Keynes Meets Merton: Examining Risk and Return Relation Based on Fundamental Forces

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Abstract

Although the intertemporal risk-return relation should theoretically be positive, it is often documented empirically to be weak and even negative. Various remedies have been proposed to address this discrepancy, such as allowing for time-varying risk-return trade-off or using more accurate measures for risk and/or return, although the empirical evidence is still mixed. We argue that the theoretically positive risk and return relation may be weakened or even reversed empirically by non-fundamental forces or "animal spirits." This could be one key reason for the mixed results, as well as for the fragility of related remedies. When we examine the risk-return relation conditioning only on fundamental forces, the positive risk and return relation is restored and those remedies are no longer fragile.

JEL classifications: C53, G02, G12, G14, G17

Keywords: Risk-return relation, Return forecasting, Fundamental predictors, Behavioral bias

1. Introduction

The intertemporal risk and return relation is supposed to be positive according to standard rational models (e.g., Merton's ICAPM model). However, numerous studies in the literature have documented insignificant, or even negative, empirical results. Many recent studies, including Brandt and Kang (2004), Ludvigson and Ng (2007), Pastor, Sinha and Swaminathan (2008) and Yu and Yuan (2011) have proposed various remedies to address this discrepancy. Taken individually, each of those remedies seems to work well, but collectively they appear rather fragile. For instance, Ludvigson and Ng (2007) report a positive (weak or negative) risk-return relation when conditioning (not conditioning) on lagged mean and lagged volatility. Brandt and Kang (2004), by contrast, find a negative risk-return relation conditioning on lagged mean and volatility, but a positive relation without conditioning on these variables.

In this study, we argue that one key reason for the weak or negative risk-return relation could be that the returns used in the mean-variance relation analysis are driven not only by fundamental forces, but also by non-fundamental forces, or the so-called "animal spirits" (Keynes (1936)). Since animal spirits can influence and guide human behavior to deviate from a rational framework, the positive risk and return relation implied by rational models may be weakened or even reversed empirically, as documented in related studies. We believe that the fragility of many existing remedies is also due to the fact that the impact of non-fundamental forces is not properly controlled for. After we control for these animal spirits, our evidence suggests a solid positive risk and return relation, and all related remedies are no longer fragile.

Specifically, we use forecasted return to proxy for expected return in examining the risk-return relation, due to the large amount of potential noise in realized return.[1] In specific, to address concerns regarding the selection of insufficient or even arbitrary predictors, we apply a Choose-all approach by projecting future returns onto a vast set of economic variables based on dynamic

[1] Although many of the studies apply realized return as the proxy for future expected return (e.g., French, Schwert and Stambaugh (1987); Nelson (1991); Chan, Karolyi and Stulz (1992); Glosten, Jagannathan and Runkle (1993); Scruggs (1998); Ghysels, Santa-Clara and Valkanov (2005); Lundblad (2007); and Rossi and Timmermann (2015)), the realized return measure tends to be notoriously noisy (e.g., Elton (1999) and Lundblad (2007)) despite providing an unbiased estimate.

factor analysis following Ludvigson and Ng (2007).[2] Additionally, we also follow Pastor, Sinha and Swaminathan (2008) in applying an implicit version of the ”Choose-all” approach, namely the Implied Cost of Capital (ICC) model. Unlike the Ludvigson and Ng (2007) approach, the ICC measure implicitly captures all relevant factors determining the expected return, thus avoiding having to explicitly select a certain number of return predictors.

Empirically, we follow the same factor analysis approach as Ludvigson and Ng (2007) in applying an explicit version of the “Choose-all” approach. We estimate the macro factors F_t from a set of 132 series of macroeconomic indicators, and the financial factors G_t from the 147 financial series. Then we combine these estimated factors with other commonly used non-estimated predictors (e.g. the earnings price ratio EP, the dividend price ratio DP, etc.) to locate the most significant predictors for estimating future returns. Specifically, we find that the earnings price ratio EP, the equity risk premium volatility $RVOL$, a macro factor $F2$ and a financial factor $G1$ turn out to be rather significant. Therefore, we employ EP, $RVOL$, $F2$ and $G1$ as the predictors to estimate future expected return in our study. We then examine the risk-return relation by conditioning the estimated future returns on fundamental economic ($ECON$) variables. Here $ECON$ variables are the first seven principle components for seven groups of macroeconomic variables respectively: $Output\ and\ Income$; $Labour\ Market$; $Housing$; $Consumption, Orders\ and\ Inventories$; $Money\ and\ Credit$; $Exchange\ Rates$; and $Inflation$.[3]

Our results show that, without conditioning on the fundamental ECON variables, the risk-return relation is overall weak or negative, which is consistent with the weak or negative risk-return rela-

[2]Some studies estimate conditional mean returns by projecting future returns onto a small set of often ad-hocly chosen conditioning variables (e.g., Harvey (2001)). However, the results produced by such estimation approaches tend to be sensitive to the choice of the conditioning variables (Harvey (2001)).

[3]To estimate the conditional variance for a given month, we average squared daily market returns over the previous month. Our estimator corresponds to the same simple variance estimator in Pastor, Sinha and Swaminathan (2008) and is the simplest variance estimator considered by French, Schwert and Stambaugh (1987). Although this approach is simpler than some other variance estimation approaches proposed in the literature, we choose it to focus on our main point of examining risk-return using expected return conditioning on fundamental predictors. There are also advantages to the realized volatility approach compared to ARCH, stochastic volatility and other parametric volatility models, as discussed in Andersen et al (2003). In addition, our results are robust to other complicated variance estimators. Finally, rational models seem to indicate that any non-diversifiable risk should be compensated by extra return. Hence, we condition the expected mean return on fundamentals, not the expected variance, when examining the risk-return relation.

tion documented in Ludvigson and Ng (2007). This is not surprising because the ”Choose-all” approach by design tries to capture everything, which potentially includes certain non-fundamentals. We believe that this may be the reason for the weak or negative risk and return relation, since the non-fundamental component is not separated or properly controlled. In fact, after we condition on the fundamental factors, this pattern clearly changes and the risk-return relation becomes significantly positive, which is also robust across various combinations of the predictors. Therefore, based on the fundamental component of expected return extracted by conditioning on fundamentals, the impact of behavioral forces is controlled and we are able to restore the positive mean-variance tradeoff.

In addition, Ludvigson and Ng (2007) also report a positive risk-return relation, but only when conditioning on lagged mean and lagged volatility. Without conditioning on lagged mean or volatility, the risk-return relation is quite weak or negative. Interestingly, Brandt and Kang (2004) find the opposite result using a latent state variable approach. Specifically, they claim a negative conditional risk-return relation conditioning on lagged mean and volatility, but a positive relation without conditioning on these variables. Our positive risk-return relation holds whether we condition on lagged mean and volatility or not, so long as we control for the impact of non-fundamental forces.

Moreover, we employ Baker and Wurgler's sentiment index to define low- and high-sentiment regimes. Unlike Yu and Yuan (2011), our positive risk-return relation holds for the high-sentiment regime as well.[4] This is also in line with our expectation that the theoretical risk-return implication should always hold as long as we control for the impact of non-fundamental forces. Furthermore, after removing the fundamental related component, we observe a very negative risk-return relation for the residual return component, which should be dominated by non-fundamental forces.[5]

We then use ICC as a return proxy to re-examine this risk-return relation. From the theoretical perspective, ICC is defined as the discount rate that equates future expected cash flows to current

[4] Moreover, the negative pattern for the residual term is always weaker during low-sentiment regimes, implying that low-sentiment regimes contain relatively fewer behavioral forces, probably due to fewer noise traders.

[5] Although the residual return component may still contain some fundamental information, its proportion is likely much smaller. Hence, the residual return component is more likely to be driven by non-fundamental forces.

stock price. Since it is in the same spirit as the internal rate of return, ICC could be considered a return measure. Given that the realized return can be very noisy, some studies (e.g. Pastor, Sinha and Swaminathan (2008)) argue that ICC is the better estimate for future expected return.[6] However, the estimated returns from this implicit "Choose-all" approach are also likely to be affected by variables related to non-fundamental. As discussed, most ICC methods rely on analyst earnings forecasts, which are subject to potentially large analyst bias.[7] In addition, investors' behavioral biases may also drive the price away from the level justified by the fundamentals.

Choosing from among various ICC methods, we follow Hou, van Dijk and Zhang (2012), because this method relies solely on accounting information and hence is immune to the potentially large impact of analyst biases. In addition, it allows us to avoid the survivorship requirement that all observations need to have analyst coverage. We firstly find that the risk-return relation is weak using ICC settings, which might be driven by the impact of investor biases on the market price. This relation again becomes significantly positive upon conditioning on fundamental factors, particularly during the low-sentiment regime.[8] That is to say, the theoretically positive risk-return relation still exists if we properly control for noise and related behavioral forces. This is consistent with our argument that the positive risk-return relation can be restored if fundamental conditioning variables are employed to control for noise.

Overall, we show that conditioning on fundamentals to mitigate the impact of behavioral forces or animal spirits is the key to restoring the theoretically positive risk-return relation. If the impact of non-fundamental forces is not properly controlled, this positive relation will be weakened, or

[6]On the international front, Lee, Ng and Swaminathan (2009) test the international asset pricing model using the ICCs estimated in the current period to proxy for firms' expected returns. They find supportive evidence, especially for the currency beta, to explain the cross-sectional variations.

[7]The ICC estimates are normally constructed using analyst earnings forecasts, which may be subject to significant behavioral biases on the part of the analysts. This may explain why Pastor, Sinha and Swaminathan (2008) find a weak risk-return relation for the US, while the same results are positive for many other countries. There is some evidence to indicate that analyst biases are much greater in US cases than in non-US countries (e.g., Chan, Karceski and Lakonishok (2007)).

[8]Moreover, this may explain why two steps are needed to extract the fundamental part of the forecasted return in the case of the factor analysis approach. If we use one step and just use the seven ECON variables (used as the conditioning variables) to predict returns, we can also obtain a forecasted return based on fundamentals only. However, for the ICC approach, we have to take two steps to first get the ICC implied forecasted return and then conduct conditioning on the seven ECON variables. To make things comparable across these two "Catch-all" approaches, it seems preferable to take the two-step procedure for both the factor analysis approach and the ICC approach.

even reversed, as documented in many studies in the literature. Therefore, we provide an intuitive explanation for the mixed and sensitive risk-return relation evidence in existing studies. Put differently, failure to control for non-fundamental component influenced by animal spirits may prevent researchers from observing the true risk-return relation implied in theories.

Finally, our study is related to but different from Yu and Yuan (2011), which shows that a strong positive mean-variance trade-off holds only during periods of low investor sentiment. In contrast, here we show that the positive risk and return relation holds even for high-sentiment regimes, as long as we condition on the fundamentals. That is to say, the fundamental part of the return extracted by *ECON* variables is positively related to risk as the rational theory implies, and this result holds even for high-sentiment regimes since behavioral disturbances have been properly controlled. On the other hand, even during low-sentiment regimes, we may still observe a weak or even negative risk and return relation if the non-fundamental part of estimated return is not separated or controlled for.

In a sense, both Yu and Yuan (2011) and our study try to control for the impact of non-fundamentals. However, Yu and Yuan (2011) rely on sentiment as an indirect control, while our approach is more direct. Specifically, we explicitly extract the fundamental part and then examine the risk-return relation using this extracted fundamental part. Yu and Yuan (2011) base their study on the co-existence of fundamentals and non-fundamentals, claiming that the non-fundamental part will have a much smaller impact or be indirectly controlled during low-sentiment regimes. But there is no guarantee that non-fundamentals will be completely muted during low-sentiment periods, and the definition of the sentiment cut-off point is arguable in terms of how low is low enough to mute these non-fundamentals. In addition, sentiment itself is not directly observable and the popular Baker and Wurgler's sentiment index (BW index) has some potential issues as well. First, it may potentially include a large amount of fundamental information, as documented in some studies (e.g., Sibley, Wang, Xing and Zhang (2016)). Secondly, it may contain unstable sentiment indicators such as turnover, which has recently been dropped from the BW index after the publication of Yu and Yuan's (2011) paper. Given these concerns and the fact that non-fundamentals may not be completely out of the picture even during low-sentiment regimes, our direct approach to controlling the impact of non-fundamentals or animal spirits seems more useful, and hence should be a better alternative to Yu and Yuan (2011).

The rest of the paper is organized as follows. We present our methodology of the explicit and implicit versions of ”Choose-all” approach in Section II. Section III reports the main empirical findings and Section IV concludes.

II. Methodology

A. Predictors

To estimate the conditional mean of excess stock market return $E_t(m_{t+1})$, we first select a series of commonly used exogenous predictors Z_t following Goyal and Welch (2008) and Neely, Rapach, Tu and Zhou (2014), and run the regression specification below:

$$m_{t+1} = a_0 + a_1 Z_t + e_{t+1} \tag{1}$$

Where m_{t+1} denotes excess return at $t+1$, and Z_t denotes a set of ten variables as follows:

- *Consumption wealth ratio*, CAY: the monthly aggregate consumption-wealth ratio;
- *Dividend price ratio*, DP: log of a twelve-month moving sum of dividends minus the log of stock prices;
- *Earnings price ratio* , EP: log of a twelve-month moving sum of earnings minus the log of stock prices;
- *Equity risk premium volatility*, $RVOL$: the moving standard deviation estimator for twelve months' returns (Mele (2007))[9];

[9]Goyal and Welch (2008) measure monthly volatility as the sum of squared daily excess stock returns for each month. This measure, however, produces a huge outlier for October of 1987. The Mele (2007) measure avoids this problem and yields more plausible estimation results.

- *Treasury bill rate*, TBL: the interest rate for three-month treasury bill (secondary market)

- *Long-term yield*, LTY: the long-term government bond yield;

- *Long-term return*, LTR: the long-term government bond return;

- *Default yield spread*, DFY: the difference between Moody's BAA- and AAA- rated corporate bond yields;

- *Default return spread*, DFR: the long-term corporate bond return minus the long-term government bond return;

- *Inflation*, $INFL$: the inflation indicator calculated using the CPIs of all urban consumers.[10]

Note that Ludvigson and Ng (2007) apply similar predictors, but construct them on a quarterly basis, whereas we not only build them using monthly data but also incorporate an additional range of commonly used stock return predictors. Hence, our predictors should better forecast equity premium in addition to capturing more time-series variations.

In addition to the exogenous predictors, we also employ two sets of estimated factors F_t and G_t, two monthly data sets consisting of various macroeconomic and financial variables respectively as in Jurado, Ludvigson and Ng (2015). The macroeconomic series contain 132 macroeconomic indicators representing general macroeconomic features. The financial series contain 147 financial indicators measuring the aggregate behaviour of the stock market as well as other general characteristics. In order to efficiently incorporate these two large series of variables in terms of estimation, we extract the common factors F_t and G_t from the two series as in Ludvigson and Ng (2007). Then we form different subsets of predictors using Z_t, F_t and G_t and find the most significant predicting combination for estimating future returns. Specifically, we regress m_{t+1} on Z_t, F_t and G_t and compare the corresponding BICs and adjusted R^2s. Following Stock and Watson (2002), we conduct a comprehensive analysis of the t-statistics, the adjusted R2 and the BIC to select the best set of predictors. Specifically, we run the regression specification below:

[10]We use lagged inflation to account for the delay in CPI releases.

$$m_{t+1} = a_0 + a_1 Z_t + a_2 F_t + a_3 G_t + e_{t+1} \tag{2}$$

The estimated conditional mean is the fitted value of the above regression:

$$u_t \equiv \hat{m}_{t+1} = \hat{a}_0 + \hat{a}_1 Z_t + \hat{a}_2 F_t + \hat{a}_3 G_t \tag{3}$$

B. ICC

To obtain ICC as a proxy for future expected return, we follow Hou, van Dijk and Zhang (2012) for the estimation. Most existing ICC studies employ annualized analyst earnings forecasts to estimate future cash flows. However, analysts' forecasts do exhibit significant biases, as indicated by a large body of existing research. At the same time, analyst coverage is rather limited and hence many small firms or firms in financial distress will be under-represented. Therefore, Hou, van Dijk and Zhang (2012) propose a new approach to estimate future cash flows based on accounting information and cross-sectional regressions. Following this study, we estimate the pooled regressions using the previous ten years of data:

$$\begin{aligned} E_{i,t+k} = a_0 + a_1 * A_{i,t} + a_2 * D_{i,t} + a_3 * DD_{i,t} + a_4 * E_{i,t} + a_5 * NegE_{i,t} + \\ a_6 * AC_{i,t} + a_7 * Ret_{i-1,t} + a_8 * Ret_{i-2,t} + a_9 * Size_{i,t} + e_{i,t+k} \end{aligned} \tag{4}$$

Where $E_{i,t+j}$ denotes earnings of firm i in year $t+1$ to $t+5$; $A_{i,t}$ is the total assets; $D_{i,t}$ is the dividend payment; $DD_{i,t}$ is a dummy variable that equals 1 for positive dividend payment and 0 otherwise; $NegE_{i,t}$ is a dummy variable that equals 1 for firms with negative earnings and 0 otherwise; and $AC_{i,t}$ is accounting accruals. The above variables exactly follow Hou, van Dijk and Zhang (2012), but here we want monthly estimates to better help re-examine the time-series risk return relation. Therefore, we add three more monthly variables: $Ret_{i,t-1}$ and $Ret_{i,t-2}$ are lag returns at $t-1$ and $t-2$ respectively, and $Size_{i,t}$ is the market capitalization. Therefore, we can conduct the pooled regression for every month and get monthly coefficients. After we estimate these coefficients using the previous ten years of data, we combine them with the current independent variables for each firm i and compute earnings forecasts up to five years in to the future. Other ICC measures must employ the consensus (mean or median) one- and two-year ahead EPS forecasts to denote future earnings cash because earnings forecasts beyond the second year are usually unavailable. This approach gives us better time-series coverage.

Next we calculate ICC, the internal rate of return that equates the current stock price to the present value of expected future cash follows. Selecting from among various ICC methods, we follow the very first and most recognized framework by Gebhardt, Lee and Swaminathan (2001). We first apply the long-run average industry growth rate as the ultimate growth rate for each firm in our ICC estimation. Put differently, cash flows beyond $t+5$ are assumed to follow a mean-reverting process, resulting in a long-run industry growth rate. Specifically, we compute forecasts from year $t+5$ to year $t+T+1$ by mean-reverting the year $t+5$ earnings growth rate to the long-run industry growth rate. Following Pastor, Sinha and Swaminathan (2008), we choose the exponential process because it allows the growth rate, which might appear extreme in earlier stages, to mean-revert rapidly. Given this rapid mean reversion, any potential biases in analysts' short-term earnings forecasts should not have large effects on the long-run growth rates. This paper chooses 15-year horizon (T=15) consistent with prior studies.

Note that only part of the EPS would be distributed to shareholders in terms of dividends. Consistent with prior studies from the literature, we employ the plowback rate as the fraction of earnings reinvested by the firm, which also equals one minus the payout ratio, to combine with future earnings and determine the exact amount of future cash flows to be discounted. Pastor, Sinha and Swaminathan (2008) claim that the plowback rate should also follow a mean-reverting process where the product of the steady-state return and plowback rate is equal to the steady-state growth rate in earnings. This measure differs from Gebhardt, Lee and Swaminathan's (2001) use of the historical dividend payout ratio, but such a dynamic conversion should be more compatible with the ultimate steady assumption, hence we employ it in this study as well. The formula for calculating the ICC estimate is expressed in the following:

$$P_t = \sum_{k=1}^{T} \frac{E_{t+k} \times (1 - b_{t+k})}{(1+r_e)^k} + \frac{E_{t+T+1}}{r_e \times (1+r_e)^T} \tag{5}$$

Where r_e is the ICC estimate, P_t is the current market price, E is the forecast earning, and b is the plowback rate.

The ICC estimates for all firms could be easily solved using the above non-linear equation at a monthly basis. However, many solutions prove to be far from realistic. Similar to prior studies we drop all estimates less than zero, but the estimate sample still contains many potential outliers that could not be reasonably trimmed using a single benchmark. As a result, if a firm's annual earnings either increase or decrease by 500%, we drop all related observations because the cross-sectional regressions based on previous accounting records are not able to predict such a large change. The predictions would either be far from the realized earnings or problematic, and that is typically where outliers are generated.

C. Fundamentals

Following Jurado, Ludvigson and Ng (2015), we employ a wide range of macroeconomic variables to condition the fundamental component of the return. Specifically, 132 macroeconomic variables are classified into eight categories: (1) *Output and Income*; (2) *Labour Market*; (3) *Housing*; (4) *Consumption*, *Orders and Inventories*; (5) *Money and Credit*; (6) *Bond and Exchange rates*; (7) *Inflation*; and (8) *Stock Market*. Given that bond and stock market variables may contain sentiment/non-fundamental features, we exclude them when extracting the fundamental part of the estimated return. By implementing principal component analysis (PCA), we obtain the first principal component for each category,[11] and they are used to extract the fundamental component of the return and thus mitigate the impact of behavioral or non-fundamental forces.

[11] We take the first principal component from each category of macroeconomic variables, as the first principal component usually captures the greatest proportion of total variations than other principal components. In addition, incorporating more principal components may increase estimating noise.

III. Empirical Results

A. Data Summary

We use six main data sets in this study. Balance sheet items are from the COMPUSTAT industrial database. Stock return information is from the Center for Research in Security Prices database (CRSP). All U.S. companies at the intersection of the NYSE, AMEX and NASDAQ stock exchanges and listed on these three main databases over the period from 1966 to 2011 are included. The 132 macroeconomic variables and 147 financial variables, as well as the consumption wealth ratio (CAY) are from Ludvigson's website. The original data for constructing the monthly predictors such as dividend price ratio (DP), earnings price ratio (EP), equity risk premium volatility ($RVOL$), treasury bill rate (TBL), long-term yield (LTY), long-term return (LTR), default yield spread (DFY), default return spread (DFR), and inflation ($INFL$) can be downloaded from Welch's website. The risk-free rate, 10-year government bond yield, comes from the St. Louise Fed for computing ICC premia. The Monthly sentiment index is from Wurgler's website.

Table 1 contains the summary statistics for all main testing variables. Altogether our sample consists of 545 observations for the estimated return case and 582 observations for the realized return case and the ICC premium case. Our sample is very comparable to related studies including Ludvigson and Ng (2007). Because ICCs are annual return estimates, we scaled them to the monthly level to better compare with estimated or realized monthly returns.

B. Results Description

Following Ludvigson and Ng (2007), we start by examining the proper predictors to be employed to estimate the conditional return. Likewise, we first employ the commonly used predictors, including consumption wealth ratio (CAY), dividend price ratio (DP), earnings price ratio (EP), equity risk premium volatility ($RVOL$), treasury bill rate (TBL), long-term yield (LTY), long-term return (LTR), default yield spread (DFY), default return spread (DFR), and inflation ($INFL$). Then we estimate macro and financial factors respectively to further choose the proper predictors from two large data sets consisting of hundreds of macroeconomic and financial variables. We denote the factors from the macro set as F_t and G_t for the financial set. The $t+1$ return information is used as the future expected return proxy, and the excess return is NYSE-AMEX-NASDAQ value-weighted index in excess of 1-month treasury bill rate. Various specifications have been estimated for comparison, and the coefficient, heteroskedasticity and serial-correlation robust t-statistics as well as BIC criterion are reported in Table 2.

In Table 2, we first employ commonly used exogenous predictors only to test their effectiveness in predicting future expected returns; Panel A shows the results. To test the effectiveness of predictors, we conduct various regression specifications, and CAY, EP, $RVOL$ and LTR appear to be the predictors that attain certain levels of significance. Therefore, next we select these four exogenous predictors and combine the macro/financial sets to further select the proper predictors for further return estimation. Note that we test all macro and financial factors, but due to space constraints we only report those that are at least significant alone in Panel B: $F2$, $F3$, $F4$ and $G5$. And as shown in the table, only $F2$ has consistently strong coefficient upon combining with other predictors. Meanwhile, among the exogenous predictors, EP and $RVOL$ still maintain their significance with the newly added macro/financial variables, while CAY and LTR somehow lose their strong predictive power. To further test the robustness of these predictors, we also conduct the same regression specifications using equal-weighted index. Table 3 reports the coefficient, heteroskedasticity and serial-correlation robust t-statistics as well as BIC criterion.

Overall, Table 3 shows a very similar pattern compared to Table 2. Again CAY, EP, $RVOL$ and LTR are the exogenous predictors that exhibit strong predictive power. After combining with the macro and financial variables, only EP and $RVOL$ maintain their significance at the 5% statistical level. Likewise, $F2$ is consistently negative across various regression specifications, and thus should also be considered a proper predictor. Nevertheless, $G1$ also appears to be significantly positive for equal-weighted returns. This is not surprising, since now all firms are weighted equally regardless of their size. Put differently, we are now testing the predictors that work in the general market, and these might deviate from those that work better for large firms. Therefore, we will employ EP, $RVOL$, $G1$ and $F2$ as predictors to estimate future expected return in the next step.

We then regress the estimated expected excess return on conditional volatility estimated as the baseline check. First, we calculate estimated future return using the strong predictors identified by previous results. To start, we again apply $t+1$ return information as the expected return proxy, and the excess return is NYSE-AMEX-NASDAQ value-weighted index in excess of 1-month treasury bill rate. Then the estimated return is calculated using EP, $RVOL$, $F2$ and $G1$ in different combinations, and we now employ fundamental factors to condition the expected return and examine how this particular fundamental part of the return measure is related to realized volatility. Specifically, we decompose the excess expected return into its fundamental and residual components, expecting to observe the positive risk-return relation for the fundamental component. Here, $ECON$ variables are the seven first principal components from seven groups of macroeconomic variables: $Output\ and\ Income$; $Labour\ Market$; $Housing$; $Consumption$, $Orders\ and\ Inventories$; $Money\ and\ Credit$; $Exchange\ Rates$; and $Inflation$. As discussed, we believe that conditioning on the fundamental $ECON$ variables should help to control for the impact of non-fundamental forces and hence to restore the positive risk-return relation as implied by asset pricing theory. Meanwhile, we also obtain the residual term of the expected return by removing the fundamental component and test whether this is what drives the weak or even negative risk and return relation. Consistent with Yu and Yuan (2011), realized volatility is the square root of realized variance constructed under the rolling-window model. We also employ sentiment information to define low- and high-sentiment regimes. Specifically, we define month t as a high-sentiment period if the past twelve-month moving average of the sentiment index is greater than zero.[12] The average slopes and Newey-West adjusted t-statistics are summarized in Table 4.

In the left part of Table 4, the risk-return relation is overall weak, which is consistent with the existing literature. But this pattern clearly changes upon conditioning on fundamental factors. Although we employ different combinations of predictors to construct the estimated return, the risk-return relation is consistently and strongly positive for all those cases. That is to say, when

[12] We also use the median level of the sentiment index to identify high and low sentiment periods and find very similar results.

we extract out the fundamental-related part of the expected return by conditioning on fundamental variables, we are able to restore the positive mean-variance tradeoff. Moreover, unlike Yu and Yuan (2011), this pattern holds for high-sentiment regimes as well. This is also in line with our expectation that the theoretical risk-return implication should always hold so long as we control for the impact of non-fundamental forces. Furthermore, we observe a very negative risk-return relation for the residual return component, which is likely dominated by non-fundamental forces. This is clearly the reason why the overall return is weakly related to risk. Put differently, failure to control for this non-fundamental part prevents the observation of the true risk-return relation. This is consistent with our hypothesis and also helps to explain the existing unclear and mixed empirical evidence.

To further test this result, we also conduct the same regression using equal-weighted returns. This allows us to obtain the general pattern and avoid letting large and giant firms dominate the results. The average slopes and Newey-West adjusted t-statistics are summarized in Table 5. The results are very clearly similar to those in Table 4, implying that the positive risk-return relation is consistent upon conditioning on fundamental variables to control for the impact of non-fundamental forces. Moreover, the negative pattern for the residual term is always weaker during low-sentiment regimes, which is also very reasonable since low-sentiment regimes contain fewer noisy traders.

Our predictors and estimation methods are very similar to those of Ludvigson and Ng (2007), but they in fact find that the positive risk-return relation largely relies on the inclusion of lagged mean and volatility. Without conditioning on lagged mean and lagged volatility, the risk-return relation becomes weak and negative. Therefore, we re-estimate the predicted returns, and then add lagged mean and volatility into the regression specification to see how they affect our results. This time we only apply the predictor combinations from Table 2 and Table 3 that are most significant in terms of predicting returns. Therefore, we choose EP, $RVOL$, and $F2$ to estimate value-weighted returns, and EP, $RVOL$, and $G1$ for equal-weighted returns respectively. The average slopes and Newey-West adjusted t-statistics are summarized in Table 6.

After including lagged mean and volatility, the current volatility remains weak or negative for the estimated value-weighted returns, while lagged mean and volatility are both strongly positive. But after decomposing the estimated returns, the risk-return relation is indeed positive for the fundamental part, which is in line with our previous results. Meanwhile, the lagged mean and volatility both lose significance. This is contrary to the results from analysis of the non-fundamental/residual part, where volatility is weak and the lagged terms are strongly positive. Therefore, the overall weak risk-return relation and strong lagged terms are driven by the non-fundamental element. If this element is not controlled, it prevents us from observing the true risk-return relation. This pattern remains the same for equal-weighted returns. Compared to Ludvigson and Ng (2007), our positive risk-return relation seems to hold whether we condition on lagged mean and lagged volatility or not. The key point is to extract out the fundamental-related part of the expected return by conditioning on fundamental variables; we then are able to restore the positive mean-variance tradeoff.

Next we employ ICC estimates to proxy for future returns as another robustness check. Given that the ICC assumptions should implicitly reflect most of the relevant factors determining future returns, it could be considered an alternative ”Choose-all” approach. And from a theoretical perspective, ICC is defined as the discount rate that equates future expected cash flows to current stock price. Since it is in the same spirit as the internal rate of return, it could be considered a return measure. In addition, ICC estimates are calculated based on forward-looking predictions and thus might potentially be a better proxy for future expected return. In fact, realized return, the commonly used proxy for future expected return, has been dubbed very noisy. Therefore, employing ICC and ICC premium may help to better determine the true risk-return relation. Selecting from among various ICC methods, we employ Hou, van Dijk and Zhang (2012)'s measure because it relies solely on accounting information. Therefore, we avoid analyst biases and the survivorship requirement that all observations need to have analyst coverage. Specifically, we construct Hou, van Dijk and Zhang (2012)'s measure on a monthly basis, then apply the ICC estimates to proxy for future expected return and again compare the risk-return pattern across the fundamental and non-fundamental parts respectively. The average slopes and Newey-West adjusted t-statistics are summarized in Table 7.

As shown in Table 7, the risk-return relation is fairly negative for value-weighted ICC premia, but it does exhibit certain weakly positive patterns upon conditioning on fundamental factors. This is in contrast to the negative signs for the residual part, implying that conditioning on fundamental variables to control for the impact from non-fundamental forces does help to restore certain level of the true risk-return relation. In fact, the t-statistics are rather strong during low-sentiment regimes, which is also in line with our expectation since the mean-variance tradeoff appears clearer when behavioral noise is low. Likewise, the result for equal-weighted ICC premia is supportive of our argument: the risk-return relation is strongly positive for the fundamental part, especially during low-sentiment regimes. The residual part again exhibits a very unclear risk-return relation. Therefore, we believe that the positive risk-return relation could be restored if correct conditioning variables are employed to control for noise.

Lastly, we apply the conditional variance constructed using Ghysel, Santa-Clara,and Valkanov(2005)'s mixed data sampling approach (MIDAS) to further check the above results. Compared with the realized variance calculated using daily returns with equal weights, MIDAS has a longer horizon and a different weighting system. Specifically, the MIDAS model employs daily data from up to 250 days previous to estimate the conditional variance, and the parameters in the weight function are estimated using the maximum likelihood method. Therefore, this MIDAS conditional variance might be a better proxy than realized variance since it involves a longer history of past returns and more flexible weighting system. Here we apply the MIDAS variance instead of the realized variance in our regression specification and re-examine the risk-return relation for fundamental and non-fundamental value-weighted returns respectively. The average slopes and t-statistics are summarized in Table 8.

For all estimated returns, the overall risk-return relation is flat. However, the risk coefficient is less negative during low-sentiment regimes. That is to say, the theoretically positive risk-return relation may still exist if we properly control for noise from non-fundamental forces. The result is clearly supportive of our argument. After we apply fundamental conditioning variables, the risk-return relation becomes strongly positive, which is also consistent across both low- and high-sentiment regimes. The residual part, however, exhibits exactly the opposite result, in that the coefficient is negative or weak. Both outcomes are consistent with our previous results. To further test this result, we also conduct the same regression using equal-weighted returns. The average slopes and t-statistics are summarized in Table 9.

Similar to Table 8, Table 9 also indicates that the risk-return relation is indeed positive as indicated by the theory, while we do need to separate the non-fundamental parts and related noise. Although the risk coefficient is negative for the overall return, it becomes significantly positive for the fundamental return component. And the negative impact clearly comes from the residual part. Therefore, our evidence is robust for MIDAS variance as well.

IV. Conclusion

Many asset pricing studies have examined the risk and return relation, but have found weak or mixed results. One potential issue that might have caused the failure in current studies is that most asset pricing tests are subject to behavioral noise or animal spirits. If proper conditioning settings are applied to control for the non-fundamental noise, we should be able to restore the theoretical positive risk-return relation.

In this study, we propose a direct control for the non-fundamentals or animal spirits. We find that the risk-return relation is consistently positive after conditioning on fundamentals. Meanwhile, the non-fundamental part exhibits a weak or even negative pattern, indicating that failure to control for the non-fundamental or behavioral forces is very likely to result in weak results. These results are very consistent across various predicted returns, as well as under ICC settings. Furthermore, this pattern is also solid across low- and high-sentiment regimes, as well as applying MIDAS volatility or controlling for lagged mean and volatility.

To sum up, our results are supportive of the positive risk and return relation upon conditioning on fundamental variables. Our study not only helps to reconcile the discrepancy between widely used theory and existing empirical evidence, but also shows the importance of properly controlling for non-fundamental behavioral biases. Future research in asset pricing might pay more attention to this area, and this analysis method may assist with practical studies as well.

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Table 1: Descriptive statistics

This table provides number of observations (N), mean (Mean), standard deviation (Std), auto-correlation ($\rho(1)$), skewness (Skew), kurtosis (Kurt), minimum (Min) and maximum (Max) of all main variables used in the paper. Consumption wealth ratio (CAY), dividend price ratio (DP), earnings price ratio (EP), equity risk premium volatility ($RVOL$), treasury bill rate (TBL), long-term yield (LTY), long-term return (LTR), default yield spread (DFY), default return spread (DFR), inflation ($INFL$), factors $F2$, $F3$ and $F4$ which are extracted from 132 macroeconomic variables, factors $G1$ and $G5$ which are extracted from 147 financial variables, and the seven first principle components constructed from the seven categories of macroeconomic variables (i.e., (1) output and income; (2) labour market; (3) housing; (4) consumption, orders and inventories; (5) money and credit; (6) exchange rates; (7) inflation) are monthly data from July 1966 to November 2011. The value-weighted/equal-weighted realized volatility, the value-weighted/equal-weighted NYSE-AMEX-NASDAQ market excess returns, and the value-weighted/equal-weighted aggregate implied cost of capital (ICC) premium are monthly data from July 1966 to December 2011.

	N	Mean	Std	$\rho(1)$	Skew	Kurt	Min	Max
CAY	545	0.00	0.02	0.98	0.16	2.21	-0.04	0.04
DP	545	-3.57	0.43	0.99	-0.31	2.14	-4.52	-2.75
EP	545	-2.82	0.47	0.99	-0.78	5.26	-4.84	-1.90
$RVOL$	545	0.15	0.05	0.96	0.68	3.32	0.05	0.32
TBL	545	5.41	3.05	0.99	0.62	4.09	0.01	16.30
LTY	545	7.27	2.43	0.99	0.84	3.32	2.65	14.82
LTR	545	0.70	3.10	0.03	0.38	5.36	-11.24	15.23
DFY	545	1.08	0.46	0.96	1.79	6.99	0.52	3.38
DFR	545	-0.01	1.50	-0.07	-0.37	9.72	-9.75	7.37
$INFL$	545	0.36	0.36	0.61	-0.21	7.13	-1.92	1.79
$F2$	545	0.00	0.27	0.70	0.75	4.76	-0.80	1.25
$F3$	545	0.00	0.26	-0.18	-0.49	10.33	-1.53	1.39
$F4$	545	0.00	0.22	0.35	0.62	10.01	-0.92	1.60
$G1$	545	0.00	0.82	0.16	-0.89	6.50	-4.91	2.93
$G5$	545	0.00	0.12	0.25	0.04	4.00	-0.52	0.39
$Output\ and\ Income$	545	0.00	2.99	0.35	-0.94	6.51	-15.80	9.21
$Labor$	545	0.00	3.20	0.80	-1.18	5.46	-14.05	8.85
$Housing$	545	0.00	2.88	0.98	-0.94	3.49	-8.54	5.14
$Consumption, Orders\ and\ Inventories$	545	0.00	1.99	0.77	-0.39	4.42	-7.93	6.08
$Money\ and\ Credit$	545	0.00	1.70	-0.21	0.00	17.30	-13.75	11.23
$Exchange\ rates$	545	0.00	1.46	0.32	-0.14	3.69	-4.70	4.99
$Inflation$	545	0.00	2.89	-0.21	-0.34	8.57	-13.50	14.77
$VW\ realized\ vol$	582	0.04	0.02	0.68	3.45	22.09	0.01	0.23
$VW\ excess\ return$	582	0.00	0.05	0.08	-0.55	4.88	-0.23	0.16
$VW\ ICC\ premium$	582	0.00	0.00	0.95	-0.16	2.60	0.00	0.01
$EW\ realized\ vol$	582	0.03	0.02	0.64	3.39	20.03	0.01	0.20
$EW\ excess\ return$	582	0.01	0.06	0.23	-0.18	5.77	-0.28	0.29
$EW\ ICC\ premium$	582	0.01	0.01	0.98	0.20	2.39	0.00	0.02

Table 2: Predictors for conditional VW return

The table reports estimates from OLS regressions of excess stock returns on lagged conditioning variables and factors. The dependent variable m_{t+1} is the return on the CRSP value-weighted stock market index over the 1-month Treasury bill rate. The exogenous conditioning variables in Z_t are CAY, DP, EP, $RVOL$, TBL, LTY, LTR, DFY, DFR and $INFL$. The regressors F_t and G_t are estimated by the method of principal components using a panel of data with 132 and 147 individual series, respectively, over the period 1966:7−2011:11. F_t is constructed from a panel of data on economic activity, G_t from a panel of data on financial returns. The sample spans the period from July 1966 to December 2011. Newey and West (1987) corrected t-statistics are reported.

Panel A: Model: $m_{t+1} = a_0 + a_1 Z_t + e_{t+1}$						Panel B: Model: $m_{t+1} = a_0 + a_1 Z_t + a_2 F_t + a_3 G_t + e_{t+1}$									
	(1)	(2)	(3)	(4)	(5)		(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
CAY	0.223				0.480	CAY		0.154	0.157	0.165			0.157	0.165	
	2.49				3.56			1.60	1.69	1.79			1.69	1.79	
DP		0.006			0.003	EP		0.011	0.011	0.012	0.012		0.011	0.012	0.012
		1.11			0.27			1.92	2.09	2.16	2.16		2.16	2.24	2.25
EP			0.002		0.020	$RVOL$		0.070	0.069	0.069	0.065	0.050	0.070	0.070	0.066
			0.36		2.09			1.83	1.80	1.80	1.67	1.31	1.84	1.83	1.71
$RVOL$				0.090	0.071	LTR		0.001	0.001				0.001		
				2.56	1.63			1.13	1.58				1.62		
TBL					-0.002										
					-1.46										
LTY					-0.003	$F2$	-0.029	-0.031	-0.030	-0.032	-0.034	-0.026	-0.032	-0.034	-0.036
					-1.31		-3.45	-3.47	-3.28	-3.36	-3.66	-2.86	-3.44	-3.58	-3.90
LTR					0.002	$F3$	-0.015	-0.014							
					2.08		-1.58	-1.49							
DFY					0.010	$F4$	0.014	0.007							
					1.17		1.41	0.63							
DFR					0.004	$G1$	0.001	0.001	0.001	0.002	0.002	0.002			
					1.55		0.44	0.26	0.46	0.56	0.57	0.84			
$INFL$					0.009	$G5$	-0.007	0.006							
					1.09		-0.30	0.28							
adj R^2(%)	0.62	0.08	-0.15	0.85	5.14	adj R^2(%)	3.72	4.86	4.74	4.37	4.12	3.16	4.87	4.47	4.22
BIC	-3.282	-3.277	-3.274	-3.284	-3.241	BIC	-3.275	-3.248	-3.276	-3.282	-3.289	-3.288	-3.287	-3.292	-3.299

Table 3: Predictors for conditional EW return

The table reports estimates from OLS regressions of excess stock returns on lagged conditioning variables and factors. The dependent variable m_{t+1} is the return on the CRSP equal-weighted stock market index over the 1-month treasury bill rate. The exogenous conditioning variables in Z_t are CAY, DP, EP, $RVOL$, TBL, LTY, LTR, DFY, DFR and $INFL$. The regressors F_t and G_t are estimated by the method of principal components using a panel of data with 132 and 147 individual series, respectively, over the period 1966:7−2011:11. F_t is constructed from a panel of data on economic activity, G_t from a panel of data on financial returns. The sample spans the period from July 1966 to December 2011. Newey and West (1987) corrected t-statistics are reported.

Panel A: Model: $m_{t+1} = a_0 + a_1 Z_t + e_{t+1}$					
	(1)	(2)	(3)	(4)	(5)
CAY	0.179				0.554
	1.59				2.89
DP		0.006			0.009
		0.99			0.71
EP			-0.002		0.023
			-0.36		1.74
$RVOL$				0.168	0.116
				3.55	2.21
TBL					-0.002
					-1.09
LTY					-0.006
					-1.76
LTR					0.002
					2.05
DFY					0.019
					1.57
DFR					0.005
					1.63
$INFL$					0.003
					0.29
adj R^2(%)	0.14	0.02	-0.15	2.01	6.82
BIC	-2.792	-2.791	-2.790	-2.811	-2.774

Panel B: Model: $m_{t+1} = a_0 + a_1 Z_t + a_2 F_t + a_3 G_t + e_{t+1}$									
	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
CAY		0.081	0.073	0.081			0.074	0.084	
		0.71	0.66	0.74			0.65	0.74	
EP		0.012	0.010	0.010	0.010		0.013	0.013	0.013
		1.61	1.40	1.48	1.48		1.79	1.89	1.89
$RVOL$		0.111	0.115	0.116	0.113	0.100	0.123	0.123	0.121
		2.26	2.28	2.27	2.24	2.01	2.42	2.40	2.37
LTR		0.001	0.001				0.001		
		1.61	1.50				1.74		
$F2$	-0.037	-0.038	-0.036	-0.037	-0.038	-0.031	-0.050	-0.052	-0.053
	-3.46	-3.27	-2.99	-3.08	-3.21	-2.75	-4.26	-4.41	-4.57
$F3$	-0.016	-0.014							
	-1.39	-1.26							
$F4$	0.002	-0.007							
	0.18	-0.52							
$G1$	0.015	0.014	0.014	0.014	0.014	0.015			
	4.30	4.14	4.09	4.11	4.11	4.40			
$G5$	0.010	0.025							
	0.39	0.91							
adj R^2(%)	8.93	10.07	10.03	9.79	9.90	9.52	6.83	6.42	6.52
BIC	-2.846	-2.820	-2.848	-2.855	-2.866	-2.872	-2.823	-2.828	-2.839

Table 4: VW risk-return relation conditioning on fundamentals

This table reports regressions of estimated conditional mean excess returns $u_t \equiv E_t(m_{t+1})$, $m_{t+1} \equiv r_{t+1} - r_{f,t+1}$, on the CRSP value-weighted stock market index over the 1-month treasury bill rate, against conditional volatility vol_t. The conditional means are estimated as fitted values from regressions of excess returns on three sets of information variables known at time t from Panel A to Panel C. In Panel A, ER denotes the fitted value from a regression of excess return on the information variables EP_t, $RVOL_t$ and $F2_t$. In Panel B, ER denotes the fitted value from a regression of excess return on the information variables EP_t, $RVOL_t$, $F2_t$ and $G1_t$. In Panel C, ER denotes the fitted value from a regression of excess return on the information variables $RVOL_t$, $F2_t$ and $G1_t$. In each panel, ERhat and ERres denote the fundamental component and residual component of ER respectively. vol_t denotes monthly realized volatility calculated in the rolling-window model. High- and low-sentiment periods are classified using Baker and Wurgler's monthly sentiment index. The sample spans the period from July 1966 to December 2011. Newey and West (1987) corrected t-statistics are reported.

Model: $u_t = a + bvol_t + \varepsilon_t$									
		ER			ERhat			ERres	
Model	a	b	$R^2(\%)$	a	b	$R^2(\%)$	a	b	$R^2(\%)$
Panel A: ER: EP $RVOL$ $F2$									
u_t	0.006	-0.030	0.50	0.003	0.037	3.41	0.003	-0.067	3.37
whole	8.18	-2.11		7.62	4.45		4.25	-4.92	
u_t	0.006	-0.039	1.42	0.004	0.020	1.73	0.002	-0.058	3.66
high	7.09	-2.63		9.08	2.19		2.42	-3.58	
u_t	0.005	-0.013	0.05	0.001	0.068	6.17	0.004	-0.081	3.16
low	4.22	-0.45		2.18	4.81		3.45	-3.19	
Panel B: ER: EP $RVOL$ $F2$ $G1$									
u_t	0.006	-0.048	1.29	0.003	0.036	3.46	0.003	-0.084	5.12
whole	9.09	-3.25		8.04	4.51		5.29	-6.01	
u_t	0.007	-0.060	3.32	0.004	0.020	1.83	0.003	-0.079	6.42
high	7.98	-3.96		9.43	2.25		3.27	-4.63	
u_t	0.005	-0.025	0.21	0.001	0.066	6.13	0.004	-0.091	3.84
low	4.79	-0.89		2.45	4.81		3.97	-3.58	
Panel C: ER: $RVOL$ $F2$ $G1$									
u_t	0.004	0.001	0.00	0.003	0.045	5.34	0.002	-0.044	1.99
whole	5.67	0.07		6.60	5.07		2.75	-2.71	
u_t	0.006	-0.025	0.92	0.004	0.028	3.54	0.002	-0.052	4.49
high	7.35	-1.45		8.09	3.03		2.99	-2.86	
u_t	0.002	0.047	0.83	0.001	0.077	8.41	0.001	-0.030	0.55
low	1.60	1.32		1.74	5.14		0.89	-1.04	

Table 5: EW risk-return relation conditioning on fundamentals

This table reports regressions of estimated conditional mean excess returns $u_t \equiv E_t(m_{t+1})$, $m_{t+1} \equiv r_{t+1} - r_{f,t+1}$, on the CRSP equal-weighted stock market index over the 1-month treasury bill rate, against conditional volatility vol_t. The conditional means are estimated as fitted values from regressions of excess returns on three sets of information variables known at time t from Panel A to Panel C. In Panel A, ER denotes the fitted value from a regression of excess return on the information variables EP_t, $RVOL_t$ and $F2_t$. In Panel B, ER denotes the fitted value from a regression of excess return on the information variables EP_t, $RVOL_t$, $F2_t$ and $G1_t$. In Panel C, ER denotes the fitted value from a regression of excess return on the information variables $RVOL_t$, $F2_t$ and $G1_t$. In each panel, ERhat and ERres denote the fundamental component and residual component of ER respectively. vol_t denotes monthly realized volatility calculated in the rolling-window model. High- and low-sentiment periods are classified using Baker and Wurgler's monthly sentiment index. The sample spans the period from July 1966 to December 2011. Newey and West (1987) corrected t-statistics are reported.

Model: $u_t = a + bvol_t + \varepsilon_t$									
		ER			ERhat			ERres	
Model	a	b	$R^2(\%)$	a	b	$R^2(\%)$	a	b	$R^2(\%)$
Panel A: ER: EP $RVOL$ $F2$									
u_t	0.008	-0.036	0.26	0.005	0.076	4.24	0.004	-0.112	3.59
whole	8.54	-1.38		8.68	4.89		4.00	-4.77	
u_t	0.010	-0.077	1.95	0.006	0.047	2.63	0.004	-0.124	5.73
high	9.62	-3.48		9.87	2.72		3.31	-4.45	
u_t	0.006	0.021	0.06	0.003	0.118	6.62	0.003	-0.096	2.00
low	3.49	0.43		3.22	4.75		2.27	-2.39	
Panel B: ER: EP $RVOL$ $F2$ $G1$									
u_t	0.014	-0.215	6.31	0.005	0.066	4.56	0.009	-0.281	12.37
whole	9.26	-4.27		11.27	5.20		6.24	-5.97	
u_t	0.016	-0.299	17.26	0.006	0.046	3.64	0.010	-0.345	22.80
high	10.88	-6.73		11.68	3.18		6.31	-7.22	
u_t	0.011	-0.099	0.95	0.004	0.094	6.15	0.007	-0.193	4.72
low	4.60	-1.24		4.96	4.59		3.40	-2.71	
Panel C: ER: $RVOL$ $F2$ $G1$									
u_t	0.012	-0.162	3.77	0.005	0.074	5.68	0.007	-0.236	9.29
whole	7.38	-2.78		10.36	5.50		4.81	-4.43	
u_t	0.016	-0.266	15.11	0.006	0.054	4.99	0.010	-0.321	21.48
high	9.95	-5.36		10.75	3.67		5.99	-6.22	
u_t	0.008	-0.016	0.03	0.003	0.102	7.08	0.004	-0.118	1.84
low	3.01	-0.18		4.57	4.59		1.86	-1.49	

Table 6: Risk-return relation conditioning on fundamentals and lagged mean/variance

This table reports regressions of estimated conditional mean excess returns $u_t \equiv E_t(m_{t+1})$, $m_{t+1} \equiv r_{t+1} - r_{f,t+1}$, on the CRSP stock market index over the 1-month treasury bill rate, against conditional volatility vol_t, controlling lagged conditional volatility vol_{t-1} and lagged conditional mean u_{t-1}. The conditional means are estimated as fitted values from regressions of excess returns on information variables known at time t. In Panel A, ER denotes the fitted value from a regression of value-weighted excess return on the information variables EP_t, $RVOL_t$ and $F2_t$. In Panel B, ER denotes the fitted value from a regression of equal-weighted excess return on the information variables $RVOL_t$, $F2_t$ and $G1_t$. In each panel, ERhat and ERres denote the fundamental component and residual component of ER respectively. vol_t denotes monthly realized volatility calculated in the rolling-window model. High- and low-sentiment periods are classified using Baker and Wurgler's monthly sentiment index. The sample spans the period from July 1966 to December 2011. Newey and West (1987) corrected t-statistics are reported.

Model: $u_t = a + bvol_t + cvol_{t-1} + du_{t-1} + \varepsilon_t$															
	ER					ERhat					ERres				
Model	a	b	c	d	$R^2(\%)$	a	b	c	d	$R^2(\%)$	a	b	c	d	$R^2(\%)$
Panel A: VW ER: $EP\ RVOL\ F2$															
u_t	0.000	-0.057	0.078	0.724	54.15	0.002	0.027	0.002	0.348	15.32	0.000	-0.086	0.086	0.638	43.78
whole	0.71	-2.92	4.61	22.25		4.16	2.54	0.14	7.95		0.09	-3.80	4.98	17.47	
u_t	0.001	-0.038	0.050	0.681	47.71	0.003	0.022	-0.005	0.125	3.21	0.000	-0.068	0.072	0.644	44.61
high	1.19	-1.94	2.86	14.32		6.62	1.77	-0.47	1.76		-0.27	-2.64	3.53	13.13	
u_t	0.000	-0.055	0.084	0.740	56.04	0.001	0.035	0.007	0.450	25.56	0.000	-0.085	0.084	0.627	41.59
low	0.11	-1.10	1.98	16.96		0.84	1.86	0.31	8.43		0.29	-2.12	2.53	11.75	
Panel B: EW ER: $RVOL\ F2\ G1$															
u_t	0.002	-0.342	0.390	0.542	40.37	0.002	0.043	0.005	0.463	26.52	0.001	-0.392	0.366	0.422	33.04
whole	1.32	-6.51	8.06	15.34		4.61	2.79	0.31	11.45		0.63	-6.90	7.61	11.30	
u_t	0.005	-0.318	0.299	0.480	38.73	0.004	0.050	-0.007	0.318	14.65	0.002	-0.376	0.297	0.412	38.32
high	2.69	-6.26	5.90	8.90		5.81	2.56	-0.45	4.93		1.29	-6.38	5.30	7.19	
u_t	0.000	-0.263	0.375	0.556	37.93	0.001	0.042	0.011	0.527	33.31	-0.001	-0.307	0.349	0.407	24.86
low	-0.07	-1.92	3.33	11.51		1.91	1.61	0.36	10.32		-0.36	-2.50	3.53	7.68	

Table 7: Risk-return relation conditioning on fundamentals upon Implied Cost of Capital settings

This table reports regressions of implied cost of capital premium icc_t, on the aggregate monthly implied cost of capital over the 1-month treasury bill rate, against conditional volatility vol_t. Results based on value-weighted and equal-weighted implied cost of capital premium (ICC) are presented in Panel A and Panel B respectively. In each panel, ICChat and ICCres denote the fundamental component and residual component of ICC respectively. vol_t denotes monthly realized volatility calculated in the rolling-window model. High- and low-sentiment periods are classified using Baker and Wurgler's monthly sentiment index. The sample spans the period from July 1966 to December 2011. Newey and West (1987) corrected t-statistics are reported.

Model: $icc_t = a + bvol_t + \varepsilon_{t+1}$									
		ICC			ICChat			ICCres	
Model	a	b	$R^2(\%)$	a	b	$R^2(\%)$	a	b	$R^2(\%)$
Panel A: VW									
icc_t	0.005	-0.008	1.37	0.004	0.001	1.62	0.000	-0.009	1.84
whole	14.09	-1.69		115.05	1.36		1.07	-2.05	
icc_t	0.004	-0.010	2.64	0.004	0.000	0.06	0.000	-0.010	2.90
high	9.07	-1.73		103.37	0.17		0.08	-1.91	
icc_t	0.005	-0.001	0.04	0.004	0.003	6.16	0.000	-0.004	0.36
low	11.73	-0.20		83.20	3.47		1.20	-0.57	
Panel B: EW									
icc_t	0.012	0.009	0.13	0.012	0.028	13.96	0.001	-0.019	0.58
whole	11.48	0.42		52.92	3.98		0.57	-0.97	
icc_t	0.010	0.023	1.15	0.012	0.019	10.84	-0.002	0.003	0.02
high	9.41	1.00		51.65	4.12		-1.68	0.14	
icc_t	0.012	0.013	0.24	0.011	0.038	18.35	0.003	-0.050	3.49
low	7.34	0.37		28.30	2.85		2.01	-1.98	

Table 8: VW risk-return relation (MIDAS variance) conditioning on fundamentals
This table reports regressions of estimated conditional mean excess returns $u_t \equiv E_t(m_{t+1})$, $m_{t+1} \equiv r_{t+1} - r_{f,t+1}$, on the CRSP value-weighted stock market index over the 1-month treasury bill rate, against conditional variance vol_t in MIDAS. The conditional means are estimated as fitted values from regressions of excess returns on three sets of information variables known at time t from Panel A to Panel C. In Panel A, ER denotes the fitted value from a regression of excess return on the information variables EP_t, $RVOL_t$ and $F2_t$. In Panel B, ER denotes the fitted value from a regression of excess return on the information variables EP_t, $RVOL_t$, $F2_t$ and $G1_t$. In Panel C, ER denotes the fitted value from a regression of excess return on the information variables $RVOL_t$, $F2_t$ and $G1_t$. In each panel, ERhat and ERres denote the fundamental component and residual component of ER respectively. $Var_t(r_{t+1})$ denotes monthly conditional variance in MIDAS model. High- and low-sentiment periods are classified using Baker and Wurgler's monthly sentiment index. The sample spans the period from July 1966 to December 2011. T-statistics in each regression are reported.

Model: $u_t = a + bVar_t(r_{t+1}) + \varepsilon_t$									
		ER			ERhat			ERres	
Model	a	b	$R^2(\%)$	a	b	$R^2(\%)$	a	b	$R^2(\%)$
Panel A: ER: $EP\ RVOL\ F2$									
u_t	0.005	-0.192	0.82	0.003	0.611	9.65	0.001	-0.286	2.43
whole	9.97	-2.10		11.38	7.34		1.48	-3.53	
u_t	0.005	-0.199	2.68	0.004	0.189	2.88	0.001	-0.264	4.26
high	9.59	-2.66		14.87	2.79		1.39	-2.93	
u_t	0.005	-0.107	0.40	0.001	1.717	21.87	0.001	-0.270	0.87
low	6.04	-0.61		1.66	8.26		1.29	-0.76	
Panel B: ER: $EP\ RVOL\ F2\ G1$									
u_t	0.005	-0.240	1.51	0.003	0.587	9.53	0.001	-0.293	2.81
whole	10.22	-2.72		11.98	7.30		1.44	-3.64	
u_t	0.006	-0.302	5.60	0.004	0.183	3.03	0.001	-0.373	7.98
high	9.81	-3.74		15.45	2.78		1.69	-4.17	
u_t	0.005	-0.232	0.78	0.001	1.652	21.74	0.001	-0.418	2.11
low	6.54	-1.31		1.97	8.22		1.96	-1.56	
Panel C: ER: $RVOL\ F2\ G1$									
u_t	0.005	-0.168	0.83	0.003	0.714	14.14	0.001	-0.288	3.39
whole	11.15	-2.07		11.20	9.15		1.77	-4.20	
u_t	0.006	-0.214	4.49	0.004	0.243	5.01	0.001	-0.292	8.26
high	13.23	-3.37		14.69	3.66		3.19	-4.54	
u_t	0.005	-0.045	0.02	0.001	1.810	26.97	0.000	-0.254	1.53
low	5.37	-0.19		1.68	9.36		0.65	-1.63	

Table 9: EW risk-return relation (MIDAS variance) conditioning on fundamentals

This table reports regressions of estimated conditional mean excess returns $u_t \equiv E_t(m_{t+1})$, $m_{t+1} \equiv r_{t+1} - r_{f,t+1}$, on the CRSP equal-weighted stock market index over the 1-month treasury bill rate, against conditional variance vol_t in MIDAS. The conditional means are estimated as fitted values from regressions of excess returns on three sets of information variables known at time t from Panel A to Panel C. In Panel A, ER denotes the fitted value from a regression of excess return on the information variables EP_t, $RVOL_t$ and $F2_t$. In Panel B, ER denotes the fitted value from a regression of excess return on the information variables EP_t, $RVOL_t$, $F2_t$ and $G1_t$. In Panel C, ER denotes the fitted value from a regression of excess return on the information variables $RVOL_t$, $F2_t$ and $G1_t$. In each panel, ERhat and ERres denote the fundamental component and residual component of ER respectively. $Var_t(r_{t+1})$ denotes monthly conditional variance in MIDAS model. High- and low-sentiment periods are classified using Baker and Wurgler's monthly sentiment index. The sample spans the period from July 1966 to December 2011. T-statistics in each regression are reported.

Model: $u_t = a + bVar_t(r_{t+1}) + \varepsilon_t$									
		ER			ERhat			ERres	
Model	a	b	$R^2(\%)$	a	b	$R^2(\%)$	a	b	$R^2(\%)$
Panel A: ER: EP $RVOL$ $F2$									
u_t	0.008	-0.208	0.71	0.005	1.433	12.14	0.001	-0.455	2.47
whole	10.82	-1.75		12.40	8.45		1.23	-3.48	
u_t	0.009	-0.524	2.33	0.008	0.133	1.53	0.001	-0.645	5.19
high	11.00	-2.55		17.65	2.46		1.80	-3.76	
u_t	0.007	-0.170	0.57	0.003	2.703	19.98	0.001	-0.393	0.75
low	6.11	-0.64		4.19	7.52		1.14	-1.28	
Panel B: ER: EP $RVOL$ $F2$ $G1$									
u_t	0.009	-1.237	9.40	0.006	1.174	11.73	0.002	-1.479	14.30
whole	11.14	-6.94		15.89	8.24		3.21	-8.55	
u_t	0.010	-1.099	19.81	0.008	0.108	1.94	0.002	-1.149	23.28
high	9.85	-7.27		21.18	4.18		1.96	-7.72	
u_t	0.010	-0.986	4.10	0.004	2.187	19.18	0.004	-1.555	8.38
low	7.08	-3.07		6.14	7.28		3.07	-3.28	
Panel C: ER: $RVOL$ $F2$ $G1$									
u_t	0.009	-1.125	8.59	0.005	1.306	14.39	0.002	-1.366	13.64
whole	11.19	-6.62		15.45	9.23		3.09	-8.53	
u_t	0.010	-1.061	20.29	0.008	0.122	1.80	0.002	-1.131	24.06
high	10.84	-7.39		20.49	2.30		2.61	-7.95	
u_t	0.009	-0.835	2.91	0.004	2.294	21.31	0.002	-1.058	6.28
low	6.47	-2.77		6.15	7.73		2.09	-4.05	