How to Look Clever and Have Envious Neighbors: Average Volatility Managed Leverage Timing

Jeramia Poland *

ABSTRACT

There's nothing very interesting here, but the format (achieved using the file `jf.sty`) makes it suitable for publication in the *Journal of Finance* even if the content doesn't. Here's a nice, informative, double-spaced abstract.

JEL classification: XXX, YYY.

*Indian School of Business, email jeramia_poland@isb.edu. Acknowledgments ...

Discussions on when to risk investment capital in the pursuit of maximum return took place over telegraph lines nearly a century before Markowitz brought formality to the notion of risk, portfolio construction and optimization in the 1950s.[1] Modern portfolio theory states that portfolios with higher variance need to generate higher mean returns to attract rational investors.(Markowitz, 1952) However, several challenges have appeared to this foundational mean-variance claim. One of the most basic is commonly referred to as the low-risk or low-volatility anomaly. Haugen and Heins (1972) found there was little to no evidence for a "risk-premium" for increased portfolio volatility. While Warren Buffet may not be an enthusiastic supporter, low volatility portfolios with unusually high expected returns present an opportunity for leveraged investing.[2] Moreira and Muir (2017) show across investment strategies and asset classes that merely managing leverage in a portfolio by that portfolio's volatility produces greater expected returns and performance ratios. These results seem to challenge the mean-variance notion of investment risk premium fundamentally. This risk-return tradeoff is central to modern financial theory, so naturally, I address this problem by making it worse. Pollet and Wilson (2010) show that the average correlation of portfolio assets is the component of portfolio volatility most related to systemic changes in the economy and is the risk component compensated with higher returns. By managing the market portfolio using the average variance of the individual asset returns in the prior period rather than the variance of the market portfolio, I generate higher expected returns and significantly better performance ratios. In addition to identifying a better strategy for investors, decoupling the idiosyncratic variance of individual returns from the that of the market portfolio returns sheds light on the risk-return trade-off dynamics of the market and allows leveraging investment into times when higher risk will be compensated and pulling out when it will not. Thankfully, this worse problem exposes evidence consistent with the explanation of low-risk anomalies which claims that investors are constrained from taking the leverage necessary in the low-risk portfolios and inconsistent with the story that investors prefer the high-risk portfolios because they enjoy lottery-like investments. As such both average variance and volatility managed portfolios represent a realization of a practical limitation of one of the assumptions of modern portfolio theory and not a fundamental problem with the concept of the risk-premium.

Since the identification of a low-risk anomaly, or the absence of a risk premium, a large number of researchers have sought to identify a positive relationship between return variance and expected returns. Campbell (1987), French, Schwert, and Stambaugh (1987), Glosten, Jagannathan, and Runkle (1993) and many, many others have found very insufficient evidence identifying a positive relationship between return variance and future returns. On the other hand, Moreira and Muir (2017) demonstrate that volatility managed portfolios which decrease leverage when volatility is high produce large alphas, increase Sharpe ratios, and produce substantial utility gains for mean-variance investors. These results hold across investment styles, e.g., value or momentum, and in different asset classes, e.g., equities and currency portfolios. The results even hold for positions which already seek to exploit the low-risk anomaly like the "betting-against-beta" strategy of Frazzini and Pedersen (2014). Additionally, other researchers have applied similar variance or volatility management to specific assets or trading styles.[3] Practitioners call approaches like this risk-parity, and as of 2016, at least $150 and as much as $400 billion sits in these funds.(Steward, 2010; Cao, 2016) The generation of higher expected returns without a commensurate increase in portfolio volatility implies that a representative investor should time asset volatility, demanding less return when its higher meaning the investors risk appetite must be higher in periods like recession and market downturns when its expected to be lower. In short, it seems risk does not equal reward. However, as with pigs, some volatility is "more equal" than other volatility.[4]

Pollet and Wilson (2010) decompose market variance into the average correlation between pairs of assets and the average variance of the individual assets. This decomposition yields a series strongly related to both future volatility and higher returns, the average correlation of market assets series, and a one strongly related to future volatility but unrelated to returns, market asset average variance. Scaling investment in the market portfolio by the inverse of the previous period average variance should then improve return performance over and above managing investment the previous market variance since it avoids, somewhat, decreasing investment when the average correlation is high and its expected compensation. Average variance is also a better candidate for portfolio management because it has a better chance to pick up economic information sooner as individual assets respond to information about their own risk and expected returns with public disclosure while changes in aggregate materialize as data across assets are combined.(Campbell, Lo, MacKinlay, et al., 1997; Campbell, Lettau, Malkiel, and Xu, 2001)

Using daily market returns from the Center for Research in Securities Prices, I follow Pollet and Wilson (2010) generating quarterly time series of stock market variance, SV, average correlation, AC, and average variance, AV. I then extend this by calculating the time series monthly. As expected, AV is strongly related to next period market variance and unrelated, at best insignificantly negatively, related to next period excess log returns. From June 1962 to the end of 2016, encompassing the sample of Pollet and Wilson (2010), asset average variance is a significant in-sample predictor of higher daily market return variance, average asset variance, pairwise correlation, and lower log excess market returns at the monthly frequency. A one standard deviation increase in annualized average variance, from .77 to 1.62, is related to an increase in next months annualized market return variance of .545 of a standard deviation or a .22 increase. This makes next months expected market variance more than double the mean. AV remains a significant predictor or next month's SV even when this month's SV is included. A one standard deviation increase in AV also anticipates a .13 standard deviation, or .58 percentage point, lower log excess return. This the following month's expected return negative. When both AV and SV are used to predict next month's return, AV is significant but SV is not. These support results at the quarterly frequency in Pollet and Wilson (2010). However, over the full, 1926 to 2016, sample average variance is a signficant predictor of higher daily market return variance, average asset variance, pairwise correlation, but not log excess market returns, as shown in table IV. This evidence supports the use of average variance as a leverage management signal. Scaling investment in the market by the inverse of average asset variance in the current month will pull funds out when the following month will have high market variance without sacrificing higher expected returns. It may, in fact, avoid negative returns. These results support the intuition from the work on volatility management in Moreira and Muir (2017) and portfolio average variance and correlation in Pollet and Wilson (2010) but in-sample regression use all available information and do not necessarily identify tradeable strategies.(Welch and Goyal, 2008)

Investors can only make decisions using the limited information available to them at a given time. For example in June of 2007 investors and investment models could only use historical information up to that month; the effects of November 2008 on the variable coefficients do not affect the predictions for July 2007. Moreira and Muir (2017) demonstrate that market volatility is an effective market portfolio management technique across the CRSP data set from 1926 to 2015. To motivate average variance as a better market portfolio leverage signal, I run expanding window out-of-sample regressions using AV on market volatility, average variance, average correlation, and log excess returns. From June 1926 to December 2016 and using the predictions from SV as a benchmark, AV is a significantly better predictor or next months AV, AC and SV. It generates better Diebold and Mariano (1995) test statistics, significantly lower mean squared forecast errors judging by the MSE-F statistic from McCracken (2007) and the emcompassing test of Harvey, Leybourne, and Newbold (1998) show that average variance contains all of the predictive information in market variance. As with the in-sample results average variance serves investors at least as well as market variance and likely better in avoiding risk without giving up return. Out-of-sample testing always raises questions about model specification, recursive expansion versus rolling window parameter estimation, and choices of the training period and prediction window. Using the techniques in Rossi and Inoue (2012), the Diebold and Mariano (1995), McCracken (2007), and Harvey et al. (1998) measures can be calculated robust to concerns on window selection for either an expanding or rolling specification. The Rossi and Inoue (2012) robust statistics show that AV is a significantly better predictor than SV robust to the choice of window or regression specification. Thus, I expect managing leverage in the market portfolio by AV will produce substantially better return performance as compared to management by SV.

As promised by the out-of-sample results, AV is a substantially better than SV as a leverage management signal. Targeting the volatility of the buy and hold market portfolio return, as in Moreira and Muir (2017), an investor without borrowing constraints earns an annualized average monthly return of 9.7% from the average variance managed portfolio. This return is a statistically significant increase of more than 1% over the SV managed portfolio; the difference in annualized average monthly returns grows to more than 2% when practical leverage constraints are applied. With unconstrained borrowing, the AV managed portfolio has significantly better performance ratios like the symmetric Sharpe ratio, .52, and more asymmetric risk-return measures, e.g., Kappa 3 and Kappa 4 at .15 and .11 respectively. The advantage of managing with AV grows with risk aversion. The most risk-averse, $\gamma = 5$, constrained investor sees a certainty equivalent return (CER) gain of more than 2% annualized; this return represents a 26.4% increase in utility nearly as substantial as the utility gains seen in return timing strategies. (Campbell et al., 1997) Targeting the volatility of the buy and hold return requires seeing into the future and knowing the buy and hold return volatility. However, this look-ahead does not affect performance ratios like the Sharpe ratio moreover, the significantly better performance of AV is robust to other choices of target volatility. The asset allocation gains are not all perfect, however, and the lower Rachev ratio performance of AV hints at a possible explanation for the low-risk anomaly seen in volatility and average variance management.

There is no such thing as a free lunch, is not only a wonderfully pervasive adage, particularly loved by economists but a provable restriction on optimization problems. (Wolpert and Macready, 1997) Here, AV provides no free lunch. The improved performance measured by expected log excess returns, Sharpe, Sortino, and Kappa ratios is betrayed by worse performance in Rachev ratio. The Rachev ratio measures the right tail reward value at play relative to the left tail value at risk. In short, it measures the ratio of expected lottery rewards and losses. The volatility managed market portfolio has higher lottery winning potential for each dollar of potential lottery loss compared to the average variance managed portfolio. Both SV and AV generate better Rachev ratios than the buy and hold return. Prior literature on the low-risk strategies proposes two explanations. Either investors are leverage constrained and unable to form the positions which generate the abnormal returns or investors have a preference for the extreme right tail, lottery, returns which are not possible when employing risk-managed strategies. As AV and SV managed portfolios have better Rachev ratios than the buy and hold strategy, it would seem they are better lotteries to play. Asness, Frazzini, Gormsen, and Pedersen (2018) take a related approach to decomposing the betting-against-beta strategy of Frazzini and Pedersen (2014) into betting-against-correlation, BAC, and betting-against-variance factors, BAV, finding the BAC factor has a significant Fama-French five-factor alpha but unrelated to behavior explanations of the low-risk anomaly. (Fama and French, 2016) From the decomposition of daily market returns, I find similar results about the more general low-risk strategy of volatility management. Management by either market variance or average asset variance increases the lottery-like returns of the market portfolio. Both strategies increase the Rachev ratios of the returns. This change is inconsistent with the notion that the low-risk anomaly is the result of a behavioral preference of investors for lottery-like returns. (Barberis and Huang, 2008; Brunnermeier, Gollier, and Parker, 2007) Instead, the generation of higher log excess returns by the AV, SV, and betting-against-beta strategies support the notion that the low-risk anomaly arises from leverage constraints first suggested in Black (1972). Boguth and Simutin (2018) link capital constraints and the betting-against-beta strategy through mutual fund betas, and more generally Malkhozov, Mueller, Vedolin, and Venter (2017) show that international illiquidity predicts betting-against-beta returns. Testing directly for changes in the capital market line, first shown to flatten when leverage is costly by Jylh (2018), I find a significant effect of many proxies for credit constraints on the returns to AV management but no significant effect for proxies of lottery preference. Financial intermediary leverage, bank credit growth, growth in margin investing and lending rates all affect the return on the AV managed portfolio and flatten the capital market line while proxies for high investor lottery preference like market capitalization of gaming industry stocks and extreme values of market daily returns are not. The evidence is consistent with leverage constraints affecting the returns to low-risk strategies, not market-wide lottery preferences.

By using the decomposition of market variance, I identify a better portfolio leverage management signal. Weighting investment leverage by the inverse of the average of individual asset variance, AV, rather than overall return variance, SV, is a new addition to the portfolio management literature letting investors capture better performance as measured by expected annualized returns. Investors also capture better investment ratios except for the Rachev ratio. The Rachev exposes the trade-off which investors must accept when managing risk by manipulating leverage conditional on average variance. The change in ratio contributes evidence against the lottery explanation of the low-risk anomaly in mean-variance analysis and supports the leverage constraints explanation. Furthur evidence shows that the returns and capital market line responds to proxies for tight lending conditions but not high lottery preference. This finding contrasts with conclusions reached in the study of cross-sectional low-risk anomalies which have been explained through the behavioral, lottery, channel.

The formation and analysis of the AV signal are relatively straightforward. It requires a few publically available datasets and a few considerations for the calculations at the monthly frequency. Most of the work is in the calculations required to show significant regression and portfolio performance.

I. Data

To calculate stock market variance, average asset variance, and average asset correlation, I use daily return data from CRSP and calculate the variance of daily returns monthly. To simplify the analysis of individual assets, I require that the asset be traded on each in the month which mitigates any liquidity effects and ensures consistent variance, covariance and correlation calculations. These conditions make the calculation of asset variance:

$$\sigma_{m,t}^2 = \frac{1}{T-1}\sum_{\tau=1}^{T}\left(R_{m,\tau} - \frac{\sum_{\tau=1}^{T} R_{m,\tau}}{T}\right)^2. \tag{1}$$

where $R_{m,\tau}$ is the daily return, including dividends, on an asset for day τ in month t. When the asset is the market portfolio, so $R_{m,\tau} = R_{s,\tau}$, the result is the variation of market returns, SV. The standard Pearsons correlation where the correlation of assets m and n for month t is:

$$\rho_{m,n,t} = \frac{\sum_{\tau=1}^{T}\left(R_{m,\tau} - \frac{\sum_{\tau=1}^{T} R_{m,\tau}}{t}\right)\left(R_{n,\tau} - \frac{\sum_{\tau=1}^{T} R_{n,\tau}}{t}\right)}{\sqrt{\left(R_{m,\tau} - \frac{\sum_{\tau=1}^{T} R_{m,\tau}}{t}\right)^2 \sum_{\tau=1}^{T}\left(R_{n,\tau} - \frac{\sum_{\tau=1}^{T} R_{n,\tau}}{t}\right)^2}}. \tag{2}$$

Unfortunately, for samples as small as the monthly series of daily returns Pearsons correlation is not an unbiased estimator of the true correlation, even if the returns are normal. Hotelling (1953)

The average month in my sample has 22 trading days however the number commonly drops into the teens.[5] For samples of these sizes, the bias causes an underestimation of the correlation which is worse the lower the true correlation. I employ an approximate correction from Olkin and Pratt (1958) such that the monthly correlation between two assets m and n is:

$$\rho_{m,n,t} = \widehat{\rho_{m,n,t}} \left(1 + \frac{1 + \widehat{\rho^{m,n}}^2}{2(t-3)} \right) \tag{3}$$

where $\widehat{\rho_{m,n,t}}$ is the Pearson correlation between a and b.[6] Average variance and average correlation are value-weighted so each month I calculate market capitalization for all of the assets available in CRSP. The capitalization used in month t for asset m is the product of the end of month price (PRC) and common shares outstanding (SHROUT) values for asset m in month t-1.

$$MCAP_{m,t} = PRC_{m,t-1} \times SHROUT_{m,t-1} \tag{4}$$

To make the analysis more computationally trackable I use only, at most, the top 500 assets in CRSP by market capitalization for a given month.[7] Given this restriction, an assets market capitalization weight is defined by:

$$w_{m,t} = \frac{MCAP_{m,t}}{\sum_{j=1}^{J} MCAP_{n,t}} \tag{5}$$

with j $\leq$ 500. Thus, the other series of interest, market variance, SV, average variance, AV, and average correlation, AC, are defined by:

$$SV_t = \frac{1}{t-1} \sum_{\tau=1}^{T} \left(R_{s,\tau} - \frac{\sum_{\tau=1}^{T} R_{s,\tau}}{t} \right)^2 \tag{6}$$

$$AV_t = \sum_{m=1}^{M} w_{m,t} \sigma_{m,t}^2 \tag{7}$$

$$AC_t = \sum_{m=1}^{M} \sum_{m \neq n}^{N} w_{m,t} w_{n,t} \rho_{m,n,t} \tag{8}$$

Figure 1 shows the time series behavior of market and average variance, in percent, as well as average correlation. With the easily noticeable exception of October 1987, spikes in both market and average variance concentrate around NBER defined recessions.

[Place Figure 1 about here]

Table I shows the summary statistics for the calculated variables. Despite the use of the actual number of trading days, the restriction to assets that trade every trading day, and the adjustment to the calculation of correlation, the quarterly calculated values are almost identical to those in Pollet and Wilson (2010) over the same sample. Over the expanded the period, the annualized monthly average variance has a mean value of .88%. The annualized stock market variance mean is much lower at .25% monthly. Average correlation is relatively consistent at .23 quarterly in the Pollet and Wilson (2010) sample, .261 monthly in the same sample and .276 over the full time period. Average variance is more volatile than the stock market variance, more than twice as much. In each sample average variance has the highest autocorrelation. While average correlation is also persistent, the stock market variance is only strongly persistent at the monthly frequency with autocorrelation of .61. All three time series are stationary rejecting the unit root null in the tests of Dickey and Fuller (1979), Ng and Perron (2001), and Elliott, Rothenberg, and Stock (1996).

[**Place Table I about here**]

As my primary interest is in the use of average variance versus market variance in the management of leverage in the CRSP market portfolio, I test AV and SV against CRSP log excess returns. Specifically, I take the difference between the natural log of one plus the CRSP market return and the natural log of one plus the risk-free rate using:

$$r_t = \log R_{m,t} - \log R_{f,t} \tag{9}$$

where $R_{f,t}$ the risk-free return for which I use the 1-month treasury bill rate from Ken French's website[8]. As shown in table II, over the full data period, each variance and correlation time series are contemporaneously correlated to lower log excess returns. Average variance, AV, is significantly correlated with next month's market variance AV, SV, and AC. Surprisingly, over the full data set, this month's AV is even nominally more correlated with next month's SV than this month's SV is, 0.625 versus .612. Over the basis period, AV is time series most negatively correlated with next months log excess return at -.129, while it is entirely unrelated to next month's return over the whole data set.

As in the prior literature, July 1963 serves as the start of the basis data period for the regression analysis.[9] For in and out-of-sample tests, I regress market and average variance, and average correlation against these excess log return values. Out-of-sample regressions require an in-sample training period which, I set this at 15% of the available time series for consistent calculation of robust out of sample statistics later in the analysis. This training window means that out of sample regressions, analysis begins at the end of July 1970 in the basis sample and December 1939 in the full sample.

Proxies for lottery preference and leverage constraints are needed to test which has a measured influence on the relationship of buy and hold market returns and volatility, or average variance managed portfolio returns. Bali, Cakici, and Whitelaw (2011) define MAX as the maximum daily return for an asset in a given month. High values for MAX are shown to be good indicators for future conditions associated with higher lottery preference behavior. High values of MAX are a significant indicator of lower future returns. I calculate $MAX1$ and $MAX5$ as the highest daily return and the average of the highest five daily returns for each portfolio in a given month. As another indicator of higher lottery preferences in the economy, I capture the market capitalization for all gaming stocks in CRSP. $GMCAP$ is the total market capitalization of all assets with SIC code 7999 in the CRSP dataset. Gaming industry firms should do better in times of high lottery preference driving higher levels of $GMCAP$. However, the total valuation may move with the overall market capitalization. To generate a measure independent of the size of the market, I calculate $GMCAP_{scaled}$ as the ratio of gaming market capitalization to total market capitalization.

To generate proxies for the lending constraints operating in the market, I look to measures of financial intermediary leverage, investors leverage, borrowing levels and interest rates. I use data on broker call money[10] rates from 1988 to 2014 from Bloomberg, $Broker_{Call}$, average bank call money rates for 1984-2005 from Datastream, $Bank_{Call}$, and bank prime lending rates for 1984-2014 from Datastream, $Bank_{Prime}$. I use a seasonally adjusted version year-on-year nominal bank credit growth, $Credit_{CHG}$, as another proxy of borrowing conditions from 1984 to 2014, similar to the variable of Gandhi (2016).[11] Typically investors use margin, borrowed from brokers, to take leverage investment positions. As a proxy for the capital available to financial intermediaries, like brokers, I use the intermediary leverage factor, LF_{AEM}, of Adrian, Etula, and Muir (2014). LF_{AEM} measures shocks to a seasonally-adjusted broker-dealer leverage ratio, the ratio of total broker-dealer financial assets and that value minus debt.

$$LF_{AEM} = \Delta Ln(\frac{FinAsst}{FinAsst - BankDbt}) \tag{10}$$

This variable is available from Asaf Manela's website[12]. The total amount of margin borrowing is available from the NYSE website.[13] I calculate MD_{1984} as the change in the level of margin debt, month to month, in real 1984 dollars.

I use the proxies for lottery preferences and lending constraints in in-sample regressions along with the Fama-French five-factors, which are taken from Ken French's website. In contrast, the fundamental relationship between AV and future returns is established through in-sample regressions needing only the time series of average variance and log excess monthly returns.

II. Regression Analysis

A. In Sample

In order to get an understanding of the relationship between stock market or average variance and returns, I begin with in sample regressions. In each of these regressions all of the information available in the sample is used to estimate the parameters. In general the regressions take this form:

$$y_{t+1} = \alpha + \beta x_t + \epsilon_t. \tag{11}$$

The cotemporaneous regressions decomposing market variance are left unreported. The results show the same relationships found in Pollet and Wilson (2010) table 2. The only difference of note is that the relationship between average correlation, AC, and next month's log excess return is weaker monthly than quarterly, if average variance is not also included. For all in-sample regressions, the series are standardized to a mean of zero and standard deviation of one. Table III contains the results of regressions run on the basis data set which spans 1962 to 2016. Panel A shows that AV is a significant predictor of next month's SV in all specifications. A one standard deviation increase in AV means a .545 standard deviation increase in next month's market variance. This represents and increase from the mean of .2 to .42 or an increase from an annualized standard deviation of .45% to .65%. There does not appear to be any real advantage to using this month's SV to predict next month's market variance over AV. The coeficient values are nearly identical, .551 vs .545, as are the adjusted R^2 values, 30.3% vs 29.6%. This month's AV even remains significant in the specification including this month's SV. Holding this month's SV constant, a one standard deviation increase in AV still signals a .257 standard deviation increase in next month's SV. Again, the inclusion of SV appears to be of little to no help as the adjust R^2 only increases from 29.6% to 31.5%. Panels B shows predictive regressions of next month's average variance. Here, unlike the prior relationship, there is a clear advantage to using this month's AV in the prediction of next month's average variance. The adjusted R^2 of this month's AV, 44.5%, is nearly twice this month's SV, 27.2% and the inclusion of SV with AV does not appear to be a significant improvement.

Pollet and Wilson (2010) argue that average correlation is a better measure of systemic market risk.

The effectiveness of either market variance or average variance as an investment management signal will be driven primarily by their relationship with future risk and return. Its the trade-off which is key to the leverage management strategy. Assuming that investors hold a portfolio with whose risk-return ratio they are indifferent. When risk increases but expected returns do not, the risk-return ratio become more unattractive and any risk averse investor would like to decrease there position. In table **??**, panel A is a replication of the relationships of current quarter stock market variance, average variance and average correlation and next quarter stock market variance. AV is a significant predictor of SV next period. This holds even when current period SV is included in the regression. In the full samples, average variance accounts for 38% and 39% of the variation in next periods market variance. This is even greater than the amount expalained by this periods market variance. Table **??** shows that with full information average variance is the dominant predictor of future market variance. When predicting next period market variance, it generates higher R^2 and t-statistics in horse races and remains significant when current market variance is included in all samples.

Table **??** panel A shows the results of my replication of table 3, panel A, from Pollet and Wilson (2010). Confirming their results, AC is a strong predictor of next quarters excess log returns, but neither AV nor SV are predictive. When appearing alone,in the full quarterly sample the coefficient on AV is negative, -.371, but insignificant so decreasing investment in the market portfolio does not mean a decrease in expected future returns if anything decreasing investment means avoiding approaching losses. However, when controlling for market variance, the coefficient on AV is not only still negative but significant. This supports evidence in Pollet and Wilson (2010) suggesting that when controlling for average correlation an increase in average variance is a negative economic signal representing risk that investors are not compensated for taking. In the full monthly sample, AV is a significantly negative predictor of next month's excess log return with a coefficent of . In the full quarterly and monthly samples SV behaves like AV with smaller coefficients and t-statics indicating a weaker relationship to future returns than AV. In either case investors are unlikely to be punished for pulling back on investment given higher values of AV or SV so long as the relationships hold with the limited information that investors have available at the time they make investment decisions.

B. *Out of Sample*

While the in sample dominance of AV is clear, the out of sample performance remains in doubt. As Welch and Goyal (2008) definitively show, out of sample performance is not guaranteed by in sample performance and is essential to any investment strategy which hopes to generate positive returns. To determine the out of sample relationships between market and average variance, average correlation and returns, I run regressions of the standard form

$$y_{t+1} = \alpha_t + \beta_t x_t + \epsilon_t \tag{12}$$

where α_t and β_t are estimated with from the data available only until time t. That is, I estimate α_t and β_t by regressing $\{y_{s+1}\}_{s=1}^{t-1}$ on a constant and $\{x_s\}_{s=1}^{t-1}$. In all the reported results, I follow an expanding window approach so that for the next period $t+2$, y_{t+2} is estimated as $\alpha_{t+1} + \beta_{t+1}x_{t+1}$, where α_{t+1} and β_{t+1} by regressing $\{y_{s+1}\}_{s=1}^{t}$ on a constant and $\{x_s\}_{s=1}^{t}$. I follow this process for all subsequent months. However, as part of a test on the robustness of the out of sample results, I demonstrate that the results do not depend on the use of an expanding window. Most critically, equation (12) prevents any look-ahead bias. The out of sample prediction tests use the same set of variables as the in sample tests. Each out of sample test requires an "in sample" training period in which parameters are estimated using all the data up to the time period before the first out of sample quarter or month.

For consistency, the first one-fourth of data, either quarterly or monthly, is used as the initial parameter estimation period with the remaining three-fourths of observations moved through recursively generating out of sample predictions. Four measures of out of sample performance are estimated.[14] I use the R^2_{oos} statistic Campbell and Thompson (2008), the mean squared error F-statistic of Clark and McCracken (2001) to evaluate the accuracy of the out-of-sample predictions. R^2_{oos} is defined as

$$R^2_{oos} = 1 - \frac{MSFE_x}{MSFE_b} \tag{13}$$

where $MSFE_x$ is the mean squared forecast error when the variable x is used to generate out-of-sample predictions. An $R^2_{OS} > 0$ suggests that $MSFE$ based on variable x is less than that based on the benchmark, b. We evaluate the statistical significance of R^2_{OS} using Clark and West (2007) statistic. This statistic tests the null hypothesis that $H_0 : R^2_{OS} \leq 0$ against the alternative $H_A : R^2_{OS} > 0$. $MSFE_b$ is mean squared forecast error when a benchmark model is used to generate out-of-sample predictions. Mean squared forecast error is defined as

$$MSFE_x = \frac{1}{T}\sum_{\tau=t}^{T}(y_\tau - \hat{y}_\tau^x)^2 \tag{14}$$

where $\hat{y}_t^x$ is the out of sample prediction of y_t generated from the a model using variable x, t is the first out of sample prediction time period, and T is the total number of out of sample time periods. The F-statistic in McCracken (2007) is calculated by

$$MSE - F = T\frac{MSFE_x - MSFE_b}{MSFE_b}. \tag{15}$$

The significance of the F-statistic is determined from bootstrapped values provided in McCracken (2007). Each of these two tests depends on the reduction of average squared error by the predictor x relative to a benchmark model. The next two measures used are forecast encompassing statistics.

Encompassing tests the more stringent requirement that the benchmark forecasts contain no useful information absent in the forecasts of variable x. Forecast encompassing tests come from the literature on optimal forecast combination. (Chong and Hendry, 1986; Fair and Shiller, 1990) An optimal forecast as a convex combination of two forecasts for time period t +1 defined as

$$\hat{y}_t^* = (1-\lambda)\hat{y}_t^b + \lambda\hat{y}_t^x \tag{16}$$

where $\hat{y}_t^x$ are predicted values generated from the model using variable x and $\hat{y}_t^b$ are forecasts from the benchmark model. I use the forecast encompassing tests of Harvey et al. (1998), ENC-HLN, and the ENC-NEW statistic of Clark and McCracken (2001). The ENC-NEW statistic is defined as

$$ENC - NEW = T\frac{\sum_{\tau=t}^{T}\left[(y_\tau - \hat{y}_\tau^b)^2 - (y_\tau - \hat{y}_\tau^b)(y_\tau - \hat{y}_\tau^x)\right]}{\sum_{\tau=t}^{T}(y_\tau - \hat{y}_\tau^x)^2}. \tag{17}$$

The significance of the ENC-NEW is determined from bootstrapped values provided in the same paper. The encompassing test of Harvey et al. (1998) directly tests the value and significance of the forecast combination λ. The test procedure rests on the calculation of a modification to the Diebold and Mariano (1995) test statistic and the consistent estimation of the long-run covariance between the difference in forecast error between the benchmark model and a model based on a competing variable, x. As such there is no one line equation that sums up the statistic used to judge the significance of λ.

Table **??** shows the results of the out of sample tests. Panel A contains the results of running out of sample expanding window regression using AV as the predictor versus using only a constant. The use of only a constant in the rolling regression is effectively using the running historical mean as a benchmark in the tests of out of sample performance. It is clear that AV is a significant improvement in the prediction of next period market variance. It generates postive and significant R^2_{oos} values in all samples. The values generated for MSE-F and ENC-NEW are very large and statistically significant; and the near 1 λ values for the ENC-HLN tests, in all samples, indicate that AV provides all the information available in the historical mean. Its also clear that AV is not a predictor of future returns. R^2_{oos} values are negative or insignificant indicating. Some positive and significant values appear in the MSE-F, ENC-NEW and ENC-HLN tests at the monthly level which is the result of how poor a predictor of monthly returns is the historical mean. Particularly around market downturns use of the historical mean generates massive prediction errors.

Panel B shows the results of running the same test with forecasts generated by SV as the benchmark model. The results for the same but the magnitudes are very different. AV is a significantly better predictor of next period's market variance in all samples. However, the performance over and above SV is much more muted than in the historical mean in panel A. At the monthly frequency, the frequency used later for asset allocation, AV is a significant improvement over SV as indicated by the positive R^2_{oos}, MSE-F, and ENC-NEW values. However, the ENC-HLN λ value is on .56. While this is statistically significant, it indicates that for the best out of sample prediction of monthly stock market variance both AV and SV should be included and at nearly equal weights. The results for the prediction of future excess log returns are even, slightly, better than those in panel A. This is again owning as much to the terrible performance of the benchmark, here SV, as to any positive performance of AV.

B.1. Robustness

Out of sample estimation always raises issues with the choices made in the specification of the model and how to split the data into in and out of sample windows. Bluntly speaking, there are no good answers. The standard practice as in Rapach and Zhou (2013),Rapach, Strauss, and Zhou (2010), Rapach, Ringgenberg, and Zhou (2016), and Huang, Jiang, Tu, and Zhou (2015), and many others, is to show performance in a few subsamples split by dates that the authors choose for unknown reasons. The concerns with subsample selection are that the window may either be "ad-hoc" and the selection may mask significant results that would appear if the subsamples had been constructed differently. A second, more cynical, concern is that the presented subsample represent significant performance that has been found either by chance or as the result of analyzing many subsample and only presenting the significant results. In any case, evaluation of the differences in performance across subsamples is often left to the imagination of the reader and whatever importance they place on the first half of the sample versus the second, the middle third versus the first and last thirds or however the data has been separated.

To avoid these issues first I present subsample results splitting the out of sample prediction window between NBER defined business cycle contractions and expansion. The purpose of this is to contrast the performance of the AV and SV based forecasts when returns are generally expected to be positive and when they are negative. These are particularly meaningful subsamples for AV, AC and SV. As Forbes and Rigobon (2002), Hartmand, Straetmans, and de Vries (2004), and Ang and Chen (2002) and many others have demonstrated the correlation between equity returns increases during crises and market downturns and decreases during upturns. As average correlation, average variance and market variance are all related by definition, contractions are likely to affect the predictive performance of AV and SV differently than expansions.

Panel A of table **??**

This indicates that average correlation is a better performing predictor in times of crises as suggested by the its best performance in Pollet and Wilson (2010) in subsamples dominated by recessions.[15]

To further address the robustness of the out of sample results and avoid the use of subsampling completely, I present encompassing statistics robust to both the specification of the prediction model, either expanding or rolling, and the choice of prediction window. Rossi and Inoue (2012) presents out of sample statistics robust to the choice of split between in and out of sample periods.

III. Preferences

A. Changes to the Capital Market Line

B. Lottery Preference

We have some reason to suspect leverage already, the constraints drive returns toward BH and some reason to doubt lottery Rachev.

However, the fundamental argument that investors prefer the buy and hold market over the average variance or volatility managed investment because the market is more lottery-like. This itself is unclear.

Bali et al. (2011) show that the maximum daily return over the past one month, MAX, is a good measure of the lottery-like payoffs of a stock and a significant indicator of lower future returns robust to size, book-to-market, momentum, short-term reversals, liquidity, and skewness. This means that for lottery seeking investors to prefer the buy and hold market its MAX measures must be significantly different from the average variance and volatility managed portfolios. Yet, as seen in table **??** the mean and median values of the highest one day returns, MAX1, and the average of the five highest daily returns within the month, MAX5, are higher for the average variance managed portfolio than either volatility or the buy and hold market portfolio. Using daily return values scaled by the prior months portfolio volatility, as in Asness et al. (2018), the volatility managed portfolio is the most lottery like with the highest mean and median values of scaled MAX1, SMAX1, and scaled MAX5, SMAX5. Notably, the average variance managed portfolio still has higher mean SMAX1 and SMAX5 values than the buy and hold portfolio. This does not mean that the buy and hold portfolio is not viewed as a lottery and investors do not take some additional utility from holding it, however it seems very unlikely that this is even greater than the lottery utility provided by the average variance or volatility managed portfolio let alone large enough to compensate for the difference in return or CER gain.

It remains possible that on some other yet unknown measure the buy and hold strategy is more lottery like. To form a more direct test of the lottery preference explaination

C. Lending Constraints

High levels of bank credit growth are associated with the overextension of credit in the past, tighter current and future lending conditions, and lower future market returns.

Large positive shock, high value of LF_{AEM}, are associated with time of high intermediary funding illiquidity. Large bank debt constrains brokers abilities to aquire more funds to lend to investors and limits there willingness to lend to "risky" investors.

To justify adding a subsection here, from now on, we'll assume

CONDITION 1: $0 < \hat{\mu} < \gamma\sigma^2$.

This condition might be useful if there was a model.

C.1. A Subsubsection with a Proposition

Let's put a proposition here.

PROPOSITION 1: *If Condition 1 is satisfied, a solution to the central planner's problem,* $V(B, D, t) \in C^2\left(\mathbb{R}_+^2 \times [0, T]\right)$*, with control* $a : [0,1] \times [0,T] \to [-\lambda, \lambda]$ *if* $\gamma > 1$ *is*

$$V(B, D, t) = -\frac{(B+D)^{1-\gamma}}{1-\gamma} w\left(\frac{B}{B+D}, t\right). \tag{18}$$

Appendix A. An Appendix

Here's an appendix with an equation. Note that equation numbering is quite different in appendices and that the JF wants the word "Appendix" to appear before the letter in the appendix title. This is all handled in `jf.sty`.

$$E = mc^2. \tag{A1}$$

Appendix B. Another Appendix

Here's another appendix with an equation.

$$E = mc^2. \tag{B1}$$

Note that this is quite similar to Equation (A1) in Appendix A.

REFERENCES

Adrian, Tobias, Erkko Etula, and Tyler Muir, 2014, Financial intermediaries and the cross-section of asset returns, *Journal of Finance* 69, 2557–2596.

Amihud, Yakov, and Clifford M. Hurvich, 2004, Predictive regressions: A reduced-bias estimation method, *Journal of Financial and Quantitative Analysis* 39, 813–841.

Ang, Andrew, and Joseph Chen, 2002, Asymmetric correlations of equity portfolios, *Journal of Financial Economics* 63, 443 – 494.

Asness, Clifford S., Andrea Frazzini, Niels Joachim Gormsen, and Lasse Heje Pedersen, 2018, Betting against correlation: testing theories of the low-risk effect .

Bali, Turan G., Nusret Cakici, and Robert F. Whitelaw, 2011, Maxing out: Stocks as lotteries and the cross-section of expected returns, *Journal of Financial Economics* 99, 427–446.

Barberis, Nicholas, and Ming Huang, 2008, Stocks as Lotteries: The Implications of Probability Weighting for Security Prices, *American Economic Review* 98, 2066–2100.

Barroso, Pedro, and Pedro Santa-Clara, 2015, Momentum has its moments, *Journal of Financial Economics* 116, 111–120.

Black, Fischer, 1972, Capital market equilibrium with restricted borrowing, *The Journal of business* 45, 444–455.

Boguth, Oliver, and Mikhail Simutin, 2018, Leverage constraints and asset prices: Insights from mutual fund risk taking, *Journal of Financial Economics* 127, 325–341.

Brunnermeier, Markus K., Christian Gollier, and Jonathan A. Parker, 2007, Optimal beliefs, asset prices, and the preference for skewed returns, *American Economic Review* 97, 159–165.

Campbell, John Y., 1987, Stock returns and the term structure, *Journal of Financial Economics* 18, 373 – 399.

Campbell, John Y., Martin Lettau, Burton G. Malkiel, and Yexiao Xu, 2001, Have individual stocks become more volatile? An empirical exploration of idiosyncratic risk, *The Journal of Finance* 56, 1–43.

Campbell, John Y, Andrew Wen-Chuan Lo, Archie Craig MacKinlay, et al., 1997, *The econometrics of financial markets*, volume 2 (princeton University press Princeton, NJ).

Campbell, John Y., and Samuel B. Thompson, 2008, Predicting excess stock returns out of sample: Can anything beat the historical average?, *Review of Financial Studies* 21, 1509–1531.

Cao, Larry, 2016, Risk Parity Made Easy: Cliffs Notes and Other Key Readings.

Chong, Yock Y, and David F Hendry, 1986, Econometric evaluation of linear macro-economic models, *Review of Economic Studies* 53, 671–690.

Clark, Todd E., and Michael W. McCracken, 2001, Tests of equal forecast accuracy and encompassing for nested models, *Journal of econometrics* 105, 85–110.

Clark, Todd E, and Kenneth D West, 2007, Approximately normal tests for equal predictive accuracy in nested models, *Journal of Econometrics* 138, 291–311.

Dickey, David A., and Wayne A. Fuller, 1979, Distribution of the Estimators for Autoregressive Time Series with a Unit Root, *Journal of the American Statistical Association* 74, 427–431.

Diebold, Francis X, and Robert S Mariano, 1995, Comparing predictive accuracy, *Journal of Business & Economic Statistics* 13, 253–263.

Elliott, Graham, Thomas J. Rothenberg, and James H. Stock, 1996, Efficient tests for an autoregressive unit root, *Econometrica* 64, 813–836.

Fair, Ray C, and Robert J Shiller, 1990, Comparing information in forecasts from econometric models, *American Economic Review* 3, 375–389.

Fama, Eugene F., and Kenneth R. French, 2016, Dissecting Anomalies with a Five-Factor Model, *Review of Financial Studies* 29, 69–103.

Forbes, Kristin J., and Roberto Rigobon, 2002, No contagion, only interdependence: Measuring stock market comovements, *The Journal of Finance* 57, 2223–2261.

Frazzini, Andrea, and Lasse Heje Pedersen, 2014, Betting against beta, *Journal of Financial Economics* 111, 1–25.

French, Kenneth R. F, G.William Schwert, and Robert F. Stambaugh, 1987, Expected stock returns and volatility, *Journal of Financial Economics* 19, 3 – 29.

Gandhi, Priyank, 2016, From the 'Long Depression' to the 'Great Recession': Bank Credit, Macroeconomic Risk, and Equity Returns, University of Notre Dame Working Paper.

Glosten, Lawrence, Ravi Jagannathan, and David Runkle, 1993, On the relation between the expected value and the volatility of the nominal excess return on stocks, *The Journal of Finance* 48, 1779–1801.

Hartmand, P, S. Straetmans, and C. G. de Vries, 2004, Asset market linkages in crisis periods, *The Review of Economics and Statistics* 86, 313–326.

Harvey, David S., Stephen J. Leybourne, and Paul Newbold, 1998, Tests for Forecast Encompassing, *Journal of Business & Economic Statistics* 16, 254–259.

Haugen, Robert, and A. Heins, 1972, On the evidence supporting the existence of risk premiums in the capital market, Technical report, Working Paper, University of Wisconsin-Madison.

Hotelling, Harold, 1953, New light on the correlation coefficient and its transforms, *Journal of the Royal Statistical Society. Series B (Methodological)* 15, 193–232.

Huang, Dashan, Fuwei Jiang, Jun Tu, and Guofu Zhou, 2015, Investor sentiment aligned: A powerful predictor of stock returns, *Review of Financial Studies* 28, 791–837.

Jones, Charles, 2002, A century of stock market liquidity and trading costs .

Jylh, Petri, 2018, Margin Requirements and the Security Market Line: Margin Requirements and the Security Market Line, *The Journal of Finance* .

Kandel, Shmuel, and Robert F Stambaugh, 1996, On the predictability of stock returns: An asset-allocation perspective, *Journal of Finance* 51, 385–424.

Kim, Abby Y., Yiuman Tse, and John K. Wald, 2016, Time series momentum and volatility scaling, *Journal of Financial Markets* 30, 103–124.

MacKinnon, James G., 2002, Bootstrap inference in econometrics, *Canadian Journal of Economics/Revue Canadienne d'Economique* 35, 615–645.

Malkhozov, Aytek, Philippe Mueller, Andrea Vedolin, and Gyuri Venter, 2017, International illiquidity .

Markowitz, Harry, 1952, Portfolio Selection, *The Journal of Finance* 7, 77.

McCracken, Michael W., 2007, Asymptotics for out of sample tests of Granger causality, *Journal of Econometrics* 140, 719–752.

McWhinnie, Eric, 2014, Warren Buffett on using leverage to invest.

Moreira, Alan, and Tyler Muir, 2017, Volatility-Managed Portfolios: Volatility-Managed Portfolios, *The Journal of Finance* 72, 1611–1644.

Ng, Serena, and Pierre Perron, 2001, Lag Length Selection and the Construction of Unit Root Tests with Good Size and Power, *Econometrica* 69, 1519–1554.

Olkin, Ingram, and John W. Pratt, 1958, Unbiased estimation of certain correlation coefficients, *The Annals of Mathematical Statistics* 29, 201–211.

Orwell, George, 1946, *Animal farm* (Harcourt, Brace and Company, New York, NY).

Pollet, Joshua M., and Mungo Wilson, 2010, Average correlation and stock market returns, *Journal of Financial Economics* 96, 364–380.

Rapach, David, and Guofu Zhou, 2013, Forecasting stock returns, in Graham Elliott, and Allan Timmermann, eds., *Handbook of Economic Forecasting*, volume 2A, 327–383 (Elsevier B.V.).

Rapach, David E., Matthew C. Ringgenberg, and Guofu Zhou, 2016, Short interest and aggregate stock returns, *Journal of Financial Economics* 121, 46–65.

Rapach, David E., Jack K. Strauss, and Guofu Zhou, 2010, Out-of-sample equity premium prediction: Combination forecasts and links to the real economy, *Review of Financial Studies* 23, 821–862.

Rossi, Barbara, and Atsushi Inoue, 2012, Out-of-Sample Forecast Tests Robust to the Choice of Window Size, *Journal of Business & Economic Statistics* 30, 432–453.

Rutterford, Janette, and Dimitris P. Sotiropoulos, 2016, Financial diversification before modern portfolio theory: UK financial advice documents in the late nineteenth and the beginning of the twentieth century, *The European Journal of the History of Economic Thought* 23, 919–945.

Steward, Martin, 2010, The truly balanced portfolio.

Welch, Ivo, and Amit Goyal, 2008, A comprehensive look at the empirical performance of equity premium prediction, *Review of Financial Studies* 21, 1455–1508.

Wolpert, David H., and William G. Macready, 1997, No free lunch theorems for optimization, *IEEE transactions on evolutionary computation* 1, 67–82.

Notes

[1]Invented by Edward A. Calahan, an employee of the American Telegraph Company in 1867 and in wide spread use starting in the 1870s, the stock ticker provided the first reliable means of conveying up to the minute stock prices over a long distances and market participants have been discusing the relationship between returns, risk, and portfolios for at least as long.(Rutterford and Sotiropoulos, 2016)

[2](McWhinnie, 2014)

[3]See, for example, Barroso and Santa-Clara (2015) and Kim, Tse, and Wald (2016) for discussions of volatility managment of the momentum portfolio.

[4](Orwell, 1946)

[5]The shortest trading month in the sample is September 2001 with 15 trading days while 17 is a common number in the months with holidays.

[6]The exact correction suggested in Olkin and Pratt (1958) is too computationally taxing for the equiptment to which I have access.

[7]The least number of assets which trade every day in a given month is 392 in August of 1932. There are regularly 500 qualifying assets by the end of the 1930s.

[8]http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html#Research

[9]CRSP has, as of 2005, backfilled NYSE daily returns to 1926, however the pre-1962 data is very different from the post-1962 data. The earlier data is much shallower having months with fewer than 400 assets total that meet the data requirements. Twice as many firms covering twice as many industries are available at the end of 1962 as compared to the end of 1961. And, as documented in Jones (2002) the pre-1962 period is significantly and persistantly more illiquid.

[10]Call money is the money loaned by a bank or other institution which is repayable on demand.

[11]Seaonally adjusted nominal monthly bank credit is available in statistical release H.8 (Assets and Liabilities of Commercial Banks in the U.S.) of the Board of Governors of the Federal Reserve System.

[12]http://apps.olin.wustl.edu/faculty/manela/

[13]http://www.nyxdata.com/nysedata/asp/factbook/viewer_edition.asp?mode=table&key=3153&category=8

[14]Additionally, in unreported results, I find the same results if we use the Diebold and Mariano

(1995) test.

[15]Average correlation predicts excess returns best in the 1974 to 1985 and 1996 to 2007 subsamples. These 80 quarters contain all of the 18 contraction quarters from 1974 to 2007. Average correlation is insignificant in the 1986 to 1995 subsample.

Figure 1. Time Series of Market Statistics: The average variance of individual asset, average correlation of asset pairs, and the variance of the CRSP portfolio calculated from daily returns.

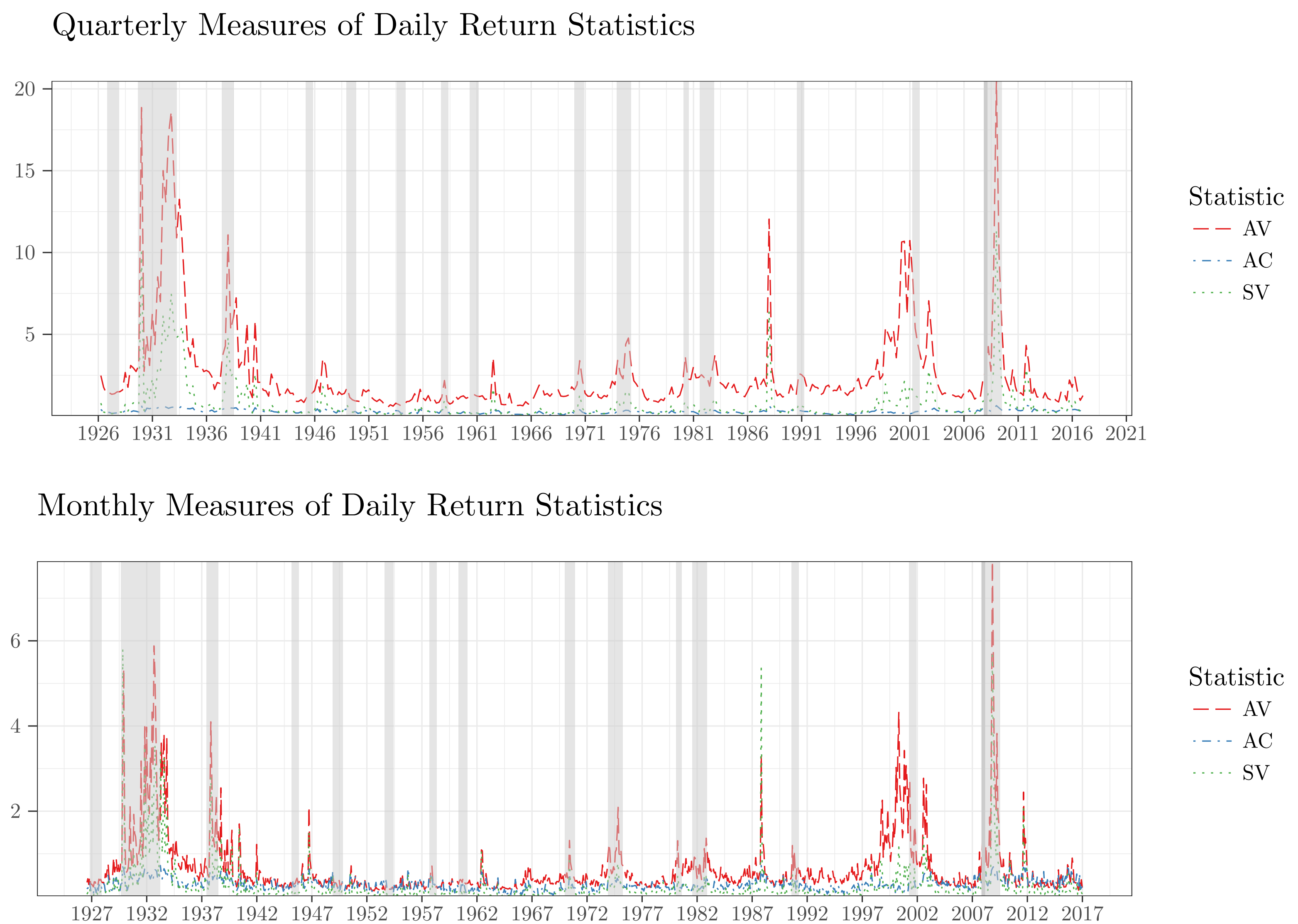

Table I:Summary statistics

The table displays summary statistics for the market variance and correlation statistics, and returns. RET is the log excess return of the CRSP market portfolio. AC is the average pairwise correlation of the daily returns of the 500 largest firms in the CRSP data set over the month or quarter. AV is the average of the individual variances of daily returns for the 500 largest firms in the CRSP data set. SV is the variance of daily CRSP market returns. See section I for details on construction.

(a) Pollet and Wilson Sample 1963Q1:2006Q4

Statistic	N	Mean	St. Dev.	Min	Max	Autocorrelation
RET	176	1.169	8.372	−30.072	19.956	0.000
AC	176	0.231	0.091	0.034	0.648	0.556
AV	176	2.221	1.827	0.634	12.044	0.695
SV	176	0.484	0.615	0.029	6.397	0.310

(b) Sample 1962M6:2016M12

Statistic	N	Mean	St. Dev.	Min	Max	Autocorrelation
RET	655	0.409	4.453	−25.985	14.515	0.810
AC	655	0.261	0.129	0.019	0.762	0.620
AV	655	0.770	0.849	0.198	10.416	0.667
SV	655	0.200	0.406	0.006	5.664	0.551

(c) Full Sample 1926M7:2016M12

Statistic	N	Mean	St. Dev.	Min	Max	Autocorrelation
RET	1,085	0.495	5.371	−34.523	33.188	0.106
AC	1,085	0.276	0.134	0.019	0.762	0.610
AV	1,085	0.881	1.281	0.154	19.540	0.718
SV	1,085	0.248	0.502	0.006	5.808	0.612

Table II:Correlations

The table displays Pearson correlation statistics for the market variance and correlation statistics, and returns. RET is the log excess return of the CRSP market portfolio. AC is the average pairwise correlation of the daily returns of the 500 largest firms in the CRSP data set over the month or quarter. AV is the average of the individual variances of daily returns for the 500 largest firms in the CRSP data set. SV is the variance of daily CRSP market returns. See section I for details on construction.

(a) Sample 1962M6:2016M12

	RET	AC	AV	SV	RET_{t+1}	AC_{t+1}	AV_{t+1}	SV_{t+1}
RET	1	0	0	0	0	0	0	0
AC	-0.244	1	0	0	0	0	0	0
AV	-0.284	0.352	1	0	0	0	0	0
SV	-0.353	0.529	0.899	1	0	0	0	0
RET_{t+1}	0.081	0.049	-0.129	-0.107	1	0	0	0
AC_{t+1}	-0.223	0.622	0.240	0.360	-0.239	1	0	0
AV_{t+1}	-0.268	0.218	0.667	0.522	-0.283	0.351	1	0
SV_{t+1}	-0.289	0.332	0.545	0.552	-0.351	0.528	0.899	1

(b) Full Sample 1926M7:2016M12

	RET	AC	AV	SV	RET_{t+1}	AC_{t+1}	AV_{t+1}	SV_{t+1}
RET	1	0	0	0	0	0	0	0
AC	-0.295	1	0	0	0	0	0	0
AV	-0.136	0.467	1	0	0	0	0	0
SV	-0.279	0.619	0.857	1	0	0	0	0
RET_{t+1}	0.106	0.011	0	-0.057	1	0	0	0
AC_{t+1}	-0.229	0.610	0.383	0.453	-0.295	1	0	0
AV_{t+1}	-0.191	0.358	0.718	0.607	-0.136	0.467	1	0
SV_{t+1}	-0.259	0.416	0.625	0.612	-0.279	0.619	0.857	1

Table III:In Sample Results - Post 1962

The table displays in sample regression results for monthly market variance, correlation and return statistics. SV is the annualized monthly variance of daily CRSP market returns. AV and AC are the monthly average variance and average pairwise correlation of daily returns for the top 500 assets in the CRSP market, as in Pollet and Wilson (2010). RET is the log return of the CRSP market portfolio minus the log return on the 1 month treasury bill. The sample period is from 1962:06 to 2016:12. The series are standardized to a mean of zero and standard deviation of one.

(a) Market Return Variance - SV_{t+1}

AV	0.545***			0.489***	0.257***
	p = 0.000			p = 0.000	p = 0.001
AC		0.332***		0.160***	
		p = 0.000		p = 0.00001	
SV			0.551***		0.320***
			p = 0.000		p = 0.00002
Constant	−0.0005	−0.0001	−0.0003	−0.0005	−0.0004
	p = 0.989	p = 0.999	p = 0.993	p = 0.989	p = 0.991
R^2	0.297	0.110	0.304	0.320	0.317
Adjusted R^2	0.296	0.109	0.303	0.318	0.315

(b) Average Asset Return Variance - AV_{t+1}

AV	0.667***			0.674***	1.030***
	p = 0.000			p = 0.000	p = 0.000
AC		0.218***		−0.019	
		p = 0.00000		p = 0.544	
SV			0.522***		−0.403***
			p = 0.000		p = 0.000
Constant	−0.001	−0.00004	−0.0003	−0.001	−0.001
	p = 0.985	p = 1.000	p = 0.994	p = 0.984	p = 0.981
R^2	0.445	0.048	0.273	0.446	0.477
Adjusted R^2	0.445	0.046	0.272	0.444	0.475

(c) Average Asset Return Correlation - AC_{t+1}

AV	0.239***			0.024	−0.438***
	p = 0.000			p = 0.470	p = 0.00000
AC		0.621***		0.613***	
		p = 0.000		p = 0.000	
SV			0.360***		0.753***
			p = 0.000		p = 0.000
Constant	−0.0002	−0.0001	−0.0002	−0.0001	−0.00003
	p = 0.996	p = 0.998	p = 0.996	p = 0.997	p = 1.000
R^2	0.057	0.387	0.130	0.387	0.167
Adjusted R^2	0.056	0.386	0.128	0.385	0.164

(d) Log Excess Market Return - RET_{t+1}

AV	−0.130***			−0.168***	−0.173*
	p = 0.001			p = 0.0001	p = 0.052
AC		0.049		0.108***	
		p = 0.212		p = 0.010	
SV			−0.107***		0.048
			p = 0.006		p = 0.588
Constant	−0.000	−0.000	−0.000	−0.000	−0.000
	p = 1.000	p = 1.000	p = 1.000	p = 1.000	p = 1.000
N	655	655	655	655	655
R^2	0.017	0.002	0.012	0.027	0.017
Adjusted R^2	0.015	0.001	0.010	0.024	0.014

Notes: ***,**, and * Significant at the 1, 5, and 10 percent levels.

Table IV:Full In Sample Results

The table displays in sample regression results for monthly market variance, correlation and return statistics. SV is the annualized monthly variance of daily CRSP market returns. AV and AC are the monthly average variance and average pairwise correlation of daily returns for the top 500 assets in the CRSP market, as in Pollet and Wilson (2010). RET is the log return of the CRSP market portfolio minus the log return on the 1 month treasury bill. The sample period is from 1926:07 to 2016:12.

(a) Market Return Variance - SV_{t+1}

AV	0.625***			0.551***	0.379***
	p = 0.000			p = 0.000	p = 0.000
AC		0.416***		0.159***	
		p = 0.000		p = 0.000	
SV			0.612***		0.288***
			p = 0.000		p = 0.000
Constant	−0.0003	−0.0001	−0.0002	−0.0003	−0.0003
	p = 0.991	p = 0.998	p = 0.993	p = 0.991	p = 0.991
R^2	0.391	0.173	0.375	0.410	0.413
Adjusted R^2	0.390	0.173	0.374	0.409	0.412

(b) Average Asset Return Variance - AV_{t+1}

AV	0.718***			0.704***	0.745***
	p = 0.000			p = 0.000	p = 0.000
AC		0.358***		0.029	
		p = 0.000		p = 0.232	
SV			0.606***		−0.031
			p = 0.000		p = 0.445
Constant	−0.0003	−0.0001	−0.0002	−0.0003	−0.0003
	p = 0.989	p = 0.998	p = 0.993	p = 0.989	p = 0.989
R^2	0.515	0.128	0.368	0.516	0.516
Adjusted R^2	0.515	0.127	0.367	0.515	0.515

(c) Average Asset Return Correlation - AC_{t+1}

AV	0.383***			0.125***	−0.018
	p = 0.000			p = 0.00001	p = 0.738
AC		0.610***		0.551***	
		p = 0.000		p = 0.000	
SV			0.453***		0.468***
			p = 0.000		p = 0.000
Constant	−0.0002	−0.0001	−0.0002	−0.0002	−0.0002
	p = 0.996	p = 0.996	p = 0.996	p = 0.995	p = 0.996
R^2	0.147	0.372	0.205	0.385	0.205
Adjusted R^2	0.146	0.372	0.204	0.384	0.204

(d) Log Excess Market Return - RET_{t+1}

AV	0.0002			−0.006	0.182***
	p = 0.996			p = 0.857	p = 0.002
AC		0.011		0.014	
		p = 0.724		p = 0.692	
SV			−0.056*		−0.213***
			p = 0.064		p = 0.0003
Constant	−0.00000	−0.00001	0.00002	−0.00001	0.00002
	p = 1.000	p = 1.000	p = 1.000	p = 1.000	p = 1.000
N	1,085	1,085	1,085	1,085	1,085
R^2	0.00000	0.0001	0.003	0.0001	0.012
Adjusted R^2	−0.001	−0.001	0.002	−0.002	0.010

Notes: ***,**, and * Significant at the 1, 5, and 10 percent levels.

Table V:In Sample Robust Results

The table displays in-sample regression results of AC_{t+1}, SV_{t+1} and RET_{t+1} on AV_t. The coeffiecients and standard errors calculated robust to Kandel and Stambaugh (1996) bias using the correction in Amihud and Hurvich (2004). Robust p-values are calculated through t-statistic wild-bootstrap simulation, as in MacKinnon (2002).

(a) AV_t: Sample 1962:06 to 2016:12

	β	t.stat	p
AC_{t+1}	0.241	6.567	0.000
SV_{t+1}	0.550	32.442	0.000
RET_{t+1}	-0.131	-3.494	0.166

(b) AV_t: Sample 1926:07 to 2016:12

	β	t.stat	p
AC_{t+1}	0.384	14.342	0.000
SV_{t+1}	0.627	40.002	0.000
RET_{t+1}	0.000	-0.016	0.562

Table VI:Full Out-of-Sample Results

The table displays out-of-sample expanding window regression results for monthly market variance, correlation and return statistics. SV is the annualized monthly variance of daily CRSP market returns. AV and AC are the monthly average variance and average pairwise correlation of daily returns for the top 500 assets in the CRSP market, as in Pollet and Wilson (2010). RET is the log return of the CRSP market portfolio minus the log return on the 1 month treasury bill. DM is the Diebold and Mariano (1995) statistic measuring for cast accuracy. MSE-F is the mean squared error improvement F-test of in McCracken (2007) and ENC-HLN is the forecast encompassing test of Harvey et al. (1998). In each panel the benchmark forecasts come from a model which uses SV_t to predict the independent variable.

(a) Sample 1970:07 to 2016:12

	DM	MSE-F	ENC-HLN
AC_{t+1}	1.074	109.736***	1
SV_{t+1}	1.53*	29.252***	1**
AV_{t+1}	2.286**	109.333***	1***
RET_{t+1}	1.278	11.801***	1*

(b) Sample 1939:12 to 2016:12

	DM	MSE-F	ENC-HLN
AC_{t+1}	1.604*	46.251***	1**
SV_{t+1}	1.041	21.57***	0.956**
AV_{t+1}	3.104***	198.267***	1***
RET_{t+1}	-2.027	-8.702	0

Table VII:Out of Sample Robust Results

The table displays out-of-sample regression results of forecasts using AV_{t+1} as a predictor. Rossi and Inoue (2012) provides the methodology to make the calculations of the out-of-sample accuracy improvements of Diebold and Mariano (1995) and McCracken (2007) and the encompassing test of Harvey et al. (1998). In each panel the benchmark forecasts come from a model which uses SV_t to predict the independent variable.

(a) Robust Expanding Window Results

Stat	Variable	DM	ENC-HLN
R_T	AC_{t+1}	28.532***	6.769***
R_T	SV_{t+1}	8.874***	1.838***
R_T	AV_{t+1}	34.347***	18.197***
R_T	RET_{t+1}	29.124***	4.871***
A_T	AC_{t+1}	19.867***	1.828***
A_T	SV_{t+1}	2.647***	0.949***
A_T	AV_{t+1}	21.751***	10.7***
A_T	RET_{t+1}	13.347***	1.68***

(b) Robust Rolling Window Results

Stat	Variable	DM	ENC-HLN
R_T	AC_{t+1}	27.398***	8.706**
R_T	SV_{t+1}	21.92***	3.973
R_T	AV_{t+1}	34.292***	29.804***
R_T	RET_{t+1}	15.964***	3.884
A_T	AC_{t+1}	8.08***	1.542
A_T	SV_{t+1}	8.218***	2.062
A_T	AV_{t+1}	21.631***	19.449***
A_T	RET_{t+1}	9.209***	1.78