the HJ bound lies in the use of the 10 size-sorted portfolios rather than a subset of the five smallest or five largest portfolios. It seems that the inclusion of all assets when estimating the HJ bound is important to capture future real activity.

4. In-Sample Predictability of Real Activity: Other Portfolio Formation Criteria

We now estimate three additional alternative measures of the HJ volatility bound by using the returns of 10 book-to-market-, momentum-, and dividend yield-sorted portfolios. As before, we employ a rolling window of five years of past monthly returns. Figure 3 displays the HJ bounds for the full sample period. We observe important differences between the alternative estimated bounds. Note that the volatility dispersion and the complex dynamic correlation behavior among the 10 portfolios in each of the four sets employed can generate potentially different time series of the HJ bounds. It seems particularly important to note that the HJ bound for the momentum portfolios increases before the recessions at the end of the 1980s and at the beginning of the new century. These peaks are probably associated with the uncertainty generated in these portfolios after the crash of October 1987 and during the dot-com bubble. On the other hand, the highest peak before the actual crisis is clearly from the HJ bound estimated with the 10 size-sorted portfolios.

We perform the forecasting regressions of equation (2) using the HJ bound estimated with the 10 portfolios of each set as well as with the two subsets of five portfolios for all three sorting criteria. Panels A to C of Table 3 report the results for the book-to-market-, momentum-, and dividend yield-sorted portfolios, respectively.

Surprisingly, independently of the forecasting horizon, none of the estimates of the HJ volatility bound constructed from these portfolio sets present significant predicting results. It may be the case that the dynamics of the volatility dispersion and the correlation between stocks included in the alternative sorted portfolios induce a different forecasting ability of real activity. Although we return to this issue in Section 7 below, we point out that the annualized volatility dispersion between the extreme portfolios contained in the descriptive statistics of Table 1 turns out to be the highest for the size-sorted portfolios. In particular, the smallest portfolios have an 18.6 percent higher annualized volatility than the largest stocks, while the dispersion is only 12.7 percent, 11.4 percent, and 0.9 percent for the book-to-market-, momentum-, and dividend yield-sorted portfolios. Similarly, the dispersion between the minimum and maximum correlations between the portfolios is 0.28, 0.24, 0.35, and 0.26 for the size-, book-to-market-, momentum-, and dividend yield-sorted portfolios. The dynamics of these volatilities and correlations seem to be a potentially key factor in explaining the different predicting capacities of the alternative HJ bound estimates. If so, sorting procedures and the corresponding time-varying diversification effects would be a relevant issue for forecasting production growth with volatility bounds.

5. In-Sample Predictability of Real Activity: Competing Predictors

Given the significant predicting ability of the HJ volatility bound estimated with 10 size-sorted portfolios, we now investigate how robust our forecasting results are to competing predictor variables of real activity. We consider predictors related to interest rates, stock market returns, and illiquidity. The justification of the selection of these alternative predictors is presented in Section 5.1 and the forecasting results are discussed in Section 5.2. In addition, lagged values of the dependent variable are included in the forecasting regression to pick up potential autoregressive dynamics in industrial production, since we consider growth rates for periods longer than one month. Section 5.3 contains the results of this analysis.

5.1. Competing Predictors of Real Activity

The term spread, measured as the difference between the interest rates on long and short maturity government debt, is probably the most common financial leading indicator of real activity. Among many others, Estrella and Hardouvelis (1991), Estrella and Mishkin (1998), Stock and Watson (2003), Ang, Piazzesi, and Wei (2006), and Fornari and Mele (2011) show the significant predictive content of the spread for production growth, including its capacity to forecast a recession indicator in probit regressions. Additionally, there is a growing body of literature exploring the transmission of credit conditions into the real economy. Among recent papers, Mueller (2009) and Gilchrist, Yankov, and Zakrajsek (2009) show the forecasting power of the term structure of credit spreads for future output growth. These authors argue that there is a pure credit component orthogonal to macroeconomic conditions that accounts for a large part of the predicting capacity of credit spreads.

Moreover, as long as stock prices equal the expected discounted value of future earnings and dividends, stock returns should also be useful in forecasting output growth. This is the insight of Fama (1981, 1990). On top of that, given the well-known evidence of the aggregate dividend yield being a powerful predictor of future market excess returns, as discussed recently by Cochrane (2011), the price–dividend ratio becomes an appropriate state variable to use for forecasting real activity. Two other stock market indicators have become popular in predicting output growth. Naes, Skjeltorp, and Arne-Odegaard (2011) argue that stock market liquidity tends to dry up before a crisis in the real economy. In fact, they show that measures of stock market liquidity contain leading information about future economic growth, even after controlling for other financial leading indicators. Finally, there has been considerable recent attention to financial stock market volatility as a predictor of real activity. Fornari and Mele (2011) argue that it is important to extract the long-run component of stock market volatility when using this variable as a predictor of future growth.[9] To isolate extreme financial episodes that may not be necessarily informative about the economy's future scenario, the authors propose a simple moving average of the past 12 months of absolute returns as the appropriate forecaster of real activity.

5.2. In-Sample Predictability with Competing Predictors

We next employ all seven variables discussed above and compare their in-sample predicting ability with that of the HJ volatility bound as estimated with 10 size-sorted

[9] See the similar arguments of Chauvet, Senyuz, and Yoldas (2011).

portfolios. We run the following regressions with individual predictors and with pairs of predictors that always include the HJ bound:

$$\Delta IPI_{t,t+\tau} = \alpha + \beta_1 \, \sigma_t(M) + \beta_2 R_{mt} + \beta_3 \sigma_t(R_{mt}) + \beta_4 PD_t + \beta_5 Def_t + \beta_6 Term_t + \beta_7 Illiq_t + \varepsilon_{t+\tau}, \tag{4}$$

where $\sigma_t(R_{mt})$ is the market return volatility estimated at each month t with overlapping sub-periods of five years of monthly returns, to be consistent with our measure of the HJ bound.

The results are reported in Table 4. Independently of the alternative state variable employed and forecasting horizon, the HJ volatility bound has always a negative and highly significant relation with future *IPI* growth. Hence, our forecasting relation is systematically estimated with high precision.

At the one-month horizon, all state variables present some evidence of predictability, except the stock market return. All predictors present the expected signs. The term spread coefficient is positive, while the rest of the state variable estimators have the theoretically correct negative sign. Note that increases in the volatility of the market, the default spread, and market-wide illiquidity signal a higher degree of uncertainty, and we also know that increases in the dividend yield forecast future positive market excess returns, which implies that increases in the price–dividend ratio should predict negative market returns and a negative impact on real activity. Once we combine on an individual basis the HJ volatility bound with the rest of the predictors, it turns out that the coefficients associated with the volatility of the market return, the price–dividend ratio, and the default spread are estimated with much more precision. This result does not seem to hold for the term and market-wide illiquidity variables. It is especially relevant the combined effects of the HJ bound and the default spread; the R^2 value at just the one-month horizon is 9.38 percent.

It is important to point out that we display the results using the volatility of the stock market estimated at each time *t* with the past five years of monthly data. We also repeat the regressions using the estimate suggested in Fornari and Mele (2011):

$$\sigma_t(R_{mt}) = \sqrt{\frac{\pi}{2}} \cdot \frac{1}{12} \sum_{k=1}^{12} \left| R_{mt+1-k} \right|, \tag{5}$$

where $\sqrt{\pi/2}$ is a scaled factor related to the use of absolute values. This measure provides slightly better results than the previous measure of market volatility. In particular, the coefficient is -0.072 and it is also estimated with higher precision, so that the *t*-statistic is -1.99 rather than -1.21. However, it does not change the conclusion about the forecasting power of the HJ bound.

At the three-month horizon, all predictors seem to be individually significant and with the correct sign. Interestingly, the volatility of the stock market loses forecasting capacity, although, as when we use the estimator given by expression (5), the coefficient is estimated with more precision, and the *t*-statistic becomes -1.6. In the combined regressions, the higher R^2 statistics are obtained when adding the volatility of the stock market, the price–dividend ratio, and the default spread to the HJ volatility bound. The regression with the HJ bound and the price–dividend ratio presents an R^2 of 15.5 percent.

Finally, for all other longer horizons, the results are similar, except that the term spread becomes much more relevant in forecasting output growth and the default spread loses its significant predicting ability. Hence, the combinations of the HJ volatility bound with the stock market return, the volatility of the market, the price–dividend ratio, and the term spread seem to be relevant factors in predicting future production growth at long horizons. At the six-month horizon the highest R^2 is observed when combining the HJ bound with the price–dividend ratio, while the combinations of the volatility bound with the term spread have the highest R^2 statistics at the 12- and 24-month horizons. At the longest horizons, the HJ bound and term spread explain 28.3 percent of the variability of future production growth. To conclude, the default spread conveys information about future economic growth at relatively short horizons, while the term spread has predicting capacity at longer horizons. In all cases, the HJ volatility bound calculated with 10 size-sorted portfolios remains a strong predictor of real activity.

5.3. Lagging the Dependent Variable

Since we make multi-step ahead predictions, serial correlation in industrial production growth is expected. This suggests that the forecasting regressions should also include lagged values of the dependent variables. Therefore, we now run the regression

$$\Delta IPI_{t,t+\tau} = \alpha + \beta_1 \, \sigma_t(M) + \beta_2 \Delta IPI_{t,t-\tau} + \varepsilon_{t+\tau}. \tag{6}$$

The results are shown in Table 5. The autoregressive structure of *IPI* growth is confirmed for horizons of one, three, and six months. However, the coefficients associated with the HJ volatility bound remain negative and statistically significant in all cases. In fact, these coefficients are very similar to those reported in Table 2. Therefore, although the inclusion of the lagged dependent variable helps predict real activity, lagging the dependent variable does not seem to have any effect on our previous conclusions regarding the importance of the HJ volatility bound as an ex ante uncertainty predictor of economic cycles.

6. Out-of-Sample Tests

The predicting tools employed so far examine the ability of the predictors had we been able to use the coefficients estimated by the full-sample regressions. We now consider tests designed to generate more closely actual real time forecasts. We employ two alternative statistics for testing the out-of-sample accuracy of two competing models: the *t*-test proposed by Diebold and Mariano (1995) and the *F*-statistic of McCracken (2007). In our case, the two compared models are always nested. The restricted model contains only one of the competing predictors already used in our in-sample tests: either the stock market return, the volatility of the stock market due to Fornari and Mele (2011), the price–dividend ratio, the default spread or the term spreads.[10] On the other hand, the unrestricted model contains such a predictor and the HJ volatility bound estimated with 10 size-sorted portfolios.

We now briefly describe this methodology. The total sample period contains $T + P$ observations, where the initial in-sample estimation period employs information from 1 to T, and the out-of-sample forecasting period goes from $T + \tau$ to $T + P$, τ being the forecasting horizon. At each forecasting period $t = T + \tau, \ldots, T + P$, we estimate the two competing nested models using information up to the previous τ periods, generate the prediction, and compute the forecasting error. More formally, the restricted model is

$$Y_s = \beta_0^R + \beta_1^R X_{s-\tau} + u_{Rs} \quad , \quad s = \tau + 1, \ldots, t - \tau \, . \tag{7a}$$

The prediction under the restricted model is

$$\hat{Y}_{Rt} = \hat{\beta}_0^R + \hat{\beta}_1^R X_{t-\tau} \, , \tag{7b}$$

and the prediction error will be

$$\hat{u}_{Rt} = Y_t - \hat{Y}_{Rt} \, . \tag{7c}$$

Similarly, the unrestricted model that includes the HJ volatility bound, the next period prediction and forecasting error are

$$Y_s = \beta_0^U + \beta_1^U X_{s-\tau} + \beta_2^U \sigma_{s-\tau}(M) + u_{Us} \quad , \quad s = \tau + 1, \ldots, t - \tau \, , \tag{8a}$$

[10] Since the market-wide illiquidity variable contains data only until the end of 2008, our out-of-sample tests do not employ this state variable.

$$\hat{Y}_{Ut} = \hat{\beta}_0^U + \hat{\beta}_1^U X_{t-\tau} + \hat{\beta}_2^U \sigma_{t-\tau}(M), \tag{8b}$$

$$\hat{u}_{Ut} = Y_t - \hat{Y}_{Ut} \ . \tag{8c}$$

We next compute the vector of loss differentials, denoted *d*, that compares the two square errors at each month *t* and the mean squared forecasting error (MSE) for each model:

$$d_t = \hat{u}_{Rt}^2 - \hat{u}_{Ut}^2 \ , \ t = T+\tau, \ldots, T+P, \tag{9}$$

$$MSE_R = (P-\tau+1)^{-1} \sum_{t=T+\tau}^{T+P} \hat{u}_{Rt}^2 , \tag{10}$$

$$MSE_U = (P-\tau+1)^{-1} \sum_{t=T+\tau}^{T+P} \hat{u}_{Ut}^2 . \tag{11}$$

The two statistics for testing equal forecasting accuracy have the null that the loss differentials are zero, on average. The Diebold–Mariano (1995) statistic is a *t*-test expressed as

$$MSE - t = (P-\tau+1)^{-1/2} \frac{\bar{d}}{\sqrt{\hat{S}_d}} \ , \tag{12}$$

where $\bar{d} = (P-\tau+1)^{-1} \sum_{t=T+\tau}^{T+P} d_t$ and $\hat{S}_d$ is a consistent estimator of the variance of the loss differential that admits heteroskedasticity and autocorrelation. We employ the Newey–West (1987) specification and, following Clark and McCracken (2011), a lag length of $k = 1.5 \cdot \tau$. Hence

$$\hat{S}_d = \sum_{j=-k}^{k} \left(\frac{k-|j|}{k} \right) (P-\tau-j+1)^{-1} \sum_{t=T+\tau}^{T+P} (d_t - \bar{d})(d_{t-j} - \bar{d}) \ . \tag{13}$$

The McCracken (2007) statistic is an *F*-test given by

$$MSE-F=\left(P-\tau+1\right)\frac{MSE_R-MSE_U}{MSE_U}. \qquad (14)$$

It must be noted that the loss differentials are measured with an error that is due to the fact that the beta coefficients are unknown. This implies that the exact distribution of both statistics is also unknown and that the asymptotic distribution can only be obtained under restrictive assumptions that include non-nested models.[11] As previously pointed out, this paper compares nested models. For this case, Clark and McCracken (2011) suggest deriving the asymptotic distribution by a fixed regressor bootstrap, and they show that the test statistics based on the proposed bootstrap have good size properties and better finite-sample power than alternative bootstraps. This method is based on the wild fixed regressor bootstrap developed by Goncalves and Killian (2004) but adapted to the multi-step framework of out-of-sample forecasts. To implement this method, we use the followings steps.

1. We estimate both the restricted and unrestricted models using the full sample period and we compute the residuals from the unrestricted model:

$$\hat{u}_{Ut}=Y_t-\hat{\beta}_0^U+\hat{\beta}_1^U X_{t-\tau}+\hat{\beta}_2^U\sigma_{t-\tau}\left(M\right), \quad t=1+\tau,\ldots,T+P.$$

2. We assume and estimate an MA (τ – 1) process to capture the implicit serial correlation in the residuals from a τ-step-ahead forecast,

$$u_{Ut}=\varepsilon_t+\theta_1\varepsilon_{t-1}+\ldots,+\theta_{\tau-1}\varepsilon_{t-(\tau-1)}, \quad t=1+\tau,\ldots,T+P.$$

3. We simulate a sequence of independent and identically distributed $N(0,1)$ random variables denoted by η_t and generate artificial residuals by using the estimates of the MA process:

$$u_{Ut}^{*}=\eta_t\hat{\varepsilon}_t+\hat{\theta}_1\eta_{t-1}\hat{\varepsilon}_{t-1}+\ldots,+\hat{\theta}_{\tau-1}\eta_{t-(\tau-1)}\hat{\varepsilon}_{t-(\tau-1)}, \quad t=2\tau,\ldots,T+P.$$

[11] See West (1996) and Clark and McCracken (2001) for a discussion.

4. We simulate an artificial series of the dependent variable using the artificial residual and imposing the null hypothesis:

$$\hat{Y}_t^* = \hat{\beta}_0^R + \hat{\beta}_1^R X_{t-\tau} + u_{Ut}^*, \ \ t = 2\tau, \ldots, T + P .$$

5. We compute both the MSE *t*-statistics and MSE *F*-statistics using these artificial data as if they were the original data.

6. Repeat steps 3–5 5,000 times and the *p*-value is the percentage of times the simulated statistic is greater than the real statistic.

The out-of-sample results are reported in Table 6. The first row for each forecasting horizon shows the relative MSE given by the expression $RMSE = MSE^U / MSE^R$. Note that when the RMSE is less than one, the inclusion of the HJ volatility bound as an additional predictor improves the forecasting capacity with respect to any of the competing standard predictors. Below each of the test statistics employed, we report the corresponding *p*-value obtained through the fixed regressor bootstrap explained above. The empirical evidence is quite conclusive. Most of the time, we show that the inclusion of the HJ bound significantly improves the predicting capacity of the model. The RMSE is practically always less than one, and the *p*-values tend to be very low. It turns out that this is the case independent of the forecasting horizon. The only variable that competes on a similar basis regarding its capacity to predict real activity is the term spread. For horizons of one, three, and six months the null of no difference between the forecasting errors of the two models is not rejected. For horizons of 12 and 24 months, the RMSE is greater than one and the null is rejected, indicating that the model including only the term spread has better out-of-sample performance. Therefore, the term spread becomes a better forecaster the longer the predicting horizon. On the other hand, the default spread presents with precisely the opposite behavior. Note that this is consistent with the in-sample results contained in

Table 4. Finally, we should mention that the stock market volatility consistently shows a higher MSE than the HJ volatility bound. In fact, the test statistics show that the inclusion of the HJ volatility bound always significantly improves the predicting capacity of the stock market volatility.

7. Principal Component Predictability

The finding that predictability of real activity occurs when HJ volatility bound is estimated by using size-sorted portfolios is both interesting and surprising. It seems that the time-varying behavior of correlations and variance dispersion between stocks may be the reason behind our results. This section provides further empirical evidence analyzing the principal components from the set of portfolio returns of the alternative sorting procedures. Principal component analysis allows us to decompose the behavior of the whole set of portfolio returns, within a given sorting procedure, into orthogonal components each corresponding to a different set of information.

By definition, the first principal component is the (normalized) linear combination of portfolio returns with maximum variance. Table 7 shows that the first three principal components explain 98.6, 96.0, 96.0, and 94.0 percent of the total variability of returns for the size-, book-to-market-, momentum-, and dividend yield-sorted portfolios, respectively. The first principal component of the size-sorted portfolios explains a higher percentage than the first principal components of the alternative sorting strategies. Additionally, we observe that the correlation coefficients between the first principal components of the book-to-market-, momentum-, and dividend yield-sorted portfolios are 0.97 for the three pairs, while the correlation between the first principal components of these portfolios and the size-sorted portfolios is slightly lower and equal to 0.95, 0.93, and 0.91, respectively. The second principal component of the size-sorted stocks has a correlation coefficient of 0.62 with the second component of the book-to-market–sorted portfolios, and much lower correlation with the rest of the second principal components. We also find correlations higher than 0.45 between the second principal components from the book-to-market- and dividend yield-sorted assets and from the momentum- and the dividend yield-sorted portfolios. Finally, correlations between the third principal components from the different sets of portfolios are relatively much lower than in all other cases.

To understand the economic factors behind these principal components, we next perform the following regressions for each of the three principal components and each portfolio set separately:

$$PC_{i,t} = \alpha + \beta X_t + u_t \,,\ i = 1,2,3 \,, \tag{15}$$

where X_t is, alternatively, the stock market return, the price–dividend ratio, the SMB or HML Fama–French factors, the default spread, the term spread, the real consumption growth, and the market-wide illiquidity factor.

The results are reported in Table 8. The variability of the first principal component from the size-sorted portfolios is clearly explained by the stock market return. However, R^2 is 86.6 percent, which is relatively lower than the percentage explained of the first principal component by the market return when using alternative sorting procedures. The R^2 values for the book-to-market-, momentum-, and dividend yield-sorted portfolios are 92.9, 93.2, and 92.6, respectively.[12] As expected, when we run the regression of the first principal component of the size-sorted portfolio returns into the SMB factor, we find that this factor explains 38.1 percent of the variability of the first component. Hence, the first principal component of the size-sorted stocks is explained

[12] The first principal component of the alternative portfolio classifications is mostly explained by the stock market return and the Fama–French factors. The price–dividend ratio, the default and term spread, and the illiquidity factor do not seem to be relevant in capturing the variability of the first principal component; however, consumption growth explains 3.8, 2.8, 2.9, and 4.0 of its variability.

not only by the aggregate market factor but also for the difference between the returns of small and large assets. We do not observe a similar result for other portfolio sets; any of the first principal components in these cases are basically explained through the stock market return. For example, the SMB and HML factors only explain 8.8 percent and 0.6 percent of the variability of the first principal component of the book-to-market–sorted portfolio returns.

The second principal component of the size-sorted portfolios is explained, as before, by the stock market return and the SMB factor, while the third principal component is basically the SMB factor with an R^2 of 44.3 percent. On the other hand, the second principal component of the book-to-market assets is mainly associated with the market return and the HML factor, and its third principal component is the HML risk factor with an R^2 of 22.4 percent. Note that this represents half of the explanatory capacity of the SMB factor for the third principal component of the size-sorted portfolios. Regarding the momentum- and dividend yield-sorted portfolios, it seem that the SMB and HML are relevant factors for the third principal component of the momentum sorting, with more explanatory capacity for SMB than for HML. Lastly, the HML factor explains as much as 53.0 percent of the variability of the second principal component of dividend yield-sorted returns.

To conclude, the size factor appears to be relevant only when we use the size-sorted portfolios. In all other cases, either the stock market return and/or the HML factor explains the behavior of the principal components.[13] Therefore, size seems to be a key characteristic in explaining the forecasting capacity of the HJ volatility bound relative to the bound's alternative measures.

[13] Only the third principal component of the momentum sorting has a higher R^2 for SMB than for HML.

To support this conjecture, we run predicting regressions using the HJ volatility bound estimated from the set of principal components instead of the set of portfolio returns. Each individual regression employs the HJ bound estimated with one, two, or three principal components for each portfolio-sorting procedure. We can then check which of these alternative bounds generates a stronger forecasting ability of real activity. Table 9 contains the results from the following predictive OLS autocorrelation-robust standard error regressions:

$$\Delta IPI_{t,t+\tau} = \alpha + \beta\,\sigma_t^{PC}\left(M\right) + \varepsilon_{t+\tau}\,, \tag{16}$$

where $\sigma_t^{PC}\left(M\right)$ now refers to the HJ volatility bound estimated with the first, the first two, or the first three principal components from each set of portfolio returns. Panel A of Table 9 contains the evidence from the HJ bounds estimated with the principal components of size-sorted portfolio returns. It shows that the first principal component does not produce significant predicting power. We need to add the second principal component to capture forecasting ability similar to that shown in Table 2 for the six-, 12-, and 24-month horizons. Moreover, we even need to add the third principal component if we want to obtain forecasting capacity at the shortest horizons. Given the relevance of the SMB factor in explaining the second and third principal components of the size-sorted portfolios, this result suggests that the dynamic behavior of the difference between the returns of small and large portfolios may be the ultimate reason behind the forecasting ability of the HJ volatility bound. It is not only the influence of the interaction between the numerator and denominator of the maximum Sharpe ratio that helps predict real activity, but also, and even more importantly, the time-varying behavior of small firms relative to large ones.

Finally, confirming the evidence provided in Table 3, Panels B to D of Table 9 show no evidence of predictability when the volatility bound is estimated using principal components from book-to-market–, momentum- or dividend yield-sorted portfolios.

8. Conclusions

The uncertainty embedded in equity portfolio returns helps predict future economic growth. This paper's main contribution is to show a new measure of capturing changes in uncertainty incorporated in stock returns that forecast real activity that is based on the HJ volatility bound. However, data employed in the estimation of the volatility bound seem to be the key issue in properly incorporating uncertainty shocks that convey information about future economic growth. Alternative equity portfolio sorting formations lead to very different conclusions regarding the forecasting ability of the bound. It turns out that sorting stocks on the basis of size generates a very powerful leading predictor. We show that the HJ volatility bound, when employing data on 10 size-sorted portfolios, generates significant predictions of real activity both in sample and out of sample. This is the case independent of the forecasting horizon and the competing standard predictor included in the predicting regressions. The inclusion of the HJ bound constructed with size-sorted portfolios significantly improves the out-of-sample forecasting ability of such well-known predictors as the stock market volatility, the term spread, or the default spread. Moreover, when we test for forecasting using the HJ bound estimated from the three principal components of equity portfolio returns based on size, book-to-market, momentum, and dividend yield, the only relevant prediction comes from the principal components of the size-sorted portfolios. It turns out we need to include both the second and third principal components of these size portfolios in the estimation of the HJ bound to find significant forecasting capacity of real activity. These second and third principal components are significantly associated with the differences in returns between the small and large portfolios. Size makes the difference. The dynamics of the time-varying second moments of returns among the size-sorted equity portfolios are a reasonable explanation of our findings. A comprehensive examination along these lines is left for future research.

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Table 1

Descriptive statistics of monthly returns for size-, book-to-market–, momentum-, and dividend yield-sorted portfolios, January 1927 to December 2010.

	P1	*P2*	*P3*	*P4*	*P5*	*P6*	*P7*	*P8*	*P9*	*P10*
					Means					
Size	1.479	1.285	1.275	1.223	1.187	1.169	1.128	1.061	1.009	0.862
BEME	0.848	0.949	0.932	0.925	1.007	1.041	1.046	1.206	1.270	1.377
Momentum	0.337	0.705	0.723	0.854	0.863	0.919	1.011	1.138	1.209	1.532
Div. Yield	0.862	0.952	0.895	0.987	0.860	0.973	1.047	1.085	1.066	1.023
					Standard deviations					
Size	10.27	8.969	8.203	7.585	7.275	6.947	6.575	6.238	5.938	5.148
BEME	5.773	5.536	5.355	6.112	5.687	6.235	6.706	7.031	7.628	9.455
Momentum	9.875	8.225	7.108	6.506	6.031	5.876	5.611	5.444	5.737	6.579
Div. Yield	6.454	5.765	5.575	5.421	5.692	5.533	5.481	5.826	6.096	6.736

Correlations		*P2*	*P3*	*P4*	*P5*	*P6*	*P7*	*P8*	*P9*	*P10*
					Size-sorted portfolios					
	P1	0.958	0.930	0.915	0.885	0.857	0.848	0.806	0.788	0.698
	P2		0.972	0.965	0.948	0.925	0.913	0.882	0.860	0.780
Max	*P3*			0.979	0.973	0.957	0.944	0.925	0.901	0.825
0.980	*P4*				0.979	0.969	0.960	0.938	0.915	0.838
Min	*P5*					0.980	0.973	0.961	0.943	0.873
0.698	*P6*						0.978	0.972	0.958	0.898
	P7							0.979	0.968	0.912
	P8								0.978	0.930
	P9									0.951
					Book-to-market–sorted portfolios					
	P1	0.928	0.899	0.863	0.836	0.831	0.795	0.780	0.768	0.714
	P2		0.940	0.904	0.886	0.873	0.847	0.829	0.827	0.773
Max	*P3*			0.910	0.899	0.884	0.860	0.835	0.839	0.784
0.950	*P4*				0.937	0.931	0.915	0.904	0.875	0.833
Min	*P5*					0.933	0.918	0.906	0.891	0.832
0.714	*P6*						0.941	0.933	0.903	0.861
	P7							0.950	0.937	0.895
	P8								0.937	0.911
	P9									0.931
					Momentum-sorted portfolios					
	P1	0.932	0.904	0.882	0.866	0.833	0.777	0.730	0.690	0.594
	P2		0.940	0.921	0.906	0.882	0.820	0.769	0.718	0.604
Max	*P3*			0.944	0.931	0.906	0.850	0.804	0.751	0.622
0.944	*P4*				0.935	0.922	0.882	0.842	0.789	0.661
Min	*P5*					0.937	0.903	0.867	0.819	0.695
0.594	*P6*						0.935	0.905	0.874	0.754
	P7							0.928	0.900	0.785
	P8								0.932	0.844
	P9									0.888
					Dividend yield-sorted portfolios					
	P1	0.926	0.901	0.864	0.837	0.809	0.818	0.773	0.728	0.667
	P2		0.913	0.892	0.869	0.835	0.837	0.793	0.762	0.689
Max	*P3*			0.910	0.881	0.868	0.863	0.814	0.771	0.716
0.926	*P4*				0.926	0.906	0.896	0.865	0.836	0.772
Min	*P5*					0.901	0.888	0.869	0.846	0.786
0.667	*P6*						0.898	0.884	0.874	0.806
	P7							0.898	0.882	0.816
	P8								0.906	0.872
	P9									0.891

Table 2

Monthly predicting regressions with the HJ volatility bound estimated with either 10 size-sorted portfolios or the five smallest or five largest portfolios, January 1965 to July 2010.

PANEL A

	10 Size $\Delta IPI_{t,t+\tau} = \alpha + \beta\sigma_t^{10}(M) + \varepsilon_{t+\tau}$			5 Small $\Delta IPI_{t,t+\tau} = \alpha + \beta\sigma_t^{Small}(M) + \varepsilon_{t+\tau}$			5 Big $\Delta IPI_{t,t+\tau} = \alpha + \beta\sigma_t^{Big}(M) + \varepsilon_{t+\tau}$		
τ	α	β	*Adj.* R^2	α	β	*Adj.* R^2	α	β	*Adj.* R^2
1	0.007 (4.26)	-0.009 (-3.02)	3.24	0.005 (3.62)	-0.007 (-2.10)	1.16	0.004 (3.48)	-0.007 (-1.96)	1.30
3	0.021 (4.89)	-0.030 (-3.42)	6.95	0.015 (4.21)	-0.023 (-2.47)	3.00	0.014 (3.70)	-0.023 (-2.10)	2.82
6	0.042 (5.34)	-0.060 (-3.66)	9.41	0.031 (4.76)	-0.049 (-2.77)	4.65	0.028 (3.98)	-0.049 (-2.32)	4.64
12	0.080 (5.91)	-0.111 (-3.95)	12.36	0.062 (5.56)	-0.101 (-3.21)	7.47	0.058 (4.73)	-0.106 (-2.79)	8.28
24	0.149 (7.16)	-0.207 (-4.74)	19.56	0.117 (6.42)	-0.190 (-3.64)	12.60	0.120 (7.46)	-0.227 (-4.51)	18.13

PANEL B

	$\Delta IPI_{t,t+\tau} = \alpha + \beta_1\sigma_t^{10}(M) + \beta_2\sigma_t^{Small}(M) + \varepsilon_{t+\tau}$				$\Delta IPI_{t,t+\tau} = \alpha + \beta_1\sigma_t^{10}(M) + \beta_2\sigma_t^{Big}(M) + \varepsilon_{t+\tau}$			
τ	α	β_1	β_2	*Adj.* R^2	α	β_1	β_2	*Adj.* R^2
1	0.007 (4.18)	-0.009 (-2.93)	0.007 (1.25)	3.49	0.007 (4.29)	-0.009 (-3.02)	0.003 (0.53)	3.15
3	0.021 (4.85)	-0.029 (-3.35)	0.017 (1.07)	7.34	0.021 (4.93)	-0.030 (-3.41)	0.009 (0.62)	6.98
6	0.041 (5.34)	-0.058 (-3.61)	0.026 (0.82)	9.68	0.042 (5.38)	-0.059 (-3.64)	0.008 (0.29)	9.30
12	0.079 (5.92)	-0.109 (-3.92)	0.020 (0.38)	12.28	0.079 (5.98)	-0.111 (-3.97)	-0.019 (-0.39)	12.31
24	0.149 (7.09)	-0.206 (-4.67)	0.014 (0.20)	19.43	0.147 (7.22)	-0.207 (-4.86)	-0.114 (-1.80)	21.40

All the panels report OLS autocorrelation-robust standard error predicting regressions of future industrial production growth, ΔIPI, on the HJ volatility bound, $\sigma(M)$, estimated with either 10 size-sorted portfolios or with the five smallest and five largest portfolios. We employ five prediction horizons: τ = 1, 3, 6, 12, and 24 months. The volatility bounds are estimated with overlapping sub-periods of five years of monthly data.

Table 3

Monthly predicting regressions with the HJ volatility bound estimated from alternative portfolio sets, January 1965 to July 2010.

$$\Delta IPI_{t,t+\tau} = \alpha + \beta\sigma_t(M) + \varepsilon_{t+\tau}$$

PANEL A: Book-to-market–sorted portfolios									
	10 BM			*5 Value*			*5 Growth*		
τ	α	β	*Adj.* R^2	α	β	*Adj.* R^2	α	β	*Adj.* R^2
1	0.001 (0.45)	0.003 (0.81)	0.04	0.001 (0.38)	0.004 (1.26)	0.30	0.001 (0.42)	0.005 (1.29)	0.38
3	0.003 (0.65)	0.006 (0.63)	0.05	0.002 (0.41)	0.013 (1.24)	0.64	0.003 (0.71)	0.011 (1.01)	0.40
6	0.008 (0.83)	0.009 (0.47)	-0.02	0.004 (0.46)	0.025 (1.18)	0.83	0.008 (1.13)	0.013 (0.64)	0.10
12	0.021 (1.36)	0.006 (0.20)	-0.16	0.010 (0.70)	0.042 (1.12)	0.88	0.026 (2.01)	-0.005 (-0.14)	-0.17
24	0.060 (2.88)	-0.027 (-0.66)	0.08	0.032 (1.85)	0.041 (0.88)	0.31	0.076 (4.13)	-0.089 (-1.64)	2.18
PANEL B: Momentum-sorted portfolios									
	10 Momentum			*5 Winners*			*5 Losers*		
τ	α	β	*Adj.* R^2	α	β	*Adj.* R^2	α	β	*Adj.* R^2
1	0.002 (1.16)	0.000 (-0.03)	-0.18	0.002 (1.26)	0.000 (0.09)	-0.18	0.002 (2.12)	0.000 (-0.01)	-0.18
3	0.007 (1.36)	-0.002 (-0.21)	-0.16	0.007 (1.69)	-0.003 (-0.24)	-0.15	0.006 (2.23)	0.000 (-0.06)	-0.18
6	0.014 (1.43)	-0.003 (-0.20)	-0.16	0.016 (2.25)	-0.012 (-0.59)	0.01	0.012 (2.27)	0.000 (0.02)	-0.18
12	0.026 (1.61)	-0.004 (-0.16)	-0.17	0.034 (3.03)	-0.029 (-0.91)	0.27	0.023 (2.37)	0.003 (0.16)	-0.17
24	0.045 (1.82)	0.003 (0.08)	-0.19	0.052 (2.75)	-0.016 (-0.31)	-0.12	0.046 (3.06)	0.001 (0.02)	-0.19
PANEL C: Dividend yield-sorted portfolios									
	10 DY			*5 High DY*			*5 Low DY*		
τ	α	β	*Adj.* R^2	α	β	*Adj.* R^2	α	β	*Adj.* R^2
1	0.000 (0.05)	0.004 (1.09)	0.23	0.001 (0.49)	0.005 (1.44)	0.44	0.001 (0.52)	0.004 (0.80)	0.10
3	0.002 (0.37)	0.009 (0.78)	0.21	0.003 (0.73)	0.012 (1.17)	0.56	0.003 (0.71)	0.009 (0.62)	0.13
6	0.008 (0.76)	0.010 (0.44)	-0.03	0.008 (1.16)	0.015 (0.72)	0.19	0.009 (1.10)	0.009 (0.32)	-0.08
12	0.023 (1.27)	0.003 (0.06)	-0.18	0.020 (1.65)	0.012 (0.31)	-0.09	0.024 (1.62)	0.000 (0.00)	-0.19
24	0.040 (1.56)	0.014 (0.24)	-0.14	0.043 (2.48)	0.010 (0.19)	-0.16	0.046 (2.23)	0.000 (0.00)	-0.19

All panels report OLS autocorrelation-robust standard error predicting regressions of future $t+\tau$ industrial production growth, ΔIPI, on the HJ volatility bounds available at time *t*, $\sigma(M)$, and estimated with either10 or five book-to-market–, momentum-, and dividend yield-sorted portfolios. We employ five prediction horizons, τ = 1, 3, 6, 12 and 24 months. The volatility bounds are estimated with overlapping sub-periods of five years of monthly data.

Table 4
Monthly predicting regressions with the HJ volatility bound estimated with 10 size-sorted portfolios and additional predictors, January 1965 to July 2010.

$$\Delta IPI_{t,t+\tau} = \alpha + \beta_1\, \sigma_t(M) + \beta_2 R_{mt} + \beta_3 \sigma_t(R_m) + \beta_4 PD_t + \beta_5 Def_t + \beta_6 Term_t + \beta_7 Illiq_t + \varepsilon_{t+\tau}$$

$\tau = 1$ *month*								
α	β_1	β_2	β_3	β_4	β_5	β_6	β_7	*Adj.* R^2
0.007 (4.26)	-0.009 (-3.02)							3.24
0.002 (4.11)		0.004 (0.45)						0.00
0.005 (2.05)			-0.068 (-1.21)					0.38
0.005 (3.29)				-0.960 (-1.64)				1.37
0.007 (6.02)					-3.344 (-3.97)			7.28
0.001 (1.28)						1.050 (2.92)		2.55
0.002 (4.15)							-0.0005 (-1.77)	0.27
0.007 (4.37)	-0.009 (-3.06)	0.003 (0.35)						3.09
0.016 (5.23)	-0.013 (-3.99)		-0.170 (-3.30)					5.93
0.014 (5.20)	-0.015 (-4.43)			-1.903 (-3.02)				8.08
0.012 (6.86)	-0.008 (-3.18)				-3.100 (-3.96)			9.38
0.005 (2.24)	-0.008 (-2.05)					0.788 (1.83)		4.49
0.006 (4.12)	-0.008 (-2.89)						-0.0005 (-1.46)	2.84
$\tau = 3$ *months*								
α	β_1	β_2	β_3	β_4	β_5	β_6	β_7	*Adj.* R^2
0.021 (4.89)	-0.030 (-3.43)							6.95
0.006 (3.82)		0.059 (2.62)						2.46
0.013 (1.74)			-0.148 (-0.90)					0.35
0.013 (3.21)				-2.659 (-1.57)				2.21
0.018 (4.60)					-7.410 (-2.81)			7.16
0.002 (1.06)						3.599 (3.66)		6.25
0.006 (4.18)							-0.001 (-2.88)	0.38
0.021 (5.01)	-0.030 (-3.58)	0.056 (2.84)						9.16
0.047 (5.27)	-0.041 (-4.20)		-0.461 (-3.17)					11.01
0.043 (5.37)	-0.046 (-4.72)			-5.605 (-3.04)				15.53
0.030 (5.78)	-0.027 (-3.73)				-6.566 (-2.77)			12.45
0.015 (2.43)	-0.024 (-2.26)					2.769 (2.34)		10.31
0.020 (4.80)	-0.029 (-3.35)						-0.001 (-2.53)	6.66

$\tau = 6$ *months*								
α	β_1	β_2	β_3	β_4	β_5	β_6	β_7	*Adj.* R^2
0.042 (5.34)	-0.060 (-3.66)							9.41
0.011 (3.96)		0.135 (3.34)						4.43
0.018 (1.19)			-0.127 (-0.39)					0.00
0.022 (2.95)				-3.816 (-1.26)				1.50
0.026 (3.37)					-8.566 (-1.63)			3.17
0.004 (1.14)						7.219 (4.26)		8.58
0.012 (4.29)							-0.003 (-2.70)	0.51
0.040 (5.44)	-0.058 (-3.86)	0.128 (3.62)						13.45
0.082 (4.97)	-0.076 (-4.28)		-0.715 (-2.60)					12.72
0.079 (5.50)	-0.085 (-4.76)			-9.349 (-2.91)				17.55
0.051 (4.70)	-0.056 (-3.88)				-6.792 (-1.50)			11.32
0.030 (2.71)	-0.047 (-2.46)					5.552 (2.72)		14.04
0.042 (5.27)	-0.061 (-3.64)						-0.002 (-2.32)	10.13
$\tau = 12$ *months*								
α	β_1	β_2	β_3	β_4	β_5	β_6	β_7	*Adj.* R^2
0.080 (5.91)	-0.111 (-3.95)							12.36
0.022 (4.64)		0.237 (4.63)						5.14
0.024 (0.82)			0.001 (0.00)					0.00
0.030 (2.36)				-2.355 (-0.49)				0.05
0.030 (2.40)					-3.360 (-0.43)			0.01
0.007 (1.14)						15.154 (5.08)		14.02
0.023 (4.89)							-0.003 (-2.00)	0.11
0.077 (5.97)	-0.109 (-4.09)	0.225 (4.88)						17.01
0.138 (4.82)	-0.136 (-4.55)		-1.051 (-2.08)					15.00
0.126 (5.76)	-0.143 (-4.79)			-11.674 (-2.48)				17.04
0.079 (4.31)	-0.111 (-4.08)				0.180 (0.03)			12.19
0.053 (2.95)	-0.084 (-2.65)					12.096 (3.49)		20.53
0.082 (5.96)	-0.117 (-4.06)						-0.002 (-1.27)	13.51

τ = 24 months								
α	β_1	β_2	β_3	β_4	β_5	β_6	β_7	Adj. R2
0.149 (7.16)	-0.207 (-4.74)							19.56
0.044 (6.33)		0.219 (3.43)						1.81
0.047 (1.14)			-0.014 (-0.02)					0.00
0.032 (1.68)				5.565 (0.81)				0.46
0.025 (1.20)					14.315 (1.08)			0.92
0.019 (2.21)						25.108 (6.26)		18.16
0.046 (6.53)							0.001 (0.48)	0.00
0.147 (7.19)	-0.207 (-4.81)	0.216 (3.77)						21.37
0.261 (5.63)	-0.257 (-5.10)		-2.00 (-2.71)					24.22
0.189 (6.16)	-0.236 (-5.19)			-9.817 (-1.53)				21.03
0.129 (4.62)	-0.206 (-4.70)				13.137 (1.15)			20.34
0.105 (4.56)	-0.158 (-3.63)					18.529 (4.72)		28.33
0.150 (7.18)	-0.208 (-4.76)						0.003 (1.18)	19.60

All panels report OLS autocorrelation-robust standard error predicting regressions of future industrial production growth, ΔIPI, on the HJ volatility bound, $\sigma(M)$, estimated with 10 size-sorted portfolios and/or an additional standard predictor that is the market portfolio return, R_m; the volatility of the market portfolio return, $\sigma(R_m)$; the log of the price–dividend ratio, PD; the default spread, *Def*, calculated as the spread between the rates of Baa corporate bonds and 10-year government bonds; the term spread, *Term*, measured as the difference between the 10-year government bond and the one-month T-bill rate; and the market-wide illiquidity measure (*Illiq*) calculated from Amihud's (2002) ratio. Each panel refers to a different prediction horizon: τ = 1, 3, 6, 12, and 24 months. Both the volatility bound and the market volatility are estimated with overlapping sub-periods of five years of monthly data.

Table 5

Monthly predicting regressions with the HJ volatility bound estimated with 10 size-sorted portfolios and controlling for persistence in the dependent variable, January 1965 to July 2010.

$\Delta IPI_{t,t+\tau} = \alpha + \beta_1 \sigma_t(M) + \beta_2 \Delta IPI_{t,t-\tau} + \varepsilon_{t+\tau}$				
τ	α	β_1	β_2	*Adj.* R^2
1	0.005 (3.49)	-0.006 (-2.74)	0.326 (4.39)	13.37
3	0.013 (3.85)	-0.019 (-3.11)	0.424 (5.57)	23.99
6	0.032 (3.92)	-0.048 (-3.11)	0.282 (2.88)	16.72
12	0.077 (5.41)	-0.107 (-3.79)	-0.003 (-0.03)	11.80
24	0.157 (7.99)	-0.193 (-4.45)	-0.299 (-2.98)	25.92

This table reports OLS autocorrelation-robust standard error predicting regressions of future industrial production growth, ΔIPI, on the HJ volatility bound, $\sigma(M)$, and the lagged growth of industrial production. We employ five prediction horizons: τ = 1, 3, 6, 12, and 24 months. The volatility bounds are estimated with overlapping sub-periods of five years of monthly data.

Table 6
Monthly out-of-sample forecast accuracy of the model that includes the HJ volatility bound, estimated with 10 size-sorted portfolios, in addition to a standard predictor, January 1965 to July 2010.

Unrestricted model: $\Delta IPI_{t,t+\tau} = \alpha + \beta_1 X_t + \beta_2 \sigma_t(M) + \varepsilon_{t+\tau}$

Restricted model: $\Delta IPI_{t,t+\tau} = \alpha + \beta_1 X_t + \varepsilon_{t+\tau}$

	R_m	$\sigma(R_m)$	PD	Def	$Term$
$\tau = 1$ *month*					
RMSE	0.9709	0.9705	0.9389	0.9886	0.9869
MSE-t	1.5537	1.2212	1.9240	0.4114	1.0460
(*p*-value)	(0)	(0)	(0)	(0)	(0.099)
MSE-F	14.6251	14.8134	31.7330	5.6467	6.4758
(*p*-value)	(0)	(0)	(0)	(0)	(0.075)
$\tau = 3$ *months*					
	R_m	$\sigma(R_m)$	PD	Def	$Term$
RMSE	0.9431	0.9589	0.8967	0.9789	0.9770
MSE-t	1.2967	0.7533	1.3724	0.3810	0.8389
(*p*-value)	(0)	(0.0004)	(0.0002)	(0)	(0.2344)
MSE-F	29.3053	20.8111	55.9710	10.4856	11.4637
(*p*-value)	(0)	(0.0004)	(0)	(0)	(0.2148)
$\tau = 6$ *months*					
	R_m	$\sigma(R_m)$	PD	Def	$Term$
RMSE	0.9284	0.9631	0.8977	0.9711	0.9767
MSE-t	1.0457	0.4293	0.9671	0.3884	0.5611
(*p*-value)	(0.0002)	(0)	(0)	(0.0008)	(0.1406)
MSE-F	37.2363	18.5075	55.0176	14.3956	11.5043
(*p*-value)	(0.0006)	(0.0002)	(0.0002)	(0.0010)	(0.1442)
$\tau = 12$ *months*					
	R_m	$\sigma(R_m)$	PD	Def	$Term$
RMSE	0.9315	0.9549	0.8932	0.9056	1.0246
MSE-t	0.6190	0.3564	0.8253	0.7871	-0.3627
(*p*-value)	(0.0004)	(0.0008)	(0)	(0.0018)	(0.0326)
MSE-F	35.1043	22.5347	57.0603	47.7192	-11.4718
(*p*-value)	(0.0014)	(0.0010)	(0.0004)	(0.0038)	(0.0210)
$\tau = 24$ *month*					
	R_m	$\sigma(R_m)$	PD	Def	$Term$
RMSE	0.9883	0.9742	0.9484	0.8680	1.1202
MSE-t	0.0592	0.1255	0.2713	0.6164	-0.6341
(*p*-value)	(0.0226)	(0.0116)	(0.0090)	(0.0182)	(0.0512)
MSE-F	5.4911	12.3342	25.2884	70.7180	-49.8949
(*p*-value)	(0.0224)	(0.0120)	(0.0114)	(0.0214)	(0.0396)

This table contains the RMSE (=MSE_U/MSE_R) and the MSE *t*-statistics and MSE *F*-statistics and their *p*-values, in parentheses, obtained by an efficient bootstrap method for simulating asymptotic critical values for tests of equal forecast accuracy. Each panel corresponds to a given forecasting horizon: τ = 1, 3, 6, 12, and 24 months. The dependent variable is the industrial production growth (ΔIPI), and the restricted model contains one of the variables indicated in the first row of every horizon panel. Here MSE_R is the mean square forecasting error of the restricted model, and MSE_U is the mean square error of the unrestricted model that always includes the HJ volatility bound as a predictor. The market volatility is estimated as the moving average of past absolute returns using a lag of 12 months to obtain volatility estimates from past returns. The initial estimation period has 60 months (from January 1965 to December 1969) and therefore the out-of-sample period has 488 - τ months.

Table 7

Three principal components from size-, book-to-market–, momentum-, and dividend yield-sorted portfolio returns, January 1927 to December 2010.

	SPC1	*SPC2*	*SPC3*	*BPC1*	*BPC2*	*BPC3*	*MPC1*	*MPC2*	*MPC3*	*DPC1*	*DPC2*	*DPC3*
% Exp	92.72	5.00	0.86	88.84	5.30	1.86	85.16	8.37	2.47	85.31	6.74	1.97
SPC1		-0.04	-0.04	**0.95**	-0.06	-0.10	**0.93**	0.08	-0.14	**0.91**	-0.01	-0.13
SPC2			-0.02	0.17	**0.62**	0.20	0.23	0.28	0.31	0.32	0.28	0.21
SPC3				0.06	0.10	-0.06	0.08	-0.04	0.21	0.10	0.04	0.03
BPC1					-0.04	0.00	**0.97**	0.08	0.02	**0.97**	-0.05	-0.07
BPC2						0.02	0.09	0.34	0.06	0.15	**0.59**	0.20
BPC3							-0.04	-0.07	0.27	0.02	-0.36	0.25
MPC1								0.00	-0.01	**0.97**	0.02	-0.08
MPC2									0.00	0.14	**0.47**	0.06
MPC3										0.08	-0.18	0.25
DPC1											0.01	-0.01
DPC2												0.02

In this table *SPC*, *BPC*, *MPC*, and *DPC* indicate the corresponding principal components of size-, book-to-market–, momentum-, and dividend yield-sorted portfolios, respectively. The first row displays the percentage explained by the corresponding principal component of the variability of portfolio returns. The correlation coefficients between alternative principal components from different sorted portfolios higher than 0.45 are indicated in bold.

Table 8

Monthly regressions of individual principal components on aggregate state variables, January 1965 to July 2010.

$$PC_{i,t} = \alpha + \beta X_t + u_t, i = 1,2,3$$

			R_m	*PD*	*SMB*	*HML*	*Def*	*Term*	ΔC	*Illiq*
Size	*PC1*	β	1.121	1.189	1.059	-0.503	4.870	3.493	3.125	5.117
		t-Value	(47.05)	(0.49)	(10.68)	(-3.70)	(0.65)	(1.73)	(5.00)	(7.40)
		R^2 *(%)*	[86.55]	[0.04]	[38.10]	[7.34]	[0.29]	[0.55]	[3.81]	[0.83]
	PC2	β	0.870	2.103	-0.971	-0.339	3.781	-1.789	1.320	-0.527
		t-Value	(15.74)	(0.71)	(-8.41)	(-1.55)	(0.64)	(-0.78)	(1.37)	(-0.14)
		R^2	[34.53]	[0.09]	[21.25]	[2.20]	[0.12]	[0.10]	[0.45]	[0.01]
	PC3	β	0.015	-7.750	-2.252	0.076	-8.376	0.796	-1.949	-8.587
		t-Value	(0.12)	(-1.89)	(-10.69)	(0.28)	(-1.03)	(0.24)	(-1.50)	(-2.33)
		R^2	[0.00]	[0.48]	[44.31]	[0.04]	[0.22]	[0.01]	[0.38]	[0.59]
Book to Market	*PC1*	β	0.963	1.200	0.422	-0.121	3.354	1.828	2.220	2.944
		t-Value	(39.51)	(0.63)	(3.36)	(-1.08)	(0.48)	(1.09)	(4.19)	(4.69)
		R^2	[92.93]	[0.07]	[8.82]	[0.62]	[0.20]	[0.22]	[2.80]	[0.41]
	PC2	β	-0.007	-1.236	0.002	-1.955	7.400	1.390	3.029	3.119
		t-Value	(9.82)	(-0.33)	(0.36)	(-10.92)	(1.44)	(0.48)	(3.30)	(1.82)
		R^2	[40.14]	[0.03]	[0.04]	[61.29]	[0.38]	[0.05]	[1.98]	[0.17]
	PC3	β	-1.604	4.832	-2.765	5.385	-27.79	-18.35	1.197	-31.65
		t-Value	(-3.83)	(0.27)	(-4.49)	(7.68)	(-0.82)	(-1.23)	(0.27)	(-2.86)
		R^2	[4.71]	[0.02]	[6.92]	[22.38]	[0.25]	[0.41]	[0.02]	[0.83]
Momentum	*PC1*	β	1.069	1.346	0.504	-0.377	6.620	2.629	2.510	4.385
		t-Value	(43.86)	(0.62)	(3.38)	(-2.67)	(0.85)	(1.39)	(4.09)	(3.80)
		R^2	[93.22]	[0.07]	[10.20]	[4.88]	[0.64]	[0.37]	[2.91]	[0.75]
	PC2	β	0.672	2.362	0.270	-0.756	-19.11	2.422	2.178	-5.668
		t-Value	(3.64)	(0.55)	(1.08)	(-2.65)	(-1.60)	(0.56)	(1.64)	(-0.52)
		R^2	[9.37]	[0.05]	[0.74]	[5.00]	[1.36]	[0.08]	[0.56]	[0.33]
	PC3	β	-0.632	2.510	-2.282	1.672	8.452	-2.285	-1.798	-9.044
		t-Value	(-3.27)	(0.34)	(-9.47)	(3.66)	(0.60)	(-0.43)	(-0.97)	(-1.23)
		R^2	[4.62]	[0.03]	[29.70]	[13.61]	[0.15]	[0.04]	[0.21]	[0.43]
Dividend Yield	*PC1*	β	0.909	1.023	0.248	-0.198	3.319	1.304	2.019	2.475
		t-Value	(38.09)	(0.55)	(1.93)	(-1.65)	(0.50)	(0.82)	(3.97)	(3.73)
		R^2	[92.62]	[0.05]	[3.39]	[1.84]	[0.22]	[0.13]	[2.59]	[0.32]
	PC2	β	9.165	5.059	5.489	-20.71	3.651	30.27	26.32	33.62
		t-Value	(8.01)	(0.11)	(3.83)	(-12.99)	(0.05)	(0.88)	(2.85)	(0.98)
		R^2	[24.62]	[0.00]	[4.36]	[52.95]	[0.00]	[0.18]	[1.15]	[0.15]
	PC3	β	0.586	7.037	-1.530	0.615	54.95	0.551	-0.821	-0.246
		t-Value	(1.44)	(0.68)	(-3.17)	(0.98)	(2.12)	(0.06)	(-0.30)	(-0.02)
		R^2	[1.32]	[0.09]	[4.44]	[0.61]	[2.08]	[0.00]	[0.02]	[0.00]

All panels report the individual OLS autocorrelation-robust standard error regressions of each of the three principal components, $PC_i, i = 1,2,3$, on one of the following variables: the market portfolio return, R_m; the log of the price–dividend ratio, PD; the *SMB* factor; the *HML* factor; the default spread between the rates of Baa corporate bonds and 10-year government bonds, *Def*; the term spread between the 10-year government bond rate and the one-month T-bill rate, *Term*; the real consumption growth on nondurable goods and services, ΔC; and Amihud's (2002) market-wide illiquidity measure, *Illiq*. Each panel refers to a different set of portfolios, that is, the size-, book-to-market–, momentum-, and dividend yield-sorted portfolio returns.

Table 9

Monthly predicting regressions with the HJ volatility bound estimated with principal components, January 1965-July 2010.

$$\Delta IPI_{t,t+\tau} = \alpha + \beta\, \sigma_t^{PC}(M) + \varepsilon_{t+\tau}$$

	1st PC			*1st PC + 2nd PC*			*1st PC + 2nd PC + 3rd PC*		
τ	α	β	Adj. R^2	α	β	Adj. R^2	α	β	Adj. R^2
Panel A: Size-sorted portfolios									
1	0.001	0.004	0.15	0.004	-0.006	0.72	0.005	-0.008	1.45
	(1.60)	(1.10)		(3.17)	(-1.63)		(3.66)	(-2.16)	
3	0.005	0.009	0.12	0.012	-0.022	1.92	0.014	-0.027	3.08
	(1.90)	(0.77)		(3.47)	(-1.90)		(4.04)	(-2.46)	
6	0.012	0.004	-0.17	0.025	-0.051	3.67	0.028	-0.054	4.46
	(0.26)	(0.16)		(4.07)	(-2.41)		(4.44)	(-2.79)	
12	0.030	-0.037	0.41	0.056	-0.128	8.62	0.059	-0.120	8.29
	(4.25)	(-0.86)		(6.23)	(-3.90)		(5.98)	(-3.82)	
24	0.066	-0.121	2.75	0.106	-0.234	13.63	0.111	-0.222	13.63
	(5.24)	(-1.55)		(7.66)	(-4.82)		(7.54)	(-4.66)	
Panel B: Book-to-market–sorted portfolios									
1	0.001	0.007	0.89	0.001	0.004	0.14	0.001	0.004	0.10
	(1.01)	(1.91)		(1.00)	(1.02)		(0.80)	(0.89)	
3	0.003	0.018	1.34	0.004	0.008	0.15	0.004	0.008	0.08
	(1.20)	(1.76)		(1.26)	(0.82)		(1.08)	(0.68)	
6	0.008	0.025	0.81	0.010	0.010	-0.04	0.010	0.007	-0.10
	(1.69)	(1.25)		(1.64)	(0.49)		(1.52)	(0.36)	
12	0.021	0.014	-0.06	0.022	0.008	-0.15	0.026	-0.006	-0.16
	(2.63)	(0.37)		(1.94)	(0.21)		(2.14)	(-0.17)	
24	0.052	-0.035	0.15	0.047	-0.002	-0.19	0.064	-0.062	0.91
	(4.02)	(-0.52)		(2.58)	(-0.04)		(3.17)	(-0.95)	
Panel C:Momentum-sorted portfolios									
1	0.001	0.006	0.29	0.001	0.004	0.25	0.002	0.000	-0.18
	(1.88)	(1.42)		(0.89)	(1.45)		(1.94)	(-0.02)	
3	0.004	0.014	0.39	0.003	0.010	0.28	0.007	-0.003	-0.13
	(2.13)	(1.17)		(1.20)	(1.11)		(2.35)	(-0.40)	
6	0.010	0.016	0.07	0.006	0.022	0.53	0.014	-0.006	-0.12
	(2.69)	(0.67)		(1.17)	(1.30)		(2.40)	(-0.40)	
12	0.025	-0.014	-0.12	0.014	0.036	0.51	0.028	-0.013	-0.08
	(3.89)	(-0.28)		(1.55)	(1.25)		(2.61)	(-0.45)	
24	0.059	-0.107	1.83	0.036	0.037	0.14	0.049	-0.010	-0.17
	(5.41)	(-1.25)		(2.40)	(0.72)		(2.68)	(-0.19)	
Panel D: Dividend yield-sorted portfolios									
1	0.001	0.006	0.61	0.001	0.006	0.62	0.001	0.005	0.24
	(1.37)	(1.72)		(0.77)	(1.53)		(0.62)	(1.04)	
3	0.004	0.017	1.06	0.003	0.015	0.94	0.003	0.012	0.44
	(1.52)	(1.68)		(0.94)	(1.43)		(0.75)	(1.01)	
6	0.008	0.025	0.75	0.007	0.024	0.83	0.006	0.022	0.50
	(1.92)	(1.28)		(1.17)	(1.23)		(0.85)	(0.94)	
12	0.021	0.020	0.03	0.017	0.029	0.36	0.015	0.033	0.40
	(2.72)	(0.50)		(1.61)	(0.75)		(1.11)	(0.76)	
24	0.050	-0.026	0.00	0.049	-0.012	-0.15	0.051	-0.017	-0.12
	(4.14)	(-0.40)		(2.91)	(-0.19)		(2.71)	(-0.27)	

All panels report OLS autocorrelation-robust standard error predicting regressions of future industrial production growth, ΔIPI, on the HJ volatility bound, $\sigma^{PC}(M)$, estimated with the first, two first, or three first principal components obtained from the alternative sets of portfolio-sorting procedures based on size, book to market, momentum, and dividend yield. We employ five prediction horizons: τ = 1, 3, 6, 12, and 24 months.

Figure 1
The HJ bound estimated with the overlapping 60-month periods of returns for 10 size-sorted portfolios

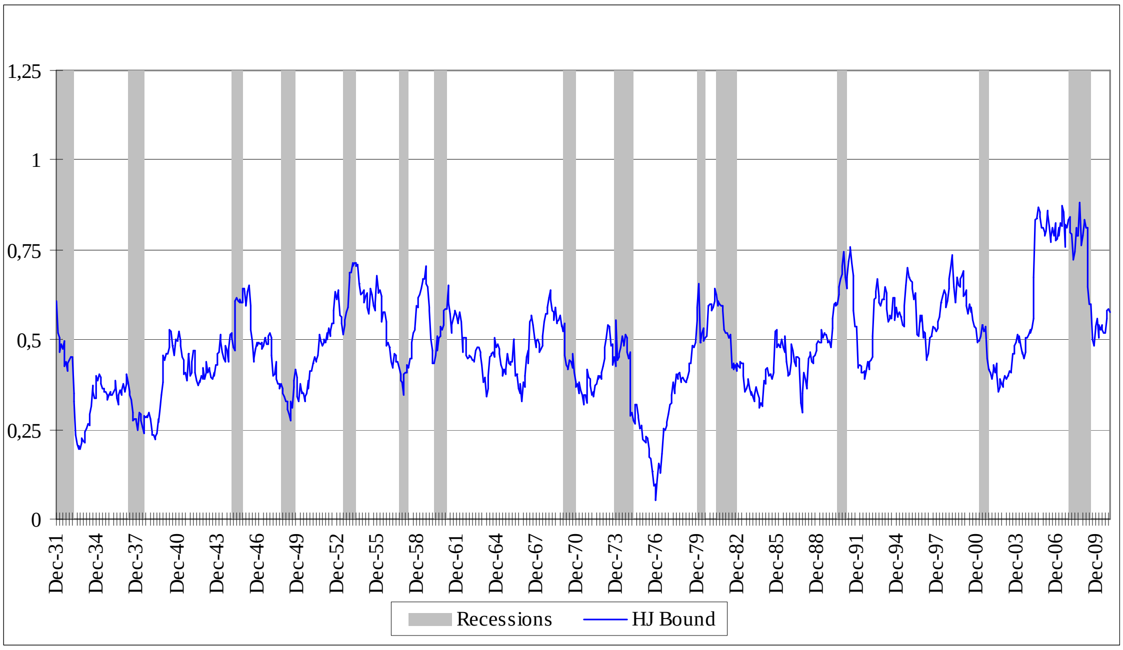

Figure 2
The HJ bound estimated with the overlapping 60-month periods of returns for 10 size-sorted and the five smallest and five largest portfolios

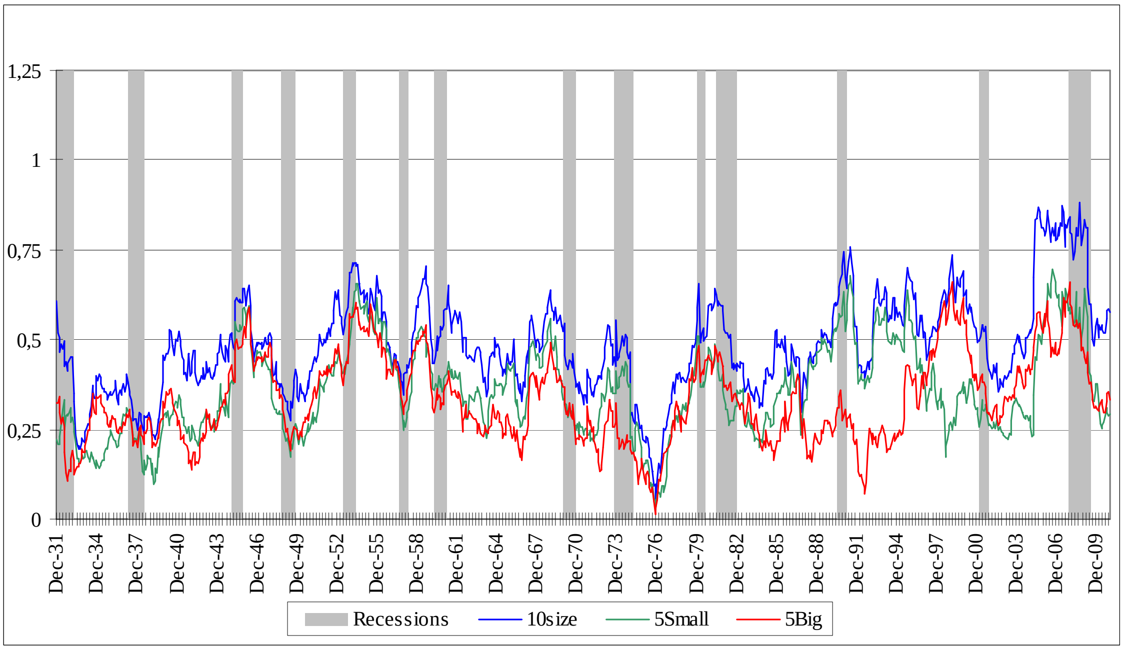

Figure 3
The HJ bound computed with the overlapping 60-month periods of returns for size-, book-to-market–, momentum-, and dividend yield-sorted portfolios