Unpublished Appendices to

'Déjà Vol:' Predictive Regressions for Aggregate Stock Market Volatility Using Macroeconomic Variables

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Appendices

A. Volatility Measurement

A.1. Construction of Daily Excess Returns

Daily total returns (capital gain plus dividends) on the S&P 500 Index and CRSP value-weighted portfolio are obtained from CRSP for the period 1927-2010. Daily excess returns are computed by subtracting from total returns the implied daily rate based on the 3-month Treasury bill for corresponding month, sourced from the Federal Reserve Bank of St. Louis's 'Federal Reserve Economic Data' database (hereafter referenced as "FRED").[1] The resulting daily excess returns form the basis of the variance proxy used in the paper (equation (1) in the main paper), as well as for most of the alternative volatility proxies discussed below.

A.2. Alternative Volatility Proxies

Results reported in the paper focus on $LVOL_t$, the natural logarithm of the volatility proxy based on the sum of squared daily excess returns (equation (1) in the main paper). In order to explore the robustness of findings discussed in the main paper, I construct a number of alternative volatility measures. One alternative proxy adjusts for low-frequency variation in expected returns. Another corrects for possible serial correlation in daily excess returns. A third measure is based on daily absolute returns rather than squared daily returns. A final proxy employs intraday price data over the limited historical period where such data are available. The remainder of this Appendix discusses details regarding the construction of these alternative proxies. Appendix C discusses the robustness of empirical findings to using these alternative proxies.

A.2.1. Correcting for Time-Variation in Expected Returns

When the expected return is zero, the sum of squared daily returns is an *ex post* unbiased estimator for the *ex ante* conditional volatility (see, e.g., Andersen, Bollerslev, Diebold, and Labys (2003)). Consider an expected return process that potentially varies across months (quarters), but remains constant within any particular month (quarter). When the mean is nonzero, the realized variance estimator will be biased. To the extent that the expected return varies with the business cycle, the resulting bias may be correlated with macroeconomic forecasting variables. Apparent forecasting power for volatility may, in fact, represent forecasting power for variation in the expected return.

To address these issues empirically, I compute two alternative realized variance measures. The first alternative proxy adjusts for low-frequency changes in the conditional mean of excess stock returns. Prior

[1] http://research.stlouisfed.org/fred2/

to computing realized variances, I estimate return forecasting regressions for excess stock returns at the monthly or quarterly frequency. For each period, the time-varying conditional mean based on the estimated forecasting regression is converted to a daily rate, and this is subsequently subtracted from each daily excess return within that month (quarter). The alternative realized variance proxy is computed as:

$$FILT_t \equiv \sum_{i=1}^{N_t} \tilde{R}_{i,t}^2, \tag{1}$$

where $\tilde{R}_{i,t}$ represents the de-meaned return for the i-th trading day of month t (quarter t). The notation $FILT_t$ reflects the fact that the approach amounts to prewhitening daily returns using a low-frequency filter. See Appendix B for details regarding the conditional mean model used to prewhiten returns.

A second alternative proxy corrects for autocorrelation in *daily* returns reflecting intra-period time-variation in the conditional mean return. When daily returns are positively autocorrelated, the sum of squared daily returns is a downward-biased estimator of variance. I follow French, Schwert, and Stambaugh (1987), who correct for this bias by adding twice the sum of the products of adjacent returns:

$$FSS_t = \sum_{i=1}^{N_t} R_{i,t}^2 + 2\sum_{i=1}^{N_t-1} R_{i+1,t}R_{i,t}. \tag{2}$$

A.2.2. Proxy based on Absolute Returns

Volatility proxies based on squared intradaily returns may be sensitive to outliers in the data. Motivated by the literature on robust estimation, alternative estimators of integrated volatility based on absolute returns have been proposed. In the absence of microstructure noise, and assuming that log prices follow a standard diffusion process, Barndorff-Nielsen and Shephard (2004) show that the following estimator is consistent for integrated volatility:

$$AVOL_t = \mu_1^{-1} N_t^{-1/2} \sum_{i=1}^{N_t} |R_{i,t}|, \tag{3}$$

where $\mu_1 = E|Z| = \sqrt{\frac{2}{\pi}}$, and Z is a random variable following the standard normal distribution. Examples of studies that employ a volatility proxy based on (3) include Schwert (1989) and Mele (2007).

A.2.3. Proxy using Intraday Price Data

A final alternative proxy explores the impact of discreteness induced by daily sampling. Realized variance estimates are computed using the realized kernel estimator of Barndorff-Nielsen, Hansen, Lunde, and

Shephard (2008) (see also Barndorff-Nielsen, Hansen, Lunde, and Shephard (2009)) based on returns sampled on a one-second grid.[2] The earliest available intraday price data related to the S&P 500 are from 1982 on the S&P Futures contract traded on the the Chicago Mercantile Exchange (CME). Over the subsequent decades, trading volume gradually shifted as new instruments were developed. The intraday prices used to construct daily realized variances used in this paper shift to follow the most active market(s) among these instruments. Specifically, intraday realized variances for 1982-1997 are based on the most active S&P Futures contract traded on the CME. For the 1998-2001, intraday realized variances are based on 'E-Mini S&P 500 Futures' contracts. Finally, for the 2002-2010 period intraday realized variances are based on intraday prices for the S&P 500 Spider ETF market.

Computing a realized variance for the whole trading day requires incorporation of overnight trading activity. For 1982-1997, overnight variance estimates are based on the close-to-open squared return on the S&P 500. For 1998-2010, overnight variance is based on a realized kernel estimate using overnight prices for E-Mini S&P 500 Futures contracts. With estimates of the overnight variance in hand, a realized variance for the whole trading day is computed following Fleming, Kirby, and Ostdiek (2003). This approach scales up the intraday variance by an adjustment factor. This adjustment factor is calibrated as the inverse of the ratio of the intraday variance to the full-day variance, defined as the sum of the intraday and overnight variances, over some historical window. In this implementation, the historical window is set to 20 trading days. See Fleming et al. (2003) for additional details.

B. Construction of Forecasting Variables: Data Sources and Additional Details

This Appendix provides descriptions and data sources for the forecasting variables used in the study, along with additional details regarding the construction of several variables.

changes in bank leverage (*blev*) Following Adrian and Shin (2010), bank leverage is computed as the ratio of total assets to total equity using U.S. Flow of Funds data for Securities, Brokers and Dealers. The bank leverage measure is constructed using data in the Flow of Funds Accounts published by the Board of Governors of the Federal Reserve System. Table F.130, "Security Brokers and Dealers" presents flow of funds data for firms that buy and sell securities for a fee, hold an inventory for resale, or both. Bank leverage is computed quarterly as the ratio of total assets, where total assets is measured

[2] I thank Barbara Ostdiek for providing these intraday volatility series.

as 'Total Financial Assets' (series FL664090005.Q) while equity is measured as total asset less total financial liabilities (series FL664190005.Q).

For the period 1952-1962, total equity computed as total financial assets less total financial liabilities is negative. In fact, total equity trends upward (becomes less negative) almost linearly over this period, and is exactly zero in 1962Q3. This rather odd behavior is primarily attributable to an 'other liabilities' line item (series FL663193005.Q) that trends downward in a similar pattern, suggesting that this item involves an *ex post* convention whereby total equity is set to zero in 1962Q3. I contacted members of the Broker and Dealer group at the Board of Governors at the Federal Reserve, but they were unable to explain what was done during this time period. The series used in this paper adjusts total liabilities over the 1952-1962 period by removing the 'other liabilities' line item. This produces a series with positive and reasonable leverage values for 1952-1962. Replication files for the paper, available from the author, contain a spreadsheet detailing this adjustment and construction of the bank leverage series.

consumption-wealth ratio (*cay*) The consumption-wealth ratio (*cay*), proposed by Lettau and Ludvigson (2001), is the residual obtained from estimating a cointegrating relation between aggregate consumption, wealth, and labor income. Data are sourced Goyal and Welch (2008), as updated by Amit Goyal through 2010.[3]

commercial paper-to-Treasury spread (*cp*) This variable captures the spread between the 3-month commercial paper rate and the rate on 3-month Treasury bills. Both series are obtained from Federal Reserve Statistical Release H.15. Commercial paper rates are averages of offering rates on commercial paper placed by leading dealers for firms rated AA or higher.[4]

default return spread (*dfr*) The default return spread is the difference between long-term corporate bond and long-term government bond returns. Data are sourced Goyal and Welch (2008), as updated by Amit Goyal through 2010.

default spread (*dfy*) The default spread is the difference between the yield on BAA-rated corporate bonds and the yield on long term US government bonds. Data are sourced Goyal and Welch (2008), as

[3] http://www.hec.unil.ch/agoyal/

[4] Following the third quarter of 1997, the commercial paper rate is based on nonfinancial firms. Prior to this period, the data do not distinguish between financial and nonfinancial firms.

updated by Amit Goyal through 2010.[5]

expected return (*exret*) This variable is a regression-based estimate of the expected excess return on the S&P 500 Index. I adopt an in-sample approach to extract a time-varying expected return series at the quarterly frequency. As noted by Goyal and Welch (2008), models that perform well in-sample may not perform well out-of-sample. In this particular application, the goal is to extract an *ex post* measure of unobserved time-varying expected stock returns. Consequently, overfitting issues are less of a concern in this exercise relative to studies that focus on successfully forecasting returns out-of-sample.

To construct the proxy, the time-varying expected excess return on the S&P 500 is assumed to be linear in a set of forecasting instruments. The forecasting instruments I consider are relatively prominent in the literature. For the longer 1927-2008 sample period, the forecasting variables include the lagged commercial paper-to-Treasury spread (*cp*), the default return (*dfr*), the default spread (*dfy*), the net payout yield (*dfy*), the inflation rate (this is the *level* of the inflation rate as opposed to the volatility of inflation used in the volatility forecasting regressions), and the term spread (*tms*). For the 1952-2008 sample period, I include as additional forecasting variables the consumption-wealth ratio (*cay*), expected GDP growth (*egdp*), and the investment-to-capital ratio (*ik*). The signs and magnitudes of the estimated regressions coefficients are similar to existing results in the literature, so I do not explicitly report them here. The fitted series of expected returns for the selected model contains some quarters where the expected return is negative. While a negative expected return is theoretically possible, I follow Campbell and Thompson (2008) and set the fitted expected return to zero for these quarters. I explored several variations on the basic methodology for constructing an expected returns proxy. In one case, I did not re-set negative fitted expected returns to zero. Another variation adopted a smaller, more conservative set of predictors based on a general-to-specific model selection strategy. The main results were unaffected by these adjustments.

current and expected GDP growth (*gdp* and *egdp*) Current economic activity is measured using the annualized growth rate in real, seasonally adjusted gross domestic product (GDP). These data are sourced from FRED II. Expected GDP growth is based on the six- to twelve-month GDP growth

[5] In the stock return forecasting literature, the default spread is frequently defined as the difference between the yields on BAA- and AAA-rated corporate bonds. My definition follows an anonymous referee's recommendation.

forecast from the Livingston Survey, which provides a real-time measure of expected economic conditions. The Livingston Survey captures economists' macroeconomic forecasts at a bi-annual frequency, and are maintained by the Federal Reserve Bank of Philadelphia. I follow Campbell and Diebold (2009) in constructing the expected GDP growth rate (*egdp*) using nominal GDP and CPI forecasts in six and twelve months' time. Specifically, $egdp$ is computed as the logarithm of the median 12-month nominal GDP forecast less the logarithm of the median 6-month nominal GDP forecast. The nominal GDP forecast is converted to a real GDP forecast by subtracting the corresponding log differenced CPI forecast. Because Livingston Survey data are available only in June and December of each calendar year, the $egdp$ series remains constant in quarters 1 and 3 of each year.

investment-capital ratio (*ik*) The investment-to-capital ratio (*ik*) proposed by Cochrane (1991) is the ratio of aggregate investment to aggregate capital for the entire economy. Data are sourced Goyal and Welch (2008), as updated by Amit Goyal through 2010.

volatility of growth in industrial production (*ipvol*) This variable is a proxy for the conditional volatility of growth in U.S. industrial production. The construction of this variable follows Engle, Ghysels, and Sohn (2008) using industrial production data sourced from the Federal Reserve Bank of St. Louis's FRED II web page.

net payout (*npy*) The net payout yield is constructed using monthly CRSP data on aggregate market capitalization, dividends, and net equity issuance. The latter quantity is computed by multiplying the (adjusted) change in shares outstanding by the average of the beginning-of-month and end-of-month (adjusted) share price. The dividend yield for month t (dy_t) is computed as aggregate dividends over months t through month $t-11$ divided by market capitalization in month t. The net equity yield for month t (ney_t) is computed as aggregate net equity issues over months t through month $t-11$ divided by market capitalization in month t. The net payout yield is then defined as $ln(0.1+dy_t-ney_t)$. The underlying series is constructed using monthly data, and is sub-sampled at the quarterly frequency for the quarterly analysis.[6]

volatility of inflation growth (*ppivol*) This variable is a proxy for the conditional volatility for inflation

[6] Michael Roberts maintains data on his personal webpage (http://finance.wharton.upenn.edu/ mrrobert/). In order to extend the series through 2010, I created my own series using Stata code available in the replication files for the paper. Over the 1927-2008 period, my constructed series exhibits a correlation of over 99% with the series posted on Roberts' webpage.

growth based on the Producer's Price Index (PPI) downloaded from the Bureau of Labor Statistics' website. The construction of this variable follows Engle et al. (2008) using data sourced from the Federal Reserve Bank of St. Louis's FRED II web page

term spread (*tms*) The term spread is the difference between the long term yield on government bonds and the T-bill rate. Data are sourced Goyal and Welch (2008), as updated by Amit Goyal through 2010.

C. Additional Figures and Tables

C.1. Time Series Properties of Volatility

Figure C.1 documents the time series properties of volatility. The upper left panel provides a time series plot of log stock return volatility, as measured by $LVOL(t)$, at the quarterly frequency. The upper right panel presents a histogram for $LVOL(t)$. For reference, the plot also displays a normal density curve with mean and variance equal to the sample estimates for $LVOL_t$. The histogram illustrates that the distribution of *log* realized volatility is approximately Gaussian, as previously documented by Andersen, Bollerslev, Diebold, and Ebens (2001). The bottom left and right panels present an autocorrelogram and partial autocorrelogram for log volatility. These plots illustrate that volatility is persistent, a fact well-established in the literature. The first-order sample autocorrelation for log volatility is approximately 0.6. Partial autocorrelations beyond the second lag are close to zero. This pattern suggests an AR(2) specification as a plausible univariate benchmark model.

C.2. Comparison of Alternative Volatility Proxies

Figure C.2 provides time series plots comparing the various volatility proxies. The top panel compares the main proxy used in the analysis ($LVOL_t$) with the natural logarithm of the alternative proxies $FILT_t$, FSS_t, and $AVOL_t$ over the period 1952-2010 at the quarterly sampling frequency. The bottom panel compares the proxy $LVOL_t$ with the proxy $HFREQ_t$ based on intraday price data over the period 1983-2008. Overall, the alternative proxies are very similar. Removing a time-varying mean at low frequency has little empirical impact on the realized volatility measure, as $LVOL_t$ and $FILT_t$ are virtually indistinguishable. This suggests that, under daily sampling, any bias due to low-frequency variation in expected returns is very small. The FSS_t proxy occasionally deviates more noticeably from $LVOL_t$. These quarters correspond to months during which daily returns exhibit relatively strong autocorrelation. The main empirical findings are robust to the particular choice of proxy. For example, out-of-sample results computed using a proxy based on (2) are very similar to those previously discussed.

Turning to the bottom panel, the close affinity between $LVOL_t$ and $HFREQ_t$ may seem surprising, since daily squared returns are known to be a noisy measure of daily integrated variance. Intuitively, although the daily squared return is a noisy estimate of variance for any particular trading day, over the 60 trading days in a quarter these measurement errors tend to cancel (owing to the law of large numbers), and consequently the difference between $LVOL_t$ and $HFREQ_t$ is typically small.

C.3. Volatility and the Business Cycle: Alternative Measures of Economic Activity

Section 2 of the main paper discusses the contemporaneous relation between stock return volatility and business conditions. Figure 1 of the main paper presents time series plots of sign-inverted log stock return volatility alongside growth in GDP at a quarterly frequency (both series are standardized for comparison). Figure C.3 presents plots similar to those displayed in Figure 1 of the main paper, with the Aruoba-Diebold-Scotti Business Conditions Index developed by Aruoba, Diebold, and Scotti (2009) shown as an alternative measure of business conditions. Figure C.4 presents plots similar to those displayed in Figure 1 of the main paper at the monthly, as opposed to quarterly, sampling frequency, where the ADS index serves as an indicator of business conditions.[7]

C.4. In-Sample Results: Robustness

The main paper reports in-sample results for volatility forecasting regressions in which several lags of the dependent variable (log stock return volatility) are included, along with one or more lagged macroeconomic predictors. For results at the quarterly frequency (Table 2 of the main paper), two lags of volatility are included. For results at the monthly frequency (Table 3 of the main paper), six lags of volatility are included. These lag orders are chosen based on a comparison of information criteria for AR specifications of various orders at each sampling frequency. Still, the preferred specification can be sensitive to the sample period examined and the choice of criterion (e.g., AIC versus BIC). As a robustness check, I ran similar forecasting regressions including 4 lags of the dependent variable (quarterly horizon) and 12 lags of the dependent variable (monthly horizon). Results are very similar. As an illustration, Table C.1 presents in-sample forecasting results at the quarterly frequency where the specification includes 4 lags of the dependent variable.

A second robustness check explores the sensitivity of results to the choice of volatility proxy. Table C.2 presents in-sample forecasting results where the dependent variable is the (natural logarithm of) the proxy

[7] The coverage of these plots is 1960-2010, since the ADS series is unavailable prior to 1960.

$AVOL_t$ (defined in (3)) based on absolute, rather than squared, daily returns. These results are very similar to those reported in Table 2 of the main paper.

C.5. Out-of-Sample Results: Robustness

C.5.1. Monthly Sampling with Recursive Estimation

The main paper reports out-of-sample results using a rolling estimation scheme at both the quarterly and monthly horizons. The paper also reports results at the quarterly frequency using a recursive (expanding window) scheme. Table C.3 reports analogous results at the monthly frequency. Results for the recursive scheme are quite similar to those using a rolling scheme (compare with Table 6 of the main paper). Perhaps the most notable difference is that the kitchen sink model typically earns positive out-of-sample ΔR^2_{OOS}-values under recursive sampling, as opposed to negative values under the rolling scheme. However; in both cases the performance differences are generally not statistically different from zero based on the Giacomini-White test.

C.5.2. Forecasting the Level of Volatility

Results reported in the main paper emphasize the natural logarithm of (realized) volatility as the target variable, motivated by the fact that the logarithmic transformation dampens the leptokurtosis and positive-skew exhibited by stock return volatility. Economic agents, however, presumably attach greater interest to forecasting the *level* of volatility, irrespective of its distributional properties. A question arises: *How robust are results to alternatively modeling the level of volatility?*

Table C.4 replicates the out-of-sample analysis, under the recursive estimation scheme, replacing the log of volatility with the level of volatility as the target variable. The Clark-West tests again reveal that variables such as the commercial paper-to-Treasury spread, default return, default spread and investment-capital ratio Granger cause stock return volatility. Once again; however, there is little evidence for Granger causality over the 1982-2008 subsample. Out-of-sample R^2 improvements relative to the benchmark forecast remain small. For the univariate and kitchen sink models, the Giacomini-White test of equal predictive ability rarely rejects, and with one exception (the investment-capital ratio over the 1972-1998 sample period) any rejections are in favor of the benchmark model. Finally, the combined forecasts tend to outperform the benchmark, with statistically significant evidence for superior predictive ability (except for the 1982-2008 subsample). In summary, the main empirical findings are robust to forecasting the level, as opposed to the logarithm, of volatility.

C.5.3. Robustness to Alternative Volatility Proxy

Table C.5 presents in-sample forecasting results where the dependent variable is the (natural logarithm of) the proxy $AVOL_t$ (defined in (3)) based on absolute, rather than squared, daily returns. Results are at the quarterly frequency using recursive sampling. These results are similar to the analogous results presented in Table 5 of the main paper. Further variations, such as monthly sampling and rolling, as opposed to recursive sampling, did not produce notable differences in results.

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Figure C.1: **Volatility: Time Series Properties**
Time series properties for the natural logarithm of annualized realized volatility: 1952Q3 - 2010Q4.

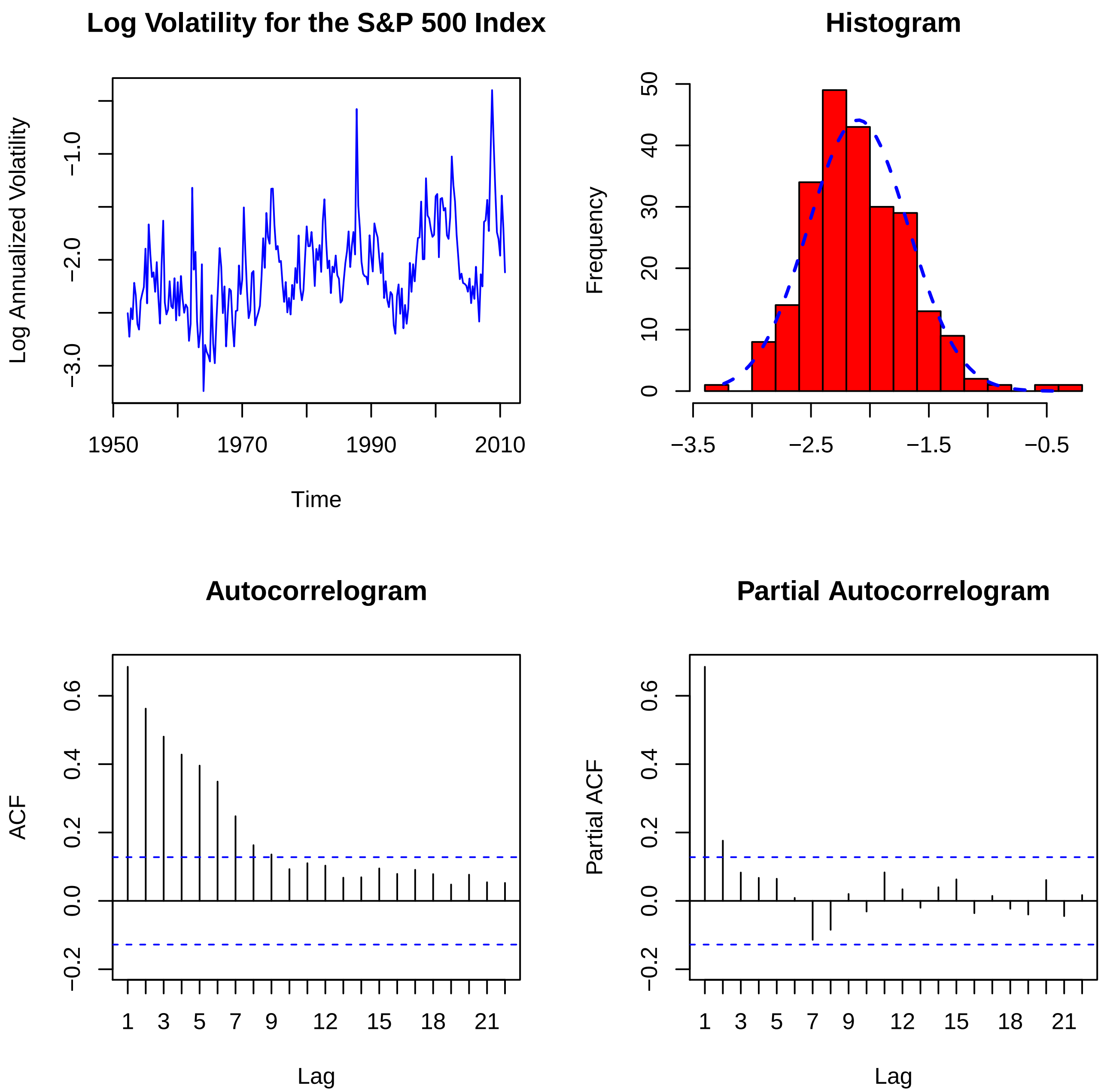
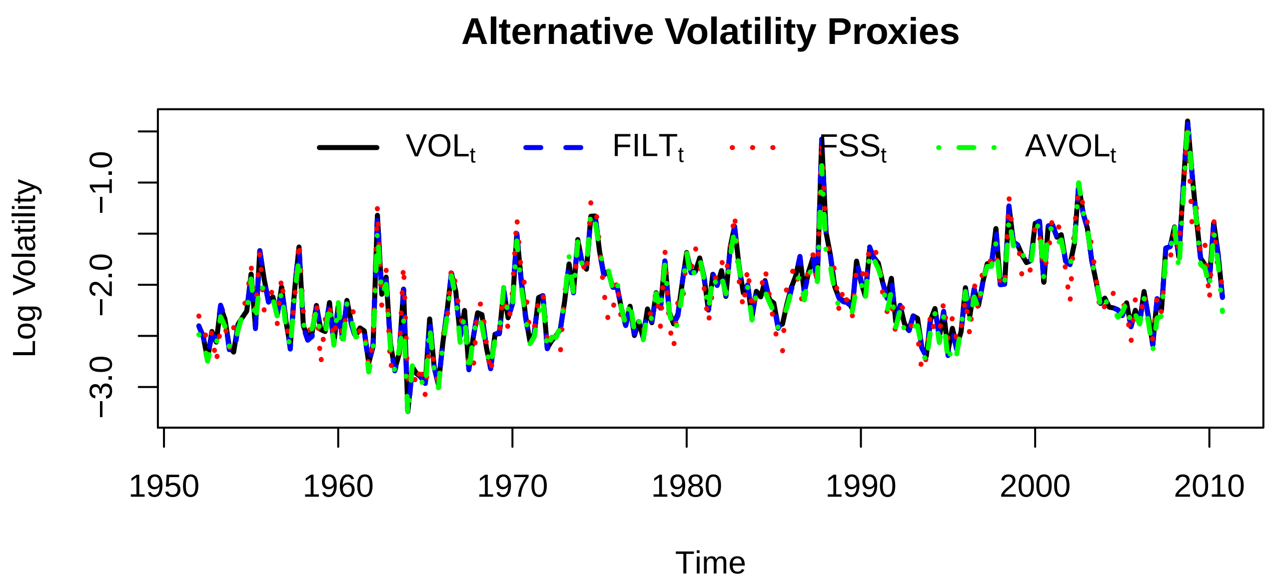


Figure C.2: **A Comparison of Alternative Volatility Proxies**
Time series plots for alternative volatility proxies. The top panel displays time series for log volatility based on several alternative proxies. These include the sum of daily squared returns, defined by equation (1) in the main paper, the proxy $FILT_t$ described by (1) that corrects for low-frequency variation in expected returns, the proxy FSS_t defined by (2) that corrects for serial correlation in daily returns, and the proxy $AVOL_t$ based on absolute returns, defined by equation (3). The bottom panel compares log volatility based on the sum of daily squared returns to the proxy $HFREQ_t$ that incorporates intraday data. The coverage for this plot is limited to 1982Q3-2010Q4, since $HFREQ_t$ is not available prior to this time.



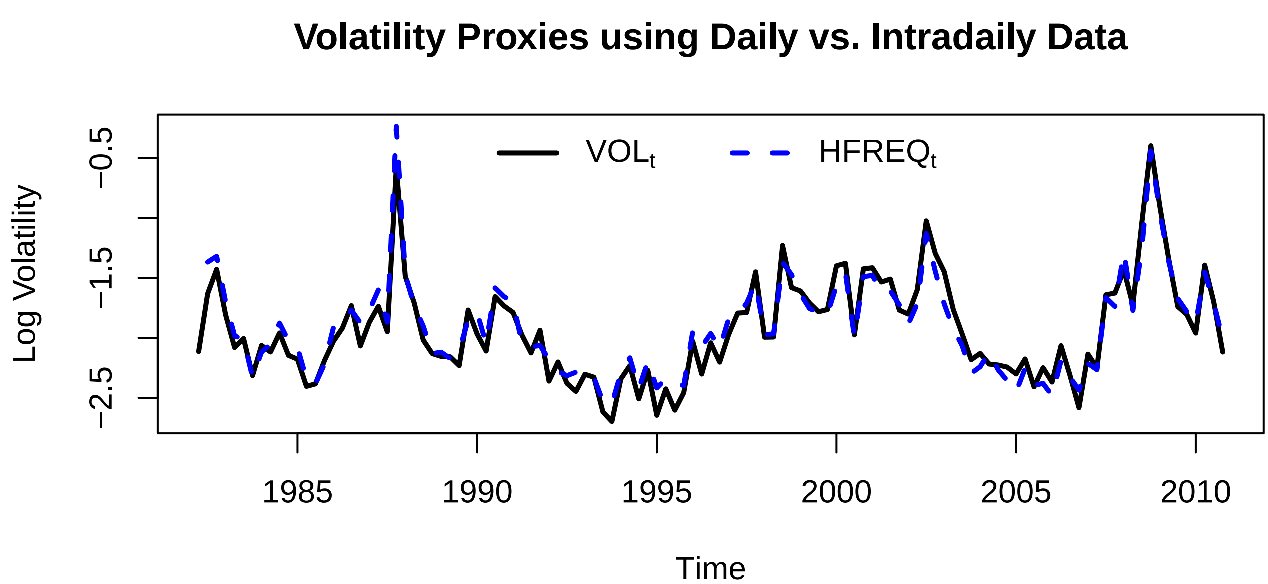


Figure C.3: **Stock Return Volatility and the Business Cycle: Robustness to ADS Proxy**
The top panel presents a time series plot of log realized volatility on the S&P 500 at the quarterly frequency for the period 1927-2010. The bottom two panels illustrate the covariation between stock return volatility and the business cycle. These panels contain quarterly time series plots of sign-inverted log realized volatility on the S&P 500 (i.e., (-1) x log volatility), along with US real GDP growth and the ADS Index over the period 1960-2010. All series are standardized for comparison. The middle panel presents raw time series while the bottom panel presents smoothed series constructed as a six quarter moving average.

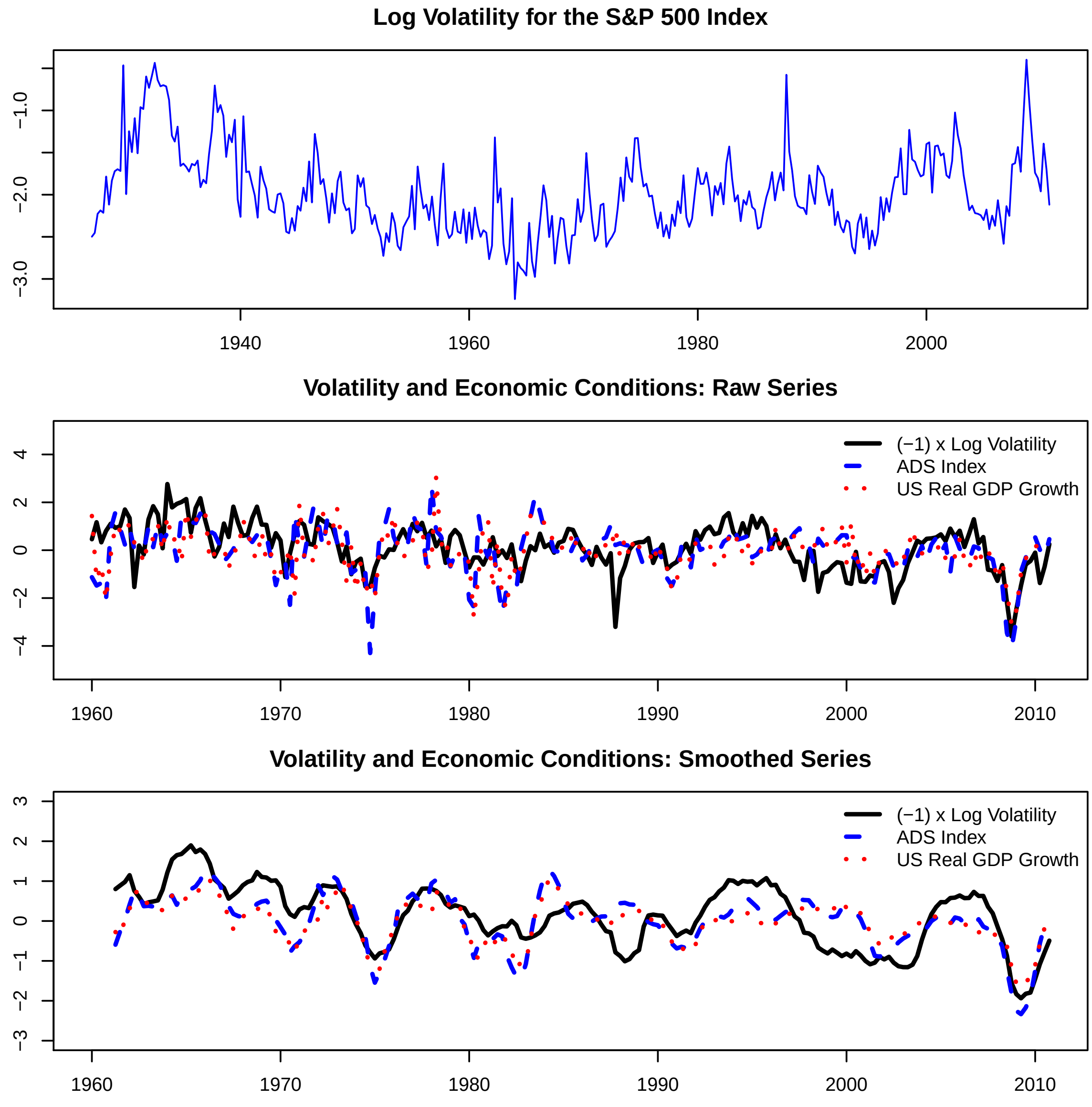


Figure C.4: **Stock Return Volatility and the Business Cycle: Monthly Data**
The top panel presents a time series plot of log realized volatility on the S&P 500 at the monthly frequency. The bottom two panels illustrate the covariation between stock return volatility and the business cycle. These panels contain monthly time series plots of sign-inverted log realized volatility on the S&P 500 (i.e., (-1) x log volatility), along with the ADS Index of current business conditions over the period 1960-2010. The series are standardized for comparison. The middle panel presents raw time series while the bottom panel presents smoothed series constructed as a six quarter moving average.

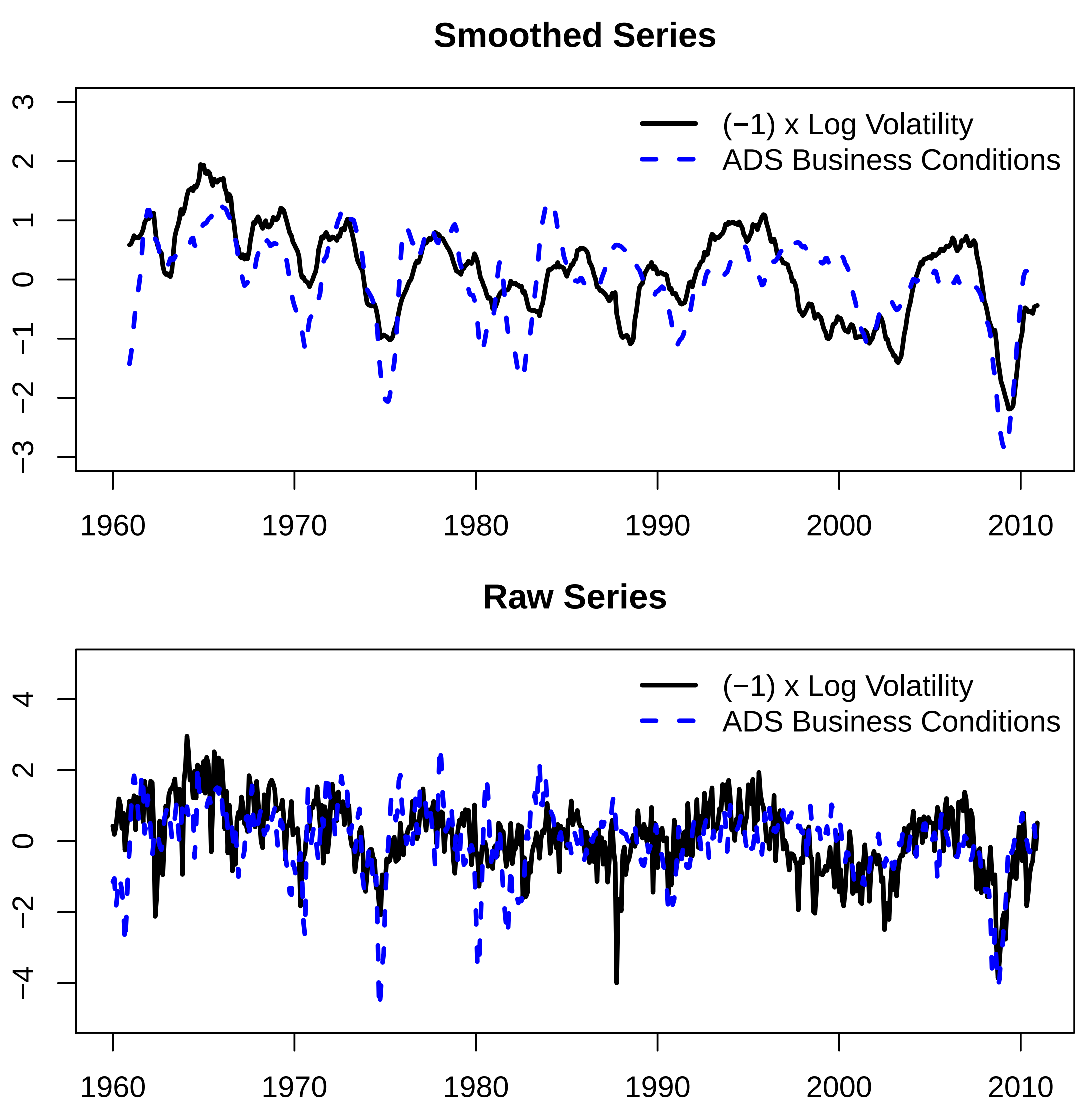


Table C.1: **In-Sample Forecasting Regressions with Quarterly Sampling: 4 lags**

The table presents results for in-sample predictive regressions for volatility using various macroeconomic and financial forecasting variables. The table reports results from regressions of the form

$$LVOL_t = \alpha + \rho_1 LVOL_{t-1} + \rho_2 LVOL_{t-2} + \rho_3 LVOL_{t-3} + \rho_4 LVOL_{t-4} + \beta' X_{t-1} + \varepsilon_t,$$

where $LVOL_t$ is the natural logarithm of return volatility, measured as in equation (1) of the main paper, and X_{t-1} represents a (possibly vector-valued) forecasting variable. For each forecasting variable, the table presents the estimated slope coefficient $\hat{\beta}$ on the forecasting variable and the increase in R^2-value relative to a benchmark univariate AR(4) regression (the above model with $\beta = 0$). The table also reports for a 'kitchen sink' regression that includes the full set of forecasting variables. In this case the table displays the F-statistic testing the null hypothesis that (vector-valued) $\beta = 0$, along with the increase in R^2-value relative to a benchmark univariate AR(4) regression. Results are reported over various estimation samples as indicated above column headers. Dashes indicate estimation samples where the corresponding forecasting variable is not available. All variables are standardized prior to estimation, and consequently the intercept α is omitted from the specification. The superscripts ***, ** and * designate statistical significance at the 1%, 5% and 10% levels, respectively, based on standard errors robust to the presence of heteroskedasticity and serial correlation.

		1927Q2-2010Q4		1952Q2 - 2010Q4		1927Q2-1951Q4		1952Q2 - 1985Q4		1986Q1 - 2010Q4	
Symbol	Name	$\hat{\beta}$	ΔR^2	$\hat{\beta}$	ΔR^2	$\hat{\beta}$	ΔR^2	$\hat{\beta}$	ΔR^2	$\hat{\beta}$	ΔR^2
blev	bank leverage	-	-	-0.03	0.11	-	-	-0.13^{**}	1.75	0.08	0.60
cay	consumption-wealth	-	-	-0.05	0.23	-	-	-0.09	0.81	-0.09	0.75
cp	cp-treasury spread	0.13^{***}	1.55	0.12^{***}	1.41	0.23^{**}	2.78	0.31^{***}	7.81	0.08	0.53
dfr	default return	-0.09^{***}	0.74	-0.14^{***}	1.78	0.04	0.17	-0.11^{*}	1.24	-0.15^{***}	1.83
dfy	default yield	0.15^{***}	0.94	0.05	0.15	0.34^{***}	3.33	0.07	0.32	0.04	0.08
egdp	expected GDP growth	-	-	-0.04	0.12	-	-	-0.03	0.07	-0.03	0.10
exret	expected return	-0.02	0.03	-0.10^{***}	0.92	-0.01	0.00	-0.10	0.92	-0.14^{**}	1.87
gdp	GDP growth	-	-	-0.01	0.00	-	-	-0.02	0.02	-0.02	0.05
ik	investment-to-capital	-	-	0.14^{***}	1.90	-	-	0.15^{***}	2.19	0.16^{***}	2.37
ipvol	ind. prod. vol.	0.00	0.00	-0.02	0.02	-0.04	0.11	-0.04	0.15	0.10	0.79
npy	net payout yield	-0.04	0.15	-0.10^{***}	0.93	-0.06	0.39	-0.02	0.05	-0.08	0.68
ppivol	infl. vol.	0.04	0.10	0.08	0.57	-0.04	0.12	0.17^{***}	2.68	0.02	0.04
tms	term spread	-0.06	0.26	-0.04	0.15	-0.08	0.40	-0.09	0.78	-0.08^{***}	0.63
		F	ΔR^2	F	ΔR^2	F	ΔR^2	F	ΔR^2	F	ΔR^2
sink	kitchen sink	4.74^{***}	3.16	5.74^{***}	6.61	3.65^{**}	5.27	7.68^{***}	10.64	9.48^{***}	7.14

Table C.2: **In-Sample Forecasting Regressions with Quarterly Sampling:** $AVOL_t$ **Proxy**

The table presents results for in-sample predictive regressions for volatility using various macroeconomic and financial forecasting variables. The table reports results from regressions of the form

$$Ln(AVOL_t) = \alpha + \rho_1 Ln(AVOL_{t-1}) + \rho_2 Ln(AVOL_{t-2}) + \beta' X_{t-1} + \varepsilon_t,$$

where $AVOL_t$ is the alternative proxy for stock return volatility described in (3), and X_{t-1} represents a (possibly vector-valued) forecasting variable. For each forecasting variable, the table presents the estimated slope coefficient $\hat{\beta}$ on the forecasting variable and the increase in R^2-value relative to a benchmark univariate AR(2) regression (the above model with $\beta = 0$). The table also reports for a 'kitchen sink' regression that includes the full set of forecasting variables. In this case the table displays the F-statistic testing the null hypothesis that (vector-valued) $\beta = 0$, along with the increase in R^2-value relative to a benchmark univariate AR(2) regression. Results are reported over various estimation samples as indicated above column headers. Dashes indicate estimation samples where the corresponding forecasting variable is not available. All variables are standardized prior to estimation, and consequently the intercept α is omitted from the specification. The superscripts ***, ** and * designate statistical significance at the 1%, 5% and 10% levels, respectively, based on standard errors robust to the presence of heteroskedasticity and serial correlation.

		1927Q2-2010Q4		1952Q2 - 2010Q4		1927Q2-1951Q4		1952Q2 - 1985Q4		1986Q1 - 2010Q4	
Symbol	Name	$\hat{\beta}$	ΔR^2	$\hat{\beta}$	ΔR^2	$\hat{\beta}$	ΔR^2	$\hat{\beta}$	ΔR^2	$\hat{\beta}$	ΔR^2
blev	bank leverage	-	-	-0.01	0.01	-	-	-0.12**	1.50	0.11*	1.06
cay	consumption-wealth	-	-	-0.05	0.29	-	-	-0.09	0.86	-0.08	0.68
cp	cp-treasury spread	0.12***	1.23	0.10**	0.96	0.23***	2.62	0.28***	6.47	0.05	0.23
dfr	default return	-0.08**	0.64	-0.13***	1.54	0.03	0.09	-0.11*	1.13	-0.15***	1.80
dfy	default yield	0.16***	1.04	0.06	0.20	0.30***	2.78	0.10	0.63	0.02	0.01
egdp	expected GDP growth	-	-	-0.02	0.03	-	-	0.00	0.00	-0.02	0.05
exret	expected return	-0.01	0.00	-0.08**	0.64	-0.01	0.00	-0.09	0.72	-0.13**	1.49
gdp	GDP growth	-	-	-0.01	0.01	-	-	-0.02	0.02	-0.02	0.04
ik	investment-to-capital	-	-	0.12***	1.49	-	-	0.12**	1.45	0.15***	2.32
ipvol	ind. prod. vol.	0.02	0.02	-0.01	0.02	-0.01	0.02	-0.03	0.07	0.08	0.54
npy	net payout yield	-0.04	0.13	-0.10***	0.97	-0.06	0.32	-0.01	0.01	-0.09*	0.77
ppivol	infl. vol.	0.04	0.14	0.08	0.58	-0.02	0.04	0.17***	2.53	0.02	0.04
tms	term spread	-0.04	0.12	-0.02	0.05	-0.07	0.35	-0.05	0.24	-0.08***	0.65
		F	ΔR^2	F	ΔR^2	F	ΔR^2	F	ΔR^2	F	ΔR^2
sink	kitchen sink	4.63***	3.12	3.83***	6.03	3.11***	4.59	6.79***	9.84	11.14***	6.55

Table C.3: **Out-of-Sample Results: Monthly Sampling and Recursive Estimation**

The table presents out-of-sample results for volatility forecasts that incorporate various macroeconomic and financial variables. The forecasting regressions take the form

$$LVOL_t = \alpha + \sum_{i=1}^{6} \rho_i LVOL_{t-i} + \beta' X_{t-1} + \varepsilon_t,$$

where $LVOL_t$ is the natural logarithm of return volatility, measured as in equation (1) of the main paper, and X_{t-1} represents a (possibly vector-valued) forecasting variable. For each forecasting model, the table presents 'CW,' the adjusted difference in MSPE (multiplied by 1000) that forms the basis of the out-of-sample test for equal MSPE suggested by Clark and West (2007). The superscripts ***, ** and * appear alongside CW test statistics to indicate rejections of the null hypothesis of no Granger causality at significance levels of the 1%, 5% and 10% levels, respectively. The table also reports ΔR^2_{OOS}, the increase in out-of-sample R^2 relative to a benchmark univariate AR(6) forecasting model. Superscripts ***, ** or * accompany ΔR^2_{OOS} when the Giacomini and White (2006) test for equal predictive ability rejects at the 1%, 5% and 10% levels, respectively. Forecasts are produced using a recursive estimation procedure with an initial estimation window of 240 months (20 years).

	Forecasting Start	1947.3		1972.3		1982.3		1972.3	
	Forecasting End	2010.12		2010.12		2010.12		2000.12	
	Out-of-sample N	246		146		106		106	
Symbol	Name	CW	ΔR^2_{OOS}	CW	ΔR^2_{OOS}	CW	ΔR^2_{OOS}	CW	ΔR^2_{OOS}
cp	cp-treasury spread	2.50**	-0.02	3.85**	0.08	0.08	-0.67	5.84***	0.65
dfr	default return	0.88**	0.18	1.60***	0.32	2.20***	0.43	0.21	0.07
dfy	default spread	2.04**	0.12	0.09	0.01	0.20	0.05	-0.14	-0.09
exret	expected return	-0.12	-0.05	1.04	-0.16	0.36	-0.16	1.63*	-0.04
ip	growth in ind. prod.	-0.17	-0.07*	-0.11	-0.05*	-0.13	-0.05	-0.02	-0.01
ipvol	ind. prod. vol.	-0.10	-0.04	-0.13	-0.07	-0.25	-0.12	0.22	0.08
npy	net payout yield	-0.04	-0.05	0.96	0.05	1.62*	0.23	0.90	0.12
ppivol	infl. vol.	0.53	0.07	1.64*	0.02	1.30	-0.21	1.44*	0.22
tms	term spread	-0.11	-0.06	0.06	-0.14	-0.53	-0.25	0.26	-0.12
sink	kitchen sink	6.42***	0.55	9.15***	0.57	5.93**	-0.05	10.94***	1.69
	Combined Forecasts:								
	mean	0.60***	0.20***	1.00***	0.35**	0.54**	0.18*	1.15***	0.48**
	median	0.06*	0.02	0.20**	0.07	0.14	0.05	0.21**	0.10*
	trim-mean	0.31***	0.11***	0.50***	0.17*	0.27*	0.09	0.59***	0.25*
	MSPE	0.63***	0.22***	1.14***	0.39**	0.60***	0.20**	1.33***	0.56**

Table C.4: **Out-of-Sample Results: Robustness to Modeling Level of Volatility**

The table presents out-of-sample results for quarterly volatility forecasts that incorporate various macroeconomic and financial variables. The forecasting regressions take the form

$$VOL_t = \alpha + \rho_1 VOL_{t-1} + \rho_2 VOL_{t-2} + \beta' X_{t-1} + \varepsilon_t,$$

where VOL_t is the *level* of return volatility, measured as in equation (1) of the main paper, and X_{t-1} represents a (possibly vector-valued) forecasting variable. For each forecasting model, the table presents 'CW,' the adjusted difference in MSPE (multiplied by 1000) that forms the basis of the out-of-sample test for equal MSPE suggested by Clark and West (2007). The superscripts ***, ** and * appear alongside CW test statistics to indicate rejections of the null hypothesis of no Granger causality at significance levels of the 1%, 5% and 10% levels, respectively. The table also reports ΔR^2_{OOS}, the increase in out-of-sample R^2 relative to a benchmark univariate AR(2) forecasting model. Superscripts ***, ** or * accompany ΔR^2_{OOS} when the Giacomini and White (2006) test for equal predictive ability rejects at the 1%, 5% and 10% levels, respectively. Forecasts are produced using a recursive estimation procedure with an initial estimation window of 80 quarters (20 years). Dashes indicate estimation samples where the corresponding forecasting variable is not available.

	Forecasting Start	1947Q3		1972Q3		1982Q3		1972Q3	
	Forecasting End	2010Q4		2010Q4		2010Q4		2000Q4	
	Out-of-sample N	254		154		114		114	
Symbol	Name	CW	ΔR^2_{OOS}	CW	ΔR^2_{OOS}	CW	ΔR^2_{OOS}	CW	ΔR^2_{OOS}
blev	bank leverage	-	-	-0.01	-0.65	-0.08	-1.18**	0.04	-0.17
cay	consumption-wealth	-	-	0.02	0.07	0.00	-0.13	0.01	-0.19
cp	cp-treasury spread	0.27**	-1.66	0.34**	1.13	0.09	-0.94	0.53**	4.82
dfr	default return	0.16	1.27	0.34*	1.91	0.39	1.57	0.09*	0.61
dfy	default spread	0.27**	-0.41	0.02	0.17	0.03	0.22	0.01	0.08
egdp	expected GDP growth	-	-	-0.01	-0.08	0.00	-0.04	0.00	-0.11
exret	expected return	-0.01	-0.26	0.05*	0.42	0.05	0.33	0.03	0.39
gdp	GDP growth	-	-	0.00	-0.09	0.00	-0.04	-0.01	-0.21
ik	investment-to-capital	-	-	0.14**	1.22	0.15*	0.94	0.17***	2.93**
ipvol	ind. prod. vol.	-0.02	-0.27**	-0.08	-1.25	-0.12	-1.48	0.02	0.22
npy	net payout yield	-0.01	-0.24*	0.09	0.21	0.15	0.54	0.08	0.63
ppivol	infl. vol.	-0.03	-0.50	0.12	-1.13	-0.03	-2.12	0.20**	0.48
tms	term spread	-0.04	-0.66*	-0.02	-0.80	-0.09	-1.06*	-0.01	-1.40
sink	kitchen sink	0.48***	-1.12	0.61***	2.31	0.41**	0.91	0.59**	3.00
	Combined Forecasts:								
	mean	0.08***	0.81**	0.08***	0.95**	0.04**	0.42**	0.09***	1.77**
	median	0.00	0.00	0.02*	0.22	0.01	0.06	0.02*	0.43
	trim-mean	0.03**	0.30*	0.04***	0.55**	0.02	0.20	0.05***	1.02**
	MSPE	0.10***	1.07***	0.10***	1.24**	0.06***	0.58**	0.12***	2.35**

Table C.5: **Out-of-Sample Results: Robustness to $AVOL_t$ Proxy**

The table presents out-of-sample results for quarterly volatility forecasts that incorporate various macroeconomic and financial variables. The forecasting regressions take the form

$$Ln(AVOL_t) = \alpha + \rho_1 Ln(AVOL_{t-1}) + \rho_2 Ln(AVOL_{t-2}) + \beta' X_{t-1} + \varepsilon_t,$$

where $AVOL_t$ is the alternative proxy for stock return volatility described in (3), and X_{t-1} represents a (possibly vector-valued) forecasting variable. For each forecasting model, the table presents 'CW,' the adjusted difference in MSPE (multiplied by 1000) that forms the basis of the out-of-sample test for equal MSPE suggested by Clark and West (2007). The superscripts ***, ** and * appear alongside CW test statistics to indicate rejections of the null hypothesis of no Granger causality at significance levels of the 1%, 5% and 10% levels, respectively. The table also reports ΔR^2_{OOS}, the increase in out-of-sample R^2 relative to a benchmark univariate AR(2) forecasting model. Superscripts ***, ** or * accompany ΔR^2_{OOS} when the Giacomini and White (2006) test for equal predictive ability rejects at the 1%, 5% and 10% levels, respectively. Forecasts are produced using a recursive estimation procedure with an initial estimation window of 80 quarters (20 years). Dashes indicate estimation samples where the corresponding forecasting variable is not available.

	Forecasting Start	1947Q3		1972Q3		1982Q3		1972Q3	
	Forecasting End	2010Q4		2010Q4		2010Q4		2000Q4	
	Out-of-sample N	254		154		114		114	
Symbol	Name	CW	ΔR^2_{OOS}	CW	ΔR^2_{OOS}	CW	ΔR^2_{OOS}	CW	ΔR^2_{OOS}
blev	bank leverage	-	-	0.29	-0.58	-2.42	-1.58***	1.13	-0.50
cay	consumption-wealth	-	-	1.03	0.00	-0.26	-0.57	0.94	-0.17
cp	cp-treasury spread	4.99**	-0.07	9.13*	0.36	0.14	-1.94	13.22**	1.69
dfr	default return	2.04*	0.57	6.09**	1.22	6.63*	1.06	2.46*	0.27
dfy	default spread	4.85**	0.42	0.33	-0.04	0.46	-0.02	0.09	-0.15
egdp	expected GDP growth	-	-	-0.30	-0.15	0.04	0.01	-0.36	-0.23
exret	expected return	-0.30	-0.19	2.39**	0.57	2.00*	0.30	1.78*	0.57
gdp	GDP growth	-	-	-0.41	-0.23	-0.23	-0.11*	-0.43	-0.31
ik	investment-to-capital	-	-	5.90***	1.64	5.40**	1.15	7.24***	3.05***
ipvol	ind. prod. vol.	-0.24	-0.11*	-0.69	-0.39	-0.78	-0.42	0.28	0.12
npy	net payout yield	0.15	-0.11	2.80	0.11	4.88*	0.87	2.42	0.20
ppivol	infl. vol.	0.44	0.00	6.36*	-0.64	0.26	-1.96*	7.86*	-0.12
tms	term spread	-0.52	-0.43	0.29	-0.65	-1.62	-0.91	1.13	-0.60
sink	kitchen sink	10.00***	0.62	15.56**	0.19	10.51**	0.46	15.40**	-1.10
	Combined Forecasts:								
	mean	1.43***	0.55**	2.56***	1.05**	1.11**	0.41	2.91***	1.49*
	median	0.07	0.02	0.80**	0.34*	0.25	0.08	1.00**	0.53
	trim-mean	0.68**	0.27**	1.64***	0.68*	0.58	0.20	1.94**	1.00*
	MSPE	1.66***	0.65***	3.12***	1.28**	1.61***	0.62**	3.64***	1.86*