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Three Essays on Asset Pricing

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Résumé

Cette thèse présente une étude empirique qui porte sur la prévisibilité du bêta du risque systématique du prochain trimestre, sur la variation temporelle de la décomposition de la volatilité du marché en flux de trésorerie et taux d'actualisation, ainsi que sur la relation entre les sentiments à propos de différents sujets d'actualité et les rendements spécifiques de l'entreprise à travers différents horizons.

Le premier chapitre combine l'approche des régressions Fama-MacBeth et les relations paramétriques pour prédire le risque systématique au prochain trimestre. Cette application surpasse de façon significative le modèle autorégressif de référence basé uniquement sur les valeurs retardées du bêta. En utilisant de nombreux tests pour évaluer la significativité statistique d'un ensemble de variables et de catégories de variables dans la prévision du bêta et après avoir étudié leur importance économique en déterminant les facteurs générant des rendements plus faibles dans une application de couverture, nous trouvons que les mesures du rendement des bonds de trésors jouent un rôle clé en termes de prévision et de couverture contre le risque systématique hors échantillon.

Dans le deuxième chapitre, nous décomposons la variance conditionnelle du marché en composantes de flux de trésorerie et de taux d'actualisation. Les contributions relatives de chacun de ces nouveaux facteurs démontrent des fluctuations importantes au fil du temps. La variation retardée de l'inflation est l'un des principaux déterminants macroéconomiques de cette variation temporelle. Nous observons également une variation temporelle des composantes des flux de trésorerie et des taux d'actualisation des bêtas du portefeuille. Nos résultats suggèrent qu'un modèle qui tient compte de la variation des nouvelles composantes des bêtas surpasse les modèles existants qui ne le prennent pas en compte.

Le dernier chapitre analyse en profondeur les principales caractéristiques des différents sujets d'actualité et la relation entre leur sentiment et le rendement des actions. Les sujets les plus fréquents sont en lien avec l'actualité des entreprises, des événements corporatives et des résultats financiers des entreprises. L'évolution des notes de crédit est le sujet d'actualité avec l'écart type le plus élevé en ton négatif. Le sentiment positif varie le plus pour la catégorie nouvelles de l'entreprise. Les sentiments positifs et négatifs pour la plupart des nouvelles sont significativement liés aux rendements contemporains spécifiques pour une entreprise. Les marchés anticipent davantage les nouvelles négatives et un effet de continuation le lendemain est observé pour les deux types de sentiments. Des tendances inverses apparaissent à long terme pour les nouvelles négatives.

Mots-clés

Risque systématique, bêta réalisé, prévisions, couverture, rendement des obligations, modèles multivariés conditionnels, décomposition des rendements, inflation, sujets d'actualité, sentiment positif, sentiment négatif, rendements.

Méthodes de recherche

Approche de Fama-Macbeth, modèle autorégressif, relations paramétriques, modèle autorégressif vectoriel,modèle de corrélation conditionnelle dynamique, modèle GARCH, régressions de panel, effets fixes.

Abstract

This dissertation studies in an empirical framework the predictability of next quarter's systematic risk beta, time variation in the decomposition of market volatility into its cash flow and discount rate news components, and the relationship between the news sentiment in different news topics and firm-specific returns across different horizons. The first chapter combines the Fama-MacBeth rolling windows approach and parametric relationships to forecast next quarter's systematic risk. This application outperforms significantly the existing benchmark autoregressive model that is based solely on betas' own lagged values. After employing a battery of tests to evaluate the statistical significance of an array of variables and categories of variables in forecasting betas and studying their economic importance by determining the factors that provide lower returns in a hedging application, we find that the bond yield measures play a key role in terms of forecasting and hedging systematic risk out-of-sample. In the second chapter, we decompose the conditional market variance into its cash flow and discount rate components. The relative contributions of each of these news factors show to fluctuate significantly throughout time. The lagged change in inflation is a main macroeconomic determinant of the time variation. We also observe a variation throughout time in the cash flow and discount rate components of portfolio betas. Our results suggest that a model that accounts for variation in news components of betas outperforms existing models that do not account for it. The last chapter conducts an extensive analysis of the main characteristics of different news topics and the relationship between their sentiment and stock returns. The most frequently occurring news topics are those of company news, corporate events, and financial results of companies. Changes in credit ratings is the news topic with the highest standard deviation in negative tone. The positive sentiment varies the most for the company news category. Both, the positive and the negative sentiments for most of the topics are strongly and significantly related to contemporaneous firm-specific returns. Markets anticipate negative news to a larger extent, and a next-day continuation effect is observed for both types of sentiments. Reverse patterns arise in the long term for negative news.

Keywords

Systematic Risk, Realized Beta, Forecasting, Hedging, Bond Yield, Multivariate Conditional Models, Return Decomposition, Inflation, News Topics, Positive Sentiment, Negative Sentiment, Returns.

Research methods

Fama-Macbeth Approach, Autoregressive Model, Parametric Relationships, Vector Autoregressive Model, Dynamic Conditional Correlation Model, Garch Model with Exogenous Variables, Panel Regressions, Fixed Effects.

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List of acronyms

CV Campbell and Vuolteenaho

CF Cash Flow

DCC Dynamic Conditional Correlation

DR Discount Rate

GARCH Generalized Autoregressive Conditional Heteroskedasticity

MVGARCH Multivariate Garch

sentNEG Negative Sentiment of News

sentPOS Positive Sentiment of News

VAR Vector Autoregressive Model

To the most beautiful soul who raised me – my grandmother, to my very dear parents who always know how to inspire me, my amazing fiancee for his endless support and invaluable motivation, and to my loving brother and sisters for always being there for me. It all gets a meaning with you by my side!

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General Introduction

This dissertation consists of three empirical articles on asset pricing. The first article centers on forecasting and hedging systematic risk beta. Given the widespread usage, importance that beta carries both to practitioners and academics, and especially the role that it plays in portfolio management, we want to provide valid forecasts of systematic risk. To the best of my knowledge, previous articles do not determine a specific category of variables that helps significantly in forecasting betas. We use realized betas in an autoregressive framework that combines the Fama-Macbeth rolling window approach and parametric relationships. This model outperforms the existing time-varying and constant-beta models. In terms of parametric relationships, we find that the bond yield measures play an important role in forecasting and hedging systematic risk out-of-sample. Moreover, the attained results are robust to a variety of specifications and sample periods.

The second article addresses a critical question in Finance: whether it is the cash flow or the discount rate news that causes the main variation in stock prices. While this question has been the main focus of several articles, the existing literature still lacks a final conclusion due to the documented conflicting results. Thus, we show in this first paper that the fluctuations in stock prices are attributed to both cash flow and discount rate news. However, the importance of each of these types of news changes throughout time. To measure the relative importance of cash flow and discount rate news, we first decompose the conditional variance into the conditional variances of its cash flow and discount rate components and their conditional covariance. We find that indeed the relative importances of cash flow and discount rate news in determining the market volatility vary significantly throughout time. Lagged changes in inflation show to be the main macroeconomic determinant of this time variation. Considering a pricing framework that consists of time-varying cash flow and discount rate betas, we observe that this model does a much better job in accounting for cross-sectional variation in expected returns when compared to other conditional or unconditional models.

The last article, News Sentiment and Stock Returns, uses a less traditional and therefore a non-yet thoroughly analyzed database to study different news topics as well as their relationship with stock returns at firm level. The database we use is the Thomson Reuters News Analytics, and the most frequently observed news topics are those of corporate events, company news, mergers, and financial results of companies. Changes in credit ratings shows to be the news topic with the highest standard deviation in negative tone. On the other side, the positive sentiment varies the most for the company news category. Both, the positive and the negative sentiments for most of the topics are strongly and significantly related to contemporaneous firm-specific returns. Markets highly anticipate negative news, and a next-day continuation effect is observed for both types of sentiments. Reverse patterns arise in the long term for negative news. Furthermore, the intensity in the tone of news for results and result forecasts has a higher impact than the news announcement itself.

Theoretical framework

The first article builds on different forecasting models used broadly to forecast systematic risk beta. A very common one is that of Fama and MacBeth (1973), which uses a rolling window of monthly observations over the past five years to forecast betas as the slope coefficient from the regression of monthly stock returns on market returns. Papageorgiou, Reeves and Xie (2016) refer to the Fama MacBeth approach as "an historical accident" based on the fact that there does not exist a plausible explanation to use monthly stock returns if daily returns are accessible. Andersen, Bollerslev, Diebold and Wu (2006) provide another approach where quarterly realized betas are computed using daily observations. Hooper, Ng and Reeves (2008) fit the beta time series to the AR(1) model for a quarter ahead predictions by using quarterly realized betas estimated from daily stocks and index returns over a five-year period. Reeves and Wu (2013) approach utilizes high frequency return data. A very recent approach has been that of Gonzalez, Nave and Rubio (2012) studying the cross-sectional variation of expected returns for a large cross section of industry and size and book-to-market portfolios. This approach implements mixed data sampling (MIDAS) to estimate a portfolio's conditional beta. MIDAS (Ghysels, Santa-Clara, and Valkanov (2005)) renders possible the use of data obtained from unequally spaced intervals. Characterized by their own strengths and weaknesses, various models are broadly used to attain beta estimates.

Ghysels and Jacquier (2006) state that the two main empirical approaches to model the dynamics of betas are either by using data driven filters such as the rolling sample estimates in Fama and MacBeth (1973) or by establishing parametric relationships between betas and macroeconomic indicators as in Shanken (1990) and Ferson and Harvey (1991, 1993, 1999). Following Ghysels and Jacquier (2006) (GJ (2006)), we combine these two approaches and show that betas can be predicted by a set of different variables.

Relevant to the second chapter, there exists a large body of the literature [1] that addresses whether the fluctuations in stock prices are attributed to revisions in investors' expectations about future cash flows, future discount rates, or a combination of the two. To capture the importance of each component, authors provide a proportion showing the contribution of each news component to stock price volatility. In agreement with the literature, we use the term news to refer to changes in investors' expectations with the arrival of new information. We also use the relative ratios to measure the contribution of each component.

Given that neither cash flow nor discount rate news are directly measurable, we utilize the popular approach of Campbell and Shiller (1988) to retrieve proxies for these news components. Authors show through an accounting identity that unexpected returns can be expressed as the difference between unexpected changes in investors' expectations of future cash flows and future discount rates, which they refer to as cash flow and discount rate news, respectively. To obtain empirical proxies for these two components, they suggest using a vector autoregressive framework to model the short-term dynamics of excess returns to obtain proxies for unexpected returns and discount rate news directly, while backing out cash flow news indirectly from the return decomposition identity. Authors assert that the relative importance of each component in determining stock price movements can be analyzed based on their relative contributions to the overall variance of stock returns. While the methodological steps are easy to apply, different papers provide differ-

[1] Vuolteenaho (2006), Chen and Zhao (2009), Campbell, Polk, and Vuolteenaho (2010), Koubouros, Malliaropulos, and Panopoulou (2010), Lustig and Verdelhan (2012), Engsted, Pedersen, and Tanggaard (2012), Campbell, Giglio, and Polk (2013), Chen, Da and Zhao (2013), Cenesizoglu (2014), BCampbell (1991), Campbell and Ammer (1993), Campbell and Mei (1993), Vuolteenaho (2002), Campbell and Vuolteenaho (2004), Hechtianchi (2015) and Campbell, Giglio, Polk, and Turley (2017)

ent findings for different sample periods and for different inputs to vector autoregressive model. We fill this gap by showing in a robust study that the contribution of each news constituent changes throughout time. We are able to decompose the conditional variance of market returns following Engle's (2002) dynamic conditional correlation model. Searching for an explanation of the observed time-varying pattern, we identify inflation to be the main macroeconomic factor determining this variation. There are several theoretical models such as that of David and Veronesi (2013) that relate inflation to stock market volatility.

The studies of Dzielinski (2011) and Ahmad et al. (2016) are the cornerstones of the third article; they both estimate the sentiment of news and study its relationship with stock returns. Dzielinski (2011) finds that news that carries a negative tone is characterized by significantly negative next-day returns. He estimates the sentiment of a firm within a day as the ratio of the sum of positive and negative probabilities of news in that specific day to the total number of news stories during the day. Dzielinski (2011) also explores the heterogeneity across firm characteristics and industries. In this chapter, we follow Dzielinski (2011) to build the news sentiment variables. However, different from his measure we construct two separate sentiment factors, one for positive and one for negative sentiment. We also consider the extent to which news is positive or negative, in addition to the dummy variables that Dzielinski (2011) uses to capture whether one type of news dominates the other during a day. The main contribution of our study emerges from its focus on analyzing an area that is not explored extensively in the literature, that of examining the tone of different news topics. On the other side, Ahmad et al. (2016) focuses on the impact of media-expressed tone on stock returns and its continuation using firm-specific data. They show that media tone has significant impact on returns occasionally. The fact that they do not distinguish among news topics might be an alternative explanation to their main result. Similar to Ahmad et al. (2016), we also consider news at firm level but do not constrain our sample to firms of large size only. In this study, we include both measures of news, but this is not the case for Ahmad et al. (2016) who build measures of news tone based only on words implying negative sentiment. The main estimation results of this chapter are generated from panel regressions in a very restrictive setting that controls for firm and day-fixed effects while using clustered standard errors.

The documented patterns for the relationship between sentiment and stock returns in the third chapter are certainly closely linked to the literature about cash flow and discount rate news (Campbell and Shiller (1988a, 1988b), Campbell (1991)) from the second chapter; our findings provide interesting insights for future work in terms of relating different news topics to the two main cash flow and discount rate channels.

Chapter 1

Forecasting and Hedging Systematic Risk

Ibrushi, Denada

Abstract

Forecasting systematic risk beta accurately is the key to building market-neutral portfolios that yield returns independent of market fluctuations. Using realized betas in an autoregressive framework that combines the Fama-MacBeth rolling windows approach and parametric relationships shows to outperform the existing benchmark autoregressive model that is based solely on betas' own lagged values. This article provides an extensive analysis of a large set of macroeconomic and financial variables to identify the main predictors for next quarter's systematic risk. We employ a battery of tests to evaluate the statistical significance of each variable and category of variables and study their economic importance by determining the factors that provide lower returns in a hedging application. We find that the bond yield measures play a key role in terms of forecasting and hedging systematic risk out-of-sample. Our results are robust to alternative specifications and

sample periods.

1.1 Introduction

Failure of widely applied models to accurately predict systematic risk has shown to carry detrimental impact for portfolios' returns. It is due to this misestimated systematic risk or Capital Asset Pricing Model[1] (CAPM) beta that portfolio managers have difficulty in constructing market-neutral portfolios. In practice, building a market-neutral portfolio is usually done through a beta-neutral portfolio, dollar-neutral portfolio, or a weighted portfolio between these two. The main interest behind such portfolios lies in their ability to provide consistent returns independent of market fluctuations, while being exposed to low levels of risk. The so-called market-neutral hedge funds turned out to have considerable systematic risk during the subprime crisis. Different studies (Asness et al. (2001), Patton (2009), and Bali et al. (2014)) indicate that hedge fund returns are exposed to market risk. Even after taking into account a variety of control variables, Bali et al. (2014) observe a significantly positive relation between the future hedge fund returns and systematic risk. In this paper, we show that measures of bond yield need to be considered in order to obtain more precise beta forecasts for the following quarter.

Beta estimates find also a wide applicability both in theory and in practice, in cost of equity estimation, in stock valuation, and in portfolio management. Ghysels (1998) and Wang (2003) show the effect of different beta forecasts on asset pricing and portfolio optimization. Given that beta is a major determinant of the cost of equity, it also plays a significant role in the cost of capital computation. Under the assumption that everything else is equal, the higher the beta of a company, the higher will be its cost of capital used as hurdle rate, implying lower present value of the future cash flows of the company. This fact clearly shows the crucial effect of beta on firm valuation.

[1] See Sharpe (1964) and Lintner (1965).

In this article, we analyze state-of-the-art methods to model and forecast systematic risk and implement these forecasts to hedge it by using the market portfolio return. To this end, we first present the theoretical foundations behind what is called realized betas to measure systematic risk. We then discuss how one can use realized betas to model and forecast this type of risk. The realized betas are the coefficient estimates from a regression of excess daily portfolio returns on the excess daily market returns within a specific quarter. In other words, it is the ratio of the realized covariance of the market and portfolio returns to the realized variance of the market. The two main forecasting models that we estimate and analyze throughout this study are the benchmark autoregressive model of order one (AR(1)) and our new autoregressive framework that accounts for a variety of predictors X (ARX). Following Cenesizoglu et al. (2017), we choose AR(1) to be the main specification representing the time-varying beta forecasting models. However, we want to explore the predictability of betas by including not only their lagged values, but also lagged values of predictor variables X. Beta forecasts for each of these models are estimated based on rolling windows of 60-quarter observations for the out-of-sample period starting in 1980. Next, we measure the performance of both models by calculating the root mean squared forecast errors (RMSFE) during the external period. In addition, Diebold-Mariano (1995) and Mincer-Zarnowitz (1969) tests are used to verify the forecasting power of our models. The former tests the null of equal predictive ability, whereas the latter tests whether the attained predictions are unbiased and efficient. Finally, we compare the significance of our results in an out-of-sample hedging application by estimating the return of a long-short position over each quarter period. We know that a perfect hedge should yield zero return (zero hedging error) and its volatility should equal to zero.

Our results suggest that using realized betas and establishing parametric relationships as in the ARX model outperforms the benchmark AR (1) model. However, it is beyond the scope of this article to claim that ARX is the optimal model that leads to the lowest forecast errors. Our central goal is to evaluate the statistical and economic power of a rich variety of variables in terms of forecasting quarterly betas. Identifying the aggregate bond yield measures to be the main statistically significant category of predictors that also improves the hedging performance substantially, we suggest practitioners and academics to take into account the role that bond yield measures play in forecasting next quarter's systematic risk. We contribute to the existing literature not only by evaluating statistically a range of potential predictors, but also by studying the commonly missed dimension of economic significance, which is indeed the main source of motivation why academics and practitioners are interested in forecasting systematic risk.

This paper is organized as follows: Part 2 presents the foundations of realized beta. Part 3 describes the data. Part 4 shows different forecasting approaches and the two cornerstone forecasting models of this study along with their testing results. Part 5 provides the results for market hedging applications along with our main suggestion, and Part 6 concludes the article.

1.2 Realized Beta

Realized beta indicates the extent to which the return of a risky asset covaries with the return on the market portfolio. Therefore, the covariance of the return rate of the risky asset with the rate of return on the market portfolio determines the expected rate of return on the risky asset. Realized beta is defined as the ratio of realized individual equities' covariance with the market to the realized market variance. Similarly to Andersen et al. (2006), we assume that p, which denotes the logarithmic Nx1 price vector, follows multivariate continuous time stochastic volatility diffusion,

$$dp_t = \mu_t d_t + \Omega_t dW_t \tag{1.1}$$

where μ_t denotes the drift vector, W_t a standard N-dimensional Brownian motion, and

Ω_t the diffusion matrix. Ω_t and μ_t are strictly stationary and jointly independent of W_t. Depending on Ω_t and μ_t, the continuously compounded return r for h-periods has the following distribution:

$$r_{t+h,h}|\sigma\left\{\mu_{t+\tau,}\Omega_{t+\tau}\right\}{}_{\tau=0}^{h}\sim N\left(\int_0^h \mu_{t+\tau}d\tau, \int_0^h \Omega_{t+\tau}d\tau\right) \tag{1.2}$$

For sampling frequency approaching infinity, the theory of quadratic variation under weak regularity conditions implies the following results for the realized market volatility and the realized covariance of individual security i with the market M:

$$\hat{v}^2_{M,t,t+h} = \sum_{j=1,\ldots,[h/\Delta]} \mathrm{r}^2_{(N),t+j\cdot\Delta,\Delta} \tag{1.3}$$

$$\hat{v}_{iM,t,t+h} = \sum_{j=1,\ldots,[h/\Delta]} \mathrm{r}_{(i),t+j\cdot\Delta,\Delta}\cdot\mathrm{r}_{(N),t+j\cdot\Delta,\Delta} \tag{1.4}$$

where N represents the total number of stocks and Δ the sampling frequency.

Once we define the realized variance and covariance, realized beta is denoted as shown below:

$$\hat{\beta}_{i,t,t+h} = \hat{v}_{iM,t,t+h}/\hat{v}^2_{M,t,t+h} \rightarrow \beta_{i,t,t+h} = \int_0^h \Omega_{(iN),t+\tau}d\tau/\int_0^h \Omega_{(NN),t+\tau}d\tau \tag{1.5}$$

Thus, we can obtain consistent beta estimates under the assumption of high sampling frequency ($\Delta \rightarrow 0$).

1.3 Data Description

Data used to estimate betas are the daily value-weighted returns on 25 portfolios formed on size and book-to-market and the excess market returns[2]. We also run our model for the 30 industry value-weighted portfolio returns. Returns for both types of portfolios are obtained from Professor Kenneth R. French's website for three sample periods: 1927-2016, 1927-1964, and 1965-2016. One main reason that motivates the split of the sample period in this manner is the adjustments that occurred in the stock market listing prerequisites. Thus, in the late 1970s NASDAQ stocks were added to the NYSE to benefit from equity financing. On the other side, strong profitability requirements existed during the early subsample for stocks to be listed. Portfolios are constructed on a yearly basis at the end of June.

The data for our predictors is from Professor Amit Goyal's website. We consider 30 variables and classify them into each of the following categories: corporate variables, equity market variables, bond yield measures, valuation ratios, macroeconomic variables, and portfolio-specific variables. These categories are presented in Table 1.

[Insert Table 1 about here]

1.4 Forecasting Systematic Risk

In this section, we start by sharing different forecasting methods from the literature. Next, we provide our two main models, the empirical steps that we follow to forecast one-quarter-ahead betas, and the testing results.

[2] In addition to the market factor obtained from Professor Kenneth French's website, we also replicate the estimations in the following sections using the S&P 500 index. The results continue to hold qualitatively.

1.4.1 Forecasting Methods

Different forecasting models are used extensively throughout literature to predict beta. A very common one is that of Fama and MacBeth (1973), which uses a rolling window of monthly observations over the past five years to forecast betas. According to this method, beta is the slope coefficient estimated from the regression of monthly stock returns on market returns. Papageorgiou et al. (2016) refer to the Fama-MacBeth approach as "an historical accident" based on the fact that there does not exist a plausible explanation to use monthly stock returns if daily returns are accessible. Andersen et al. (2006) provide another approach where quarterly realized betas are computed using daily observations. Hooper et al. (2008) fit the beta time series to the AR(1) model for a quarter ahead predictions by using quarterly realized betas estimated from daily stocks and index returns over a five-year period. The Reeves and Wu (2013) approach utilizes high frequency return data. A very recent approach is that of Gonzalez et al. (2012) studying the cross-sectional variation of expected returns for a large cross section of industry and size and book-to-market portfolios. This approach implements mixed data sampling (MIDAS) to estimate a portfolio's conditional beta. MIDAS (Ghysels et al. (2005)) renders possible the use of data obtained from unequally spaced intervals. Characterized by their own strengths and weaknesses, various models are broadly used to attain beta estimates.

Ghysels and Jacquier (2006) summarize the existing empirical approaches by stating that the two main methods to model the dynamics of betas are either by using data driven filters, such as the rolling sample estimates in Fama and MacBeth (1973), or by establishing parametric relationships between betas and economic state proxies as in Shanken (1990) and Ferson and Harvey (1991, 1993, 1999). Following Ghysels and Jacquier (2006), we combine these two approaches and show that betas can be predicted by a set of different variables. We also take into account the mean and median of beta forecasts across each set of variables to analyze whether the aggregate categories have a higher forecasting power compared to the individual variables. As mentioned in Ghysels and Jacquier (2006), using approximately 22 daily returns per month results in highly volatile betas and biased estimates. This issue can be corrected by the use of intra-daily returns (Andersen et al. (2006)). However, intra-daily returns are available for relatively short data spans. Considering the frequency of available potential predictors along with the fact that high frequency data such as intra-daily returns are available for shorter spans, we decide to use daily frequency as the optimal one to estimate realized betas with a large enough number of observations.

1.4.2 Evaluating AR(1) and ARX Model

Here, we regress intraperiod excess portfolio returns on intraperiod excess market returns to compute realized betas based on the slope coefficient in the regression equation. Thus, we assume that quarterly estimation of realized betas from daily returns is the optimal frequency leading to less noise and more reliable values. Therefore, we obtain quarterly betas based on the linear regression of excess daily portfolio returns on the excess daily market returns for each sample period (1927-2016, 1927-1964, 1965-2016).

We use two distinct models for the out-of-sample estimations. The first one is the traditional AR (1) model:

$$\beta_{i,t} = b_{i,0} + b_{i,1}\beta_{i,t-1} + u_{i,t} \tag{1.6}$$

and our predictive factors' model, which differs from (7) and includes the lagged values of predictive variables x:

$$\beta_{i,j,t} = b_{i,j,0} + b_{i,j,1}\beta_{i,t-1} + b_{i,j,2}x_{j,t-1} + u_{i,j,t} \tag{1.7}$$

where β indicates the realized beta, i the portfolio, j the predicting variable, and t the corresponding quarter.

We refer to model (6) as the benchmark model, where betas are predicted based solely on their lagged values. The set of explanatory variables in Model (7) includes the three Fama-French (1992) factors: excess market return, return difference between small and large sized firms (SMB), and the value premium between value and growth stocks (HML).

Even if there are no clear-cut rules on the choice of sampling frequency and the number of lags, current literature still uses the rolling windows of 60 monthly returns as in Fama and MacBeth (1973). We obtain beta forecasts by estimating the two models based on overlapping windows of 60 quarters of observations for the out-of-sample period between the 1st quarter of 1980 and the last quarter of 2016. To illustrate, for the first quarter in the out-of-sample period (1980Q1), the model is estimated using 15 years of quarterly data between 1965Q1 and 1979Q4.

$$\hat{\beta}^{f}_{i,1980Q1} = \hat{b}_{i,0} + \hat{b}_{i,1}\beta_{i,1979Q4}$$
$$\hat{\beta}^{f}_{i,j,1980Q1} = \hat{b}_{i,j,0} + \hat{b}_{i,j,1}\beta_{i,1979Q4} + \hat{b}_{i,j,2}x_{j,1979Q4}$$

$\hat{b}_{i,0}, \hat{b}_{i,1}, \hat{b}_{i,j,0}, \hat{b}_{i,j,1}, \hat{b}_{i,j,2}$ are estimated using the data from the period starting 1965Q1 until 1979Q4. $\hat{\beta}^{f}$ is the obtained beta forecast.

We estimate the ARX model for each of the predictive factors individually and for the seven aggregate measures: corporate variables, equity market variables, bond yield measures, valuation ratios, macroeconomic variables, portfolio-specific variables, and the universal category that includes all the variables. We obtain the beta forecasts of each category by estimating the mean and median of betas obtained from an ARX model for each variable listed in the corresponding category in Table 1. Individually, there are 30 variables including employment and unemployment levels, which we exclude while averaging into groups because we consider the employment growth rate and unemployment growth rate good enough representatives.

The main test that we run to evaluate our forecasting models statistically is the Root Mean Squared Forecasting Error test, where we compute the forecasting error as shown in the formula below:

$$RMSFE_{i,j} = \left({}^{1}\!/_{T} \sum_{t=1980Q1}^{2016Q4} \left(\beta_{i,t} - \hat{\beta}^{f}_{i,j,t} \right)^{2} \right)^{1/2} \tag{1.8}$$

Here, $\hat{\beta}^{f}_{i,j,t}$ is the estimate for the beta forecast of portfolio i in quarter t based on the predicting category j. β represents the realized beta.

Table 2 reports the averages across portfolios in the differences in Root Mean Squared Forecast Errors (RMSFE) between ARX and the benchmark AR(1) model estimated as shown in Equation (8). The results for 30 industry portfolios are as shown in Panel (a) and for 25 size and book-to-market portfolios in Panel (b). Negative values indicate that ARX dominates AR based on RMSFE and positive ones show that AR model outperforms our ARX model. The average differences are mainly negative but significantly so across different sample periods and types of portfolios especially for the categories of bond yield measures, portfolio-specific variables, and certainly for the overall category of variables. We also consider in untabulated results[3] the RMSFE values for each variable separately and we find that treasury bill rate, long-term yield, and long-term rate of return are the main ones, which also explains why the category of bond yield measures dominates.

[Insert Table 2 about here]

To assess the superiority of one model over the other and the validity of our results in general, we implement the Diebold-Mariano (1995) test and the Mincer-Zarnowitz (1969) regression. Diebold and Mariano (1995) (DM) test the null of equal predictive

[3]Results available upon request.

accuracy of two models under general assumptions. The statistic is calculated based on the loss differential under the assumption that the latter process is stationary. In essence, it is a z-test of the hypothesis that the mean of the loss differential series is zero. DM also corrects for the autocorrelation that multi-period forecast errors usually exhibit. An efficient h-period forecast has forecast errors following MA (h-1) processes. DM uses a Newey-West type estimator for the sample variance of the loss differential to overcome this issue. On the other side, Mincer-Zarnowitz regression tests for unbiased and efficient forecasts by regressing the realized systematic risk beta on a constant and the beta forecast.

In Table 3, we present the number of portfolios for which our ARX model dominates the AR(1) benchmark based on the Diebold- Mariano test at 5% significance level. Focusing on 30 industry portfolios in Panel (a), we observe that the bond yield measures and portfolio-specific category dominate the AR(1) model for a larger number of portfolios compared to the other classes of predictors. When we consider the whole set of variables, more than 21 out of 30 portfolios outperform AR (1) for the whole sample period. The corresponding values are even higher for the size and book-to-market portfolios in Panel (b), where again the bond yield measures show a better forecasting accuracy. All these figures are even more promising when we consider the 10% significance level.

[Insert Table 3 about here]

In Table 4, we show the Mincer-Zarnowitz test results to determine whether the predictions from a forecasting model are unbiased and efficient. Hence, the reported results are based on a Wald test for a null hypothesis of zero intercept and unit slope coefficient in the following regression equation:

$$\beta_{t+h} = \alpha + \beta * \hat{\beta^f}_{t+h|t} + e_{t+h|t} \tag{1.9}$$

t here indicates the current time period and the forecast is made for h-steps ahead. In our context, h equals one. After estimating the parameters of this regression, we use the Wald test for the following joint hypothesis:

$$H0: \alpha = 0, \beta = 1$$

Failure to reject the null indicates unbiased ($\alpha = 0$) and efficient ($\beta = 1$) forecasts. At 5% level of significance, we observe that the number of portfolios for which we reject the null is higher particularly during the early sample period across different categories. Bond yield measures show to have the lowest number of portfolios for which the null hypothesis is rejected. Stated differently, the null fails to be rejected and therefore indicates unbiased and efficient estimates for a larger number of portfolios for the bond yield category.

[Insert Table 4 about here]

Finally, we conduct several asset pricing tests. To improve the power of the estimates, we use Newey-West estimators for the pricing tests. The pricing error consists of the residuals emerging from the regression of portfolio returns on each of the seven aggregate estimates of beta. After attaining the pricing errors, we estimate the root mean squared errors in a similar way with Equation (8). As shown in Table 5, while the order of the categories with the lowest pricing errors changes across periods and portfolios, bond yield measures take place consistently in the three main groups of predictors that yield the lowest squared pricing errors. In unreported results, we observe that the bond yield measures and the valuation ratios are the two main classes for which ARX outperforms AR (1) significantly for the majority of the portfolios.

[Insert Table 5 about here]

1.5 Hedging Systematic Risk

In order to compare the economic significance of our results in an out-of-sample hedging implementation and moreover to determine the specific variables and group of variables that work best in terms of hedging, we hedge the systematic risk by using the return on the market portfolio. The return of the hedged position is estimated as follows:

$$D_{i,j,t} = r_{i,t} - \hat{\beta}^{f}_{i,j,t} \cdot r_{M,t} \tag{1.10}$$

To conduct this hedging application, we short-sell $\hat{\beta}^{f}_{i,j,t}$ dollars of the market portfolio M and long the portfolio i. More specifically, $\hat{\beta}^{f}_{i,j,t}$ corresponds to the average beta forecast across the group of variables listed under each category. Knowing that the perfect hedge should yield a zero return (alternatively stated, zero hedging error) and zero volatility, we seek to identify the factors that yield the lowest hedging errors and reduce volatility more when hedging occurs.

In Table 6, we present the differences in the hedging errors of the ARX model and AR(1) depending on the mean and median forecasts of variables classified under each of the aggregate corporate variables, equity market variables, bond yield measures, valuation ratios, macroeconomic variables, portfolio-specific variables, and mean and median categories. We estimate the hedging error as the absolute value for the return on the hedging position $D_{i,j,t}$ defined in Equation (10). A negative difference in the hedging errors indicates that the hedging error is lower for the ARX model and therefore ARX outperforms AR(1) and vice versa.

In Panel (a) of Table 6, we can clearly observe that the differences in the hedging errors are mainly negative, especially for industry portfolios, indicating in this way the dominance of ARX. The main class of factors that shows consistency across different samples and portfolios is that of bond yield measures. If we would focus on the number of portfolios for which ARX dominates AR(1) for the given mean bond yield category, we find that for the whole sample period there stand 18 out of 25 size and book-to-market portfolios that outperform the AR(1) model. Furthermore, six of them outperform significantly at a 5% level and eight portfolios at 10%. This pattern also holds for the industry portfolios.

[Insert Table 6 about here]

Taking our estimates a further step ahead, we consider the volatility of hedging returns[4]. In this context, aggregate bond yield measures, equity risk factors, and the mean across all the variables show to yield less volatile hedging returns. Based on our untabulated results, it is worth noting that 22 individual variables dominate the benchmark for more than ten industry portfolios. This hedging test indicates that there are some strong predictive variables such as lty, ltr, tms, tbill, dfr, ep, and Fama-French factors that beat the benchmark significantly and consistently across different periods. The individual results for lty, dfr, tbill, tms, ltr, and Fama-French factors explain the reported dominance of bond yield and sometimes of equity risk measure categories.

Simply put, we consider the crucial impact of accurately forecasting betas[5] in portfolio optimization. We document that the combination of rolling sample and parametric relationship models not only forecasts betas at a significant extent, but also is superior to the benchmark AR (1) model in the applied hedging position. Based on our results, we suggest that aggregate bond yield measures and mean forecast in model (7) yield considerably accurate forecasts of beta that lead to the achievement of many researchers' and portfolio managers' aim to efficiently hedge systematic risk.

[4]These results are qualitatively similar to Table 6 and available from the authors upon request.

[5]We also replicate our results to determine the predictors for coefficient loadings on value (HML) and size (SMB) factors. The results continue to hold for SMB and are particularly strong for HML. These findings provide interesting insights for additional research in the future.

1.6 Conclusion

In this article, we examine in a Fama-Macbeth structure the predictability of systematic risk based on our autoregressive ARX model that establishes parametric relationships with next period's beta. Based on the obtained forecasts, we find that bond yield measures produce statistically significant forecasts and reduce the return of the hedged position by a larger extent when compared to other predicting variables or the benchmark AR(1) model.

First, we find that in addition to realized betas from historical data, portfolio managers should pay particular attention to past bond yield measures and Fama-French risk factors when trying to mitigate the systematic risk. While the presence of Fama-French risk factors in our findings is not surprising, the measures of bond yield are new and not necessarily expected or documented elsewhere. We suggest practitioners to consider constructing market-neutral portfolios by taking into account beta forecasts from bond yield measures.

Our second contribution lies in the methodological aspect; it is important to consider exogenous predictors in an autoregressive model of realized betas. These exogenous variables yield out-of-sample statistically and economically significant forecasts. The three main tests that we use to check statistically are the test of the root mean squared forecast errors, the Diebold-Mariano test, and the Mincer-Zarnowitz regression. Considering the economic significance, we estimate the return of a position where we short-sell an amount of dollars of the market portfolio equal to the beta forecast and long the portfolio i return. This study is sophisticated with a variety of tests, models, and variables.

There are certainly other potential research directions worth considering for the future. While we do not discuss in this article the main sources associating systematic risk with measures of bond yield, in the literature it is documented that term structure of interest rates is related significantly to business cycles. Similarly, a recent study of

Gilchirst et al. (2009) shows that portfolio bond spreads predict future economic activity. Studies examining in a theoretical framework the relationship between bond yield measures and the market risk beta would complement this paper tremendously. In addition, our preliminary results suggest that some of portfolio-specific predictors such as kurtosis and skewness also play an important role in forecasting one-quarter-ahead beta. Thus, enriching the set of predictors with portfolio-specific variables might yield interesting insights. Another absorbing avenue would be exploring the channel through which each category predicts systematic risk by decomposing the overall beta into cash flow and discount rate components as in Campbell and Vuolteenaho (2004). In a similar vein, it would also be important to consider the role of different measures of news sentiment in forecasting systematic risk.

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Appendix

Table 1.1 – Classification of Predicting Variables

Aggregate Variables					
Corporate	Equity	Bond Yield	Valuation Ratios	Macroeconomic	Firm-Specific
div	mktrf	lty	dp	cwi	vol
nexp	smb	tms	dy	ic	skew
	hml	dfy	ep	emp	kurt
	mom	dfr	bm	unemp	mval
	svar	infl	ep(10)	prodind	dpi
	ltr	tbill			bmi

Notes: This table presents the categories of variables used to predict systematic risk. Each predicting variable is classified into the following aggregate groups: Corporate Variables, Equity Market Variables, Bond Yield Measures, Valuation Ratios, Macroeconomic Variables, and Portfolio-Specific Variables. Predictors' data is obtained from Professor Amit Goyal's website. The abbrevations in the table are used to denote the subsequent variables: dividend payout ratio (div), net equity expansion (nexp), market return in excess of the riskless rate (mktrf), small minus big factor (smb), high minus low factor (hml), momentum factor (mom), stock variance (svar), long-term rate of return (ltr), long-term yield (lty), term spread (tms), default yield spread (dfy), default return spread (dfr), inflation (infl), treasury bill rate (tbill), dividend-price ratio (dp), dividend yield (dy), earnings-price ratio (ep), book-to-market ratio (bm), 10-years moving average of earnings-price ratio (ep(10)), consumption-wealth-income ratio (cwi), investment-to-capital ratio (ic), employment growth rate (emp), unemployment growth rate (unemp), production index (prodind), volatility (vol), skewness (skew), kurtosis (kurt), market value (mval), dividend-price ratio for each portfolio i (dpi), and book-to-market ratio for each portfolio i (bmi).

Table 1.2 – ARX Performance Based on RMSFE

(a) 30 Industry Portfolios

	1929-1964		1965-2016		1929-2016	
	Mean	Median	Mean	Median	Mean	Median
Aggregate Corporate Variables	-0.0016**	-0.0016**	0.0000	0.0000	-0.0005*	-0.0005*
Equity Market Variables	-0.0002	-0.0005***	0.0003	-0.0000	-0.0002	-0.0003**
Bond Yield Measures	-0.0036***	-0.0019***	-0.0020***	-0.0018***	-0.0033***	-0.0023***
Aggregate Valuation Ratios	0.0007	0.0008	-0.0034***	-0.0023***	-0.0019***	-0.0012**
Macroeconomic Variables	-0.0010	-0.0002	-0.0029***	-0.0008**	-0.0022***	-0.0006*
Firm-specific Variables	-0.0040***	-0.0031***	-0.0025***	-0.0013***	-0.0038***	-0.0025***
All Variables	-0.0031***	-0.0012***	-0.0033***	-0.0016***	-0.0038***	-0.0017***

(b) 25 Size and Book-to-Market Portfolios

	1929-1964		1965-2016		1929-2016	
	Mean	Median	Mean	Median	Mean	Median
Aggregate Corporate Variables	-0.0030***	-0.0030***	0.0004	0.0004	-0.0005	-0.0005
Equity Market Variables	-0.0009***	-0.0009***	-0.0007**	-0.0005**	-0.0012***	-0.0009***
Bond Yield Measures	-0.0053***	-0.0040***	-0.0028***	-0.0024***	-0.0036***	-0.0025***
Aggregate Valuation Ratios	0.0010*	0.0007	-0.0011**	-0.0008*	0.0000	0.0002
Macroeconomic Variables	-0.0007	0.0003	-0.0014***	-0.0006**	-0.0011***	-0.0003
Firm-specific Variables	-0.0034***	-0.0017***	-0.0010***	-0.0008***	-0.0025***	-0.0017***
All Variables	-0.0035***	-0.0016***	-0.0022***	-0.0013***	-0.0029***	-0.0015***

Notes: This table presents the averages across portfolios in the differences in Root Mean Squared Forecast Errors (RMSFE) between ARX and the benchmark AR(1) model estimated as shown in Equation (8). The results for 30 industry portfolios are as shown in Panel (a) and for 25 size and book-to-market portfolios in Panel (b). A negative value indicates that ARX dominates AR(1) based on RMSFE, and a positive one shows that the AR model outperforms the ARX model. We report the mean and median estimates across the variables classified under each of the categories listed in the first column for the early (1929-1964), modern (1965-2016), and the whole sample period (1929-2016). ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 1.3 – ARX Performance Based on Diebold Mariano Test

(a) 30 Industry Portfolios

	1929-1964		1965-2016		1929-2016	
	Mean	Median	Mean	Median	Mean	Median
Aggregate Corporate Variables	4	4	0	0	0	0
Equity Market Variables	2	2	0	0	2	3
Bond Yield Measures	5	5	6	7	11	11
Aggregate Valuation Ratios	2	2	4	3	5	3
Macroeconomic Variables	3	3	5	1	8	2
Firm-specific Variables	7	6	6	3	14	9
All Variables	11	11	12	12	23	21

(b) 25 Size and Book-to-Market Portfolios

	1929-1964		1965-2016		1929-2016	
	Mean	Median	Mean	Median	Mean	Median
Aggregate Corporate Variables	5	5	0	0	0	0
Equity Market Variables	1	1	2	4	10	7
Bond Yield Measures	10	10	9	9	17	16
Aggregate Valuation Ratios	0	0	1	1	0	1
Macroeconomic Variables	0	0	0	0	2	0
Firm-specific Variables	9	3	1	2	11	9
All Variables	17	17	13	14	21	24

Notes: This table presents the number of portfolios for which our ARX model dominates the AR(1) benchmark based on the Diebold-Mariano statistic at 5% level of significance. The results for 30 industry portfolios are as shown in Panel (a) and for 25 size and book-to-market portfolios in Panel (b). We report the mean and median estimates across the variables classified under each of the categories listed in the first column for the early (1929-1964), modern (1965-2016), and the whole sample period (1929-2016).

Table 1.4 – ARX Performance Based on Mincer-Zarnowitz Test

(a) 30 Industry Portfolios

	1929-1964		1965-2016		1929-2016	
	Mean	Median	Mean	Median	Mean	Median
Aggregate Corporate Variables	9	9	4	4	6	6
Equity Market Variables	10	9	5	5	5	5
Bond Yield Measures	5	7	5	5	5	5
Aggregate Valuation Ratios	10	10	7	9	8	9
Macroeconomic Variables	10	10	5	5	5	5
Firm-specific Variables	10	10	5	5	3	3
All Variables	9	9	4	5	3	5

(b) 25 Size and Book-to-Market Portfolios

	1929-1964		1965-2016		1929-2016	
	Mean	Median	Mean	Median	Mean	Median
Aggregate Corporate Variables	14	14	2	2	7	7
Equity Market Variables	17	16	1	1	7	7
Bond Yield Measures	12	14	0	0	6	6
Aggregate Valuation Ratios	15	15	0	0	7	7
Macroeconomic Variables	17	17	1	1	8	8
Firm-specific Variables	15	16	0	0	6	6
All Variables	14	14	0	1	6	7

Notes: This table presents the number of portfolios for which the null hypothesis of efficient and unbiased estimates is rejected at 5% level of significance. The results for 30 industry portfolios are as shown in Panel (a) and for 25 size and book-to-market portfolios in Panel (b). We report the mean and median estimates across the variables classified under each of the categories listed in the first column for the early (1929-1964), modern (1965-2016), and the whole sample period (1929-2016).

Table 1.5 – ARX Performance Based on RMSPE

(a) 30 Industry Portfolios

	1929-1964		1965-2016		1929-2016	
	Mean	Median	Mean	Median	Mean	Median
Aggregate Corporate Variables	0.5805	0.5805	0.4921	0.4921	0.3680	0.3680
Equity Market Variables	0.5792	0.5801	0.4781	0.4800	0.3564	0.3577
Bond Yield Measures	0.5846	0.5838	0.4877	0.4875	0.3633	0.3630
Aggregate Valuation Ratios	0.5982	0.5996	0.4746	0.4716	0.3719	0.3740
Macroeconomic Variables	0.5783	0.5759	0.4826	0.4868	0.3634	0.3644
Firm-specific Variables	0.5881	0.5894	0.4805	0.4790	0.3675	0.3641
All Variables	0.5858	0.5837	0.4811	0.4823	0.3639	0.3624

(b) 25 Size and Book-to-Market Portfolios

	1929-1964		1965-2016		1929-2016	
	Mean	Median	Mean	Median	Mean	Median
Aggregate Corporate Variables	0.4969	0.4969	0.4993	0.4993	0.3980	0.3980
Equity Market Variables	0.4979	0.5009	0.4992	0.4960	0.4120	0.4102
Bond Yield Measures	0.5011	0.4080	0.4983	0.5012	0.4062	0.4087
Aggregate Valuation Ratios	0.5073	0.5058	0.4960	0.4966	0.4054	0.4025
Macroeconomic Variables	0.5121	0.5065	0.5035	0.4978	0.4149	0.4112
Firm-specific Variables	0.4987	0.5010	0.4929	0.4928	0.4023	0.4069
All Variables	0.5020	0.5007	0.4974	0.4960	0.4053	0.4094

Notes: This table presents the Root Mean Squared Pricing Errors (RMSPE) of our ARX model for every category of variables. The results for 30 industry portfolios are as shown in Panel (a) and for 25 size and book-to-market portfolios in Panel (b). We report the mean and median estimates across the variables classified under each of the categories listed in the first column for the early (1929-1964), modern (1965-2016), and the whole sample period (1929-2016).

Table 1.6 – ARX Performance Based on Hedging Application

(a) 30 Industry Portfolios

	1929-1964		1965-2016		1929-2016	
	Mean	Median	Mean	Median	Mean	Median
Aggregate Corporate Variables	-0.0038	-0.0038	-0.0017	-0.0017	-0.0019	-0.0019
Equity Market Variables	0.0018	0.0028	0.0009	-0.0006	0.0043	0.0027
Bond Yield Measures	-0.0018	-0.0008	-0.0020	-0.0026	-0.0072	-0.0056
Aggregate Valuation Ratios	0.0009	0.0017	0.0020	0.0058	0.0157	0.0178
Macroeconomic Variables	0.0028	0.0034	-0.0064	-0.0051	-0.0034	-0.0004
Firm-specific Variables	-0.0027	-.0066	-0.0031	-0.0040	-0.0035	-0.0060
All Variables	-0.0015	0.0004	-0.0051	-0.0028	-0.0027	-0.0008

(b) 25 Size and Book-to-Market Portfolios

	1929-1964		1965-2016		1929-2016	
	Mean	Median	Mean	Median	Mean	Median
Aggregate Corporate Variables	-0.0090	-0.0090	0.0111	0.0111	0.0105	0.0105
Equity Market Variables	-0.0063	-0.0022	0.0042	0.0041	0.0020	0.0037
Bond Yield Measures	-0.0143	-0.0063	-0.0070	-0.0067	-0.0138	-0.0096
Aggregate Valuation Ratios	0.0051	0.0045	0.0029	0.0105	0.0264	0.0327
Macroeconomic Variables	0.0066	0.0072	0.0062	-0.0014	0.0030	0.0012
Firm-specific Variables	-0.0033	-0.0061	0.0099	0.0047	0.0031	-0.0013
All Variables	-0.0059	-0.0023	0.0019	-0.0002	0.0019	0.0010

Notes: This table presents the averages across portfolios in the differences between hedging errors of the ARX model and hedging errors from the AR model. Hedging error is the absolute value for the return on the hedging position defined in Equation (10). A negative difference in the hedging errors indicates that the hedging error is lower for the ARX model and vice versa. The results for 30 industry portfolios are as shown in Panel (a) and for 25 size and book-to-market portfolios in Panel (b). We report the mean and median estimates across the variables classified under each of the categories listed in the first column for the early (1929-1964), modern (1965-2016), and the whole sample period (1929-2016).

Chapter 2

Time Variation in Cash Flows and Discount Rates

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Abstract

We decompose the conditional variance of market returns into the conditional variances of cash flow and discount rate news and their conditional covariance. The relative importance of cash flow and discount rate news in determining the conditional variance of market returns exhibits significant variation over time. We identify lagged changes in PPI inflation as the main macroeconomic determinant of this time variation. An increase in PPI inflation makes cash flow news more, and discount rate news less, important. We analyze the economic importance of these results by allowing for time variation in cash flow and discount rate betas in Campbell and Vuolteenaho's (2004) asset pricing framework. A conditional version of their two-beta framework with conditional betas obtained by estimating multivariate conditional variance models not only provides reasonable es-

timates of risk prices and relative risk aversion coefficients but also outperforms other conditional and unconditional models in accounting for the cross-sectional variation in expected returns. Our results are robust to a battery of checks, including alternative empirical specifications and sample periods.

2.1 Introduction

Stock prices vary over time due to either changes in investors' expectations about future cash flows, discount rates, or a combination of both. Which one of these two components is more important in determining stock price movements is a central question in finance. Hence, it is not surprising to find a large literature trying to answer this question.[1]

One challenge in answering this question is the fact that investors' expectations about neither future cash flows nor future discount rates are directly observable. Thus, one needs to obtain empirical proxies for investors' expectations of these two components. One such approach to obtain these proxies is the return decomposition approach of Campbell and Shiller (1988). Although there are some other alternatives, the return decomposition approach of Campbell and Shiller (1988) is by far the most popular, mostly due to its ease of implementation. Specifically, they first derive an identity that expresses unexpected returns as the difference between unexpected changes in investors' expectations of future cash flows and future discount rates, which they refer to as cash flow and discount rate news, respectively. To obtain empirical proxies for these two components, they suggest using a vector autoregressive framework to model the short-term dynamics of excess returns to obtain proxies for unexpected returns and discount rate news directly,

[1]The list of articles includes, but is not limited to, Campbell (1991), Campbell and Ammer (1993), Campbell and Mei (1993), Vuolteenaho (2002), Campbell and Vuolteenaho (2004), Hecht and Vuolteenaho (2006), Chen and Zhao (2009), Campbell, Polk, and Vuolteenaho (2010), Koubouros, Malliaropulos, and Panopoulou (2010), Lustig and Verdelhan (2012), Engsted, Pedersen, and Tanggaard (2012), Campbell, Giglio, and Polk (2013), Chen, Da and Zhao (2013), Cenesizoglu (2014), Bianchi (2015) and Campbell, Giglio, Polk, and Turley (2017).

while backing out cash flow news indirectly from the return decomposition identity. In other words, one only needs to estimate a linear vector autoregressive system with excess returns and a set of predictive variables to obtain proxies for cash flow and discount rate news.

Campbell and Shiller (1988) suggest that one can then answer the question "What moves stock prices?" based on these empirical proxies for cash flow and discount rate news. Specifically, they show that the variance of stock returns can be expressed as the sum of the variances of these two components minus two times their covariance. They then argue that the relative importance of each component in determining stock price movements can be analyzed based on their relative contributions to the overall variance of stock returns. This simple intuition combined with the ease of implementation lead to a large literature using this approach to analyze not only the sources of stock price movements, but also other related questions in finance, macroeconomics and accounting.[2] However, most studies analyze the relative importance of cash flow and discount rate news in determining the overall unconditional variance of stocks returns and do not consider the conditional variance and its potential variation over time.

In this paper, we fill this gap by analyzing the time variation in the relative importances of cash flow and discount rate news in determining the conditional, instead of unconditional, variance of market returns, as well as the macroeconomic determinants and asset pricing implications of this time variation. Similar to the previous literature, we obtain cash flow and discount rate news based on the return decomposition by considering a vector autoregressive system (VAR) with excess returns, term spread, dividend yield and small value spread as predictor variables. However, differently from the previous literature, we consider the decomposition of the conditional, rather than unconditional, variance of unexpected market returns. We do this by estimating a multivariate condi-

[2] In addition to those listed above, there are a few articles using the Campbell and Shiller (1988) approach in macrofinance, such as Bernanke and Kuttner (2005), and in accounting such as Callen and Segal (2004), Callen, Hope, and Segal (2005), and Callen, Livnat, and Segal (2006).

tional variance model with dynamic conditional correlations (Engle (2002)) for cash flow and discount rate news. Compared to the unconditional variance decomposition, this approach allows us to decompose the conditional variance of market returns and analyze the time variation in the relative importance of its components.

In line with the stylized facts about the conditional variance dynamics of market returns documented in the literature, we find that the conditional variances of its components vary significantly over time and are highly persistent but stationary. As the market goes through volatile and tranquil periods, the conditional variances of its components, not surprisingly, follow these dynamics closely. For example, both cash flow and discount rate news become, on average, more volatile in recessions compared to expansions. Furthermore, the conditional covariance between the two components also exhibits significant variation over time and is also persistent.

More importantly, the relative contribution of these components to the conditional variance of unexpected market returns also varies significantly over time. The contribution of discount rate news varies between 24% and 65% with a standard deviation of 9%, while that of cash flow news is less volatile and varies between 15% and 61% with a standard deviation of 7%. The contribution of the covariance varies between 10% and 45% with a standard deviation of approximately 6%. The discount rate news is more important than cash flow news during the beginning of the Great Depression. This changes in the middle of the Great Depression and cash flow news becomes more important than discount rate news. The cash flow news stays, on average, more important than the discount rate news between the mid-1930s and the mid-1950s, although there are still periods during which the opposite holds. However, since the mid-1950s, the relative importance of cash flow news steadily declines and the discount rate is the main determinant of conditional aggregate market movements. This changes once again around 2008 but this time more dramatically and the cash flow news becomes the main determinant during the Global Financial Crisis.

We analyze whether this time variation in the determinants of stock price movements is related to macroeconomic conditions. We consider four variables to capture macroeconomic conditions which have been shown to be important determinants of stock market volatility: industrial production index, producer price index, unemployment rate, and total nonfarm payroll. We first analyze whether these variables are related to the conditional variances of cash flow and discount rate news. We find that an increase in the industrial production index and nonfarm employment significantly decreases the conditional variance of cash flow news while an increase in the producer price index and unemployment significantly increases it. On the other hand, an increase in the producer price index significantly increases the conditional variance of discount rate news while all other variables have statistically insignificant effects. We then turn our attention to the effect of these variables on the relative importances of cash flow and discount rate news; we find the producer price index to be the only variable with a statistically significant effect. Specifically, an increase in the PPI inflation (inflation) rate makes the cash flow news more, and discount rate news less, important in determining the conditional variance of market returns. Furthermore, the effects of inflation on the relative importances of cash flow and discount rate news are significantly different from each other.

Having identified inflation as the main determinant, we take a closer look at its effect on the time variation in the conditional variance decomposition of market returns. We first distinguish between positive and negative changes in the producer price index to analyze any asymmetries between the effects of an increase and a decrease in inflation. We find that an increase in inflation significantly increases the relative importance of cash flow news while it decreases the relative importances of both discount rate news and the conditional covariance components, although insignificantly. The opposite holds for a decrease in inflation. We then distinguish between expected and unexpected inflation. We find that it is the unexpected, and not the expected, inflation that drives the relative importance of both components. An increase in the unexpected inflation significantly increases the relative importance of cash flow news and significantly decreases that of discount rate news. We also distinguish between expansion and recession periods as defined by the National Bureau of Economic Research (NBER) and analyze any asymmetries over the business cycles. An increase in inflation significantly increases the relative importance of cash flow news in both expansions and recessions, with a slightly bigger effect in recessions. Inflation does not have a significant effect on the relative importance of discount rate news when we distinguish between expansions and recessions. We also analyze its long-term effect based on impulse response functions obtained from a VAR that includes the relative importance of cash flow and discount rate news and changes in inflation. A positive shock to inflation increases the relative importance of both components in the long run.

Finally, we turn our attention to the economic importance of our results by estimating a conditional version of the Campbell and Vuolteenaho's (2004) (CV) framework. We argue that it is economically important to account for time variation in decomposing the portfolio's overall beta with the market if a model which captures this time variation performs better than models ignoring it. To this end, we consider a conditional version of the two-beta framework with time-varying betas obtained by estimating multivariate conditional variance models for cash flow news, discount rate news and demeaned returns on the 25 size and book-to-market portfolios one at a time. We show that this conditional asset pricing model provides reasonable estimates of risk prices and relative risk aversion coefficients, and performs much better than several alternative models, such as the unconditional CV two-beta model, CAPM and the three-factor model of Fama and French (1996), in several dimensions. First, the constant is not significantly different from zero in both the constrained and unconstrained estimation of this model, while the same cannot be said for most competitor models considered. Second, the cash flow news has a significantly positive risk price of approximately 1.6% per month (19% per annum), which is quite reasonable, while other models produce either too high or insignificant risk prices. Third, this conditional framework implies very reasonable values for the relative risk aversion coefficient of between 3 and 11, while other models sometimes imply negative coefficients. Finally, this model accounts for slightly more than 60% of the variation in the cross-section of expected returns, which is on par with the Fama–French three-factor model and better than other conditional and unconditional models.

The paper proceeds as follows: Section 2 describes the approach to obtain proxies for cash flow and discount rate news. Section 3 presents the model for estimating conditional variances and covariance, and reports the empirical results for time variation in the conditional variance decomposition of returns. Section 4 studies the relation between decomposition of conditional variance of the market and main macroeconomic indicators. Section 5 presents the pricing implications of our time-varying approach, and Section 6 concludes.

2.2 Cash Flow and Discount Rate Proxies

In this section, we first briefly discuss the Campbell and Shiller (1988) return decomposition approach before discussing our empirical choices for its implementation. Based on the log-linear approximation of returns in Campbell and Shiller (1988), Campbell (1991) shows that unexpected returns can be decomposed into changes in investors' expectations about discounted sum of future cash flows and discount rates, which are generally referred to as cash flow (CF) and discount rate (DR) news, respectively. Specifically, Campbell (1991) derives the following relation:

$$\begin{aligned} r_{m,t+1} - E_t r_{m,t+1} &= (E_{t+1} - E_t) \sum_{j=0}^{\infty} \rho^j \triangle d_{t+1+j} - (E_{t+1} - E_t) \sum_{j=1}^{\infty} \rho^j r_{m,t+1+j} \\ &= CF_{t+1} - DR_{t+1} \end{aligned} \tag{2.1}$$

where E_t represents expectation at time t. $r_{m,t}$ and d_t denote log returns and dividends at time t, respectively, and ρ is a parameter of linearization that depends on the long-term mean of the log dividend–price ratio. Equation (1) suggests that unexpected returns are higher if future cash flows are higher than expected or future discount rates are lower than expected or a combination of the two. One can then analyze the overall contribution of each component by decomposing the unconditional variance of unexpected return r as follows:

$$var(r_{t+1}) = var(CF_{t+1}) + var(DR_{t+1}) - 2cov(CF_{t+1}, DR_{t+1}) \tag{2.2}$$

The ratio of each component on the right-hand side of Equation (2) to unconditional variance of stock returns can then be interpreted as the relative contribution of that component in determining the overall movements in stock prices.

To implement this decomposition empirically, Campbell and Shiller (1988) propose modeling the short-run dynamics of expected returns to obtain forecasts of future expected returns and, thus, a proxy for discount rate news and back out cash flow news from Equation (1). They also suggest that this can be easily achieved in a VAR of order one which includes returns and its common predictors. Thus, the standard approach in the literature is to estimate the following VAR (1):

$$\mathrm{Z}_{t+1} = \alpha + \Pi \mathrm{Z}_t + u_{t+1} \tag{2.3}$$

where Z_t is a $(n \times 1)$ vector whose first element is the market return and other elements are variables that might have some power in predicting market returns. Proxies for cash flow and discount rate news can then be obtained based on estimated VAR parameters and a choice of ρ as follows:

$$\begin{aligned} \widehat{DR}_{t+1} &= e1'\hat{\lambda}\hat{u}_{t+1} \\ \widehat{CF}_{t+1} &= (e1' + e1'\hat{\lambda})\hat{u}_{t+1} \end{aligned} \tag{2.4}$$

where $e1$ is a $(n \times 1)$ vector whose first element is equal to one while others are equal to zero and $\hat{\lambda} \equiv \rho\hat{\Pi}(I - \rho\hat{\Pi})^{-1}$.

The final step in the empirical implementation of the standard approach is to choose a value for ρ and, more importantly, the variables to include in the VAR as predictors for the market return. As mentioned above, ρ is a function of the long-run mean of the log dividend–price ratio and, thus, can be easily estimated. We choose ρ to be equal to 0.996 for our set of monthly data. As discussed above, the first variable in the VAR system is the market return, which we proxy by the continuously compounded excess return on the Standard & Poor's (S&P) 500 index. The choice of predictor variables is much more difficult. This is mostly due to the fact that the empirical results tend to be quite sensitive to the choice of predictor variables, as shown in Chen and Zhao (2009). That said, Engsted, Pedersen and Tanggaard (2012) argue that this sensitivity is reduced when one includes a price-scaled variable as a predictor variable in the VAR system. More specifically, they show that one needs to include the dividend–price ratio for the VAR to be theoretically valid.

In this paper, we follow their suggestion and include dividend–price ratio as our price-scaled variable. In addition to dividend–price ratio (dp), we include term spread (tms) and small stock value spread (svs) in the VAR system for our main set of results. Term spread is the difference between long-term yield on government bonds and Treasury-bill yield, and dividend–price ratio is the logarithm of the ratio of 12-month moving sum of dividends to price. Both of these variables are from Amit Goyal's website. Small stock value spread is obtained by subtracting the log book-to-market ratio of small growth stocks from the log book-to-market ratio of small value stocks as in CV. We use the six size and book-to-market sorted portfolios from Ken French's website to compute small stock value spread. While term spread and dividend price ratio have been widely used as predictors in the literature, CV propose small stock value spread as a predictor of market returns. They argue that ICAPM rectifies the value anomaly once small value stock returns forecast higher market returns, and small growth stock returns lower market returns. In each section, we discuss the robustness of our results to using alternative sets of predictor variables.

We obtain monthly proxies for cash flow and discount rate news by estimating the VAR system using monthly data between 1929 and 2014. Table 1 presents some summary statistics for the variables in the VAR system.

[Insert Table 1 about here]

Table 2 presents the estimates of the parameters in the VAR system. The first row is the equation for returns and suggests that lagged returns, term spread and dividend yield have predictive information about returns but the associated adjusted R^2 is low, suggesting that the overall predictive power of these variables is low, as it is well known. The predictor variables are highly persistent with autoregressive coefficients varying between 0.96 and 0.99. The dividend yield is predicted also by lagged return and lagged term spread.

[Insert Table 2 about here]

Table 3 presents the decomposition of the unconditional variance in Equation (2) for S&P 500 returns in basis points, i.e. the variance estimates are multiplied by 10,000, as well as the relative contribution of each component. The unconditional variance of unexpected S&P 500 returns (in basis points) is about 30 during our sample period. Discount rate and cash flow news explain 36% and 30% of the unconditional variance of S&P 500 returns, respectively, while the remaining 33% is due to the covariance between the two components. These results are broadly consistent with those in literature. For example, Chen and Zhao (2009) also report approximately equal contributions of CF and DR news to the unconditional market variance when dividend yield is used instead of the price–earnings ratio in the VAR system.

[Insert Table 3 about here]

2.3 Time Variation in Cash Flows and Discount Rates

It is well known that the conditional variance of market returns exhibits significant variation over time. This in turn implies that the components of the market return, i.e. cash flow and discount rate news, might also have time varying conditional variances and co-variances. More importantly, the contributions of these components to the conditional variances of stock returns might also be changing over time and might be quite different from their contributions to the overall unconditional variance.

In this section, we analyze the time variation in the contribution of each component in determining the conditional variance of market returns. One can obtain the conditional variance decomposition of market returns by replacing the unconditional quantities in Equation (2) with their conditional counterparts. This, of course, requires proxies for the conditional variances of each component as well as for their conditional covariance. We do this by estimating multivariate conditional variance models for cash flow and discount rate news. Specifically, we consider the dynamic conditional correlation model (DCC) of Engle (2002) where the conditional variance of each component is modeled as a univariate symmetric GARCH(1,1) model and the correlations have their own autoregressive dynamics. Given that both cash flows and discount rates have zero mean by construction, we can directly model their conditional variances and correlations without having to estimate a specification for their mean. Let η_{t+1} denote the (2×1) vector of cash flow and discount rate news at time $t+1$, i.e. $\eta_{t+1} = [CF_{t+1}, DR_{t+1}]'$, and $\sum_t$ denote their (2×1) conditional variance matrix based on information at time t. We then model

$$\begin{aligned}
\Sigma_t &= \begin{bmatrix} var_t\left(CF_{t+1}\right) & cov_t\left(CF_{t+1}, DR_{t+1}\right) \\ cov_t\left(CF_{t+1}, DR_{t+1}\right) & var_t\left(DR_{t+1}\right) \end{bmatrix} \\
&= \begin{bmatrix} \sigma^2_{CF,t} & \sigma_{CF,DR,t} \\ \sigma_{CF,DR,t} & \sigma^2_{DR,t} \end{bmatrix} \\
&= D_t R_t D_t
\end{aligned} \tag{2.5}$$

where

$$R_t = Q_t \oslash Q_t^*,$$

$$Q_t = (1-a-b)\bar{R} + a\varepsilon_{t-1}\varepsilon'_{t-1} + bQ_{t-1}, \tag{2.6}$$

$$Q_t^* = \begin{bmatrix} q_{CF,t} & \sqrt{q_{CF,DR,t}} \\ \sqrt{q_{CF,DR,t}} & q_{DR,t} \end{bmatrix}$$

and ε_t is the (2×1) vector of standardized cash flow and discount rate news, i.e. $\varepsilon_t = [{}^{CF_t}/_{\sigma_{CF,t}}, {}^{DR_t}/_{\sigma_{DR,t}}]$, and $\oslash$ denotes element-by-element division. D_t is the diagonal matrix with conditional standard deviations of cash flow and discount rate news, i.e. $D_t = \left[\sigma_{CF,t}, \sigma_{DR,t}\right]$, which themselves are modeled as GARCH(1,1) processes. The DCC MV-GARCH model is estimated via maximum likelihood based on a three-step approach. The first step fits univariate symmetric GARCH(1,1) models for cash flow and discount rate news. The second step estimates the constant conditional correlation based on the usual correlation estimator using the standardized residuals. The final step consists of plugging the correlation estimate into the equation for Q_t to obtain the estimates of a and b, which govern the dynamics of the conditional correlations. Table 4 presents the results from the estimation of this model.

[Insert Table 4 about here]

Given the stylized facts about the conditional variance dynamics of market returns, it is not surprising to find that the conditional variances of its components are time-varying and highly persistent, but stationary. Furthermore, their conditional correlation is also time-varying and highly persistent. Figure 1 presents this time variation in conditional variance of cash flow and discount rate news and their conditional covariance along with the conditional variance of market returns between 1929 and 2014.

[Insert Figure 1 about here]

As the market goes through volatile and tranquil periods, the conditional variances of its components, not surprisingly, follow these movements closely. For example, it is well known that market returns tend to be more volatile during recessions compared to expansions. It is then not surprising that both cash flow and discount rate news also become, on average, more volatile in recessions compared to expansions. However, several interesting, and not necessarily expected, facts emerge from Figure 1. First, there are some periods during which one of the components becomes more volatile while the other does not. For example, discount rate news becomes considerably more volatile than cash flow news during the recession caused by the 1973 oil crisis. Second, the conditional covariance between cash flow and discount rate news increases (in magnitude) in recessions, especially during the Great Depression, the oil crises and the Global Financial Crisis. Last but not least, discount rate news seems to be relatively more volatile, on average, than cash flow news. That said, this relation seems to change over time and cash flow news is more volatile during most of the Great Depression and for several months during the Global Financial Crisis. Overall, these results suggest that the conditional variance of cash flow and discount rate news, as well as their conditional covariance, vary significantly over time. More importantly, these time variations are not symmetric and exhibit significant differences during certain periods. This, in turn, implies that the relative contribution of each component to the conditional variance of market returns also varies over time.

To analyze more closely the time variation in the relative contribution of each component to the conditional variance of market returns, we compute the ratio of the conditional variance of each component as well as their conditional covariance to the conditional variance of unexpected market returns, i.e.$\sigma^2_{CF,t}/\sigma^2_{m,t}$, $\sigma^2_{DR,t}/\sigma^2_{m,t}$, $-2\sigma(CF,DR)_t/\sigma^2_{m,t}$. The sum of these ratios is equal to one.

Table 5 presents some basic summary statistics on these ratios. The cash flow and discount rate news contribute, on average, about 30% and 41% to the conditional variance of market returns, and their conditional covariance contributes, on average, about 29%. These results are very similar to the unconditional variance decomposition of market returns reported in Table 3. The contribution of discount rate news varies between 24% and 65% with a standard deviation of 9%, while that of cash flow news is less volatile and varies between 15% and 61% with a standard deviation of 7%. The contribution of the covariance varies between 10% and 45% with a standard deviation of approximately 6%.

[Insert Table 5 about here]

Figure 2 presents the variation of these ratios over time. The contribution of both components to the conditional variance of market returns varies significantly over time. The relative importance of discount rate news increases, on average, since the Great Depression and reaches its peak around the burst of the dotcom bubble and the 2001 recession. It then steadily declines up until the end of the Global Financial Crisis around 2011 and 2012. The relative importance of cash flow news is comparatively more stable in the earlier sample period up until the early 1960s. It then starts to decline and stays at a lower level up until the recession caused by the Global Financial Crisis when it jumps and reaches its highest level. Campbell et al. (2013) argue that the 2001 downturn is mainly related to positive revisions in return expectations, while the Global Financial Crisis is mainly related to negative revisions in cash flows. CV also analyze the relationship between the two types of news and NBER cycles. Similarly, they associate the 2001 crisis with rising discount rates, and the Great Depression with both CF and DR news. Different from our work, inferences in both of these papers are based on smoothed news levels rather than on conditional variances.

[Insert Figure 2 about here]

It is also easy to see from Figure 2 that the increase in the relative importance of discount rate news comes at the expense of the relative importance of the conditional covariance between cash flow and discount rate news. To be more precise, the relative importance of the conditional covariance decreases from about 45% in 1929 to about 15% around the early 1950s. Its contribution then stays around 25%, starts to decline in the early 1990s, and reaches its lowest values during the 2001 and 2008 recessions.

To understand the time variation in the contribution of cash flow relative to that of discount rate news, we also compute the ratio of the conditional variances of cash flow and discount rate news, i.e. $\sigma^2_{CF,t}/\sigma^2_{DR,t}$. Figure 3 presents the variation of this ratio over time, where a ratio greater than one implies that the conditional variance of cash flow news is relatively more important than that of discount rate news in determining the conditional variance of market returns.

[Insert Figure 3 about here]

The cash flow news is more important than discount rate news for about one third of our sample period. However, this changes significantly over time. For example, the cash flow news is, on average, the main determinant of the conditional market variance in the earlier part of the sample before the mid-1950s, although there are still periods, especially recessions, during which discount rate news becomes more important relative to the cash flow news. However, the discount rate is the main determinant of the conditional market variance between the mid-1950s and the Global Financial Crisis. This changes dramatically during the Global Financial Crisis and the cash flow news once again becomes the main determinant. These results about the Global Financial Crisis are consistent with those in Campbell et al. (2013).

2.3.1 Robustness Checks

In this section, we analyze the robustness of these results to making alternative empirical choices. We performed all the analysis discussed above under alternative empirical assumptions. For the sake of brevity, we summarize our findings without presenting any results.

We start with the robustness of our results to using alternative predictor variables in the original VAR system used to obtain cash flow and discount rate proxies. As discussed in Section 2, it is well known that the return decomposition approach of Campbell and Shiller (1988) tends to be sensitive to the choice of predictor variables in the VAR system. To analyze whether this sensitivity affects our findings, we consider several alternative sets of predictor variables in the VAR system. In all these different specifications, we always include a price-scaled variable, such as dividend yield or price–earnings ratio, since Engsted, Pedersen and Tanggaard (2012) argue that a price-scaled variable is required for the VAR system to be valid and stress the fact that dividend yield is indeed the theoretically correct one. Specifically, we perform the above analysis using cash flow and discount rate news proxies obtained based on the following sets of predictor variables: (1) excess returns, term spread, price–earnings ratio, small stock value spread; (2) excess returns, term spread, dividend yield, small stock value spread, default spread. Our findings suggest that cash flow and discount rate proxies based on different sets of predictor variables are highly correlated with each other. The conditional variances of CF and DR news based on the original set of predictor variables have 0.94 and 0.71 correlations with those based on the first set of alternative predictor variables. We find an approximate correlation of 0.93 between CF and DR variances obtained from our original set of state variables and their counterparts from the second set of alternative predictor variables. However, our results also confirm the findings of the previous literature on the sensitivity of the unconditional variance decomposition. That said, we find that conditional variance decomposition is much less sensitive to the choice of predictor variables than the unconditional variance decomposition. More importantly, as we will discuss below, our findings on the relation between relative importances and macroeconomic variables are robust to using alternative sets of predictor variables. Finally, we also consider different values for ρ, which do not yield qualitatively different conditional variances of cash flow and discount rate news or relative importance ratios.

Following CV, we also distinguish between the early sample (1929–1963) and the modern sample (1963–2014). There are two main reasons motivating this split. First, the results emerging from the earlier period are highly affected by the Great Depression. As CV remark, it is quite reasonable to believe that during these early years most of the unconditional variance is attributed to CF news due to the fact that the sample is dominated by highly leveraged firms. CV show that DR uncertainty is almost flat during this period, thus explaining why their two-beta model and CAPM perform equally well for these months. The second reason emanates from the adjustments in stock market listing prerequisites. While in the early period there existed strong profitability requirements for stocks to be listed, in the late 1970s NASDAQ stocks were added to the NYSE to benefit from equity financing. Hence, this scenario also supports the idea that CF was unsurprisingly more important than DR during the pre-1963 period, well before firms with high exposure to DR risk started co-existing in the index. In this paper, we mostly focus on the overall sample since we consider time variation and can analyze different periods individually. Furthermore, as in Bianchi (2015), we also believe that the extreme events in the early sample period affect investors' expectations and should therefore be included when obtaining empirical proxies. Nevertheless, we still obtain cash flow and discount rate news for the modern sample period by estimating the VAR system in the modern sample and thus completely ignoring the early sample period. We find that our original cash flow and discount rate news are highly correlated with these ones.

We also performed a further decomposition of the discount rate news into unexpected changes in investors' expectations about future risk premia and risk-free rate. Engsted, Pedersen and Tanggaard (2012) suggest that risk-free rate should be a right-hand variable based on the fact that we are predicting the excess returns on the left-hand side. To this end, we included the risk-free rate as an additional predictor variable in the VAR system in Equation (3). One can then decompose the unexpected returns into news about cash flows, risk premia and riskless rate following Campbell and Ammer (1993). This decomposition is very similar to the standard Campbell and Shiller (1988) decomposition and we, thus, refer the reader to the Campbell and Ammer (1993) for additional details. The obtained conditional variances show to be almost perfectly correlated with the conditional variances from our model where risk-free rate is not a predictor variable. The results remain robust when we estimate VAR under the modern sample instead of the whole sample.

2.4 What Explains the Time Variation in Cash Flows and Discount Rates?

So far, we have documented significant time variation in the relative importance of different components in determining the conditional variance of market returns. We have also alluded to the possibility that this time variation might be related to economic conditions. In this section, we analyze the relation between the conditional variance decomposition of market returns and macroeconomic conditions. To do this, we consider four variables to capture macroeconomic conditions: industrial production index (ip), producer price index (ppi), unemployment rate $(unemp)$ and total nonfarm payroll (emp). We choose to focus on these four variables following the previous literature, such as Schwert (1989), Flannery and Protopapadakis (2002) and Engle et al. (2008), which show these four variables to be important determinants of stock market volatility. These variables are available from the Federal Reserve Bank of St. Louis and we consider their latest available vintage. We restrict the sample period to between 1948 and 2014 since the unemployment rate is only available starting 1948. We start by analyzing whether these variables have an effect on the conditional variance of unexpected market returns. To this end, we estimate the following GARCH(1,1) specification with lagged exogenous variables for the conditional variance of unexpected market returns:

$$\sigma_{m,t}^2 = exp\left(\gamma_m^{'} X_{t-1}\right) + \alpha_m \varepsilon_{m,t-1}^2 + \beta_m \sigma_{m,t-1}^2 \tag{2.7}$$

where X_{t-1} is a $(k \times 1)$ vector of lagged exogenous variables including a constant. We analyze the effect of exogenous variables in exponential form to guarantee that the estimated variance is positive without having to impose restrictions on their coefficients. We first consider the lagged (log) changes of these macroeconomic variables separately and then jointly as exogenous variables in the conditional variance specification.[3] When considered both separately and jointly, the change in the producer price index is the only variable that has a significant effect on the conditional variance of unexpected returns. An increase in the producer price index increases the conditional variance of unexpected returns on the aggregate index, in line with the findings in the previous literature.

A variable might still have a significant effect on the conditional variances of the components, even if it does not have a significant effect on the conditional variance of unexpected returns. To this end, we now analyze the effect of these variables on the

[3]We also considered lagged (log) changes of these variables separately as well as jointly in the mean equation for unexpected returns. None of them has a statistically significant effect in the mean equation of unexpected returns in separate and joint regressions at the 5% level. To be consistent with our analysis in Section 3, we present the results based on the estimation without controlling for the effect of these variables in the mean equation of unexpected returns. Nevertheless, we analyzed the effect of these macroeconomic variables on the conditional variance of unexpected returns after having removed their effect on the mean of unexpected returns and our results are very similar to those presented.

conditional variances of cash flow and discount rate news. We estimate the GARCH(1,1) specification with exogenous variables in Equation (7), rather than a simple GARCH(1,1) specification, in the first step of a multivariate dynamic conditional correlation specification similar to that in Equation (5) and Equation (6). The columns titled CF and DR in Table 6 present the coefficient estimates of macroeconomic variables in the conditional variance specifications of cash flow and discount rate news, respectively. The column titled F-stat presents the F-statistic of the null hypothesis that the coefficient estimates of a given macroeconomic variable are equal in the conditional variance specifications of cash flow and discount rate news. We start with the results in Panel (a) where we consider the effect of each macroeconomic variable separately. An increase in the industrial production index and nonfarm employment significantly decreases the conditional variance of cash flow news, while an increase in the producer price index and unemployment significantly increases it. On the other hand, an increase in the producer price index significantly increases the conditional variance of discount rate news while all other variables have statistically insignificant effects. When we consider the effect of these variables jointly, our results remain similar. The only exception is the effect of the industrial production index on the conditional variance of cash flow news which becomes statistically insignificant when we control for the effect of other variables. In both separate and joint specifications, none of the macroeconomic variables has statistically different effects on the conditional variances of cash flow and discount rate news.

[Insert Table 6 about here]

We now analyze whether macroeconomic conditions affect the relative importance of cash flow and discount rate news in determining the conditional variance of unexpected returns. We do this by regressing the relative importance of cash flow and discount rate news on the macroeconomic variables. We do not consider the relative importance of their conditional covariance since it is simply one minus the sum of the relative importances of cash flow and discount rate news. Given that we only consider linear effects in our regressions, one can simply compute the effect of a given macroeconomic variable on the relative importance of the conditional covariance as the negative of the sum of its effects on relative importances of cash flow and discount rate news. Given that the relative importances of both components are quite persistent, as discussed in Section 3, we control for their lagged values in these regressions. To be more precise, we estimate the following specification via seemingly unrelated regressions:[4]

$$
\begin{aligned}
\sigma^2_{CF,t}/\sigma^2_{m,t} &= \theta^{'}_{CF}X_{t-1}+\phi_{11}\sigma^2_{CF,t-1}/\sigma^2_{m,t-1}+\phi_{12}\sigma^2_{DR,t-1}/\sigma^2_{m,t-1}+\varepsilon_{CF,t} \\
\sigma^2_{DR,t}/\sigma^2_{m,t} &= \theta^{'}_{DR}X_{t-1}+\phi_{21}\sigma^2_{CF,t-1}/\sigma^2_{m,t-1}+\phi_{22}\sigma^2_{DR,t-1}/\sigma^2_{m,t-1}+\varepsilon_{DR,t}
\end{aligned}
\tag{2.8}
$$

Table 7 presents the coefficient estimates on the macroeconomic variables from the estimation of the regression models in Equation (8) as well as their differences and the negative of their sum from the equations for cash flow and discount rate news.

[Insert Table 7 about here]

The producer price index is the only variable that has significant effects on the relative importances of CF and DR news. Specifically, an increase in the producer price index increases the relative importance of the cash flow conditional variance while it decreases the relative importances of discount rate conditional variance and their conditional covariance. In other words, an increase in inflation makes the cash flow news more important in determining the conditional variance of returns at the expense of discount rate news. Furthermore, the effects of inflation on the relative importances of cash flow and discount rate news are significantly different from each other.

[4]We also estimated this specification via generalized method of moments where we use X_{t-1} , $\sigma^2_{CF,t-1}/\sigma^2_{m,t-1}$ and $\sigma^2_{DR,t-1}/\sigma^2_{m,t-1}$ as instruments. This allows us to obtain the same coefficient estimates as SUR estimation but correct the standard errors via heteroscedasticity and autocorrelation consistent standard errors à la Newey–West. Our conclusions based on HAC standard errors remain similar to those presented.

Having identified inflation as the main determinant of the conditional variances of cash flow and discount rate news, as well as their relative contributions to the conditional variance of unexpected returns, we focus on the effect of inflation on the conditional variance decomposition. We first discuss the intuition behind why inflation affects the conditional variance decomposition. We then break down its total effect in several dimensions.[5]

2.4.1 Discussion on the Effect of Inflation

Many studies as early as Officer (1973) have analyzed the relation between stock market volatility and macroeconomic variables. In a widely-cited paper, Schwert (1989) relates stock market volatility to the level and volatility of macroeconomic activity. Following the seminal paper of Schwert (1989), Engle et al. (2008) also analyze the effect of inflation and industrial production on stock market volatility. Specifically, they find that increases in industrial production decrease volatility and more inflation leads to high stock market volatility. Given these results, it is then not too surprising to find that industrial production and inflation have similar effects on the conditional variances of the cash flow and discount rate news. What is interesting in our results is the finding that an increase in the inflation rate makes cash flow news more important in determining the conditional variance of market returns. Before discussing potential explanations for why cash flow news might become relatively more important following an increase in inflation, we discuss some further results related to this finding. In our main set of results, we decompose the

[5]We performed all the analysis below for the other variables but we did not find any significant results, confirming that inflation is the main determinant of the conditional variance decomposition of unexpected returns. Motivated by the work of Campbell and Cochrane (1999), we also consider the possibility that changing risk aversion leads to varying discount rates and therefore varying cash flow news too. We use the the Variance Risk Premium (VRP) of Bollerslev et al. (2011) as a proxy for risk-aversion. Given the noise in the the measure along with the fact that authors use macroeconomic variables to smooth the risk aversion proxy, we interpret the risk aversion as the channel relating our relative ratios to macroeconomic conditions rather than the main determinant itself. This observation is subject to change for alternate and more robust proxies of risk aversion. Finally, we consider the highly persistent measure of investors' sentiment (IS) as in Baker and Wurgler (2006). IS affects significantly and negatively the relative importance of cash flow news and positively that of discount rate news.

log returns in excess of the risk-free rate into cash flow and discount rate news. Although these returns are nominal, in the strict sense of the word, we believe that using log returns in excess of the risk-free rate removes the direct effect of inflation on our decomposition. In other words, we believe that our finding on the effect of inflation on the relative importance of cash flow news cannot be explained by our use of "nominal returns" in excess of the risk-free rate. We nevertheless consider decomposing the real returns, computed as the log returns in excess of the inflation rate. We first show that they are indeed highly correlated (98%) with log returns in excess of the risk-free rate. We then proceed to perform the same analysis above in Section 4, and find that an increase in the inflation rate makes cash flow news more important in determining the conditional variance of real market returns. As mentioned in Section 3.1, one can also consider a further decomposition of the nominal returns into news about cash flows, discount rates and real-rate of returns. When we consider this further decomposition, we find that the log change in the producer price index continues to increase significantly the relative importance of cash flow news in determining the conditional variance of nominal market returns, while it significantly (at 10% level) decreases that of discount rate news and increases, but insignificantly so, that of news about real-rate of returns. Overall, these two sets of additional results suggest that our main finding about the effect of inflation on the relative importance of cash flow news is not due to using "nominal" excess returns. We now turn our attention to other potential explanations. Although there are several theoretical models relating inflation to stock market volatility (see for example David and Veronesi (2013)), these studies do not provide much theoretical guidance on our finding since they treat inflation as a fundamental alongside cash flow and discount rate news. One such potential explanation might follow from the relation between inflation and uncertainty about economic activity and policy. It is well known, at least since Friedman (1977), that an increase in inflation creates higher economic uncertainty (see for example Holland (1995)). There is also a literature in corporate finance documenting that higher economic uncertainty results in higher uncertainty about firms' investment decisions and, thus, their cash flows. Although higher inflation might also increase uncertainty about future discount rates, one would expect this effect to be stronger for cash flows than discount rates. Based on these two channels, it is then not difficult to argue that cash flows become more volatile than discount rates following an increase in inflation. Another potential explanation might be tax-related. For example, Feldstein (1980) argues that higher inflation can reduce real profits through its effect on taxes paid by firms on their earnings. To be more precise, taxable profits in the US are computed by subtracting depreciation from net operating income. This depreciation amount depends on the book value of the asset rather than its market value. When inflation increases, this method of depreciation, called historic-cost depreciation, causes the real value of the tax shield provided by the depreciation and, thus, the real taxable profits, to decrease. He also argues that this effect of inflation might be smaller on the discount rates compared to earnings. However, he does not explicitly discuss the effect of inflation on the volatility of earnings and discount rates. That said, it is not difficult to argue based on his findings that higher inflation might increase the volatility of earnings more than the volatility of discount rates. This might then explain our finding on the relative importances of cash flow and discount rate news in determining the conditional variance of market returns.

2.4.2 A Closer Look at the Effect of Inflation

In this section, we analyze different dimensions related to the effect of inflation on the conditional variance of unexpected market return and its components as well as on the relative importances of these components. In each of the following subsections, we perform the same analysis as above. Specifically, we first estimate the specification in Equation (7) where we include different inflation components as exogenous variables in the conditional variance of unexpected returns. We then consider these inflation components as exogenous variables in the conditional variance specifications of cash flow and discount rate news in a multivariate conditional variance specification. This allows us to understand the sources of any potential asymmetries in the effects of inflation components on the conditional variance of unexpected returns. Finally, we estimate the specification in Equation (8) where we consider different inflation components as exogenous variables in the system. This, in turn, allows us to analyze potential asymmetries in the effect of different inflation components on the relative importances of cash flow and discount rate news.

The Effects of Positive and Negative Changes in Inflation

We first distinguish between positive and negative changes in the producer price index to analyze any asymmetries between the effects of an increase and a decrease in inflation. In our sample period between 1948 and 2014, inflation increases in 467 months and decreases in 226 months, while it remains unchanged in 110 months. Panel (a) of Table 8 presents the coefficient estimates on the positive and negative changes in the producer price index in the conditional variance specifications of unexpected returns, cash flow and discount rate news. An increase in inflation significantly increases the conditional variances of both cash flow and discount rate news, which in turn explains its positive significant effect on the conditional variance of unexpected returns. On the other hand, a decrease in inflation significantly increases the conditional variance of cash flow news but decreases, although insignificantly, the conditional variance of discount rate news. These mixed results, in turn, explain the insignificant effect of a decrease in inflation on the conditional variance of unexpected returns. Panel (b) of Table 8 presents the coefficient estimates on positive and negative changes in inflation in the equations for the relative importances of cash flow and discount rate news. An increase in inflation significantly increases the relative importance of cash flow news, while it decreases, although insignificantly, relative importances of both discount rate news and the conditional covariance components. The opposite holds for a decrease in inflation. In other words, a decrease in inflation significantly decreases the relative importance of cash flow news, while it increases, although insignificantly, relative importances of both discount rate news and the conditional covariance components. More importantly, both increases and decreases in inflation have significantly different effects on the relative importances of cash flow and discount rate news. These results suggest that both positive and negative changes in inflation affect mostly cash flow news, in line with our previous findings on the effect of the overall change in inflation.

[Insert Table 8 about here]

The Effects of Expected and Unexpected Changes in Inflation

We now distinguish between expected and unexpected changes in inflation, similar to Schwert (1989) and Engle et al. (2008). Specifically, we estimate the following autoregressive model with 12 lags and monthly dummy variables for the change in the producer price index:

$$\Delta\log(ppi_t) = \delta_0 + \sum_{i=1}^{12} \delta_i \Delta\log(ppi_{t-i}) + \sum_{i=1}^{11} \kappa_i D_{i,t} + \mathrm{v}_t \tag{2.9}$$

where Δ is the first difference operator and $D_{i,t}$ is a dummy variable that takes the value one if the period t is i^{th} month of the year. The fitted values from this model can then be interpreted as the expected inflation while the estimated residual term, $\hat{\mathrm{v}}_t$, can be interpreted as the unexpected inflation. Panel (a) of Table 9 presents the coefficient estimates on the expected and unexpected inflation in the conditional variance specifications of unexpected returns, cash flow and discount rate news. An increase in the expected inflation significantly increases the conditional variances of both cash flow and discount rate news, which in turn explains its positive significant effect on the conditional variance of unexpected returns. On the other hand, the results are somewhat mixed regarding the effect of unexpected inflation. An increase in unexpected inflation significantly increases the conditional variance of cash flow news while it decreases, although insignificantly, the conditional variance of discount rate news. The overall effect of unexpected inflation on the conditional variance of unexpected returns is negative but only marginally significant at the 10% level, suggesting a decrease in the conditional variance of unexpected returns following an increase in the unexpected inflation. When we consider the effect of expected and unexpected inflation on the relative importances of cash flow and discount rate news presented in Panel (b) of Table 9, it is the unexpected inflation that drives the relative importances. To be more precise, expected inflation does not significantly affect any of the relative importances, while an increase in the unexpected inflation significantly increases the relative importance of cash flow news and significantly decreases that of discount rate news. More importantly, the effects of unexpected inflation on the relative importances of cash flow and discount rate news are also significantly different from each other, in line with our findings for the total change in inflation itself.

[Insert Table 9 about here]

The Effects of Inflation in Expansions and Recessions

Here, we distinguish between expansion and recession periods as defined by the National Bureau of Economic Research (NBER) and analyze any asymmetries in the effect of inflation on the conditional variance decomposition of unexpected returns over the business cycles. To this end, we consider the interaction terms between the change in producer price index and recession and expansion dummy variables as exogenous variables in the conditional variance and relative importance specifications. Panel (a) of Table 10 presents the coefficient estimates on the change in inflation in expansions and recessions in the conditional variance specifications of unexpected returns, cash flow and discount rate news. The overall effect of inflation on the conditional variance of unexpected returns and its components is driven by its effects in recessions. To be more precise, an increase in inflation during a recessionary period significantly increases conditional variances of unexpected returns and both of its components. Although an increase in inflation during an expansionary period also increases the conditional variance of unexpected returns, it does not significantly affect the conditional variances of cash flow and discount rate news at the 5% level. Turning our attention to the relative importances, we find that an increase in inflation significantly increases the relative importance of cash flow news in both expansions and recessions, with a slightly bigger effect in recessions. Although inflation decreases the relative importances of discount rate news and the conditional covariance, these effects are not statistically significant at any conventional level. More importantly, the effects of inflation on the relative importances of cash flow and discount rate news are also significantly different from each other during both expansionary and recessionary periods.

[Insert Table 10 about here]

Long-run Effects of Inflation

So far, we have provided empirical evidence on the immediate effect of inflation on the conditional variance decomposition. We now analyze its long-term effect on the relative importances of cash flow and discount rate news. To this end, we compute the impulse response functions of the relative ratios to a standard deviation shock to the change in the producer price index. We do this by estimating a simple first order VAR with the relative importances of cash flow and discount rate news and the change in the producer price index as state variables. Figure 4 presents the generalized impulse response functions as described by Pesaran and Shin (1998), which are based on an orthogonal set of innovations that do not depend on the ordering of the variables in the VAR system.[6]

[6]The generalized impulse responses to a specific variable are derived based on the Cholesky factor computed with that variable at the top of the Cholesky ordering. We also considered standard impulse responses where we considered the change in the producer price index as the first variable in the VAR system, assuming that the innovations to the producer price index contemporaneously affect the relative importances of cash flow and discount rate news but not vice versa. The standard impulse responses of relative importances of cash flow and discount rate news are very similar to their generalized impulse responses presented here.

[Insert Figure 4 about here]

In line with our previous findings, the relative importance of cash flow news increases following a standard deviation positive shock to the change in the producer price index. The impulse response is statistically different from zero since the first month, suggesting a significant impact response of relative importance of cash flow news to inflation shocks. It continues to remain significant during the following months to reach its peak after 4 months before leveling off after approximately 40 months. Furthermore, it is statistically different from zero after 100 months, suggesting a relatively permanent effect of inflation on the relative importance of cash flow news. The impulse response function of the relative importance of discount rate news reveals results slightly different from our previous findings. Specifically, it is positive but insignificant after one month. It is negative between two and nine months but remains insignificant. After ten months, it is positive but significantly so only after 29 months. These results suggest that inflation does not have a significant effect on the relative importance of the discount rate news in the short run, but it has a significant positive effect in the long run after about 30 months.

Finally, we also analyze whether changes in inflation cause (in the sense of Granger (1969)) the relative importances of cash flow and discount rate news to change. For each equation in the VAR system, Table 11 presents the Wald statistics for the significance of the coefficient estimates on other lagged endogenous variables. The statistic in the last row is the statistic for the joint significance of all other lagged endogenous variables in that equation. There is strong statistical evidence that changes in inflation Granger cause the relative importance of cash flow news to change since we reject the null at any conventional significance level. Changes in inflation also Granger cause the relative importance of discount rate news to change but only marginally so at the 10% significance level. Not surprisingly, the relative importance of each component Granger causes the relative importance of the other to change. Furthermore, relative importance of discount rate news causes changes in inflation while that of cash flow news does not.

[Insert Table 11 about here]

Robustness Checks

In this section, we analyze the robustness of our results on the effect of changes in inflation on the conditional variance decomposition to making alternative empirical assumptions. We performed all the analysis discussed above under alternative empirical assumptions, which we will discuss below. For the sake of brevity, we summarize our findings without presenting all these results, which are available from the authors upon request.

We start with one of the robustness checks in Section 3. Specifically, we consider cash flow and discount rate news proxies obtained based on the sets of predictor variables discussed in Section 3.1. Our results on the effect of inflation on the conditional variances and covariance of cash flow and discount rate news, as well as on their relative importances discussed above, continue to hold when we use these alternative cash flow and discount rate news proxies.

We then consider including inflation volatility as an additional exogenous variable in our analysis. Among others, Schwert (1989) and Engle et al. (2008) provide empirical evidence that inflation volatility is one of the main determinants of stock market volatility. To this end, we obtain two proxies for inflation volatility by estimating a simple GARCH(1,1) model for either the demeaned (total) log changes or unexpected changes in producer price index, the latter of which is calculated as discussed in Section 4.2.2. We then include lagged or contemporaneous values of estimated conditional volatilities from these models as exogenous variables in the conditional variance specifications and relative importance regressions of cash flow and discount rate news. In line with the presented findings, we find that the conditional volatility of unexpected market returns and its components increase with increasing inflation volatility. However, we only find weak empirical evidence of the inflation volatility affecting the relative importances of the components, with the relative importance of cash flow news decreasing with increasing inflation volatility but only marginally significant.

Finally, we turn our attention to the robustness of our results to using alternative sample periods. As discussed in Section 4, we focus on the sample period between 1948 to 2014 in our main set of results, since the unemployment rate is only available starting 1948. However, if we focus solely on inflation, we can consider January 1929 as the starting point as data on *ppi* is available during this earlier period. Thus, we consider this longer period between January 1929 and December 2014 an alternative sample for our results. Furthermore, we split our sample on July 1963 between early and modern periods in our asset pricing tests, following CV, which we will discuss in Section 5. We use this modern period between July 1963 and December 2014 as another sample for our results. We also exclude the period after December 2006 to remove any effect of the financial crisis on our results. We then use the period between January 1948 and December 2006 as an additional sample. Our results based on these alternative samples are quite similar to those based on our original sample, suggesting the robustness of our results to using different sample periods.

2.5 Economic Importance in the Time Variation of Cash Flow and Discount Rate Betas

In this section, we analyze the economic importance of our results by allowing for time variation in the decomposition of overall market beta. To this end, we follow closely CV which show that the market beta of an asset $\beta_{i,m}$ can be decomposed into cash flow $\beta_{i,CF}$ and discount rate betas $\beta_{i,DR}$ as follows:

$$\beta_{i,m} = \beta_{i,CF} + \beta_{i,DR} \tag{2.10}$$

where

$$\beta_{i,CF} \equiv \frac{cov\left(r_{i,t}, CF_t\right)}{var(r_{m,t} - E_{t-1} r_{m,t})}$$
$$\beta_{i,DR} \equiv \frac{cov\left(r_{i,t}, -DR_t\right)}{var(r_{m,t} - E_{t-1} r_{m,t})} \tag{2.11}$$

However, differently from CV, we are interested in the conditional versions of these betas.[7] Specifically, we obtain conditional betas by estimating multivariate conditional variance models, similar to that in Equations (5) and (6), for the demeaned return on a test asset in addition to the cash flow and discount rate news. However, differently from the models considered in Section 3, we estimate asymmetric, instead of symmetric GARCH models in the first step, which allows us to capture any asymmetries in the conditional variances of returns on test assets.[8] Furthermore, following CV, we also allow for one additional lag of the news components due to the possibility of thin and non synchronous trading, especially in the earlier part of the sample, and obtain the conditional cash flow and discount rate betas as follows:

$$\widehat{\beta}_{i,CF,t} = \frac{\widehat{cov_t}\left(r_{i,t+1}, \widehat{CF}_{t+1}\right)}{\widehat{var_t}\left(\widehat{CF}_{t+1} - \widehat{DR}_{t+1}\right)} + \frac{\widehat{cov_{t-1}}\left(r_{i,t+1}, \widehat{CF}_t\right)}{\widehat{var_t}\left(\widehat{CF}_{t+1} - \widehat{DR}_{t+1}\right)}$$
$$\widehat{\beta}_{i,DR,t} = \frac{\widehat{cov_t}\left(r_{i,t+1}, -\widehat{DR}_{t+1}\right)}{\widehat{var_t}\left(\widehat{CF}_{t+1} - \widehat{DR}_{t+1}\right)} + \frac{\widehat{cov_{t-1}}\left(r_{i,t+1}, -\widehat{DR}_t\right)}{\widehat{var_t}\left(\widehat{CF}_{t+1} - \widehat{DR}_{t+1}\right)} \tag{2.12}$$

We consider the standard 25 size and book-to-market sorted Fama–French port-

[7] CV are mostly interested in the unconditional version of their model with betas estimated once over the whole sample period. In their robustness checks, they nevertheless consider conditional covariances estimated using a rolling window of observations. Our results, which we will discuss below, suggest that conditional betas based on multivariate conditional variance models perform better in accounting for the cross-sectional variation in expected returns compared to conditional betas based on rolling window regressions. Our results also suggest that both sets of conditional betas perform better than unconditional betas, which in turn signifies the importance of capturing the time variation in cash flow and discount rate news.

[8] $\sigma^2_{CF,t} = \alpha_{0,CF} + \alpha_{1,CF} CF^2_{t-1} + \alpha_{2,CF} I_{t-1} CF^2_{t-1} + \alpha_{3,CF} \sigma^2_{CF,t-1}$, $\sigma^2_{DR,t} = \alpha_{0,DR} + \alpha_{1,DR} DR^2_{t-1} + \alpha_{2,DR} I_{t-1} DR^2_{t-1} + \alpha_{3,DR} \sigma^2_{DR,t-1}$, where I_{t-1} is equal to one for positive CF and positive DR news, respectively.

folios as our test assets and obtain their conditional cash flow and discount rate betas as in Equation (12) using monthly data between 1929 and 2014.[9] Figure 5 presents the conditional cash flow and discount rate betas along with their averages over the whole sample period for the four extreme portfolios: small-growth, small-value, large-growth and large-value portfolios. On average, the cash flow and discount rate betas of small-growth and small-value portfolios are higher than those of large-growth and large-value stocks, respectively. Following CV, we also distinguish between two subsamples: the early period between January 1929 and June 1963 and the modern period between July 1963 and December 2014.[10] In unreported analysis, we computed the averages of the conditional betas in the early and modern samples separately. In the early sample period, both cash flow and discount rate betas are, on average, higher for small and value stocks compared to large and growth stocks. In the modern sample period, small stocks continue to have, on average, both higher cash flow and discount rate betas than large stocks and value stocks also continue to have higher cash flow betas than growth stocks, while their discount rate betas are much lower than those of growth stocks. This pattern in the averages of conditional betas is broadly consistent with those reported in CV.

What is more important for the purposes of our paper is the time variation of conditional betas around their averages. Specifically, in line with our findings for the conditional variances of cash flow and discount rate news, Figure 5 reveals that the conditional cash flow and discount rate betas also exhibit significant variation over time. For example, discount rate betas are slightly higher than cash flow betas in the early sample period for

[9] CV consider a larger set of test assets which includes the risk-sorted portfolios in addition to the 25 size and book-to-market sorted portfolios. Using their data available on the website of the American Economic Review, we replicated the results reported in their paper. We then considered the smaller set of test assets of 25 size and book-to-market sorted portfolios and found that the results are qualitatively very similar. Thus, we decided to focus on the 25 size and book-to-market sorted portfolios. This choice of test assets also allows us to compare our results with those in literature, which also mainly focuses on these assets. Furthermore, we also considered including ten portfolios formed on momentum and 30 industry portfolios to the set of test assets. The conditional betas based on multivariate conditional variance models continue to outperform unconditional betas in accounting for the cross-sectional variation in expected returns on portfolios in these larger sets of test assets.

[10] They argue that this sample split makes sense since COMPUSTAT data becomes more reliable beginning July 1963 and the book-to-market anomaly is obtained in the modern sample.

both small-growth and large-growth portfolios but the spread between the two betas for both of these portfolios steadily increases in the modern sample period, reaching its peak around the burst of the dotcom bubble and the ensuing recession. On the other hand, the cash flow and discount rate betas are quite similar over the whole sample period for both small-value and large-value portfolios. That said, the cash flow betas are slightly higher than the discount rate betas in the earlier sample for both portfolios while the opposite holds in the modern period. Figure 5 also reveals that both betas of small portfolios tend to be more volatile than the corresponding betas of large portfolios.

[Insert Figure 5 about here]

Before considering the asset pricing implications of this time variation, we analyze the relation between these conditional betas and inflation, the main macroeconomic determinant of the conditional variance decomposition of market returns. Similar to our analysis in Section 4, we estimate linear regressions of cash flow and discount rate betas on lagged (log) changes in the producer price index. We estimate these linear regressions via SUR while controlling for the lagged values of the corresponding cash flow and discount rate betas in each regression. Table 12 presents the coefficient estimates on lagged (log) changes in the producer price index from these regressions for cash flow betas in Panel (a) and discount rate betas in Panel (b) and their difference in Panel (c). The inflation has a positive effect on the cash flow betas of all 25 portfolios and significantly so for most of them. This effect seems to be stronger on the cash flow betas of large and value portfolios compared to those of small and growth portfolios. On the other hand, the effect of inflation on discount rate betas is mostly negative, but significantly so only for few large portfolios. Unlike the effect of inflation on the cash flow betas, there does not seem to be a clear pattern in the magnitude of the effect of inflation on the discount rate betas of different portfolios. Furthermore, the effects of inflation on the cash flow and discount rate betas of the same portfolio are significantly different from each other, as suggested by significant differences in Panel (c). Overall, these results suggest that the inflation rate is an important determinant of cash flow betas, but not of discount rate betas, in line with our findings in Section 4 where we identify the inflation rate as an important determinant of the conditional variance decomposition of market returns. More importantly, these results show that an increase in the inflation rate significantly increases the cash flow betas, especially those of large and value portfolios. In other words, cash flow risk in equity markets increases significantly following an increase in the inflation rate.

[Insert Table 12 about here]

We now turn our attention to the asset pricing implications of this time variation in conditional betas. Based on Campbell's (1991) approximate discrete-time version of Merton's (1973) ICAPM, CV derive the following asset pricing equation relating the risk premium to cash flow and discount rate betas:

$$E_t\left[r_{i,t+1}\right] - r_{f,t+1} + \frac{\sigma_{i,t}^2}{2} = \gamma\sigma_{p,t}^2\beta_{i,CF_p,t} + \sigma_{p,t}^2\beta_{i,DR_p,t} \tag{2.13}$$

where $r_{i,t+1}$ and $\sigma_{i,t}^2$ are, respectively, the log return on portfolio i in period $t+1$ and its conditional variance based on information in period t, $r_{f,t+1}$ is the risk-free rate. Equation (13) implies that the risk price of cash flow news should be γ times greater than the risk price of discount rate news, which, itself, should be equal to the variance of the return on portfolio p. CV modify Equation (13) in three ways. First, they use simple, instead of log, returns on the left-hand side of the equation. They argue that using simple returns makes the results easier to compare with those in the literature. Second, they use a market index as the reference portfolio. They argue that this reflects the fact that they are testing the optimality of the market portfolio for a long-horizon investor. Third, they derive an unconditional version of Equation (13) to avoid estimation of the conditional moments. We follow CV and implement the first two of their modifications but ignore the third one since we are exactly interested in the conditional, rather than unconditional, version of Equation (13) and its performance in explaining the cross-section of expected returns.

CV also distinguish between constrained and unconstrained versions of their model. The constrained version, which they refer to as the two-beta ICAPM, imposes the restriction that the risk price of discount-rate news is equal to the variance of the market portfolio. This in turn implies that the only free parameter in Equation (13) is the coefficient of relative risk aversion. The unconstrained version, on the other hand, leaves the risk prices of both cash flow and discount rate betas as free parameters to be estimated. They argue that the unconstrained version can be interpreted as a slight generalization of their model that allows investors' portfolio to include risk-free asset as well as stocks.

In addition to the constrained and unconstrained versions of CV framework with unconditional and conditional cash flow and discount rate betas, we also consider unconditional versions of CAPM and three-factor Fama–French models with constant factor loadings as benchmarks for comparison purposes. We estimate all these models based on the Fama–MacBeth (1973) approach. To this end, we first estimate the following cross-sectional regression in each period:

$$R^x_{i,t} = R_{i,t} - R_{f,t} = \alpha_{i,t} + \sum_{k=1}^{N} \gamma_{k,t} \hat{\beta}_{i,k,t} + v_{i,t} \tag{2.14}$$

where $\hat{\beta}_{k,t}$ is the beta of the k^{th} factor in an N factor model, and R^x is the simple return in excess of the risk-free rate R_f.

We estimate each model in two different forms following CV. In the first one, we restrict zero-beta rate to be equal to the risk-free rate by estimating the cross-sectional regression in Equation (14) without a constant. This forces each model to explain the risk premia on test assets in addition to the unconditional equity premium. In the second one, we do not impose this restriction and estimate the cross-sectional regressions with a constant. Unlike the first form, the second one does not attempt to account for the unconditional equity premium.

The estimates of risk premia (and the constant) and their standard errors are then obtained as the sample averages and standard deviations (divided by the square root of the number of periods) of the period-by-period estimates, respectively.[11] The performance of each model is evaluated based on three related metrics. The first one is the composite pricing error considered by CV, which is computed as $\bar{\hat{v}}\hat{\Omega}^{-1}\bar{\hat{v}}$ where $\hat{\Omega}$ is a diagonal matrix composed of return volatilities, and $\bar{\hat{v}}$ is the average pricing error. The second one is the number of mispriced portfolios at the 5% significance level based on the t-statistics from the standard Fama–MacBeth approach. The last one is the adjusted R^2 that can be obtained as $1-\left[(T-1)/(T-P)\right]\left[\left(\bar{\hat{v}}'\bar{\hat{v}}\right)/\left((\bar{R}^x-\mathbf{1}'\bar{R}^x)'(\bar{R}^x-\mathbf{1}'\bar{R}^x)\right)\right]$ where T is the total number of periods, P is the number of factors including the intercept, and $\mathbf{1}$ is a vector of ones with appropriate dimensions.

When estimating the unconditional models, we use constant betas estimated once using the sample period under consideration. In this paper, we are interested in the performance of the conditional CV framework using conditional betas based on multivariate conditional variance models as described above. For completeness, we nevertheless consider an alternative set of conditional betas based on the covariances and variances estimated from three-year rolling windows of observations, as in CV.

Table 13 presents our results for the modern sample. Before comparing different models, we start by discussing the estimation results for the conditional CV framework with betas estimated based on a multivariate conditional variance model, our main model of interest. First of all, asset pricing theory implies that the constant in the cross-sectional regression should not be statistically distinguishable from zero. The constant in both the constrained and unconstrained estimation of our main model is not significantly different from zero, suggesting that our main model can capture this implication of asset pricing

[11] CV consider standard errors based on a bootstrap approach instead of the Fama–MacBeth approach. Although their bootstrap approach is relatively straightforward to implement for unconditional models, the same cannot be said for conditional models with time-varying betas. Furthermore, in our replication of CV, we did not find any significant differences between results based on bootstrapped and Fama–MacBeth standard errors, which are identical to those obtained based on a single cross-sectional regression of average returns on unconditional betas for unconditional models. To be more precise, the same coefficients are statistically significant at 5%, which also allows us to compare our results to other studies in the literature.

theory. Second, the cash flow news has a reasonable risk price of 1.69% and 1.62% per month in the unconstrained and constrained estimation, respectively. Restricting the zero-beta rate to be the risk-free rate does not alter the results and cash flow beta continues to have a significant risk price. On the other hand, the risk price of discount rate beta is insignificant and small compared to that of cash flow beta. Third, this framework implies very reasonable values of relative risk aversion coefficient (RRA). Depending on whether we impose the zero-beta restriction, the implied RRA is either 3.04 or 4.23 in the unconstrained estimation and either 8.32 or 10.60 in the constrained estimation. Fourth, there are five and seven mispriced portfolios in the unconstrained estimation while there are only three mispriced portfolios in its constrained estimation. This is much better than any other model considered. Furthermore, when we impose the zero-beta restriction in its constrained estimation, it can also account for the expected return on the small-growth portfolio, which is known to be quite difficult to price, while all other models fail to do so. Finally, this model accounts for slightly more than 60% of the variation in the cross-section of expected returns and it is quite stable across different estimations. Overall, these results suggest that our main model of interest provides not only reasonable estimates of risk prices and RRA but also performs quite well in accounting for the cross-sectional variation in expected returns on the 25 size and book-to-market sorted portfolios.

[Insert Table 13 about here]

When we turn our attention to the unconditional models, the economic importance of capturing the time variation in cash flow and discount rate betas becomes clear. We briefly discuss the benchmark models, the CAPM and Fama–French (FF) three-factor model, before turning our attention to the unconditional CV framework. The constant is significantly different from zero for both the CAPM and FF three-factor model when we do not impose the zero-beta restriction. This suggests that both of these models fail to capture the implication of asset pricing theory that the constant should be zero. As it is well known, CAPM performs relatively poorly in accounting for the expected returns on these test assets. It has a very low, or even negative, adjusted R^2 and cannot correctly price thirteen portfolios. On the other hand, FF cannot account for the expected returns on seven to nine portfolios. That said, FF performs quite well in accounting for the cross-sectional variation in expected returns, in terms of adjusted R^2 and composite pricing error. Nevertheless, our main model performs on par with the FF model in terms of adjusted R^2 and better in terms of the number of mispriced portfolios, especially when we impose the restriction that zero beta is equal to the risk-free rate. When we consider the unconditional CV framework, the constant is not significantly different from zero and the cash flow beta has a significantly positive risk price, similar to our main model of interest. However, the unconditional framework implies not only negative RRA values in its unconstrained estimation but also underperforms in accounting for the cross-sectional variation in expected returns relative to our main model of interest.[12] Furthermore, this model results in nine mispriced portfolios compared to three in our main model of interest. These results suggest that ignoring the time variation in cash flow and discount rate news and their relation to stock returns can have important effects on the implications and performance of the CV framework.

Last, but not least, we consider the conditional CV framework where betas are obtained from regressions based on a rolling window of observations. First of all, this conditional CV model, even if it is based on these betas from rolling window regressions, continues to outperform the unconditional CV model. This in turn points to the

[12]The performance of the unconditional CV framework in its unconstrained estimation is comparable to that reported in CV. On the other hand, its performance in its constrained estimation is quite poor when compared to that reported in CV. In an unreported analysis, we identify two main reasons for this discrepancy. The first, and most important, is the sample period. CV consider the sample period between July 1963 and December 2001, which does not include the financial crisis. We, on the other hand, consider the sample period between July 1963 and December 2014, which does not only include the financial crisis, but also its aftermath. When we estimate the unconditional CV framework for the sample period in CV, its performance in the constrained estimation improves but remains lower than that reported in CV. The second reason is the set of predictor variables used in the VAR to obtain the cash flow and discount rate news. As discussed above, CV use the term spread, small value spread, and price–earning ratio, while we replace the price–earning ratio with the dividend yield. This also affects the performance of the unconditional CV framework but less so compared to the sample period. Nevertheless, the combined effect of the sample period and the set of predictor variables results in the observed discrepancy between the results reported in Table 13 and those in CV. Furthermore, this discrepancy is much lower in the early sample period.

importance of capturing the time variation in cash flow and discount rate betas. When we compare the two conditional CV models, the results suggest that the time variation in conditional cash flow and discount rate betas can be better captured by multivariate conditional models than rolling window regressions, and this has important effects on the implications and performance of the CV asset pricing model. To be more precise, the risk price of cash flow beta in the conditional CV model, with betas obtained from rolling window regressions, becomes significant only when we impose the restriction that zero-beta rate is equal to the risk-free rate. This in turn suggests that investors are compensated for holding cash flow risk only when we impose this restriction in this framework. In our main model, the cash flow risk has a significantly positive risk price under both specifications. Similar to the unconditional CV framework, the unconstrained estimation of the conditional CV framework with rolling betas results in negative values for the RRA coefficient and its constrained estimation underperforms in accounting for the cross-sectional variation in expected returns relative to our main model of interest.

2.5.1 Robustness Checks

Here, we briefly discuss the robustness of the asset pricing results to making alternative empirical choices. For the sake of brevity, we discuss these results without presenting them.

We start with the robustness of our results to using alternative sample periods. Although CV present results for both early and modern sample periods, they mostly focus on the modern sample period for two main reasons. First of all, they argue that book-to-market anomaly is obtained from the modern period. Second, and more importantly, they show that the cash flow beta is practically a constant fraction of the CAPM beta for different assets and, thus, the two-beta model cannot add much explanatory power during the early period. Following CV, we also focus on the modern sample period in this paper. That said, we considered several alternative sample periods including the early sample period. Our results in the early period are broadly consistent with CV and we also find that the CAPM performs on par with the conditional and unconditional two-beta model in the early sample period. More importantly, the conditional framework continues to outperform the unconditional framework in the early sample period but the difference between them is not as pronounced as in the modern sample period. Furthermore, we also considered the modern sample period until December 2001 (the modern sample period considered in CV) and until December 2006 to exclude the financial crisis from our sample.[13] The results based on these alternative modern sample periods are very similar to those presented in Table 13.

We then consider alternative empirical choices in obtaining the proxies for cash flow and discount rate news. Specifically, as in Section 2, we focus on two factors, namely the set of predictor variables and the value of ρ in Equation (4). We consider the same options for these two factors as in Section 3.1 and obtain alternative cash flow and discount rate news. We then repeat our asset pricing exercise using these alternative proxies. Given the high correlation between different empirical proxies of both news components discussed in Section 3, it is then not surprising to find that our conclusions in the asset pricing tests do not change significantly. To be more precise, the conditional framework with conditional betas based on MVGARCH models continues to provide more reasonable estimates and better performance than other conditional and unconditional models considered.

2.6 Conclusion

In this paper, we analyze the time variation in the decomposition of the conditional variance of market returns as well as its macroeconomic determinants and asset pricing implications. We do this by estimating a multivariate conditional variance model with dynamic

[13] To make sure that we omit any impact of the Global Financial Crisis, we also consider an earlier sample ending in June 2006. The results remain similar for this new sample period.

conditional correlations for cash flow and discount rate news obtained based on the standard Campbell and Shiller (1988) decomposition approach. Our paper contributes to the existing literature in three empirical dimensions.

First, we provide empirical evidence that not only the components of the conditional market variance but also their relative importances exhibit significant time variation. For example, both cash flow and discount rate news become, on average, more volatile in recessions compared to expansions. More importantly, the relative contributions of these components to the conditional variance of unexpected market returns also vary significantly over time. To be more precise, the contribution of discount rate news varies between 24% and 65%, while that of cash flow news 15% and 61% but is relatively less volatile.

Our second contribution is on the macroeconomic determinants of this time variation. We identify lagged changes in inflation as the main macroeconomic determinant of this time variation in the short run. An increase in inflation makes cash flow news more important and discount rate news less important in the short run. This short-run effect is mostly driven by increases and unexpected changes in inflation during recessions. We also find that an increase in inflation increases the relative importances of both components in the long run at the expense of the relative importance of their conditional covariance.

Our third and final contribution is related to the economic importance of the time variation in conditional cash flow and discount rate betas. We do this by considering its asset pricing implications. Specifically, we argue that it is economically important to account for time variation in beta decomposition if a model which captures this time variation performs better than models ignoring it. To analyze this, we consider a conditional version of the two-beta framework of Campbell and Vuolteenaho (2004) with time-varying betas obtained by estimating multivariate conditional variance models for cash flow news, discount rate news and demeaned returns on the 25 size and book-to-market portfolios one at a time. We show that this conditional asset pricing model provides reasonable estimates and outperforms other conditional and unconditional models in accounting for the cross-sectional variation in expected returns.

From a practical viewpoint, our results might have important portfolio implications for risk-averse investors. For example, our results suggest that both cash flow and discount rate risk vary significantly over time, especially with changing inflation rates. More importantly, we find that the cash-flow risk increases significantly following an increase in inflation. As a result, risk-averse investors might want to tilt their portfolios away from high cash-flow-risk stocks, such as value stocks, or hedge the cash-flow risk of their portfolios more aggressively after observing increasing inflation.

There are several research avenues that we did not explore in this paper. For example, Campbell et al. (2010) decompose the unexpected returns on portfolios, instead of the market, into their cash flow and discount rate news. Similarly, Vuolteenaho (2002) analyzes the unconditional variance decomposition of individual stocks. One can then analyze the conditional, rather than unconditional, variance of unexpected returns on portfolios and individual stocks based on the approach in our paper. We believe that such an analysis might yield interesting insights into the time variation in the relative importances of the two news components in determining the conditional variances of different portfolios and stocks.

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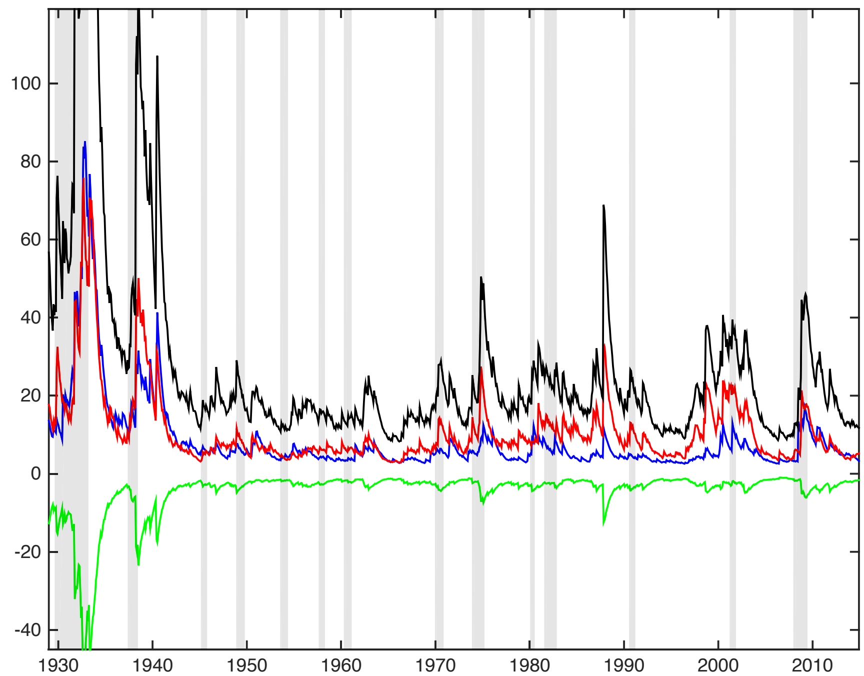
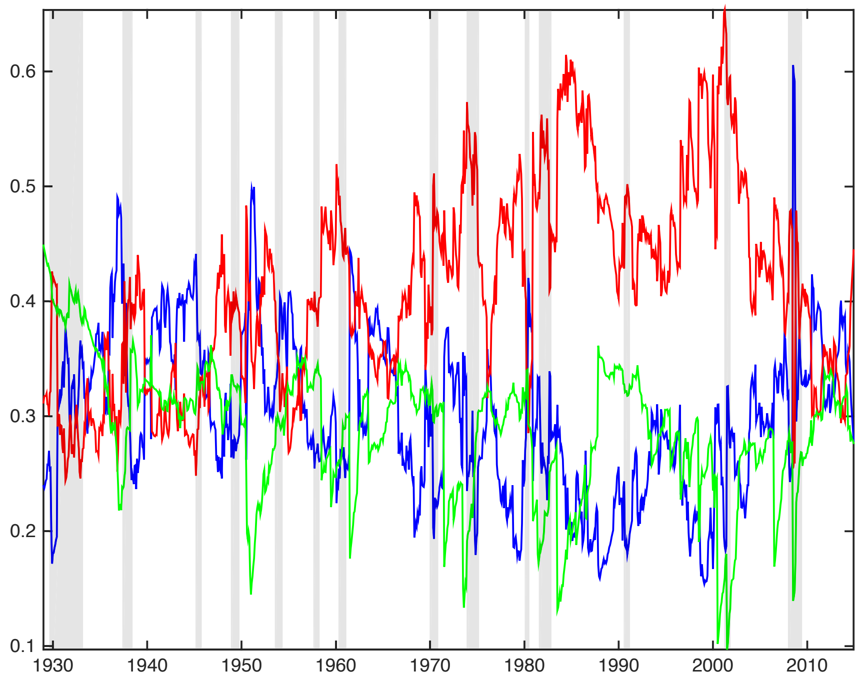
Appendix

Figure 2.1 – Conditional Variance of Unexpected Market Return and its Components



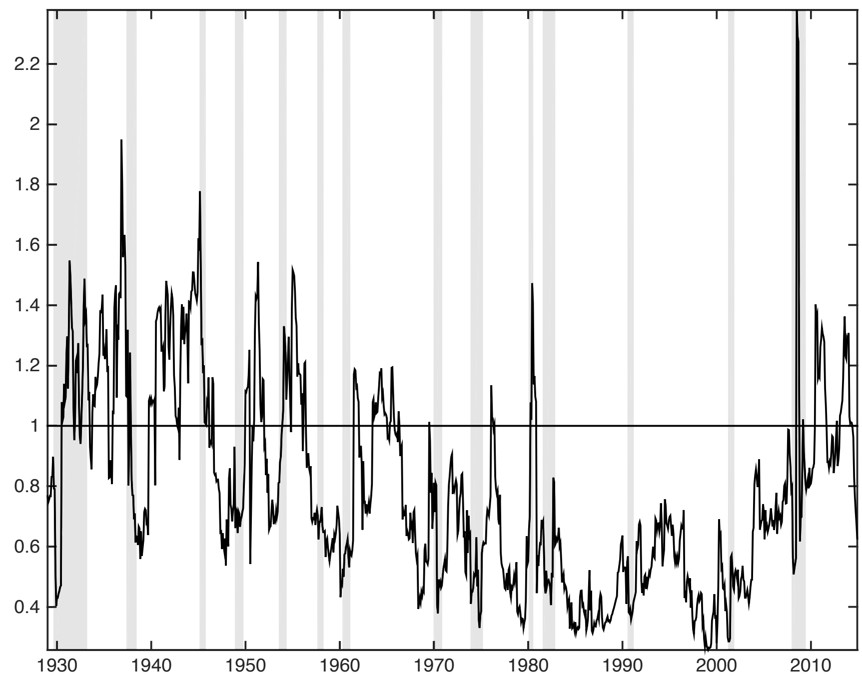
Notes: This figure presents the conditional variance of unexpected returns on the S&P 500 index (black), conditional variance of the cash flow news (blue), conditional variance of discount rate news (red), and the conditional covariance between cash flow and discount rate news (green). The conditional variances and covariances are obtained by estimating the multivariate conditional variance model in Equation (5) and Equation (6) using monthly data between 1929 and 2014.

Figure 2.2 – Relative Contributions of News Components to the Conditional Variance of Market Returns



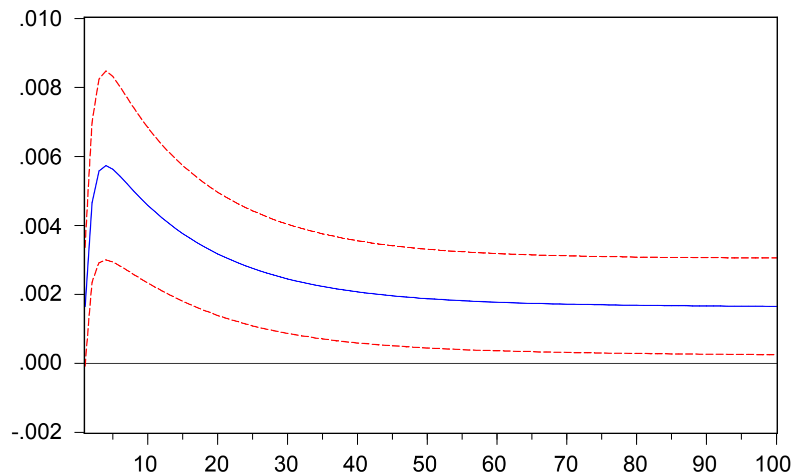
Notes: This figure presents the ratio of the conditional variances of cash flow news (blue), discount rate news (red) and their conditional covariance (green) to the overall conditional variance of unexpected market returns between 1929 and 2014.

Figure 2.3 – Ratio of the Conditional Variances of Cash Flow and Discount Rate News

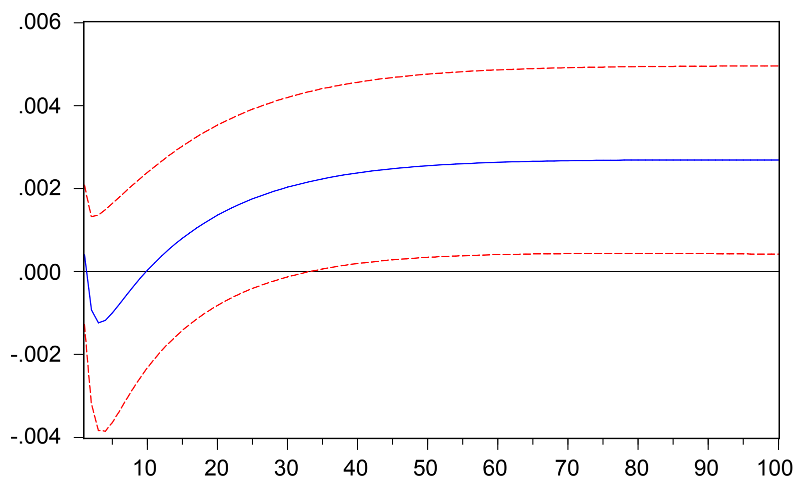


Notes: This figure presents the contribution of cash flow news relative to that of discount rate news between 1929 and 2014. A ratio greater than one implies that the conditional variance of cash flow news is relatively more important than that of discount rate news in determining the conditional variance of market returns.

Figure 2.4 – Impulse Response Functions of Relative Importances of Cash Flow and Discount Rate News to an Inflation Shock



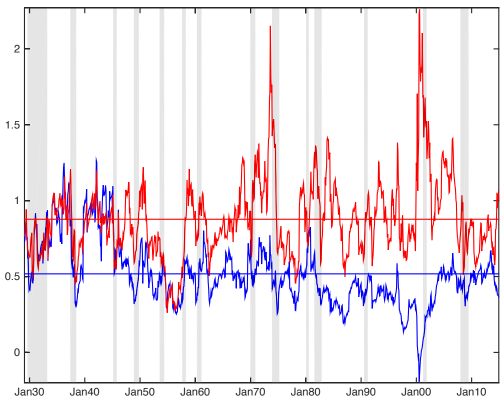
(a) Cash Flow Rel Ratio



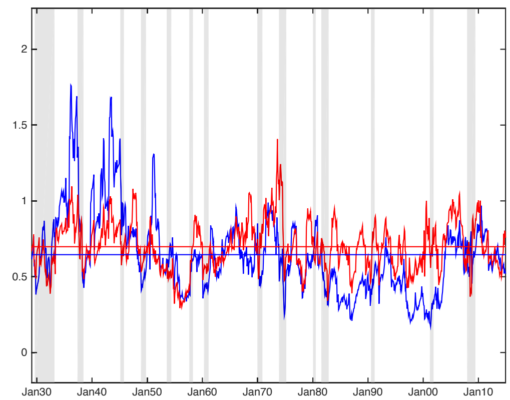
(b) Discount Rate Rel Ratio

Notes: This figure presents the generalized impulse response functions of the relative importances of cash flow (Panel (a)) and discount rate news (Panel (b)) to a one standard deviation positive shock to the change in the producer price index. These generalized impulse response functions are based on an orthogonal set of innovations that do not depend on the ordering of the variables in the VAR system as described by Pesaran and Shin (1998). The dashed lines are the corresponding 95% confidence intervals.

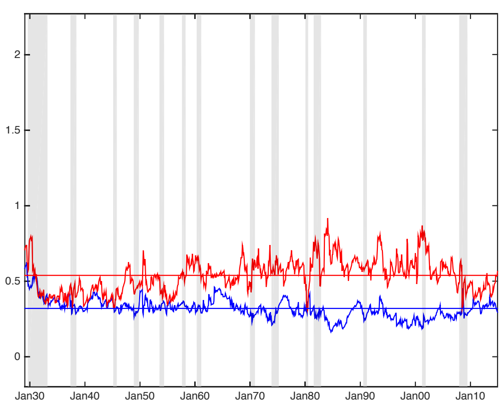
Figure 2.5 – Time Series of the Conditional Cash Flow and Discount Rate Betas



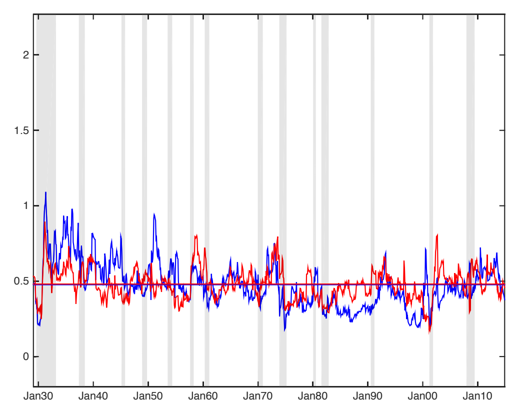
(a) Small-Growth Portfolio



(b) Small-Value Portfolio



(c) Small-Value Portfolio



(d) Small-Value Portfolio

Notes: This figure presents the conditional betas of the four extreme portfolios of the 25 size and book-to-market sorted portfolios between 1929 and 2014. The conditional cash flow (blue) and discount rate (red) betas are obtained based on Equation (12) where the conditional variances and covariances are from the estimation of multivariate conditional variance models for cash flow news, discount rate news and demeaned returns on the 25 size and book-to-market portfolios one at a time.

Table 2.1 – Descriptive Statistics of VAR State Variables

	r_m	tms	dp	svs
Mean	0.0045	0.0175	-3.3604	1.6141
Median	0.0093	0.0178	-3.3373	1.5203
St.Dev	0.0551	0.0130	0.4624	0.3271
Max	0.3463	0.0455	-1.8732	2.6981
Min	-0.3393	-0.0365	-4.5240	1.1861
Autocorrelation (1)	0.0900	0.9595	0.9926	0.9884
Correlations				
r_m	1	0.0508	-0.0788	-0.0383
tms	0.0508	1	-0.1190	0.2147
dp	-0.0788	-0.1190	1	0.2518
svs	-0.0383	0.2147	0.2518	1

Notes: This table presents some summary statistics on the monthly variables in the VAR system. The sample period is between 1929 and 2014. r_m denotes the (log) excess return on the S&P 500 index. tms denotes the term spread computed by subtracting the yield on the three-month Treasury bill from the long-term yield on government bonds. dp is the (log) ratio of 12-month moving sum of dividends to the index level. svs is the small-value spread computed as the difference between log book-to-market ratio of small growth stocks and log book-to-market ratio of small value stocks.

Table 2.2 – Parameter Estimates of the Vector Autoregressive Model

	Const.	$r_{m,t}$	tms_t	dp_t	svs_t	R^2 (%)
$r_{m,t+1}$	0.0405	0.0900	0.2850	0.0081	-0.0087	1.18
	(0.0175)	(0.0311)	(0.1366)	(0.0039)	(0.0056)	
tms_{t+1}	0.0001	0.0018	0.9550	0.0000	0.0004	92.04
	(0.0012)	(0.0021)	(0.0091)	(0.0003)	(0.0004)	
dp_{t+1}	-0.0378	-0.0847	-0.3255	0.9903	0.0066	98.54
	(0.0178)	(0.0317)	(0.1394)	(0.0040)	(0.0057)	
svs_{t+1}	0.0221	-0.0238	0.1464	0.0008	0.9864	97.69
	(0.0158)	(0.0282)	(0.1239)	(0.0035)	(0.0051)	

Notes: This table presents the estimates of the parameters in each equation of the first-order VAR system. The dependent variables are as shown in the first column. Each equation is estimated via OLS and the standard errors are provided in parentheses below. r_m denotes the (log) excess return on the S&P 500 index. tms denotes the term spread computed by subtracting the yield on the three-month Treasury bill from the long-term yield on government bonds. dp is the (log) ratio of 12-month moving sum of dividends to the index level. svs is the small-value spread computed as the difference between log book-to-market ratio of small growth stocks and log book-to-market ratio of small value stocks. R^2 is the adjusted R^2 of the regression. The sample period is between January 1929 and December 2014.

Table 2.3 – Unconditional Variance Decomposition of Market Returns

	Value (basis points)	Relative Ratio
σ^2_{CF}	9.0450	0.3022
σ^2_{DR}	10.8864	0.3637
$-2\sigma_{CF,DR}$	10.0025	0.3342
σ^2_m	29.9340	1

Notes: This table presents the decomposition of the unconditional variance of market returns. σ^2_{CF} and σ^2_{DR} are the variances of cash flow and discount rate news, respectively. $\sigma_{CF,DR}$ denotes the unconditional covariance between cash flow and discount rate news, and σ^2_m is the unconditional variance of unexpected market returns. The Relative Ratio in the last column indicates the contribution of each component to the overall unconditional variance. The sample period is between January 1929 and December 2014.

Table 2.4 – Parameter Estimates of Multivariate Conditional Variance Model for Cash Flow and Discount Rate News

	Coeff.	se	t-stat	p-val
$\alpha_{0,CF}$	0.0000	0.0000	2.3254	0.0202
$\alpha_{1,CF}$	0.0799	0.0198	4.0438	< 0.01
$\alpha_{2,CF}$	0.8930	0.0226	39.5246	< 0.01
$\alpha_{0,DR}$	0.0000	0.0000	2.2088	0.0274
$\alpha_{1,DR}$	0.0982	0.0213	4.6038	< 0.01
$\alpha_{2,DR}$	0.8829	0.0213	41.4450	< 0.01
$(1-a-b)$	-0.4229	0.0573	-7.3817	< 0.01
a	0.0228	0.0158	1.4426	0.1494
b	0.9378	0.0279	33.6369	< 0.01

Notes: This table presents the parameter estimates of the following multivariate conditional variance specification:

$$\sigma^2_{CF,t} = \alpha_{0,CF} + \alpha_{1,CF} CF^2_{t-1} + \alpha_{2,CF}\sigma^2_{CF,t-1}$$
$$\sigma^2_{DR,t} = \alpha_{0,DR} + \alpha_{1,DR} DR^2_{t-1} + \alpha_{2,DR}\sigma^2_{DR,t-1}$$
$$q_{CF,DR,t} = (1-a-b)\,\kappa_{CF,DR} + a\left(\varepsilon_{CF,t-1}\varepsilon_{DR,t-1}\right) + b q_{CF,DR,t-1}$$

where $\kappa_{CF,DR}$ is the unconditional correlation between $\varepsilon_{CF,t}$ and $\varepsilon_{DR,t}$ and $\varepsilon_{CF,t} = {}^{CF_t}/_{\sigma_{CF,t}}$, $\varepsilon_{DR,t} = {}^{DR_t}/_{\sigma_{DR,t}}$. The sample period is between January 1929 and December 2014. Standard errors, t-statistics and p-values are reported in the last three columns, respectively.

Table 2.5 – Descriptive Statistics of the Relative Contributions of Each Component

	$\sigma^2_{CF,t}/\sigma^2_{DR,t}$	$\sigma^2_{CF,t}/\sigma^2_{m,t}$	$\sigma^2_{DR,t}/\sigma^2_{m,t}$	$-2\sigma(CF,DR)_t/\sigma^2_{m,t}$
Mean	0.7855	0.2983	0.4131	0.2886
Median	0.7032	0.2937	0.4092	0.2978
St.Dev	0.3339	0.0699	0.0878	0.0583
Max	2.3781	0.6059	0.6538	0.4487
Min	0.2573	0.1541	0.2442	0.0970
Autocorrelation (1)	0.9302	0.9293	0.9600	0.9647

Notes: This table presents some summary statistics for the relative contributions of each component to the conditional variance of market returns. $\sigma^2_{CF,t}/\sigma^2_{DR,t}$ is the ratio of conditional variances of cash flow and discount rate news. $\sigma^2_{CF,t}/\sigma^2_{m,t}$ denotes the relative importance of cash flow news variance in the overall conditional variance of unexpected returns. $\sigma^2_{DR,t}/\sigma^2_{m,t}$ is the relative importance ratio for discount rate news and $-2\sigma(CF,DR)_t/\sigma^2_{m,t}$ for the covariance between cash flow and discount rate news. The sample period is between January 1929 and December 2014.

Table 2.6 – The Effects of Macroeconomic Variables on the Conditional Variance of Market Return and its Components

(a) Separate Regressions with Individual Macroeconomic Variables

	r	CF	DR	$F-stat$
ip	0.3166	-62.1794***	-39.5290	0.45
ppi	64.1109***	62.0529***	69.0415***	0.16
$unemp$	-1.5281	13.3032***	4.9769	1.67
emp	60.9110	-158.9785***	21.0644	2.47

(b) Joint Regression with All Macroeconomic Variables

	r	CF	DR	$F-stat$
ip	-15.3363	25.8687	-15.7236	1.10
ppi	65.1310***	61.4467***	66.0295***	0.07
$unemp$	11.3791	10.3585***	8.0658	0.13
emp	136.1793	-136.8803***	86.8085	2.17

Notes: This table presents the effects of macroeconomic variables on the conditional variance of unexpected market return and its components. Panel (a) considers each macroeconomic variable separately as an exogenous variable in the corresponding conditional variance specification. Panel (b) considers all macroeconomic variables jointly as exogenous variables in the corresponding conditional variance specification. The column titled r presents the parameter estimates from the estimation of the model in Equation (7) for the unexpected market returns. Columns titled CF and DR present the parameter estimates from the estimation of a multivariate conditional variance specification with dynamic conditional correlations for cash flow and discount rate news. The column titled $F-stat$ presents the Wald statistic testing the equality of the coefficients on each macroeconomic variable in the conditional variance specifications for cash flow and discount rate news. ip, ppi, $unemp$, and emp denote lagged (log) changes in industrial production index, producer price index, unemployment rate, and total nonfarm payroll, respectively. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels.

Table 2.7 – The Effects of Macroeconomic Variables on the Relative Contribution of Components to the Conditional Variance of Market Returns

(a) Separate Regressions with Individual Macroeconomic Variables]

	$\sigma^2_{CF,t}/\sigma^2_{m,t}$	$\sigma^2_{DR,t}/\sigma^2_{m,t}$	$-2\sigma(CF,DR)_t/\sigma^2_{m,t}$	$Difference$
ip	0.1074	0.0199	-0.1274	0.0875
ppi	0.3774***	-0.1818*	-0.1956*	0.5592***
$unemp$	-0.0185	-0.0003	0.0187	-0.0183
emp	0.1067	-0.0608	-0.0459	0.1675

(b) Joint Regression with All Macroeconomic Variables]

	$\sigma^2_{CF,t}/\sigma^2_{m,t}$	$\sigma^2_{DR,t}/\sigma^2_{m,t}$	$-2\sigma(CF,DR)_t/\sigma^2_{m,t}$	$Difference$
ip	0.1749	0.0490	-0.2239*	0.1259
ppi	0.3904***	-0.1811*	-0.2093**	0.5715***
$unemp$	-0.0127	-0.0013	0.0140	-0.0115
emp	-0.5640	-0.0927	0.6567	-0.4713

Notes: This table presents the effects of macroeconomic variables on the relative contribution of each component to the conditional variance of market returns. Panel (a) considers each macroeconomic variable separately as an independent variable in the system in Equation (8). Panel (b) considers all macroeconomic variables jointly as independent variables in the system in Equation (8). The equations in the system are estimated via SUR. The second and third columns present the parameter estimates of the equations for the relative contributions of the conditional variances of cash flow and discount rate news, respectively. The fourth column presents the coefficient estimates for the relative contributions of the conditional covariance between cash flow and discount rate news. This is simply the negative of the sum of the coefficients in the second and third columns. The last column presents the difference between the estimates in the second and third columns and the significance is based on a Wald statistic testing their equality. ip, ppi, $unemp$, and emp denote lagged (log) changes in industrial production index, producer price index, unemployment rate, and total nonfarm payroll, respectively. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels.

Table 2.8 – The Effects of Positive and Negative Changes in Inflation

(a) Conditional Variance Specifications

	r	CF	DR	$F-stat$
pos	63.9241***	63.3769***	59.6043***	0.04
neg	74.0019	-47.9991***	442.9469	0.96

(b) Relative Importance Ratios

	$\sigma^2_{CF,t}/\sigma^2_{m,t}$	$\sigma^2_{DR,t}/\sigma^2_{m,t}$	$-2\sigma(CF,DR)_t/\sigma^2_{m,t}$	$Difference$
pos	0.3260**	-0.1355	-0.1905	0.4615*
neg	0.4583**	-0.2547	-0.2036	0.7131**

Notes: This table presents the effects of positive (*pos*) and negative (*neg*) changes in inflation on the conditional variance of market returns and its components in Panel (a) as well as on the relative contribution of each component in Panel (b). Panel (a) considers positive and negative changes in inflation jointly as exogenous variables in the corresponding conditional variance specification. The column titled r presents the parameter estimates from the estimation of the model in Equation (7) for the unexpected market returns. Columns titled CF and DR present the parameter estimates from the estimation of a multivariate conditional variance specification with dynamic conditional correlations for cash flow and discount rate news. The column titled $F-stat$ presents the Wald statistic testing the equality of the coefficients on each macroeconomic variable in the conditional variance specifications for cash flow and discount rate news. Panel (b) considers positive and negative changes in inflation jointly as independent variables in the system in Equation (8). The equations in the system in Panel (b) are estimated via SUR. The second and third columns present the parameter estimates of the equations for the relative contributions of the conditional variances of cash flow and discount rate news, respectively. The fourth column presents the coefficient estimates for the relative contributions of the conditional covariance between cash flow and discount rate news. This is simply the negative of the sum of the coefficients in the second and third columns. The last column presents the difference between the estimates in the second and third columns and the significance is based on a Wald statistic testing their equality. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels.

Table 2.9 – The Effects of Expected and Unexpected Changes in Inflation

(a) Conditional Variance Specifications

	r	CF	DR	$F-stat$
exp	118.0056***	110.1873***	167.0928***	1.04
unexp	-33.8324*	40.8453**	-21.6814	2.46

(b) Relative Importance Ratios

	$\sigma^2_{CF,t}/\sigma^2_{m,t}$	$\sigma^2_{DR,t}/\sigma^2_{m,t}$	$-2\sigma(CF,DR)_t/\sigma^2_{m,t}$	$Difference$
exp	0.1866	0.0847	-0.2713	0.1020
unexp	0.4308***	-0.2565**	-0.1744	0.6873***

Notes: This table presents the effects of expected (*exp*) and unexpected (*unexp*) changes in inflation on the conditional variance of market returns and its components in Panel (a) as well as on the relative contribution of each component in Panel (b). Panel (a) considers expected and unexpected changes in inflation jointly as exogenous variables in the corresponding conditional variance specification. The column titled r presents the parameter estimates from the estimation of the model in Equation (7) for the unexpected market returns. Columns titled CF and DR present the parameter estimates from the estimation of a multivariate conditional variance specification with dynamic conditional correlations for cash flow and discount rate news. The column titled $F-stat$ presents the Wald statistic testing the equality of the coefficients on each macroeconomic variable in the conditional variance specifications for cash flow and discount rate news. Panel (b) considers expected and unexpected changes in inflation jointly as independent variables in the system in Equation (8). The equations in the system in Panel (b) are estimated via SUR. The second and third columns present the parameter estimates of the equations for the relative contributions of the conditional variances of cash flow and discount rate news, respectively. The fourth column presents the coefficient estimates for the relative contributions of the conditional covariance between cash flow and discount rate news. This is simply one minus the sum of the coefficients in the second and third columns. The last column presents the difference between the estimates in the second and third columns and the significance is based on a Wald statistic testing their equality. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels.

Table 2.10 – The Effects of Inflation in Recessions and Expansions

(a) Conditional Variance Specifications

	r	CF	DR	$F-stat$
rec	95.716***	89.692***	92.703***	0.02
exp	37.314**	28.202	50.984*	0.52

(b) Relative Importance Ratios

	$\sigma^2_{CF,t}/\sigma^2_{m,t}$	$\sigma^2_{DR,t}/\sigma^2_{m,t}$	$-2\sigma(CF,DR)_t/\sigma^2_{m,t}$	$Difference$
rec	0.4223***	-0.2156	-0.2068	0.6379**
exp	0.3499***	-0.1611	-0.1888	0.5110**

Notes: This table presents the effects of changes in inflation on the conditional variance of market returns and its components in recessions (rec) and expansions (exp) in Panel (a) as well as on the relative contribution of each component in Panel (b). Panel (a) considers changes in inflation in recessions and expansions jointly as exogenous variables in the corresponding conditional variance specification. The column titled r presents the parameter estimates from the estimation of the model in Equation (7) for the unexpected market returns. Columns titled CF and DR present the parameter estimates from the estimation of a multivariate conditional variance specification with dynamic conditional correlations for cash flow and discount rate news. The column titled $F-stat$ presents the Wald statistic testing the equality of the coefficients on each macroeconomic variable in the conditional variance specifications for cash flow and discount rate news. Panel (b) considers changes in inflation in recessions and expansions jointly as independent variables in the system in Equation (8). The equations in the system in Panel (b) are estimated via SUR. The second and third columns present the parameter estimates of the equations for the relative contributions of the conditional variances of cash flow and discount rate news, respectively. The fourth column presents the coefficient estimates for the relative contributions of the conditional covariance between cash flow and discount rate news. This is simply one minus the sum of the coefficients in the second and third columns. The last column presents the difference between the estimates in the second and third columns and the significance is based on a Wald statistic testing their equality. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels.

Table 2.11 – Granger Causality Tests

	ppi	$\sigma^2_{CF,t}/\sigma^2_{m,t}$	$\sigma^2_{DR,t}/\sigma^2_{m,t}$
ppi does not Granger cause	-	14.5337***	3.1050*
$\sigma^2_{CF,t}/\sigma^2_{m,t}$ does not Granger cause	0.6260	-	19.5218***
$\sigma^2_{DR,t}/\sigma^2_{m,t}$ does not Granger cause	6.9420***	15.3000***	-
All others do not Granger cause	30.3035***	32.824***	22.5112***

Notes: This table presents the Wald statistics testing the null hypotheses in the first column with the corresponding variables in the headings for the second, third and fourth columns. For example, the first row presents the Wald statistics testing the null that change in inflation does not Granger cause the relative contributions of cash flow (in the third column) and discount rate news (in the fourth column). The last row presents the Wald statistic testing the null hypotheses that the two other variables do not Granger cause the variable in the column heading. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels.

Table 2.12 – The Effects of Inflation on the Conditional Cash Flow and Discount Rate Betas

(a) Inflation Effect on Cash Flow Betas

	Growth	*Quintile2*	*Quintile3*	*Quintile4*	*Value*
Small	0.0928	0.2178	0.3468**	0.4245**	0.4007 *
Quintile2	0.1629	0.3450**	0.3435**	0.3954**	0.2924
Quintile3	0.1312	0.3528***	0.3880***	0.3064*	0.2813*
Quintile4	0.2244**	0.2970**	0.5331***	0.2514	0.4386**
Large	0.3314***	0.4882***	0.5125***	0.4561***	0.3689**

(b) Inflation Effect on Discount Rate Betas

	Growth	*Quintile2*	*Quintile3*	*Quintile4*	*Value*
Small	0.0759	-0.0120	0.0279	0.1333	-0.0072
Quintile2	-0.4059	-0.1696	-0.1545	-0.2466	-0.1809
Quintile3	-0.6103*	-0.2890	-0.0700	-0.2568	-0.1856
Quintile4	-0.5521*	-0.4188**	-0.2917	-0.4394***	-0.3930**
Large	-0.2534	-0.3787**	-0.2272	-0.4451***	-0.3344*

(c) Differences between Effects on Cash Flow and Discount Rate Betas

	Growth	*Quintile2*	*Quintile3*	*Quintile4*	*Value*
Small	0.0169	0.2298	0.3188	0.2912	0.4079*
Quintile2	0.5688	0.5146**	0.4980**	0.6420***	0.4733**
Quintile3	0.7415**	0.6418***	0.4580**	0.5631***	0.4670**
Quintile4	0.7765**	0.7158***	0.8248***	0.6907***	0.8316***
Large	0.5848***	0.8669***	0.7397***	0.9012***	0.7033***

Notes: This table presents the effects of inflation on the portfolio-specific conditional cash flow and discount rate betas in an equation similar to Equation (8), where relative contributions of cash flow and discount rate variances are replaced with the conditional cash flow and discount rate betas, respectively. Panel (a) and Panel (b) consider lagged (log) change in producer price index as an independent variable. The dependent variables consist of cash flow beta (Panel (a)) and discount rate beta (Panel (b)). The equations in the system are estimated via SUR. Panel (c) presents the difference between the corresponding coefficient estimates from Panel (a) and Panel (b) and the significance is based on a Wald statistic testing their equality. *Growth* represents the lowest book-to-market ratio, *Value* the highest book-to-market ratio, *Small* the lowest market value, and *Large* the highest market value. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels.

Table 2.13 – Asset Pricing Results

(a) Conditional and Unconditional CV models

	Conditional CV framework with *MVGARCH* Betas				Conditional CV framework with Rolling Betas				Unconditional CV framework with Constant Betas			
	Unconstrained		Constrained		Unconstrained		Constrained		Unconstrained		Constrained	
	ZB unrest.	ZB rest.	ZB unrest.	ZB rest.	ZB unrest.	ZB rest.	ZB unrest.	ZB rest.	ZB unrest.	ZB rest.	ZB unrest.	ZB rest.
α	0.0008	0	0.0008	0	0.0053	0	0.0020	0	-0.0036	0	-0.0065	0
	(0.0023)	0	(0.0026)	0	(0.0021)	0	(0.0022)	0	(0.0039)	0	(0.0035)	0
γ_{CF}	0.0169	0.0163	0.0162	0.0207	0.0100	0.0236	0.0085	0.0162	0.0335	0.0265	0.0266	0.0129
	(0.0051)	(0.0056)	(0.0059)	(0.0060)	(0.0073)	(0.0068)	(0.0056)	(0.0050)	(0.0084)	(0.0057)	(0.0087)	(0.0044)
γ_{DR}	0.0040	0.0054	0.0019	0.0019	-0.0065	-0.0053	0.0019	0.0019	-0.0065	-0.0069	0.0019	0.0019
	(0.0046)	(0.0042)			(0.0048)	(0.0043)			(0.0042)	(0.0040)		
Implied RRA	4.2340	3.0414	8.3173	10.6015	-1.5304	-4.4273	4.5270	8.6192	-5.1699	-3.8276	14.3767	6.9709
Mispriced Portfolios	7	5	3	3	6	8	7	6	13	13	9	9
Adjusted $\widehat{R^2}(\%)$	66.49	67.52	66.74	60.86	70.54	49.81	35.87	10.71	52.81	50.58	19.26	11.63
Pricing Error	0.0119	0.0111	0.0113	0.0145	0.0108	0.0169	0.0177	0.0266	0.0166	0.0188	0.0218	0.0260

(b) Unconditional CAPM and Fama–French Models

	CAPM		Three-factor *FF* model	
	ZB unrest.	ZB rest.	ZB unrest.	ZB rest.
α	0.0113	0	0.0120	0
	(0.0036)	0	(0.0026)	0
$MKT-RF$	-0.0036	0.0066	-0.0066	0.0049
	(0.0040)	(0.0019)	(0.0032)	(0.0018)
SMB			0.0019	0.0020
			(0.0013)	(0.0013)
HML			0.0040	0.0044
			(0.0012)	(0.0012)
Mispriced Portfolios	13	13	7	9
Adjusted $\widehat{R^2}(\%)$	6.96	-49.24	71.37	60.08
Pricing Error	0.0377	0.0446	0.0099	0.0130

Notes: This table presents the results from the estimation of the unconditional and conditional CV models in Panel (a) and the unconditional CAPM and FF models in Panel (b). We estimate each model in two different forms. ZB rest. restricts zero-beta rate to be equal to the risk-free rate by estimating the cross-sectional regression in Equation (14) without a constant. ZB. unrest. does not impose this restriction and estimates the cross-sectional regressions with a constant. The estimates of risk premia (and the constant) and their standard errors are obtained as the sample averages and standard deviations (divided by the square root of the number of periods) of the period-by-period estimates, respectively. The cash flow and discount rate news are obtained from the whole sample between January 1929 and December 2014, while the models are estimated over the modern sample between July 1963 and December 2014. The performance of each model is evaluated based on the number of mispriced portfolios, the adjusted R^2s and the composite pricing errors that are presented in the last three rows. In Panel (a), the constrained estimation imposes the restriction that the risk price of discount rate news is equal to the variance of the market portfolio, while the unconstrained estimation leaves the risk prices of both cash flow and discount rate betas as free parameters to be estimated. γ_{CF} and γ_{DR} are the prices of cash-flow and discount-rate risk, respectively. The implied RRA presents the coefficient of relative risk aversion implied by the ratio of γ_{CF} to γ_{DR}. $MKT-RF$ represents the market excess return, SMB the small-minus-big factor, and HML the high-minus-low factor.

Chapter 3

News Sentiment and Stock Returns

Ibrushi, Denada

Abstract

This article analyzes extensively the characteristics of different news topics and studies the relationship between the sentiment of news and stock returns. The most frequently observed news topics are those of corporate events, company news, mergers, and financial results of companies. Changes in credit ratings is the news topic with the highest standard deviation in negative tone. The positive sentiment varies the most for the company news category. Both, the positive and the negative sentiments for most of the topics are strongly and significantly related to contemporaneous firm-specific returns. Markets highly anticipate negative news, and a next-day continuation effect is observed for both types of sentiments. Reverse patterns arise in the long term for negative news. News announcement days for categories such as results and result forecasts are not significant per se, but the intensity in the tone of news plays the key role in affecting returns.

3.1 Introduction

The stock markets are highly loaded with news announcements and traders admit to consider that information. However, in addition to quantitative information conveyed, there is also an intense amount of qualitative information as well. Since this type of information is mainly transmitted as unstructured text, there have been continuous attempts in the literature to quantify it especially by using automatic algorithms. In this context, Li (2006) puts particular attention on words “uncertain” and “risk” in the firm reports. Tetlock (2007) uses the Harvard-IV-4 dictionary to estimate the proportion of negative words in a column of Wall Street Journal. Tetlock et al. (2008) add to WSJ the Dow Jones Newswire and consider all firm-specific news. These articles document that accurate textual analysis helps in explaining stock returns better. Thomson Reuters was the first in the financial industry to apply state-of-the art reading algorithm to its archive of firm-specific news. The news considered is public news, at least public to professional investors via the news messages broadcasted. A score is assigned to each news message appearing on the trades’ screen as different companies are mentioned. The given sentiment score is also the sentiment measure that we use in this article and it captures the probability that the author sentiment is positive, negative or neutral. The main reason that the author is central to measuring the sentiment and not the recipient is to avoid endogeneity issues; the recipient would categorize news into bad and good based on the market movements.

Studying the impact of negative news on stock returns is a critical topic in the literature of news announcements. Many studies have implemented different techniques to identify as well as quantify negative news. Several papers [1] have shown that news of a negative tone is followed by significantly negative next-day returns. A recent study by Ahmad et al. (2016) is one of the few that analyze the impact of media-expressed tone on stock returns and its continuation using firm-specific data. Authors assert that using an aggregate measure of the tone in news might average out interesting effects that occur at

[1](Tetlock (2007), Dzielinski (2011), Garcia (2013), Heston and Sinha (2017)).

the firm level.

In the same spirit with Ahmad et al. (2016), we use news for individual firms to first analyze the characteristics of different news topics and then study the relationship between news and stock returns. To the best of my knowledge, current literature does not consider different news topics and their corresponding sentiments simultaneously. Dzielinski (2011) explores the heterogeneity across firm characteristics and industries, whereas our central focus is to distinguish among different news categories. Different from Ahmad et al. (2016) that use only the sample of the large Dow firms, we merge the stock universe to include AMEX, NASDAQ, and NYSE stocks. While it is not the goal of this paper to document the return forecasting power of news sentiment, there is ample space that could be attributed to different news categories. We let the data speak and report the observed patterns for lagged, contemporaneous, and returns subsequent to news arrival. Results reported in the literature might be shadowed by the fact that these papers do not distinguish among various news topics.

This study provides a rich set of summary statistics for our news variables and firm characteristics across 37 different news topics. More frequent news topics are corporate events, company news, mergers, and financial results of companies. The less frequent ones are expansions and share splits. Changes in credit ratings and company news have the highest standard deviations in the negative and positive tone of news, respectively. Topics with the highest negative tone are also among those with the lowest returns.

In order to examine the impact of different news topics on returns, we run panel regressions in a very restrictive setting that controls for firm and day-fixed effects while using clustered standard errors. Indeed, there exists a significant relationship between the positive and negative sentiments of news with returns, where the former is related to higher returns and the latter to lower returns. The markets anticipate the negative tone in news correctly but this does not hold for positive news. A significant next-day continuation effect is shown for both sentiments. This effect lasts few more days for positive news. In addition, negative news depicts high reversals 120 days after the announcement. News announcements which are strongly related to stock returns regardless the intensity of news tend to exhibit a lower impact of the news tone on returns. On the other side, categories such as results and result forecasts show that more than the news announcement itself, it is the tone of news that affects the returns for these two topics. Other categories for which negative news affects returns are company news, mergers, listings, and share splits. The positive tone in news about product status change and divestitures is related to higher stock returns. The reversal pattern in the long run is strongest for result news.

Overall, we provide a comprehensive study of the publicly available news classified under different news topics. This study reports several interesting and not necessarily expected results that help in asking the right questions to relate news to returns. Despite the previously built expectations or dissemination of private information, public news and its sentiment remain still much important.

The paper proceeds as follows: Section 2 describes the data and reports characteristics per news topics. In Section 3, we analyze the impact of different types of news topics on stock returns. This section presents several results for different windows prior, during, or post news announcement. Section 4 concludes.

3.2 Data Description

Our universe of stocks comprises AMEX, NASDAQ and NYSE. The considered sample period starts in January 2003 and ends in December 2017. The data is available at daily frequency. We exclude financial firms and the remaining dataset consists of 19 million stock-day observations where 1.5 million are news-day observations. More specifically, there are 729,071 positive-news days, 264,615 negative-news days, and 489,672 neutral-news days totalling an exact number of 1,483,358 news days.

3.2.1 News Measures of TRNA

Making use of techniques for quantifying qualitative data has been a major trend in recent years across many fields. In the financial sector, processing textual content to be able to assess the impact of financial reports or news on the markets has gained much interest (Tetlock (2007), Jegadeesh and Wu (2013), Loughran and McDonald (2016)). In this study, we use a major news provider's (Thomson Reuters) database of algorithmically classified news called Thomson Reuters News Analytics (TRNA). Thomson Reuters provides a hybrid system of the existing approaches such as lexicon matching, grammatical analysis, and machine learning. It benefits from these methods and avoids their main weaknesses. The database is build on the newswire messages, and the authors of the newswire messages are around 3,000 journalists.

TRNA database scores a stock's news items along three main axes in particular: Sentiment, Relevance, and Novelty. It is important to understand what sentiment means for the TRNA database; to avoid interpretation that a reader may have about a given news, sentiment relates to the author's interpretation of the text[2]. What matters is how the author presents the facts about the company being analyzed. Another important characteristic of the sentiment measure is that it is attributed at entity-level (for each firm) and not over the whole news story, which allows for a much finer and reliable analysis. The relevance score is measured based on the number of times a company is measured in the text in comparison to other firms in an article. In this paper, we filter our news for 100% relevance. TRNA uses also a news content clustering technology to generate in the form of novelty score what they refer to as "breaking news detector". Thus, the novelty measure shows the uniqueness of a news article based on news from the preceding periods. Here, we account only for novel news that is the first issue within the last 24 hours.

[2]Look at this extreme example provided by Thomson Reuters: A-"An explosion occurred in Iraq today killing 20 people". and B- "A horrific explosion occurred in Iraq today murdering 20 people". Although sentences A and B convey the exact same information (that any reader would interpret as being very bad). the first sentence would be classified as neutral. whereas the second one as negative.

TRNA uses a proprietary procedure to classify their stock news[3]. The first step in the procedure consists of pre-processing the raw text into a representation that allows to extract features from the words and parts of sentences. They quantify sentiment by searching for negation (words inverting the sentiment of others), intensification (giving more strength to the sentiment) and verb resolution (e.g. active vs. passive verb use). Reuters uses lexicons created and validated by different experts. Using all their extracted features, they proceed to the final stage of news classification where each stock is assigned a sentiment score that is decomposed into three components: the probability of news being classified as positive, negative or neutral. Given that they are probability values, these three outputs sum up to one.

News topics are based on the topic code data available by Thomson Reuters, and it refers to the subject matter of news. The topic codes and the corresponding news included under each category are as described in Appendix B. We allocate news announced after the markets close to the following trading date.

3.2.2 News Descriptive Statistics

Our main variables of interest are the scaled measures of news sentiment; we construct these variables after the Dzielinski (2011) measure since it is more consistent with the given database. The Dzielinski sentiment factor accounts for the total number of stories in the denominator, avoiding in this way the bias exposed by using the overall news tone or the sum of probabilities assigned to news articles relevant to a firm within a certain day. In other words, an overall summation measure would be biased towards firms that are associated with a higher number of articles per day. We scale the news sentiment measures by the total number of stories in that day. The effect of neutral news is implemented indirectly in the denominator. Hence, if there is more neutral news available, the

[3]Described in one of the THR white papers: https://sircaknowledgebase.force.com/servlet/fileField?id=0BEw0000000bloH

denominator will make the overall sentiment measure lower. Different from Dzielinski (2011) who uses both positive and negative tones in the numerator to capture the spread in probabilities, our measures in Equation (1) and (2) are two separate ratios for positive and negative tone of news. In this way, we can better determine the impact of each type of news when running our main estimations in section 3.

$$sentPOS = \frac{\sum 1 \cdot prob_{pos}}{n_{pos} + n_{neut} + n_{neg}} \in [0\ 1] \tag{3.1}$$

$$sentNEG = \frac{\sum 1 \cdot prob_{neg}}{n_{pos} + n_{neut} + n_{neg}} \in [0\ 1] \tag{3.2}$$

News Topics and Firm Characteristics

In unreported results, we document that the news topics with the highest proportion of negative news-days are deals, accounting issues, class actions, and layoffs. This proportion varies between 86-100%. The corresponding ratio for results and result forecasts is around 50%. The fraction of negative news-days to overall number of news-days is less than 50% for management issues, share buybacks, or IPOs.

Table 1 provides the summary statistics for different news topics, ranked in decreasing order of total news-days per topic. Panel (A) reports the descriptives for more frequent topics, and the less frequent ones are as shown in Panel (B). There are more days in which there is an announcement about corporate events, company news, results, result forecasts, and mergers. Not surprisingly, these are also the topics with the largest number of different firms making announcements in the corresponding categories. Thus, there are on average 382 firms with company news announcements in a day. After excluding the financial sector, the Industry variable in the last column shows that most of the announcements are related to firms that operate in the IT sector.

[Insert Table 1 about here]

Table 2 describes the scaled measures of sentiment. The topics with the highest negative sentiment are those of class actions (CLASS) and corporate litigation (CASE1), whereas dividends (DIV) and strategic combinations (ALLCE) have the lowest negative tone. The opposite holds for positive sentiment; the news topics with a higher sentiment on average are strategic combinations (ALLCE) and dividends (DIV). Corporate litigations and class actions have the lowest positive sentiment. Focusing on the variability of sentiments per topic, changes in credit ratings (AAA) have the highest standard deviation in the negative tone and company news (CMPNY) the highest variability in terms of positive sentiment. The topics with the lowest standard deviations for negative and positive sentiments are dividends (DIV) and class actions (CLASS), respectively.

[Insert Table 2 about here]

Finally, in table 3 we provide the characteristics of topics based on the firms that are related to announcements in these categories. We can get an initial idea about the relationship between the negative sentiment and firm-level returns by realizing that the topics with the highest means in negative sentiment are also among those with the lowest returns. For example, returns are lowest for accounting issues which stand among the topics with the highest negative sentiment. The average firm size appears to be lowest for results because most firms (large and small) report financial results of their companies.

[Insert Table 3 about here]

3.3 News Impact on Stock Returns

In this section, we study the impact of positive and negative news sentiments, different topics, the interactions effects between the two as well as discuss from the literature potential channels that can explain the attained relationships. To analyze the impact of positive and negative news sentiments on stock returns, we estimate a pooled OLS with day and firm fixed-effects where the standard errors are clustered on a daily basis. The staleness in news is not an issue for this study because the data is filtered for news of 100% relevance or stated alternatively visible news.

3.3.1 Panel Data Analysis

We estimate a panel regression of daily returns on the positive sentiment, negative sentiment, news dummies for 37 different news topics, and sentiment interactions with the news topics:

$$
\begin{aligned}
R_{i,t} = {} & sentPOS_{i,t} + sentNEG_{i,t} \\
& + \sum_{k=1}^{37} \theta_k D_{i,k,t} + \sum_{k=1}^{37} \theta_k^{pos} sentPOS_{i,t} \cdot D_{i,k,t} \\
& + \sum_{k=1}^{37} \theta_k^{neg} sentNEG_{i,t} \cdot D_{i,k,t} + \varepsilon_{i,t} \qquad (3.3)
\end{aligned}
$$

where R indicates the cumulative returns for different time t windows, D the news dummies, sentPOS the positive sentiment of news, sentNEG the negative sentiment, and the subscripts i and k represent the firm and the news topic, respectively. The sentiment news measures are scaled by the number of stories as described in the Data section above. In order to control for possible regime changes, we normalize the positive and negative sentiment measures by demeaning and dividing by the standard deviation of the corresponding sentiment computed over the past year. In this way, we are certain to use stationary sentiment variables as well as better able to interpret our results economically. The positive interaction term is available only when positive sentiment dominates the negative one and vice versa. Thus, we are estimating the impact of the interaction terms only when that specific sentiments exceeds the other one. We run our panel regression for multiple windows. For brevity, we report the results only for the following windows: (-5:-3), (-1), (0), (+1), (+1:+5), (+2:+5), (+10:+20), and (+120:+240). Interested in determining if there is any significant pattern between news variables and stock returns in a longer term, we decide to include the last two windows of (+10:+20) and (+120:+240).

The setting in Equation (3) is chosen over the commonly considered vector autoregressive (VAR) model because it is not feasible to measure the news sentiment for every lag included in the VAR. In other words, we do not have consecutive data available for the sentiment variables. We understand the Ahmed et al. approach of dealing with this limitation by replacing with zeros the sentiment observations where no news is available and assuming in this way that no news can be considered neutral news. Nevertheless, we prefer a more restrictive approach and conduct our analysis based solely on the data available; having no news is not equivalent to receiving neutral news. Moreover, replacing no-news days by zeros is a more serious issue for our framework of multiple news topics. In short, our approach allows us to measure quantitatively the effects of independent news terms on the return and make statistical inferences based on the obtained p-values of the coefficients.

We include firm fixed effects to remove stock-specific sensitivity to news announcements and cluster our errors by date in order to account for possible cross-sectional correlations. Additionally, we use day fixed-effects. The rationale behind including day-fixed effects lies in the fact that it removes all systematic factors that are common across stocks but vary on a day-by-day basis. Hence, all risk factors such as market, size, and value factors that can possibly influence stock prices are accounted for. Consequently, we observe an increasing adjusted R2 as the window of forecast increases; risk factors explain a larger amount of variation in low-frequency than high-frequency returns, where the latter is more subject to idiosyncratic shocks. All in all, this model is very restrictive and we believe that statistical inference made based on those results is much less subject to concerns of p-hacking than other studies in the literature.

3.3.2 Main Results

The main analysis studies the association between positive tone of news, negative tones, multiple news topics, and interactions of sentiment with topics and stock returns. Regressions are estimated for contemporaneous returns, lagged cumulative returns over previous windows, and cumulative returns over subsequent periods. The reported results account also for 3 lags in firm returns. To make our tables easier to read, we do not report the autoregressive coefficients.

Considering that both a positive and a negative probability score is assigned to every news story, we want to estimate the impact of each form of sentiment in the presence of the other. Thus, we seek to determine how important negative sentiment is when we control for the positive one and vice versa. This is why we interact the sentiment with news-day polarity dummies. Interacting the sentiment with the dummy for positive (negative) days allows us to capture the impact of negative (positive) sentiment only on days where the primary signal is negative (positive). For instance, while the coefficients on the overall sentiment measures indicate how positive or negative sentiments are related to stock returns, the interaction terms show that for a given negative (positive) day, how much does the intensity of the negative (positive) signal additionally impact returns. On the other side, the coefficient estimates on the dummy variables show the difference in the average daily returns on a given topic during the specified window and average daily returns outside the window. Simply put, news dummies reported in Table 4 indicate the impact of news topic whereas the sentiment variables the impact of the intensity in news.

The results for Equation (3) are reported in three different panels in Table 4. In each panel, we include our baseline estimates for sentPOS and sentNEG to make the comparison between the parameters easier. All sentiments are for news arriving at time t.

[Insert Table 4 about here]

Panel (A) shows that one standard deviation increase in positive sentiment is linked to an increase of 9 basis points in returns on the same day. The contemporaneous association of one standard deviation increase in the negative sentiment is more than twice as large; it is related with 20 basis points lower returns. The direction of these patterns continues to hold for both positive and negative news on the next day. For positive news, the initial unit increase in standard deviation is still related to higher returns of approximately 2 basis points (22% of initial effect) and similarly for negative news to 2 basis points (9% of initial effect) in following-day returns. The continuation effect stops for negative sentiment but is present for the next 5 days after the positive news announcement. There is no reversal occurring for the positive sentiment. Conversely, a strong reversal arises for negative sentiment after 120 days. Thus, the stronger the negative sentiment of news at time 0, the higher the returns in the longer term.

Considering the returns over different windows before the announcement, we report that negative news is correctly anticipated. When accumulating the impact over the 3 to 5 days preceding a news announcement, one standard deviation increase in negative sentiment is associated with .08 bps lower returns. In agreement with the findings of Dzielinski (2011), we also assert that this is either evidence of partial leakage of information or incomplete sample of more-informed investors. In contrast with negative sentiment news, positive news is falsely anticipated. While we do not take a definite stand as why it would be the case, we consider as an alternative story the fact that investors might have anticipated correctly the arrival of news but not the direction of it. Overall, the approach of negative news is accurately anticipated whereas only news coming is correctly anticipated for positive news and not the positive nature of it. It can also be the case that markets are consistently building negative expectations when news days approach, regardless of them being positive or negative.

Dummies for the news topics in Panel (A) present the difference between the average daily returns in the news day/window of each topic and the average daily returns outside the day/window. Topics with a highly significant (at 1% level) positive impact on stock returns are mergers (84 basis points), company news (+36 basis points), and deals (20 basis points). News topics with noticeably negative effect on returns are monopolies (-160bps), accounting issues (-159bps), IPOs (-155bps), change of CFO (-85 bps), equity capital changes and divestitures (-70 bps), reorganizations (-54 bps), shareholders' meeting (-51 bps), management issues (-32 bps), production status change (-23 bps), and corporate events (-7 bps). Except for deals and changes in credit ratings, all the topics exhibit the same sign in the preceding days. Therefore, we can state that investors anticipate not only the upcoming negative tone of the news but also the kind (topic) of news to be released. However, it is important to stress that regardless the sign of the coefficients, the news about results and result forecasts is not anticipated. News about companies, corporate events, mergers, and management issues show to be strongly anticipated. We observe instances of strong reversal for management issues, change in the status of the product, and reorganizations.

In Panel (B) ,we report the parameter estimates for the interaction terms. It is worth noting that these parameters cannot be interpreted without considering the baseline coefficients of sentPOS and sentNEG in the first two rows of the table to be able to report the overall effect of news tone when announcements of different topics are released. Hence, on days where there is announcement about company news, results, results forecasts (warnings), mergers, security listings, and share splits, an even stronger association between the negative tone of news and returns is documented. To illustrate, a one standard deviation increase in the negative tone on company-news days leads to 74bps lower returns. The negative tone has a weaker impact on days where news about corporate events, changes in credit ratings, or dividends is released. The impact of negative sentiment is positive for topics such as management issues, deals, change of status of product, reorganizations, monopoly, shareholders' meeting, products and services. Company news, result forecasts, and the credit rating changes are more highly anticipated when the tone of news is negative. On the other hand, corporate events, merges, and deals are characterized by less anticipation. The impact of negative tone continues in the first day after the announcement for result forecasts and share splits. The reverse effect for results is very strong 120 days after the announcement. In contrast, company news does not affect a stock's future expected return as its coefficient in the long run cancels out with the baseline effect.

Panel (C) presents the results for interactions of news topics and positive sentiment of news. The impact of positive news tone on stock returns is significantly positive for main topics such as those of results, result forecasts, managerial issues, divestitures, monopolies, product status change, buybacks etc. Hence, a unit increase in the standard deviation of positive sentiment on result announcements is linked to an increase of 18 bps in returns or even much more for result forecasts (+128 bps). The opposite shows to happen for company news, mergers, deals, and IPOs. There is an anticipation of the positive tone of news only for product status change and share buybacks. While there are no noticeable reversal emerging in the long run, news about divestitures continues even after 120 days post-announcement when the sentiment of news is positive.

In short, both positive and sentiment tone of news is significantly related to announcement day returns. Negative news is correctly anticipated and a reversal effect arises in a longer term. Positive tone of news continues longer in the post-announcement days and no reversal shows to happen afterwards. Different news topics are strongly linked to returns at day zero and most of them are correctly anticipated by the market. The effect of the negative tone of news is the strongest for company news category, results, and result forecasts. Results and result forecasts continue to hold the strongest effect of positive tone on stock returns. It is interesting to notice how reaction to results and result forecasts is mainly due to the tone of news rather than the announcement per se. Our approach is highly restrictive and other alternative specifications lead to even stronger significance present for a larger number of topics.

3.3.3 Explaining the News Impact

This section provides potential explanatory channels to the reported results. It is also worth noting that when we add the market, size, value, and momentum factors (Fama and French (1992, 1993, 2015), Jegadeesh and Titman (1993)) to the panel regression, the significance and patterns of different news topics as well as the interaction terms continue to hold. This can be expected given the fact that we run our main estimations for day-fixed effects.

We start by considering whether our results are mainly driven by smaller stocks and therefore their illiquidity. Naturally, one could state that these stocks are less able to deal with shocks and continuation occurs because of the illiquid nature of our firms. For this reason, we replicate our results for the largest quintile of stocks; results show to be weaker for biggest stocks but still highly significant. This implies that illiquidity due to smaller stocks present in the sample could partially explain the attained results. Dzielinski (2011) also examines the possibility that impact of news analytics is obtained from the uncertainty around stocks. Using the idiosyncratic volatility of Ang et al. (2006), he finds that indeed the effect of news is higher for more uncertain stocks but still strongly significant for the less uncertain ones.

Paying attention to the literature about cash flow and discount rate news (Campbell and Shiller (1988a, 1988b), Campbell (1991)), the transitory and enduring effects of news could plausibly be related to the discount rate and the cash flow components of returns, respectively. Thus, the longer-term reversal in negative news can be simply put as "the stronger the negative news sentiment at time 0, the higher the expected return in the longer term". In other words, investors revise their long-term return expectations (discount rate) upwards resulting in a lower price value today; that is compensated by higher returns in the future. This in turn emposes another question; is the negative tone of news equivalent to a positive revision in discount rates? The same applies to the cash flow part;

we infer that the continuation (with no reversal) for the impact of positive sentiment in product status changes might be due to a positive change in investors' expectations about future cash flows. By definition, cash flow news is the new information linked to firm's production. Nevertheless, the current literature (Chen et al. (2013)) relates cash flow news to the accounting information of the firm and not news that is straightforward about the production itself. In contrast, news about results, which is the category including the earnings announcements, shows to depict more discount rate patterns for both positive and negative tone. The baseline coefficients for sentPOS and sentNEG motivate us to allude to the possibility that a company can become more risky much faster, and it takes more time to become less risky. We leave for future research to explore the efficiency of the incorporation of cash flow and discount rate news. It is important to distinguish carefully between positive and negative news among different topics before classifying it into broader cash flow and discount rate categories.

Our results are not necessarily contradicting those of Ahmad et al. (2016), where media tone has significant return effects on occasional episodes. On the contrary, our results suggest that these occasional occurrences might be due to different news topics as well as due to the intensity of news tone. Furthermore, they do not provide an explanation related to cash flow and discount rate channels in their paper.

3.4 Conclusion

In this article, we examine the main characteristics of different news topics from THRNA database and study the association between news sentiment and returns. Based on the obtained results, we find that in addition to the news announcement itself, the intensity and direction of news sentiment also matters. Nevertheless, the magnitude of the impact for each of these right-hand side variables changes across topics. Empirical results of this article for both sentiments, multiple news topics, and different time windows address the gap that exists in the literature.

Our first contribution lies in a descriptive perspective; we determine that the most frequent news topics are those of company news, corporate event, mergers, results, and result forecasts. The highest variability in negative sentiment occurs for changes in credit ratings. The corresponding topic for the positive sentiment is company news. Dividends and class actions have the lowest standard deviations in negative and positive sentiments, respectively.

Second, we find that sentiment of news is at least as important as the existence of news itself. The tone of different news categories has different impacts on returns during different horizons. Overall, negative tone is highly anticipated and corrected in the long term. Company news, results, and result forecast are the topics with the highest impact. For several categories, the existence of the announcement is more important for returns than the intensity of news.

There are certainly other potential research directions worth considering for the future. For instance, our preliminary results suggest that negative news might consist mainly of a discount rate effect. If positive news is mainly cash flow news, then it would be worth analyzing the efficiency of incorporating cash flow and discount rate news after building their proxies based on real-news announcements. It is important to study what news topic is mainly news about the cash flow or the discount rate components of returns. Another avenue for upcoming research is to consider building a trading strategy that takes long and short positions in stocks that announce more commonly under certain news topics. An important contribution to the existing literature would also rise from distinguishing carefully in a valid framework between the impact of the sentiment in news announcements and that of numerical figures present in the news.

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Appendix A - Results

Table 3.1 – Descriptive Statistics of News Articles

(a) More Frequent Topics

News Topic	Total News Days	Articles/Day	Firms/Day	Industry
BACT	1.18E+06	1.70	204.17	IT
CMPNY	1.04E+06	1.46	382.63	IT
RES	6.31E+05	1.82	92.04	IT
RESF	3.58E+05	2.34	40.52	IT
MRG	1.99E+05	2.26	23.39	IT
MNGISS	1.50E+05	1.94	21.51	Consumer Discretionary
DEAL1	1.43E+05	2.07	40.94	IT
DIV	7.54E+04	1.84	10.98	Industrials
AAA	7.22E+04	2.13	9.23	Consumer Discretionary
FINE1	3.24E+04	2.59	7.47	Health Care
BOSS1	2.16E+04	2.31	9.23	Consumer Discretionary
IPO	1.82E+04	2.35	2.74	Health Care
BUYB	1.44E+04	2.73	3.16	Consumer Discretionary
DVST	1.25E+04	3.13	3.35	Consumer Discretionary
STAT	1.23E+04	2.00	4.84	Energy
ALLCE	1.11E+04	2.08	5.61	IT
REORG	8.07E+03	3.24	2.13	Consumer Discretionary
SISU	6.94E+03	2.55	1.82	Health Care
CPROD	6.92E+03	2.85	3.37	Consumer Discretionary
CASE1	5.57E+03	2.64	2.38	IT
STK	5.47E+03	2.32	3.15	Consumer Discretionary

(b) Less Frequent Topics

News Topic	Total News Days	Articles/Day	Firms/Day	Industry
MONOP	4.27E+03	3.06	2.00	Consumer Discretionary
BKRT	4.24E+03	2.60	1.34	Health Care
CLASS	2.44E+03	2.58	1.50	Consumer Discretionary
CEO1	2.31E+03	2.79	2.24	Consumer Discretionary
MEET1	2.23E+03	2.77	1.56	Consumer Discretionary
CFO1	2.13E+03	2.41	2.28	Health Care
LIST1	1.79E+03	3.46	1.31	Health Care
SHRACT	1.78E+03	2.78	2.01	Consumer Discretionary
LAYOFS	1.56E+03	3.51	1.62	Consumer Discretionary
HOSAL	1.11E+03	4.75	1.36	Consumer Discretionary
DBTR	1.06E+03	2.51	1.32	Health Care / IT
DDEAL	9.97E+02	2.81	1.31	Consumer Discretionary
ACCI	9.00E+02	2.96	1.35	IT
CHAIR1	8.32E+02	2.59	1.40	Consumer Discretionary
SPLITB	7.27E+02	2.42	1.14	Consumer Discretionary
XPAND	6.88E+02	2.85	1.34	Consumer Discretionary

Notes: This table presents the summary statistics for the news topics listed in the first column. The statistics for the frequent topics of more than 5,000 news days are available in Panel (a) and for the less frequent ones in Panel (b). Total News Days shows the overall number of days where an announcement occured in a certain topic for the given sample period (January 2003 - December 2017). Articles/Day indicates the average daily number of articles published for a firm on a certain news topic. Firms/Day reports the number of unique firms making an announcement per a certain topic during a day. The last column reports the industries of the firms on which there are more articles for each news topic. The industry classifications are based on Global Industry Classification Standards.

Table 3.2 – Descriptive Statistics of News Sentiment

(a) More Frequent Topics

	Negative Sentiment			Positive Sentiment		
News Topic	Mean	Median	St.Dev	Mean	Median	St.Dev
BACT	0.20	0.14	0.18	0.37	0.32	0.24
CMPNY	0.24	0.14	0.23	0.44	0.46	0.25
RES	0.25	0.17	0.18	0.35	0.31	0.20
RESF	0.27	0.22	0.18	0.32	0.28	0.15
MRG	0.22	0.15	0.18	0.45	0.47	0.21
MNGISS	0.24	0.15	0.21	0.40	0.38	0.22
DEAL1	0.22	0.12	0.18	0.49	0.53	0.22
DIV	0.17	0.09	0.14	0.50	0.53	0.22
AAA	0.28	0.21	0.25	0.39	0.37	0.23
FINE1	0.24	0.17	0.20	0.46	0.49	0.22
BOSS1	0.22	0.14	0.16	0.45	0.48	0.19
IPO	0.21	0.15	0.17	0.49	0.53	0.20
BUYB	0.22	0.14	0.16	0.48	0.53	0.20
DVST	0.29	0.27	0.18	0.42	0.42	0.18
STAT	0.33	0.29	0.22	0.38	0.36	0.21
ALLCE	0.19	0.09	0.14	0.56	0.65	0.19
REORG	0.34	0.31	0.20	0.34	0.32	0.17
SISU	0.26	0.20	0.23	0.39	0.39	0.20
CPROD	0.32	0.27	0.23	0.39	0.38	0.21
CASE1	0.49	0.58	0.19	0.28	0.21	0.15
STK	0.27	0.18	0.18	0.38	0.30	0.18

(b) Less Frequent Topics

	Negative Sentiment			Positive Sentiment		
News Topic	Mean	Median	St.Dev	Mean	Median	St.Dev
MONOP	0.39	0.42	0.20	0.37	0.34	0.17
BKRT	0.39	0.42	0.22	0.31	0.27	0.17
CLASS	0.52	0.64	0.17	0.27	0.20	0.13
CEO1	0.25	0.17	0.17	0.41	0.42	0.16
MEET1	0.28	0.23	0.19	0.42	0.42	0.20
CFO1	0.24	0.17	0.15	0.39	0.39	0.16
LIST1	0.29	0.27	0.19	0.44	0.44	0.18
SHRACT	0.31	0.28	0.19	0.39	0.39	0.17
LAYOFS	0.41	0.42	0.18	0.30	0.26	0.14
HOSAL	0.32	0.28	0.20	0.38	0.40	0.17
DBTR	0.39	0.39	0.23	0.34	0.30	0.19
DDEAL	0.30	0.22	0.19	0.36	0.32	0.16
ACCI	0.43	0.42	0.22	0.30	0.27	0.16
CHAIR1	0.24	0.16	0.15	0.40	0.44	0.16
SPLITB	0.34	0.34	0.24	0.36	0.35	0.22
XPAND	0.23	0.16	0.15	0.42	0.44	0.16

Notes: This table presents the summary statistics for the negative and positive sentiment measures of each news topic listed in the first column. The statistics for frequent topics of more than 5,000 news days are available in Panel (a) and for less frequent ones in Panel (b). The scaled news measures are constructed following the estimate of Dzielinski (2011) as shown in Equations (1) and (2). The considered sample period starts in January 2003 and ends in December 2017.

Table 3.3 – Descriptive Statistics Based on Firm Characteristics

(a) More Frequent Topics

News Topic	Size	Ebitda	Return	Trading Volume
BACT	3.34E+06	376.22	0.28	4.29E+07
CMPNY	4.49E+06	484.20	0.30	4.84E+07
RES	3.31E+06	366.59	0.49	5.10E+07
RESF	3.40E+06	377.86	0.52	6.81E+07
MRG	3.65E+06	398.39	0.52	6.71E+07
MNGISS	3.78E+06	422.79	0.20	4.28E+07
DEAL1	5.21E+06	549.80	0.42	7.74E+07
DIV	6.98E+06	827.04	0.98	9.11E+07
AAA	7.63E+06	909.39	0.41	1.08E+08
FINE1	6.67E+06	692.57	0.54	1.14E+08
BOSS1	7.74E+06	812.52	0.23	7.65E+07
IPO	5.88E+06	673.05	-0.80	1.02E+08
BUYB	8.90E+06	956.44	1.39	1.43E+08
DVST	1.36E+07	1470.72	1.75	1.88E+08
STAT	3.61E+07	4703.37	0.17	2.55E+08
ALLCE	1.25E+07	1182.82	0.34	9.84E+07
REORG	1.36E+07	1564.38	-0.29	1.88E+08
SISU	1.09E+07	1120.79	-0.67	1.36E+08
CPROD	2.12E+07	2015.12	0.39	1.54E+08
CASE1	2.10E+07	2290.60	0.17	1.68E+08
STK	1.15E+07	1138.74	7.91	1.38E+08

(b) Less Frequent Topics

News Topic	Size	Ebitda	Return	Trading Volume
MONOP	4.06E+07	4381.98	0.08	3.55E+08
BKRT	1.18E+07	1688.85	-0.51	1.27E+08
CLASS	2.87E+07	3145.12	-0.05	2.25E+08
CEO1	1.28E+07	1357.65	-0.38	1.46E+08
MEET1	2.41E+07	2741.01	0.71	2.02E+08
CFO1	6.59E+06	664.34	-0.77	9.21E+07
LIST1	2.10E+07	2310.89	0.12	2.84E+08
SHRACT	2.43E+07	2460.66	4.12	2.32E+08
LAYOFS	3.11E+07	3171.53	-0.99	2.68E+08
HOSAL	5.82E+07	5573.70	0.45	8.74E+08
DBTR	2.36E+07	2826.37	-0.99	2.26E+08
DDEAL	3.49E+07	3420.39	19.78	3.46E+08
ACCI	2.85E+07	2911.41	-0.99	3.31E+08
CHAIR1	1.40E+07	1392.79	-0.63	1.29E+08
SPLITB	1.81E+07	1818.02	-0.98	2.31E+08
XPAND	5.61E+07	5575.26	1.65	3.28E+08

Notes: This table presents the summary statistics for each news topic in the first column based on firms' size, ebitda, return, and trading volume. Size is market capitalization as of the end of the previous year. Ebitda is drawn from COMPUSTAT. Return is in annualized percentages, and trading volume is the average number of shares traded per day. The statistics for the frequent news topics with more than 5,000 news articles are available in Panel (a) and for the less popular ones in Panel (b).

Table 3.4 – Panel Analysis for Sentiment Measures

(a) Sentiment and News Topics

News Topic	r(-5:-3)	r(-1)	r(0)	r(+1)	r(+1:+5)	r(+2:+5)	r(+10:+20)	r(+120:+240)
sentPOS	-0.021**	-0.048***	0.087***	0.019***	0.036***	0.014	0.001	0.064
sentNEG	-0.076***	-0.175***	-0.196***	-0.017***	-0.013	0.004	0.011	0.441***
CMPNY	0.068***	0.120***	0.356***	-0.003	0.008	0.011	-0.035**	0.021
BACT	-0.045***	-0.105***	-0.073***	-0.005	-0.007	-0.004	0.032	-0.338***
RES	-0.027*	-0.010	-0.026	-0.002	0.013	0.015	0.086***	0.245**
RESF	-0.001	0.005	0.046	-0.002	-0.018	-0.019	-0.086**	-0.399***
MRG	0.071***	0.149***	0.836***	-0.014	-0.028	-0.014	0.009	0.323**
MNGISS	-0.081***	-0.058***	-0.320***	0.013	-0.019	-0.030	0.017	0.793***
DEAL1	-0.020	-0.066***	0.203***	-0.002	0.047	0.040	-0.127***	0.115
DIV	-0.011	-0.005	-0.058*	0.042**	0.050	0.013	-0.144***	-0.375**
AAA	-0.001	0.133***	-0.178***	0.003	-0.051	-0.057	-0.036	-0.326
FINE1	0.226	-0.024	-0.696***	-0.050	-0.241	-0.189	0.167	0.951
BOSS1	-0.034	0.011	-0.115	0.019	-0.006	-0.017	-0.158	-0.470
IPO	-0.078	-0.245**	-1.552***	-0.057	0.129	0.179	-0.108	-1.205*
STAT	-0.106**	-0.072***	-0.227***	0.010	-0.051	-0.062	-0.019	1.991***
BUYB	-0.397**	-0.052	0.353	0.086	0.402**	0.309*	-0.198	-0.451
ALLCE	-0.150	-0.116	0.607	-0.081	-0.070	0.013	-0.093	-0.122
DVST	-0.068	-0.068	-0.704***	-0.071	-0.084	0.002	-0.060	-1.840***
SISU	0.155	-0.203	-0.541**	0.030	0.429	0.419	-0.290	0.594
REORG	0.174	0.017	-0.536***	-0.050	-0.188	-0.146	0.680**	1.640**
CPROD	-0.231**	0.070	-0.337	-0.073	-0.111	-0.040	0.205	-0.357
STK	-0.001	0.075	0.153	0.225**	0.238	0.006	-0.314	0.882
CASE1	-0.121	0.300*	0.261	0.111	-0.076	-0.156	-0.188	-2.304**
BKRT	0.365	0.418	-1.163**	0.138	1.176**	1.168**	-1.546	0.693
MONOP	-0.233**	-0.148*	-1.604***	0.027	0.159	0.141	0.385*	0.449
CLASS	0.669	-0.189	0.065	-0.071	-0.258	-0.221	1.052**	3.120**
CFO1	0.212	-0.205	-0.848***	0.067	-0.063	-0.139	-0.455	-0.170
MEET1	-0.054	0.292	-0.510***	-0.166	-0.051	0.112	0.168	-0.843
CEO1	-0.226	-0.128	-0.252	0.155	0.584	0.377	-0.352	0.968
SHRACT	0.337	0.049	0.407*	-0.003	0.205	0.215	0.130	-2.392*
LIST1	-0.376	0.429	0.543	-0.065	-0.589	-0.514	-0.617	-2.322
LAYOFS	0.059	-0.063	-0.583	0.068	0.806*	0.822*	-0.820*	0.884
DBTR	-0.155	-0.449	-1.720	-0.322	0.284	0.787	1.366	1.147
DDEAL	-1.208**	-0.077	0.008	-0.233	-0.438	-0.180	-0.174	-2.558
SPLITB	-2.163**	-0.442	-0.081	1.548	1.422	0.211	-2.091	-6.698*
CHAIR1	0.348	0.042	0.087	-0.306	-1.036**	-0.722*	0.706	1.004
ACCI	-0.734	-0.141	-1.589***	0.537*	0.144	-0.372	0.510	-4.552*
HOSAL	0.027	0.016	-0.178	-0.157	0.075	0.242	0.307	2.073
XPAND	0.859**	-0.704***	-0.275	-0.037	0.140	0.255	-0.525	-1.853

(b) Interaction Effects of Negative Sentiment

News Topic	r(-5:-3)	r(-1)	r(0)	r(+1)	r(+1:+5)	r(+2:+5)	r(+10:+20)	r(+120:+240)
sentPOS	-0.021**	-0.048***	0.087***	0.019***	0.036***	0.014	0.001	0.064
sentNEG	-0.076***	-0.175***	-0.196***	-0.017***	-0.013	0.004	0.011	0.441***
sentNEG_CMPNY	-0.091***	-0.105***	-0.548***	0.003	-0.001	-0.006	-0.018	-0.432***
sentNEG_BACT	0.079***	0.119***	0.077***	0.008	-0.032	-0.036*	-0.025	0.216
sentNEG_RES	-0.010	0.039***	-0.502***	-0.044***	-0.080***	-0.035	0.029	0.516***
sentNEG_RESF	-0.054	-0.050***	-0.569***	-0.021	0.039	0.056*	0.035	0.115
sentNEG_MRG	0.146***	0.163***	-0.206***	-0.026	0.018	0.041	-0.104	-0.123
sentNEG_MNGISS	0.088	0.087***	0.396***	0.011	0.077*	0.067*	0.087	-0.123
sentNEG_DEAL1	0.213***	0.285***	0.339***	0.037	0.008	-0.034	0.133*	0.271
sentNEG_DIV	-0.030	-0.033	0.173**	-0.021	-0.042	-0.024	-0.162	0.654
sentNEG_AAA	-0.099**	-0.073**	0.200***	-0.049**	0.024	0.082*	0.176*	1.173***
sentNEG_FINE1	-0.068	-0.023	-0.069	0.035	0.270	0.203	-0.392	0.333
sentNEG_BOSS1	-0.026	-0.088	0.087	-0.002	0.070	0.047	0.055	0.066
sentNEG_IPO	0.064	-0.083	0.252*	0.002	-0.220	-0.207	0.046	-1.938**
sentNEG_STAT	0.061*	0.119***	0.503***	0.004	0.031	0.029	0.018	-1.102***
sentNEG_BUYB	0.145	0.129	0.125	0.061	0.126	0.111	0.793**	-0.757
sentNEG_ALLCE	-0.196	-0.140	-0.311	-0.113	-0.097	-0.001	0.643	3.529*
sentNEG_DVST	-0.255*	-0.359***	0.142	0.169*	0.101	-0.053	-0.083	-0.618
sentNEG_SISU	-0.080	0.040	0.258	0.200	-0.192	-0.377	1.119**	-0.693
sentNEG_REORG	-0.129	-0.217	0.446**	-0.069	0.121	0.227	-0.636*	0.453
sentNEG_CPROD	0.227***	0.003	0.714***	-0.015	0.111	0.122	-0.151	0.390
sentNEG_STK	1.226	-0.523	-0.038	0.040	0.566	0.527	-0.080	-2.849**
sentNEG_CASE1	-0.028	-0.182*	0.081	-0.039	0.066	0.078	0.028	1.576**
sentNEG_BKRT	-0.260	-0.451**	0.176	0.023	-0.594**	-0.564**	2.012	1.425
sentNEG_MONOP	-0.107	-0.161**	0.922***	-0.003	-0.143	-0.147	0.005	0.396
sentNEG_CLASS	-0.557*	0.185*	0.132	0.009	-0.088	-0.082	-0.478	-1.582*
sentNEG_CFO1	0.380	-0.026	-0.956*	0.122	-0.123	-0.116	0.460	2.071
sentNEG_MEET1	-0.186	-0.478**	0.702***	-0.013	-0.439	-0.420	0.425	0.319
sentNEG_CEO1	0.187	-0.170	-0.404	0.131	-0.435	-0.480	0.725	0.569
sentNEG_SHRACT	-0.701**	-0.131	0.058	-0.047	0.862	0.890	-0.967**	0.883
sentNEG_LIST1	-0.371	0.027	-1.650***	-0.157	-0.302	-0.157	0.244	-0.002
sentNEG_LAYOFS	-0.043	-0.035	-0.429	-0.073	-0.587	-0.599	1.300***	2.464
sentNEG_DBTR	0.087	-0.191	-0.616	-0.096	-0.344	-0.229	-0.890	-3.320*
sentNEG_DDEAL	-1.654	-0.047	-0.634	-0.317	-1.274*	-0.971	0.290	2.385
sentNEG_SPLITB	1.783*	0.342	-1.654**	-1.584**	-1.668	0.158	4.989	8.313
sentNEG_CHAIR1	-0.246	0.450	-0.902	0.127	0.911	0.753	-1.502	-0.366
sentNEG_ACCI	-0.009	-0.373	0.057	-0.254	-0.282	-0.033	-0.417	1.799
sentNEG_HOSAL	-0.060	-0.174	0.700**	0.269	0.474	0.181	0.030	-3.556***
sentNEG_XPAND	-1.322**	0.946**	0.246	0.003	0.477	0.439	-0.930	-0.837

(c) Interaction Effects of Positive Sentiment

News Topic	r(-5:-3)	r(-1)	r(0)	r(+1)	r(+1:+5)	r(+2:+5)	r(+10:+20)	r(+120:+240)
sentPOS	-0.021**	-0.048***	0.087***	0.019***	0.036***	0.014	0.001	0.064
sentNEG	-0.076***	-0.175***	-0.196***	-0.017***	-0.013	0.004	0.011	0.441***
sentPOS_CMPNY	-0.045***	-0.037***	-0.173***	-0.005	-0.000	0.005	0.039**	-0.021
sentPOS_BACT	0.004	-0.010	-0.007	0.007	-0.006	-0.010	-0.049*	0.366***
sentPOS_RES	-0.013	0.007	0.095***	-0.014	-0.002	0.010	-0.082*	-0.357**
sentPOS_RESF	0.106**	0.042	1.197***	0.038	0.043	0.006	0.143*	0.092
sentPOS_MRG	0.074**	-0.045*	-0.259***	0.033*	0.050	0.012	-0.098**	-1.048***
sentPOS_MNGISS	0.006	0.056**	0.071**	0.016	-0.005	-0.030	-0.063	-0.229
sentPOS_DEAL1	-0.006	0.054**	-0.131**	-0.022	-0.093**	-0.063	0.136**	0.071
sentPOS_DIV	0.031	0.046**	-0.002	-0.019	0.002	0.020	0.036	0.287
sentPOS_AAA	0.082	0.003	-0.028	-0.025	-0.012	0.017	0.145*	-0.246
sentPOS_FINE1	-0.176	-0.270*	-0.136	0.159	0.496**	0.335*	0.252	-1.908*
sentPOS_BOSS1	0.114	0.092	0.221**	-0.079	-0.104	-0.006	0.094	0.930
sentPOS_IPO	-0.169	0.020	-0.419***	0.043	-0.250	-0.287*	-0.282	0.478
sentPOS_STAT	0.233***	0.057	0.134***	-0.046	0.098	0.149**	0.478***	-0.155
sentPOS_BUYB	0.162	0.277*	0.507**	-0.070	-0.455*	-0.386*	-0.204	2.413*
sentPOS_ALLCE	0.025	0.018	-0.481	0.060	0.173	0.114	0.012	0.851
sentPOS_DVST	0.365*	0.373	0.490**	-0.075	-0.268	-0.154	0.203	2.103**
sentPOS_SISU	-0.611	1.097***	-0.039	0.141	-0.013	-0.234	-1.063*	0.500
sentPOS_REORG	-0.200	0.278	0.414	-0.124	0.464	0.647	-1.393**	-1.065
sentPOS_CPROD	0.479***	0.112	0.162	0.073	0.396	0.309	0.326	0.257
sentPOS_STK	-0.090	0.586	1.364**	-0.052	1.305	1.363	0.374	-4.602*
sentPOS_CASE1	0.336	-0.253	-0.086	-0.611*	-2.254***	-1.659***	-0.538	4.494
sentPOS_BKRT	-0.452	-0.722	2.081**	-0.789*	-1.116	-0.473	0.742	-3.368
sentPOS_MONOP	-0.029	-0.140	0.907***	0.165	-0.233	-0.432	0.797	0.105
sentPOS_CLASS	-0.014	0.406	0.158	1.169**	1.255	0.154	-0.846	-8.138*
sentPOS_CFO1	-1.075	0.246	0.880	-0.436	-0.115	0.362	1.865	2.393
sentPOS_MEET1	-0.150	-0.485*	0.229	0.139	-0.370	-0.503	-0.148	0.916
sentPOS_CEO1	0.439	0.118	1.085	-0.102	2.001	1.463	-0.827	-6.148*
sentPOS_SHRACT	-0.290	-0.260	-0.366	-0.125	-0.080	0.058	-0.960	-1.179
sentPOS_LIST1	1.858***	0.475	1.008	-0.628	-0.512	0.069	0.787	-2.975
sentPOS_LAYOFS	0.452	0.285	-1.231	0.192	-0.666	-0.760	-0.858	2.576
sentPOS_DBTR	0.822	2.337*	2.796	-1.273	-1.514	-0.315	-1.086	1.184
sentPOS_DDEAL	-1.911	-0.185	4.326	0.114	-2.576	-2.734**	2.453	-0.306
sentPOS_SPLITB	0.853	0.729	0.032	-1.484	-1.363	-0.167	2.358	17.849**
sentPOS_CHAIR1	0.064	0.134	-0.438	0.668	1.340	0.830	-1.896	5.122
sentPOS_ACCI	18.672	4.987	4.596	-3.692	-6.402**	-2.375*	1.827	3.843
sentPOS_HOSAL	0.835*	-0.997**	0.860	1.034	2.005	0.948	0.348	-3.535
sentPOS_XPAND	-1.184	0.855***	-0.176	-0.061	-0.000	-0.048	0.503	-0.684

Notes: This table presents the coefficient estimates from a panel analysis that captures the return impact of positive and negative sentiments, different news topics, as well as interaction effects of sentiments and topics in basis points. The dependent variables are as shown in the first column of every panel. Independent return windows are presented in the first raw of each panel and day 0 is the day of news arrival. Panel (A) shows the parameters for the overall positive sentiment, negative sentiment, news dummies, and lagged returns. The interaction effects of the negative sentiment are available in Panel (B) and the interaction effects of positive sentiment in Panel (C). "***", "**" and "*" indicate significance levels at 1%, 5%, and 10% respectively.

Appendix B - Topic Codes and Descriptions

AAA

Credit/Debt Ratings: The issuing of an assessment of the credit worthiness of borrowers and potential borrowers. These published ratings for securities such as preferred stock and debt issues are based on the likelihood of consistent and timely payments.

ACCI

Accounting Issues: Issues regarding an organization's financial accounting and the auditing of the organization's financial statements and accounting records. The company's adherence to generally accepted accounting principles, in all material respects. Also accounting-related investigations by regulatory agencies, accounting-related internal investigations and audits, and auditor changes.

ALLCE

Strategic Combinations: Any announcements of strategic alliance arrangement between two companies who have decided to collaborate or share resources in a specific project, or the formation of a joint venture where two or more companies are pooling resources to create a separate entity, or updating of an existing joint venture.

BACT

Corporate Events: All business events relating to companies and other issuers of securities.

BKRFIG

Bankruptcy Figures: The number of business failures nationally. Bankruptcy and liquidation figures.

BKRT

Bankruptcy/Insolvency: News about companies being declared insolvent or put into administration, their administration and liquidations. Includes a company announcing its plans to file for bankruptcy protection, filing an initial or revised plan of reorganization, the granting of bankruptcy court approval to the company's plan of reorganization, and a company's emergence from bankruptcy protection.

BONS

Bonus Share Issues: When a company makes a free issue of shares to shareholders based upon the number of shares that a shareholder owns. Also known as a Bonus Issue, Free Issue, a Capitalization Issue or a Pro Rata Issue.

BOSS1

Key Personnel Changes: Changes of senior personnel in a corporation / organization, including the chairperson, president, CEO and CFO.

BUYB

Share Buybacks/Repurchases: The purchase by a company of its own shares in the open market or by tender offer, usually based on the belief that the shares are undervalued and that buying them will provide a better investment return than putting cash into the underlying business of the company.

CASE1

Corporate Litigation: Legal actions involving or affecting corporations and/or corporate officers. Includes news of moves to take legal action, judgments and dismissals of lawsuits.

CEO1

Change of CEO: Change of a company's chief executive officer.

CFO1

Change of CFO: Change of a company's chief financial officer / finance director.

CHAIR1

Change of Chairperson: Change of a company's chairperson.

CLASS

Class Actions: A legal action against a company or companies where an individual represents a group in a court claim. The judgment from the suit is for all the members of the group (class).

CM1

Competitive Bond Sales: News about competitive bond sales, including presale stories.

CMPNY

Company News: Company news (added automatically when a story contains any company RIC).

CNSL

Share Consolidations: Consolidations of shares in issue, sometimes called reverse stock splits.

CORGOV

Governance/Social Responsibility: Rules, processes, or laws by which businesses are operated, regulated, and controlled; ways in which an organization achieves a balance or integration of economic, environmental, and social imperatives while at the same time addressing shareholder and stakeholder expectations.

CPROD

Products/Services: News about products and services, including their development, launches, recalls, safety, litigation, regulatory approvals, sales and marketing.

DBTR

Corporate Debt Restructurings: The restructurings of corporate debt by altering the terms and provisions of the existing debt issue or issuance of new debt to replace existing debt. Includes financial restructurings undertaken under administration and bankruptcy protection proceedings.

DDEAL

Directors Dealings: The purchase or sale of shares by directors or other key employees or by their agents in the publicly quoted companies for which they work.

DEAL1

Deals: News about any actual or possible purchase of a company, combination or unification of two or more companies, units, subsidiaries, major assets, or complete product lines. Also includes news about change of ownership in a significant stake in a company, spin-offs of business units and sales and acquisitions of significant or potentially significant stakes in a company, as well as news about alliances and joint venture agreements between companies.

DIV

Dividends: Dividend forecasts, declarations and payments. Announcements or projections of payment of a dividend and any major increases or decreases to its dividend.

DVST

Divestitures/Spin-Offs: News of a company disposing of a significant part of its business.

Could involve converting the business to be disposed of into a new, separate company with shareholders in the parent being given shares in the offshoot.

FIND1

Corporate Debt Financing: News about companies raising finance by selling bonds, bills, or notes. Includes news of the issuance of new debt, pricing, redemptions and bankruptcies.

FINE1

Equity Capital Changes: News about equity capital changes including IPOs and secondary share offers, buybacks, share redemptions and consolidations, share splits, bonus and scrip issues. Includes announcements that a company plans to make equity offering/placing, the pricing of offerings/placing and their completion.

HOSAL

Home Sales: New and existing home sales. Housing affordability indices.

IPO

Initial Public Offerings: News about initial public share offers - includes initial offers to professional investors such as via placings.

LAYOFS

Job Cuts: Workforce reductions including temporary layoffs and plans to cut jobs gradually through natural wastage.

LIST1

Security Listings/Delistings: When instruments are listed on or listed instruments are delisted from individual commercial exchanges. These can be exchanges trading in securities, options, futures or commodities. Includes movements from one sector to another sector and changes of listing category. e.g. from small cap to large cap.

MEET1

Shareholder Meetings: News about a company's annual general meetings (AGMs), including business concerns addressed, ballots for company initiatives and company board elections; also includes news about extraordinary general meetings (EGMs) and other shareholder meetings and the issues behind them.

MNGISS

Management Issues/Policies: Management issues including internal controls, executive pay, bonuses and corporate governance. Also includes corporate litigation and accounting issues, shareholder activism and shareholder protection plans.

MONOP

Monopolies/Antitrust Issues: Issues concerning competition law, including investigations into companies suspected of anti-competitive behaviour, and proposed takeovers and mergers, price-fixing and other restrictive business practices.

MRG

Mergers/Acquisitions/Takeovers: Includes news of any actual or possible purchase of a company, combination or unification of two or more companies, units or subsidiaries. and the acquisition of major assets such as infrastructure operating concessions or complete product lines. Also includes a company or party gaining more than a 50% stake in another company or increasing its control above that level.

NAMEC

Corporate Name Changes: Corporate changes of identity, including rebranding, new logos, marketing slogans. Changes in the persona of a corporation which are designed to accord with and facilitate the attainment of business objectives, and are usually visibly manifested by way of branding and the use of trademarks.

PRES1

Change of President: Change of a company's president.

PRIV

Privatization: The sale of a state-owned company or sale of a significant government stake in a company to a private investor or group of investors.

RECLL

Product Recalls: Requests made or actions taken by a manufacturer or seller to recall or withdraw a product from the market due to concerns about possible or actual safety issues or product defects.

REORG

Restructuring/Reorganization: A significant modification made to a company's existing operations or organizational structure, such as when a company closes a location and/or lays off a significant proportion of its workforce. Can include divestments but not acquisitions.

RES

Performance/Results/Earnings: All corporate financial results; tabular and textual reports, dividends, accounts, annual reports, forecasts and estimates of future earnings, corporate insolvencies and bankruptcies.

RESF

Results Forecasts/Warnings: Forecasts or "guidance" given by a company about its future results, including profit warnings.

SHRACT

Shareholder Activism: An initiative by a shareholder to put pressure on the management of a public company on one or several issues such as board control, board representation, forcing or opposing an M&A transaction or reorganization or change in strategic direction. It can take several forms, such as proxy fights, negotiations with management, publicity campaigns, litigation, shareholder resolutions. See also Shareholder Meetings [MEET1].

SISU

Secondary Share Offerings/Issues: Secondary share issues. The issue of new stock or derivatives such as warrants and convertible bonds from a company that has already made its initial public offering (IPO). Includes placings and rights issues. Does not include bonus issues.

SL1

Bond Sales: News about all bond sales, including presale stories.

SPLITB

Share Splits/Bonus Issues: Moves to increase a company's shares in issue without increasing shareholder funds, such as stock splits and bonus issues.

STAT

Production Status Changes: A disruption and/or resumption of production or services.

XPAND

Expansions/New Markets/New Units: A company moving into a new area of business or expanding its existing business. Includes a company expanding geographically by market or product or service offering, creating a new unit or starting a new line of business. Excludes acquisitions of other companies, which are covered by Mergers/Acquisitions/Takeovers [MRG].

General Conclusion

This dissertation consists of three empirical articles that study the predictability of systematic risk, time variation in cash flow and discount rate news, and the relationship between news sentiment and stock returns for different topics.

The first chapter fills the existing gap in the forecasting literature of systematic risk by establishing parametric relationships in the existing benchmark autoregressive model, providing a sophisticated array of tests and predictors, and suggesting to take into account bond yield measures when forecasting next quarter's beta. Thus, it documents that bond yield measures produce statistically significant forecasts and reduce the return of a hedged position to a higher extent when compared to other predicting variables or the benchmark AR(1) model.

The following chapter contributes to the literature by showing that the relative importance ratios for each news component of market volatility exhibit significant variation throughout time. It also identifies lagged changes in inflation as the main macroeconomic determinant of this time variation in the short run. In an asset pricing framework, we argue that it is economically important to account for time variation in beta decomposition if a model which captures this time variation performs better than models ignoring it. Indeed, our results suggest that this conditional asset pricing model outperforms other conditional and unconditional models in accounting for the cross-sectional variation in expected returns.

Last, the third chapter provides summary statistics for a rich set of different news topics from Thomson Reuters News Analytics Database and studies the association between news sentiment and stock returns. We find that there is more news occurring in the categories of company news, corporate event, mergers, results, and result forecasts. The main contribution consists of showing that sentiment of news is at least as important as the existence of news itself. Thus, tone of different news topics affects returns differently at different horizons. The reversal patterns carry premises in linking different topics to the two main cash flow and discount rate channels.

The empirical nature of these papers, the fact that they are conducted at the market or the firm level when necessary, along with the easiness to implement them in practice, makes me eager to believe that they will be important to upcoming research in terms of accounting for exogenous variables when predicting betas, considering the time variation when decomposing returns into their news components, and paying particular attention to news tone of various news topics when constructing different trading strategies or addressing asset-pricing puzzles.