Keynes Meets Merton: Examining Risk and Return Relation Based on Fundamentals

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Abstract

Although the intertemporal risk-return relation should be theoretically positive, it is often documented to be empirically weak and even negative. Various remedies, such as allowing for time-varying risk-return trade-off or using more accurate measures for risk and/or return, have been proposed to fix this puzzle. However, we show that those remedies are fragile in a collective sense. We argue that the theoretically positive risk and return relation might have been weakened or even reversed empirically by non-fundamental forces. This could be one key reason for the mixed empirical results, as well as the fragility of related remedies. When we examine the risk-return relation conditioning on fundamentals only, a positive risk and return relation can be restored and those remedies are no longer fragile, because the impact of non-fundamental forces has been largely controlled.

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

Keywords: Risk-return relation, Return forecasting, Fundamental predictors, Behaviorial 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 have documented insignificant or even negative empirical results in the literature. 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 fix this puzzle. Each of those remedies seems working well individually, but would appear rather fragile collectively. 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 while 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 ones.[1] Therefore, the positive risk and return relation implied by rational models could be weakened or even reversed empirically by the non-fundamental forces as documented by many studies in the literature. We believe that the fragility of many existing remedies is also due to the fact that the impact of the non-fundamental forces is not properly controlled. After we control for this impact, our evidence suggests a solid positive risk and return relation, and all related remedies are no longer fragile.

In particular, we use forecasted return to proxy for expected return in examining the risk-return relation due to the potentially large noises in realized return.[2] In specific, to reduce the concern of selecting not enough or even an arbitrary set of predictors, we apply a "Choose-all" approach by projecting future returns onto a vast set of economic variables based on dynamic factor analysis

[1]The non-fundamental forces can be linked to the so-called "animal spirits" (Keynes (1936)).

[2]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 of providing unbiased estimate.

following Ludvigson and Ng (2007).[3] Besides, we also follow Pastor, Sinha and Swaminathan (2008) to apply an implicit version of the "Choose-all" approach, namely the implied cost of capital model. While we may regard the above dynamic factor approach as an explicit version of "Choose-all" approach since it explicitly choose almost "all" predictors, the ICC approach instead implicitly captures all relevant factors determining the expected return, thus avoid having to explicitly select a certain number of return predictors.

Empirically, we follow the factor analysis approach as Ludvigson and Ng (2007) to apply the 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 (i.e. the earnings price ratio EP, the dividend price ratio DP, etc.) to locate the most significant predictors for estimating future returns. In particular, 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 will 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: $Output\ and\ Income$, $Labour\ Market$, $Housing$, $Consumption$, $Orders\ and\ Inventories$, $Money\ and\ Credit$, $Exchange\ rates\ and\ Inflation$.[4]

Our result shows that without conditioning on the fundamental $ECON$ variables, the risk-return

[3] Some studies estimate the 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)).

[4] 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 upon 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 indicating that for any non-diversifiable risk, it should be compensated by extra return. Hence, we condition the expected mean return not the expected variance on fundamentals when examine the risk-return relation.

relation is overall weak or negative, which is consistent with the weak or negative risk-return relation documented in Ludvigson and Ng (2007). This is not surprising since the estimated expected returns based on factor analysis approach likely capture not only fundamental information but also non-fundamental one, given that the factor analysis approach is a "Choose-all" approach, aiming to capture everything including potentially lots of non-fundamentals by design. This may be the reason why we find weak or negative risk and return relation if the non-fundamental part is not controlled. However, once upon conditioning on the fundamental factors, this patten has clearly changed and the risk-return relation becomes significantly positive. And this positive relation is robust across various combinations of the predictors. Therefore, based on the fundamental part of expected return extracted by conditioning on fundamentals only, the impact of behaviorial 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. Particularly, they claim a negative conditional risk-return relation conditioning on lagged mean and volatility, while a positive relation without conditioning on these variables. However, our positive risk-return relation holds no matter conditioning on lagged mean and volatility or not, as long as we control for the impact of non-fundamental forces.

Moveover, we also employ Baker and Wurgler's sentiment index to define the low- and high-sentiment regimes. Dislike Yu and Yuan (2011), our positive risk-return relation holds for high-sentiment regime as well.[5] 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 do observe a very negative risk-return relation for the residual return component, which should be dominated by

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

non-fundamental forces.[6]

Then we 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 stock price. Since it is in the same spirit as the internal rate of return, ICC could be considered as a return measure. Given that the realized return can be very noisy, some studies, i.e. Pastor, Sinha and Swaminathan (2008), argue that ICC should be the better estimate for future expected return.[7] However, the estimated expected returns based on this implicit version of "Choose-all" approach are also likely to be affected by non-fundamental forces related variables. As discussed, most ICC methods rely on analyst earnings forecasts, which are subject to potentially large analyst biases.[8] In addition, investors' behaviorial biases may also drive the price away from the level justifiable by the fundamentals.

Among various ICC methods, we follow Hou, van Dijk and Zhang (2012) because this method purely relies on accounting information and hence makes it immune from the potentially large impact of analyst biases. In addition, we can avoid the survivorship requirement that all observations need to have analyst coverage. The risk-return relation again turns out to be weak, which might be driven by the investor biases' impact on the market price. However, this relation becomes significantly positive upon conditioning on fundamental factors, particularly during the low-sentiment regime.[9] That is to say, the theoretically positive risk-return relation still exists if we properly control the noises and related behavioral forces. Therefore, we show that the positive risk-return

[6]Although the residual return component may still contain some fundamental information, its proportion is likely much smaller. Hence, the residual return component should more likely to be driven by non-fundamental forces compared to the original return without removing the fundamental component.

[7]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 do find supportive evidence especially for the currency beta to explain the cross-sectional variations.

[8]The ICC estimates are normally constructed using analyst earnings forecasts, which could be subject to large behaviorial biases of the analysts. This may explain why Pastor, Sinha and Swaminathan (2008) find weak risk-return relation for US while the same result is positive for many other countries. There are some evidence indicates that the analyst biases are much larger in US case than non-US countries (e.g., Chan, Karceski and Lakonishok (2007)).

[9]Moreover, now we may understand that why we need two steps in extracting the fundamental part of the forecasted return in the factor analysis approach case. 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 better to take the two steps procedure for both factor analysis approach and the ICC approach.

relation could be restored if the fundamental conditioning variables are employed to control for noises.

Overall, we show that conditioning on the fundamentals to mitigate the impact of behaviorial forces or animal spirits is the key for restoring the theoretically positive risk-return relation. In contrast, if do not control for the impact of non-fundamental forces, we show that this positive relation can be weakened or even reversed, same as documented in many studies the literature. Therefore, we provide a potentially key reason why the overall return is weakly related to risk as evidenced in existing mixed and sensitive empirical results. Put differently, failure to control for non-fundamental part influenced by animal spirits would prevent people from observing the true risk-return relation.

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 low investor sentiment periods. 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. This is because when the estimated returns are conditioning on the fundamental *ECON* variables to extract out the fundamental part, this fundamental part of the return should be positively related to risk as the rational theory implied even for the high sentiment regimes given that the behaviorial disturbances have been properly controlled. On the other hand, even during the low sentiment regimes, we may still observe a weak or even negative risk and return relation if we use the non-fundamental part of estimated return.

In some sense, both Yu and Yuan (2011) and our study are trying to control for the impact of non-fundamentals. However, Yu and Yuan (2011) is more like an indirect control while our approach is more like a direct control. Particularly, we first directly take out the fundamental part and then do the examination of the risk-return relation using this extracted fundamental part. In contrast, Yu and Yuan (2011) do not take out the fundamental part directly. Instead, they admit that the fundamental part and non-fundamental part co-exist together. They assume during low sentiment regime, the non-fundamental part should have much smaller impact or sort of being controlled in an indirect sense while the fundamental part should play the main role. However, even during low sentiment regime, it is not guaranteed that non-fundamentals will be muted completely. Moreover, it would be rather disputable to define how low should be deemed as low enough to mute the non-fundamentals, such as whether the medium level is a low enough cut-off point. In addition, sentiment itself is not directly observable. The popular Baker and Wurgler's sentiment index (BW index) has some potential issues. First, it may potentially contain 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 been dropped from the BW index recently after Yu and Yuan (2011)'s paper got published. Therefore, the BW index may not provide an accurate or stable proxy for the directly unobservable investor sentiment. Given this concern and the above issues of how low is low and non-fundamentals may not be out of the map completely during low sentiment regime, our direct approach for controlling the impact of non-fundamentals or "animal spirits" seems a useful or even better alternative to Yu and Yuan (2011)'s indirect approach.

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 following:

- *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))[10];
- *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 return for long-term government bond;
- *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.[11]

Note that Ludvigson and Ng (2007) apply similar predictors but construct them at quarterly basis, while 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 as well as capturing more time-series variations.

[10]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.

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

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. In particular, 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 R^2 and the BIC to select the best set of predictors. Specifically, we run the regression specification below:

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

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 the annualized analyst earnings forecasts to denote future cash flows. However, analysts' forecasts do exhibit important biases as suggested by a large body of existing research. Meanwhile, analyst coverage is rather limited and hence many small firms or firms with 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:

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

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 are exactly following Hou, van Dijk and Zhang (2012), but here we want monthly estimates to better help re-examining 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 every month and get monthly coefficients. After we get such coefficients estimated 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. In fact, other ICC measures have to 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 is usually unavailable, hence now we also have better time-series coverage.

Next we will calculate ICC, the internal rate of return that equates the current stock price to the present value of expected future cash follows. Among various ICC methods, we follow the very first and most recognized framework by Gebhardt, Lee and Swaminathan (2001). We firstly 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 be following a mean-reverting process, resulting in long-run industry growth rate at the end. In particular, 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), the exponential process is chosen because it would allow 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 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, FE 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 will drop all related observations because the cross-sectional regressions based on previous accounting records will not be able to predict such a large change. The predictions would either be far from the realized earnings or problematic, and that is typically where the outliers are generated.

C. Fundamentals

Following Jurado, Ludvigson and Ng (2015), we employ a wide range of macroeconomic variables to condition the fundamental part of return. In particular, 132 series of 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 it while locating the fundamental part of the estimated return. Through implementing the principal component analysis (PCA), we obtain the first principal component for each category,[12] and they will be used to locate the fundamental return part, hence mitigate the impact of behaviorial or non-fundamental forces.

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 NYSE, AMEX and NASDAQ stock exchanges and listed on these three main databases over the period from 1966 to 2014 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. Monthly sentiment index is from Wurgler's website.

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

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 so 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), e-quity 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 t-wo 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 would be 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 terms of predicting future expected returns and show the result in Panel A. To test the effectiveness of predictors, we conduct various regression specifications, and CAY, EP, $RVOL$ and LTR appear to be the predictors that have certain level of significance. Therefore, next we will select these four exogenous predictors and combine the macro/financial sets to further select the proper predictors for further return estimation. Note that we have tried all macro and financial factors, but for better presentation 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 prediction 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 as compared to Table 2. Again CAY, EP, $RVOL$ and LTR are the exogenous predictors that exhibit certain strong predictive power. After combining with the macro and financial variables, only EP and $RVOL$ maintain their significance at 5% statistical level. Likewise, $F2$ is consistently negative across various regression specifications, hence should also be considered as the proper predictor to use. Nevertheless, $G1$ also appears to be significantly positive for equal-weighted returns. This is not surprising since we now grant the same weight for each firm regardless of their size. Put differently, we are now testing the predictors which works in the general market and it might deviate from those that work better for large firms. Therefore, we will employ EP, $RVOL$, $G1$ and $F2$ as the 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 strong predictors implied in 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 $G1$ through different combinations, and we now employ fundamental factors to condition expected return and examine how this particular fundamental part of return measure is related to realized volatility. In particular, we would decompose the excess expected return into fundamental and residual components, expecting to observe the positive risk-return relation for the fundamental part. Here $ECON$ variables are the seven first principle 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 after removing the fundamental related part and test whether this part 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 the sentiment information to define low- and high-sentiment regimes. Specifically, we define month t as in high sentiment period if the past twelve-month moving average of sentiment index is greater than zero.[13] 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 clearly this patten has changed upon conditioning on the 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 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. Moveover, dislike Yu and Yuan (2011), this pattern holds for high-sentiment regime as well. This is also in line with our expectation that the theoretical risk-return implication should always hold as long as we can control for the impact from non-fundamental forces. Furthermore, we do 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 would prevent people to observe 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. Therefore, we can obtain the general pattern and avoid letting the large and giant firms dominant the result. The average slopes and Newey-West adjusted t-statistics are summarized in Table

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

5. Clearly the results are very 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 from 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 conditional on lagged mean and lagged volatility, the risk-return relation becomes weak and negative. Therefore, we will re-estimate the predicted returns, then add lagged mean and volatility into the regression specification to see how they affect our results. This time we only apply the most significant predictor combinations in terms of predicting returns from Table 2 and Table 3. 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 adding 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 the significance. This is in contrary to the results of the non-fundamental/residual part, where the 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 part. If this part is not controlled, it would prevent us to observe the true risk-return relation. Such pattern remains the same for equal-weighted returns. Compared to Ludvigson and Ng (2007), our positive risk-return relation seems to hold no matter conditional 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, then we are able to restore the positive mean-variance tradeoff.

Next we will 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 as 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 as a return measure. Besides, ICC estimates are calculated based on forward-looking predictions, hence might be a potentially better proxy for future expected return. In fact, realized return, the commonly used proxy for future expected return, has been considered very noisy. Therefore, the employment of ICC and ICC premium might help better locate the true risk-return relation. Among various ICC methods, we employ Hou, van Dijk and Zhang (2012)'s measure because it purely relies on accounting information. Therefore, we avoid analyst biases and the survivorship requirement that all observations need to have analyst coverage. In particular, we construct Hou, van Dijk and Zhang (2012)'s measure at 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 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 is rather strong during low-sentiment regimes, which is also in line with our expectation since the mean-variance tradeoff would appear clearer when behavioral noises are low. Likewise, the result for equal-weighted ICC premia is in supportive of our argument: the risk-return relation is strongly positive for the fundamental part, especially during the low-sentiment regime. The residual part again exhibit a very unclear risk-relation. Therefore, we believe that the positive risk-return relation could be restored if "correct" conditioning variables are employed to control for noises.

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 up to the previous 250 days 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 the 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 risk-return relation is overall flat. However, the risk coefficient is less negative during low-sentiment regime. That is to say, the theoretically positive risk-return relation might still exist if we properly control for the non-fundamental noises. Clearly the result is in supportive of our argument. After we apply fundamental conditioning variables, the risk-return relation becomes strongly positive, which is also consistent across low- and high-sentiment regimes. The residual part, however, exhibits exactly the opposite result that the coefficient is negative or weak. Both evidence is 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 noises. Although the risk coefficient is negative for the overall return, it becomes significantly positive for the fundamental return part. And clearly the negative impact 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, finding weak or mixed results. There exists one potential issue that might have caused the failure in current studies: most asset pricing tests are subject to behavioral noises or animal spirits. If proper conditioning settings are applied with the non-fundamental noises controlled, we might still be able to restore the theoretically positive risk-return relation.

In this study, we propose a direct control for the non-fundamentals or “animal spirits”. Then 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 a weak result. 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 result is in supportive of the positive risk and return relation upon conditioning on fundamental variables. Our study not only helps to compromise the discrepancy between widely used theory and existing empirical evidence, but also shows the importance of properly controlling for the non-fundamental behaviorial 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 (e.g., (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 2014.

	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 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 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 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 2014. 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 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 2014. 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	