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Abstract

This thesis concerns the empirical relationships among firm cash flows and macroeconomic dynamics through the lens of asset pricing. It consists of four chapters, which can be read independently. The common theme across all four chapters is the relation between asset prices and macroeconomic dynamics. All chapters in this thesis document new empirical facts that help us understand how macroeconomic dynamics affect asset prices. The following provides summaries of the individual papers. These summaries clarify each papers' contribution.

The first chapter addresses why the dividend-price ratio in U.S. cannot predict future dividend growth. We argue that the public debt drives the co-movement among stock returns and dividend growth. The co-movement components are offsetted on the dividend price ratio, which leads to failure of cash flow predictability by the dividend yield. We first document that the higher debt-to-GDP ratio can predict both higher dividend growth and higher stock returns. The finding is consistent with Lettau and Ludvigson (2005)'s argument that there exists a common component among stock returns and dividend growth which resolves the US asset pricing puzzle that the dividend-price ratio can only predict discount rates but not cash flows. To rationalize this finding, we propose a production-based asset pricing model incorporating a cash-retention friction on the corporate sector. The model can produce testable predictions that the increase in public debt moves both dividend payment and the cost of capital in the same direction, resulting in the capture of the common component.

The second chapter explores the inflation non-neutrality in an international context and studies how the inflation non-neutrality affects the asset prices. We

document that both the dividend yield and earnings yield can predict future inflation across advanced economies. The inflation predictability reinforces the return predictability and reduces the dividend growth predictability. We show that both discount rates and cash flows play an important role in determining prices. We test three hypotheses related to the future growth prospect, risk aversion, and behavior bias to justify the positive correlation among inflation and dividend (earnings) yields. High expected inflation correlates with periods of lower real economic growth and higher discount rates which lead to the drop in today's prices. To rationalize the inflation predictability, we develop and estimate a long-run risk model featuring inflation non-neutrality. The estimated model can reproduce both the inflation predictability and the documented asset pricing facts.

The third chapter addresses the question of why value premium waves and disappeared during the low inflation period. In the long history of value investing, the value premium has disappeared for several times and this paper provides a risk-based explanation for its disappearance. I document a positive linear relationship among the value premium and the expected inflation at both high frequency and lower business cycle frequency. A heterogeneous cash flow model featuring inflation non-neutrality is proposed to justify the observed pattern. The estimated results suggest that value firms are more exposed to high-frequency fluctuations in aggregate consumption growth but less exposed to the low-frequency consumption risk. This finding is consistent with the documented inflation-return relationship but it contrasts with the previous findings suggesting that value firms are more sensitive to long-run consumption risk. Simulation-based results show that the positive linear relationship among the value premium and the expected inflation can be recovered when inflation is non-neutral and the relationship turns into uncorrelated when inflation is neutral. Therefore we argue that inflation non-neutrality can justify the positive relationship among inflation and value premium. Meanwhile, value firms tend to underperform growth firms when the inflation is in low range, and it leads to the disappearance of the value premium.

The fourth chapter studies the role of cash flow risk in cross-sectional industry

returns. Chava, Hsu, and Zeng (2019) find that investors don't fully incorporate business cycle variation in cash flow growth and thus conditional Sharpe ratio can be informative for future industry returns. It suggests that cash flow risk at the idiosyncratic level is not fully incorporated into the prices by investors. I develop a stochastic volatility framework to evaluate the unexpected cash flow news through the variance decomposition perspective and apply the method to U.S. industry data. I find that i) The common cash flow volatility estimated from unexpected industry-level cash flow news is highly correlated to Uncertainty index constructed by Jurado, Ludvigson, and Ng (2015); ii) the idiosyncratic cash flow risk is robustly priced and the explanation power cannot be consumed by current well-known risk factors and firm characteristics; iii) stocks with high conditional Sharpe ratios tend to have higher idiosyncratic cash flow volatility and higher compensated returns, which is consistent with Chava, Hsu, and Zeng (2019)'s finding. A strategy that goes long the decile portfolio with the largest idiosyncratic cash flow volatility and short the decile portfolio with the smallest idiosyncratic cash flow volatility yields a Fama-French-Five-Factor alpha of 37 bps per month (t-stat: 6.90) in long sample (1931-2018) and 64 bps per month (t-stat: 12.28) in the modern sample (1963-2018).

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Contents

Chapter 1

Government Debt, Dividend Growth, and Stock Returns

Abstract: This paper documents that the increase in public debt can lead to higher dividend payout to shareholders, which suggests public debt can be a strong cash flow predictor which help better predict future stock returns. Specifically, the higher public debt-to-GDP ratio can predict both higher dividend growth and higher stock returns. The finding is consistent with Lettau and Ludvigson's (2005) argument that there exists a common component among stock returns and dividend growth. We argue that i) public debt can drive the co-movement among returns and dividend growth, and the existence of a common component can resolve the US asset pricing puzzle as emphasized by Cochrane (2007, 2011) that the dividend-price ratio can only predict discount rates but not cash flows; ii) the strong cash flow predictability of the public debt-to-GDP ratio can not be consumed by the popular consumption-to-wealth ratio (cay) and many other macroeconomic states variables; iii) future stocks returns can be better out-of-sample predicted after controlling for public debt. The evidence documented in the US aggregate market can also be extended to the US cross-section and the international markets, especially for the advanced financial markets, which help to explain the weak cash flow predictability documented by Rangvid et al. (2014) and Maio et al. (2015). To rationalize the finding, we propose a production-based asset pricing model incorporating cash-retention friction on the corporate sector. The model can produce testable predictions that the increase in public debt moves both dividend payment and the cost of capital in the same direction, resulting in the capture of the common component.

JEL classification: E20, G10, G12.
Keywords: Cash retention friction; Dividend predictability; Long-run productivity; Public debt.

"The variance of dividend yields or price-dividend ratios corresponds entirely to discount-rate variation, but as much as half of the variance of ... returns $r_{t+1} \approx$ â$\rho dp_{t+1} + dp_t + \Delta d_{t+1}$ *corresponds to current dividends* Δd_{t+1}. *This fact seems trivial but has caused a lot of confusion." - John Cochrane (2011's Presidential Address: Discount Rates)*

1.1 Introduction

The mechanism through which fiscal variables impact stock returns remains an open question while there is an extensive literature that analyzes the impact of monetary policy on financial markets. We conjecture that the government's fiscal and debt policy can affect the financial market through the uncertainty channel which contributes to the growing literature on the effect of fiscal policies on the stock market. Tracing the unambiguous effect of economic policies on equity returns would require data on government taxation, spending, deficit and debt, which are what we concern. We start the research to explore whether certain fiscal variables can predict stock returns and the firm's future cash flows. We document that the debt-to-GDP ratio can predict both the dividend growth and stock returns and the debt factor can explain the roughly same variations in both returns and dividend growth. Another way to say is that the debt factor loadings in two predictive regressions are close to each other in magnitudes.

The finding is directly related to the confusing "facts" introduced by [Cochrane, 2007, Cochrane, 2011]. The conventional wisdom suggest that most of the variations of dividend yields come from the discount rates and the dividend yield cannot predict the dividend growth. Therefore, if there is factor that can predict both returns and dividend growth, then this factor can be a potential candidate to resolve the US asset pricing puzzle because there exists co-movement among contemporaneous returns and dividend growth, and the co-movement parts are offsetted in the dividend yield decomposition. The argument is first proposed by

[Lettau and Ludvigson, 2005] that there exists a common component between stock returns and dividend growth which dividend yields fail to capture. The offsetted common component can resolve the puzzle if this common component is important in predicting dividend growth. We documented that higher public debt leads to higher dividend growth and higher stock returns. The similar predictive coefficients of the debt-to-GDP ratio on dividend growth and stock returns suggest that the debt-to-GDP captures this common component. To test the debt factor captures the common component, we construct a GMM estimation and we find the common component hypothesis can not be rejected.

Critically, we document that the surges in government debt predict higher dividend payout. The reason is that the rise in public debt leads to higher tax uncertainty which is accompanied by subsequent declines in corporate investment. With the money lying on firms' balance sheets, which is supposed to be invested, firms face the costly cash-retention friction and would like to pay part of it to shareholders as dividends. Meantime, the high public debt increases the cost of capital for firms as documented by [Croce et al., 2018]. Therefore we can document that the increase in public debt moves both dividend payment and the cost of capital in the same direction, resulting in the co-movement of returns and dividend growth and resulting in the capture of the common component by the debt-to-GDP ratio.

To interpret our findings and provide guidance on further empirical tests, we propose a production-based asset pricing model where the firm's trade-off behaviors are introduced. In the model, firms facing uncertainty need to decide their corporate bond issuance, cash retention, and investment. Movements in government debt drive the dynamics of tax rates and the corresponding uncertainty, which affect corporate investment and bond issuance and thus the dividend payout. We find that the model quantitatively rationalizes our empirical evidence on both the dividend and return predictability. The mechanism behind the result can be explained as follows. As public debt increases, uncertainty about future tax rates rises endogenously and the increasing uncertainty depresses the firm's investment. By introducing costly cash-retention friction, the delay in investment leads to the firm's higher dividend payout. Therefore higher government debt results in higher dividend growth.

Related Literature It starts from whether certain fiscal variables can predict future stocks. We surveyed the literature and found several government-related variables can help us to predict stock returns. The candidate fiscal variables include public debt, government spending, government investment, and cyclical fiscal policy etc.. For public debt related literature, [Croce et al., 2012] argued that public debt raises tax uncertainty, and the aggregate stock market should carry a sizeable risk premium. [Liu, 2019] argued that fiscal uncertainty reflected by public debt predicts higher aggregate excess stock returns and corporate bond risk premium. [Croce et al., 2018] argued that public debt raises growth concerns, and high R&D firms should carry a higher risk premium. For other government-related variables, [Belo et al., 2013] found the predictable variation in cash flows and stock returns over political cycles by exploiting a novel measure of industry exposure to government spending. [Belo and Yu, 2013] found that high rates of government investment in public sector physical capital forecast high aggregate stock market returns. [Da et al., 2018] found that firms headquartered in states with counter-cyclical fiscal policies have lower average stock returns provided their investors have a local investment bias, and thus counter-cyclical fiscal policies can influence asset prices. In this paper, we emphasize both the return predictability and the dividend predictability. We start from the new finding that public debt can lead to higher dividend payout and then we relate the cash flow predictability to the return dynamics.

There is a large literature on dividend growth predictability. It's important to predict the future dividend growth because cash flow predictability can help us better predict future stock returns. [Lacerda and Santa-Clara, 2010] argue that we can better predict stock returns if we can better predict dividend growth. They assume that investors forecast dividend growth from a past average and adjust the dividend price factor to obtain better forecast power. [Koijen and Van Nieuwerburgh, 2011] argue that dividend growth and return predictability are two sides of the same coin. Most papers focus on the dividend predictability by dividend yields and the weak cash flow predictability is documented in various previous research. [Cochrane, 2007, Cochrane, 2011] surveyed and argued that the cash flows are unpredictable at the US aggregate level. [Maio and Xu, 2018] extended the analysis to the US cross-section level and found that the dividend price ratios cannot predict the future dividend grow for the large and growth firms. At the international level, [Rangvid et al., 2014] found that dividend predictability is weaker in large and developed markets where dividends are smoothed more, the average firm size is large, and volatility is lower. However, many other papers provide evidence of strong predictability on dividend growth rates. For examples, there are evidences documented by [Binsbergen et al., 2010], [Bansal and Yaron, 2004], and [Lettau and Ludvigson, 2005]. [Binsbergen et al., 2010] develop a latent variables approach to aggregate the whole history of price-dividend ratios and dividend growth rates by expanding the information set to estimate expected returns and expected growth rates. They find that U.S. market-wide dividends are predictable in the present-value model. [Bansal and Yaron, 2004] model dividend growth as containing a persistent observable component that is common to consumption growth. [Lettau and Ludvigson, 2005] are able to forecast dividend growth from a stationary linear combination of consumption, dividends, and labor income. These studies shows that we may need to depart from the assumption that expected dividend growth is known and constant. [1] While most papers focus on the dividend predictability by dividend yields, less macroeconomic variables, e.g. the debt-to-GDP ratio, are explored. The question would be whether dividend growth rates are

[1] [Chen, 2009a] documents the reversal of return and dividend growth predictability around 1950s. They show that the prewar data suggests a constant return and time-varying dividend growth while the postwar data suggests the time-varying return and a constant dividend growth.

predictable. We find that the dividend growth can be proxy-ed by the debt-to-GDP ratio and further evidence shows that other macroeconomic variables can also predict the future dividend growth. Since public debt can drive the dividend payouts and the public debt-to-GDP can be a strong cash flow predictor, the dividend predictability can also be turned into better return predictability.

To rationalize the finding, we propose a production based asset pricing framework incorporating the firm's dynamic trade-off behavior. Methodologically, our theoretical work builds on recent papers by [Livdan et al., 2009], [Croce et al., 2012], [Palazzo, 2012], [Croce, 2014], and [Croce et al., 2018]. [Croce et al., 2012] study the role of fiscal policy and taxation on investment, growth and returns. They find that high debt-to-GDP ratio leads to higher tax uncertainty which will depress firms' investment. The results are empirically consistent with what [Bloom et al., 2007, Bloom, 2009] documented that higher tax uncertainty or fiscal policy uncertainty makes firms wait and postpone their investment.

Besides the trade-off between the corporate debt benefit and expected tax shield, we extend the framework to incorporate firm's cash-retention behavior to capture the financing friction among internal and external financing. The setting allows the model to produce testable predictions consistent with the common component argument that higher public debt leads to both higher cost of capital and higher dividend payouts. Here we model the cash retention of firms because it introduces the precautionary saving motivation of firms and it is a risk channel ignored before. Intuition suggests that firms may have an incentive not to pay out all the available end-of-period cash flows to shareholders and they would hold cash flow on their balance sheet for cases that the financing constraint becomes binding. For the cash-retention literature, [Acharya et al., 2007] build a model to show that firms that issue debt and hoard cash transfer income from high cash flow states to fund investment in all states. [Bates et al., 2009] shows cash ratios increase because firms' cash flows become riskier and the precautionary motive for cash holdings plays an important role in explaining the increase in cash ratios. [2] [Harford et al., 2014] argue that firms with high refinancing risk tend to hold more cash. Firms use cash reserve to mitigate the under-investment problem. The cash-holding behavior is closely related to the firm's investment. Financial constraints create an inter-temporal trade-off between current and future investments. [Han and Qiu, 2007] show that when future cash flow risk cannot be fully diversified, the inter-temporal trade-off gives constrained firms the incentives of precautionary savings: they increase their cash holdings in response to increases in cash flow volatility. The argument is consistent with what [Minton and Schrand, 1999] documented that investment is negatively related to cash flow volatility and current cash holdings is positively related to cash flow volatility. [Gao et al., 2017] shows that systematic uncertainty increases firm cash holdings and firms with cyclical access to external financing are more affected by systematic uncertainty through the cost-of-capital channel. The way we model the cash holding can be related to the firm's financing flexibility argument which are proposed by [DeAngelo et al., 2017]. They find that cash-balance accumulation to acquire flexibility to meet possible future funding needs could also matter for firms. When the economy uncertainty increases, firms may choose under-investment behavior, increase cash holding, and payout more dividends.

More broadly, our paper shares its focus with the growing literature on asset pricing in general equilibrium models with production. We consider our contribution as follows. First, we document that the debt-to-GDP factor captures the common component between dividend growth and stock returns which resolves the US asset pricing puzzle ([Cochrane, 2007, Cochrane, 2011]) - dividend yield cannot predict future dividend growth. The finding is consistent with the argument made by [Lettau and Ludvigson, 2005] that there exists a co-movement among the

[2][Duchin et al., 2010] take the financial crises as the unexplored negative shock to the supply of external finance for non-financial firms and find that the greatest negative effect on investment is for firms with low cash reserves and firms reliant on external capital.

contemporaneous returns and dividend growth. Therefore, we argue that the public debt is the driving force of this co-movement. It could also contribute to explain the weak cash flow predictability at the US cross-section ([Maio and Xu, 2018]) and the international level ([Rangvid et al., 2014]) since public debt can drive the co-movement at difference asset classifications. Second, we propose a production based asset pricing framework incorporating firm's cash retention to rationalize the finding that high public debt leads to high dividend payout, and the model generates testable predictions regarding the common component argument. Under the three-sector model featuring the cash-retention friction, firms increase rather than decrease their dividend payouts when government debt increases. It suggests that firm's cash holdings which relaxes firm's financing constraints can be a risk channel. We can obtain reasonable risk premium by considering the financial costs from cash retention behavior.

The rest of the paper is organized as follows. In the next section we present evidence on the predictability of both stock returns and dividend growth and we test that the debt-to-GDP ratio can capture the common component. We show the significance of the debt-to-GDP ratio holds after controlling the CAY and other macroeconomic variables in section 3. In section 4, we propose a general equilibrium framework to incorporate both public debt and corporate cash holding to study how the fiscal policy shocks are transmitted in the firm's dynamic trade-off model. Section 5 provides out-of-sample tests to show the role of expected dividend growth in predicting the stock returns. Section 6 provides U.S. cross-section evidence (value/growth and small/large) and section 7 provides international evidence (20 developed countries and 24 emerging markets) on that public debt drives the co-movement among returns and dividend growth. The last section concludes.

1.2 Empirical Evidence

We start from the long-horizon regressions to test the predictive relationship. The predictability of dividend growth and stock returns holds across different samples and different specifications. High public debt-to-GDP ratio can predict high future dividend growth and high future stock returns. The similar factor loadings of the debt-to-GDP ratio on dividend growth and stock returns suggest that the debt-to-GDP ratio captures this common component. To test the debt factor can capture the common component, we construct a GMM estimation and results suggest that the common component hypothesis can not be rejected. The public debt explain the same variation in dividend growth and stock returns.

1.2.1 Long-Horizon Forecasting Regressions

We report the evidence from the long-horizon forecasting regression in Tables 1.1. In this paper, we consider predictive regressions for quarterly data with horizons ranging from one to five years. We consider the quarterly data for the Standard&Poor's ($S\&P$) 500 index from 1966Q1 to 2017Q4 taken from Robert Shiller's web site, and dividends are 12-month moving sums of dividends paid on the $S\&P$ 500 index. These series coincide with those used in [Welch and Goyal, 2007], and made available at Amit Goyal's website. A full description of all data used in our empirical analysis is provided in Appendix 1.9.1.

Tables 1.1 reports the evidence for forecasting returns and dividend growth based on the following benchmark model:

$$ret_{t,t+H} = \beta_0 + \beta_1 \widetilde{dp_t} + \epsilon^r_{t,t+j} \tag{1.1}$$

$$\Delta d_{t,t+H} = \gamma_0 + \gamma_1 \widetilde{dp_t} + \epsilon^d_{t,t+j} \tag{1.2}$$

$$H = 1, \cdots, 5$$

where $ret_{t,t+H} \equiv \frac{1}{H}\sum_{j=1}^{H} r_{t+j}$, $\Delta d_{t,t+H} \equiv \frac{1}{H}\sum_{j=1}^{H} \Delta d_{t+j}$, and $\widetilde{dp_t} \equiv dp_t - \overline{dp_t}$.

Here we adjust the dividend-price ratios with structural break methods applied by [Lettau and Van Nieuwerburgh, 2007]. LVN use a century of U.S. data to show evidence on the breaks in the constant mean dp_t. As a matter of fact, the evidence from uni-variate tests for non-stationarity and bi-variate co-integration tests do not lead to the rejection of the null of the presence of a unit root in dp_t. [Lettau and Van Nieuwerburgh, 2007] identify two statistically significant breaks in the mean of dp_t, in 1954 and 1994. Then they provide evidence that deviations of dp_t from its time-varying means have a much stronger forecasting power for stock market returns than deviations of dp_t from a constant mean. The evidence toward a slowly evolving mean in dp_t has been reported as a pure statistical fact.[Lettau and Van Nieuwerburgh, 2007] give some hints on possible causes for the breaks arising from economic fundamentals due to technological innovation, changes in expected returns, etc., but do not explore the possible effects of fundamentals any further. [Favero et al., 2011] illustrate how the theoretical model by [Geanakoplos et al., 2004] implies that a specific demographic variable, MY, the proportion of middle-aged to young population, explains fluctuations in the dividend yield. In figure 1 we show the adjusted dividend-price ratio and we document the consistent struck breaks at 1954Q2 and 1995Q2 based on structural break tests using quarterly data.

[Insert Figure 4.1 near here]

[Insert Table 1.1 near here]

Using US post-war data, we document that the dividend price ratio can predict stock returns but fail to predict the dividend growth, which is consistent with previous research [Cochrane, 2007, Cochrane, 2011].

Before we introduce the debt-to-GDP factor ($\frac{D}{Y}$) into the regressions, we first check the correlation relationship among factors and find that the debt-to-

GDP factor has very low correlation with the de-meaned dividend-price ratio and the consumption-over-wealth ratio (CAY) while it's highly negatively related to the dividend yield. Controlling for dividend-price ratios will not subsume the predictability of the debt-to-GDP ratio but will bias the estimate of coefficients. Therefore we introduce the adjusted factor $\widetilde{dp_t}$ and CAY_t into the regressions, which ensures the unbiased coefficient estimate of $\frac{D}{Y}$.

[Insert Table 3.2 near here]

We introduce the debt-to-GDP factor into regressions and the new specification can be represented as:

$$ret_{t,t+H} = \beta_0 + \beta_1 \frac{D}{Y}_t + \beta_2 \widetilde{dp_t} + \epsilon^r_{t,t+j} \tag{1.3}$$

$$\Delta d_{t,t+H} = \gamma_0 + \gamma_1 \frac{D}{Y}_t + \gamma_2 \widetilde{dp_t} + \epsilon^d_{t,t+j} \tag{1.4}$$

$$H = 1, \cdots, 5$$

Using US data, we document the fact that high government debt-to-GDP ratio is related to high equity returns and high dividend growth. We provide results at different horizon specifications. All regressions are run at quarterly frequency but all dependent variables in regressions are annualized returns and annualized dividend growth. The evidence is summarized as follows: for stock return regressions, $\frac{D}{Y}_t$ is always significant along with adjusted dp_t in all the forecasting regressions for real stock market returns (Panel A, Table 1.3). The R^2 of the predictive regression at quarterly frequency increases with the horizon from 0.182 at the 1-year horizon to 0.307 at the 5-year horizon. For dividend growth predictions, $\frac{D}{Y}_t$ is always significant along with adjusted dp_t in all the forecasting regressions for real dividend growth (Panel B, Table 1.3). The R^2 of the predictive regression at quarterly frequency increases with the horizon from 0.193 at the 1-year horizon to 0.416 at the 5-year horizon. Results suggest that the public debt-to-GDP ratio can predict both returns and dividend growth while the adjusted dividend yield can only predict the future stock returns. The interesting finding here is that the similar factor loading of the debt-to-GDP ratio on dividend growth and on stock returns may suggest the debt-to-GDP ratio explains the same variations among the returns and dividend. If this is the case, then the public debt can be a potential candidate that captures the common component among dividend growth and stock returns.

[Insert Table 1.3 near here]

1.2.2 Revisit dp_t Ratio

The debt-to-GDP ratio has predictive power on both returns and dividend growth. Therefore one way to argue is that stock returns can be represented as a function of dividend growth and the factor that can predict future dividend growth may better predict future stock returns.

$$ret_{t+j} = f(dp_t, \Delta d_{t+j}) \tag{1.5}$$

Another potential argument is that the raw debt-to-GDP ratio captures the off-setted common component among expected returns and dividend growth. The argument that dividend yield can not capture the common component has been made by previous papers such as [Lettau and Ludvigson, 2005].

Here we start from the most classic decomposition made by [Campbell and Shiller, 1988]. They decompose the dp_t ratio as

$$dp_t \simeq -\frac{\kappa}{1-\rho} + E_t \sum_{j=1}^{\infty} \rho^{j-1} r_{t+j} - E_t \sum_{j=1}^{\infty} \rho^{j-1} \Delta d_{t+j} \tag{1.6}$$

where $\rho = \frac{1}{1+exp(E[dp])}$ is a (log-linearization) discount coefficient that depends on the mean of dp, $\kappa = -log(\rho) + (1-\rho)log(\frac{1}{\rho} - 1)$, r_{t+j} is the log return to stock market wealth and Δd_{t+j} is the log dividend growth. This equation says that if the log dividend-price ratio is high, agents must be expecting either high future returns on stock market wealth or low dividend growth rates. However, this expression does not predict which variables on the right-hand side should be forecastable. Many studies have documented that dp_t can forecast stock returns over long horizons but explains vary little of variations in future dividend growth. Other studies find that the forecasting power of single dp_t for future excess returns over shorter horizons is statistically weak.

[Lettau and Ludvigson, 2005] argue that the positively correlated fluctuations in expected dividend growth and expected returns have offsetting effects on the log dividend-price ratio. They argue that the dp_t ratio fails to capture the common variations among the expected returns and the dividend growth while both *cay* and *cdy* can capture this common component. The capture of the common component can be considered as a way to resolve the asset pricing puzzle that the dividend yield can not predict the future dividend growth.

Following the argument above, we can say that fluctuations in expected returns and expected dividend growth have a common component and offset the effects on dp_t ratio. Therefore a single dp_t factor cannot predict the dividend growth. Based on the empirical evidence of predictability on dividend growth and stock returns, we can argue that the public debt-to-GDP ratio can predict the offsetted common component.

We argue that the losing explanation power of dp_t is due to the existing common component among r_{t+j} and Δd_{t+j}. Take a simple example:

$$\Delta d_{t+j} = x_{d,t+j} + \eta_{t+j} \tag{1.7}$$

$$r_{t+j} = x_{r,t+j} + \phi \cdot \eta_{t+j} \tag{1.8}$$

where η_{t+j} is the common component, $x_{d,t+1}$ is the idiosyncratic component of dividend growth, $x_{r,t+1}$ is the idiosyncratic component of stock return, and ϕ is the loading of the common component on returns. Then take the difference between return and dividend growth, we have

$$r_{t+j} - \Delta d_{t+j} = x_{r,t+j} - x_{d,t+j} + (\phi - 1)\eta_{t+j} \tag{1.9}$$

If $\phi = 1$, the common component information η_{t+j} cannot be reflected by the difference $(r_{t+j} - \Delta d_{t+j})$ of returns and dividends. The equation is reduced to the following:

$$r_{t+j} - \Delta d_{t+j} = x_{r,t+j} - x_{d,t+j} \tag{1.10}$$

Theoretically we can recover the missing component η_{t+j} by controlling for a factor which can predict both r_{t+j} and Δd_{t+j}. Based on the empirical evidence, we can argue that the public debt-to-GDP ratio can predict the missing common component which will resolve the asset pricing puzzle and we can control for this factor when we predict stock returns through the dividend growth predictability.

Joint Hypothesis Test: To test the predictive power on returns is transmitted through the predictive power on dividend growth and the debt-to-GDP ratio captures the common component, we run the following GMM estimation and run the hypothesis test.

$$\begin{aligned} ret_{t,t+H} &= \phi_{0,H} + \phi_{1,H} E_t[\Delta d_{t,t+H}] + \phi_{2,H} \widetilde{dp_t} + \epsilon^r_{t,t+j} \\ \Delta d_{t,t+H} &= \gamma_{0,H} + \gamma_{1,H} \frac{D}{Y}_t + \epsilon^d_{t,t+j} \\ H &= 1, \cdots, 5 \end{aligned} \tag{1.11}$$

In the estimation system, five return regressions and five dividend growth regressions are included. Each dividend growth is predicted (instrumented) by the public debt-to-GDP ratio and each return is predicted by the expected dividend growth and adjusted dividend price ratio. Results in table 1.4 show the expected dividend growth is significant in explaining the variations in corresponding stock returns. The factor loading $\phi_{1,H}$ is close to 1 across all horizons. Each dividend growth is instrumented by the debt-to-GDP ratio and the explanation power increases with horizons. We run the joint test whether the factor loadings of expected dividend growth on corresponding stock returns are equal to one, which is $\phi_{1,1} = \phi_{1,2} = \phi_{1,3} = \phi_{1,4} = \phi_{1,5} = 1$. The p-value is 0.9787 which is very close to one and we cannot reject the null hypothesis that the public debt-to-GDP ratio can capture the common component among stock returns and dividend growth. We also run a new estimation letting $\phi_{1,1} = \phi_{1,2} = \phi_{1,3} = \phi_{1,4} = \phi_{1,5} = \phi_1$ and the new estimated $\phi_1 = 1.0542$. The null hypothesis $\phi_1 = 1$ also cannot be rejected.

[Insert Table 1.4 near here]

1.3 Debt-to-GDP Ratio and Other Factors

1.3.1 Debt-to-GDP Ratio and CAY

In this section, we provide further evidence by controlling for the CAY factor. [Lettau and Ludvigson, 2001, Lettau and Ludvigson, 2005] find that dividend growth and stock returns are predictable by the long-run equilibrium relationship derived from a linearized version of the consumer's intertemporal budget constraint. The excess consumption with respect to its long-run equilibrium value is defined by Lettau and Ludvigson (2001) alternatively as a linear combination of labor income and financial wealth, CAY. CAY is a much less persistent time series than dp_t, and it is a predictor of both stock returns and dividend growth, and when included in a predictive regression relating stock market returns to dp_t, CAY swamp the significance of the dividend price ratio.

[Lettau and Ludvigson, 2001] derive CAY as a tri-variate co-integration relation involving three observable variables: c_t, a_t and y_t, where c_t is the log of consumption, a_t is the non-human or asset wealth, and y_t is log labor income.

$$cay_t \equiv c_t + \omega a_t + (1-\omega) y_t = E_t \sum_{t=1}^{\infty} \rho_\omega^i (\omega r_{a,t+i} - \Delta c_{t+i} + (1-\omega)\Delta y_{t+1+i})$$

$r_{a,t}$ is the log return to asset wealth. Under the maintained hypothesis that asset returns, consumption growth, and labor income growth are covariance-stationary and the above equation says that consumption, asset wealth, and labor income are co-integrated and that deviations from the common trend in c_t, a_t, y_t summarize expectations of returns to either asset wealth, consumption growth, or labor income growth, or some combination of all three. The wealth shares ω and $1-\omega$ are co-integration coefficients. The derived relationship does not necessarily suggest that the CAY can predict the asset returns or consumption growth. However, [Lettau and Ludvigson, 2005] find that CAY has predictive power for both future returns and future dividend growth, with high values of CAY predicting high returns and high dividend growth rates. What [Lettau and Ludvigson, 2005] did not explore is that whether the CAY's predictability of stock returns is from the predictability of dividend growth.

The new specification controlling for CAY is as following

$$ret_{t,t+H} = \beta_0 + \beta_1 \frac{D}{Y}_t + \beta_2 \widetilde{dp_t} + \beta_3 CAY_t + \epsilon^r_{t,t+j} \tag{1.12}$$

$$\Delta d_{t,t+H} = \gamma_0 + \gamma_1 \frac{D}{Y}_t + \gamma_2 \widetilde{dp_t} + \gamma_3 CAY_t + \epsilon^d_{t,t+j} \tag{1.13}$$

$$H = 1, \cdots, 5$$

[Insert Table 1.5 near here]

When we evaluate the predictive power of $\frac{D}{Y}_t$ in the long-run forecasting, it is important to also control for CAY. There are several reasons to do so. First, it is a parsimonious way of evaluating the model with CAY, against all financial ratios traditionally adopted to predict returns. In fact, [Lettau and Ludvigson, 2001, Lettau and Ludvigson, 2005] show superior performance in predicting long-run returns of CAY, with respect to all the traditionally adopted financial ratios, such as the detrended short-term interest rate (Campbell (1991), Hodrick (1992)), the log dividend-earnings ratio and the log price-earnings ratio ([Lamont, 1998]), the term spread of long-term bond yield over three-month T-bill, and the default spread of corporate bond rates. Second, it would allow further investigation on the presence of a common component in dividend and stock market returns suggested by [Lettau and Ludvigson, 2005]. As we see in Table 1.4 that $\frac{D}{Y}_t$ can predict both long-horizon returns and dividend growth. It could shed further light on the relative importance of CAY to $\frac{D}{Y}_t$, for predicting returns and dividend growth in the dynamic dividend growth model.

We found that CAY and $\frac{D}{Y}_t$ are both significant in long-run stock return regressions but CAY lose significance in the long-run dividend growth (table 1.5). The evidence supports that $\frac{D}{Y}_t$ have stronger predictive power on the future dividend growth and we relate this to the presence of a common component in dividend growth and stock market returns.

Joint Hypothesis Test: Similar as before, to test the debt-to-GDP's predictive power on returns is transmitted through the predictive power on dividend growth, we run the following GMM estimation and the hypothesis test.

$$ret_{t,t+H} = \phi_{0,H} + \phi_{1,H}(\gamma_{1,H}\frac{D}{Y}_t) + \phi_{2,H}(\gamma_{2,H}CAY_t) + \phi_{3,H}\widetilde{dp_t} + \epsilon^r_{t,t+H} \tag{1.14}$$

$$\Delta d_{t,t+H} = \gamma_{0,H} + \gamma_{1,H}\frac{D}{Y}_t + \gamma_{2,H}CAY_t + \gamma_{3,H}\widetilde{dp_t} + \epsilon^d_{t,t+H} \tag{1.15}$$

$$H = 1, \cdots, 5$$

where $\phi_{1,i}$ measures the variance contribution ratio from the debt-to-GDP ratio and $\phi_{2,i}$ measures the variance contribution ratio from CAY. Results in Table 1.6

show that the expected dividend growth is significant in explaining variations of stock returns. The dividend growth is mainly instrumented by the debt-to-GDP ratio and the explanation power increases with horizons. We run the joint test whether the factor loadings of dividend growth on corresponding stock returns are equal to one which is $\phi_{1,1} = \phi_{1,2} = \phi_{1,3} = \phi_{1,4} = \phi_{1,5} = 1$. The p value is 0.1146 and we cannot reject the null hypothesis that the debt-to-GDP ratio can capture the common component among stock returns and dividend growth. We also run a new estimation letting $\phi_{1,1} = \phi_{1,2} = \phi_{1,3} = \phi_{1,4} = \phi_{1,5} = \phi_1$ and the new estimated $\phi_1 = 0.9872$. The null hypothesis $\phi_1 = 1$ also cannot be rejected. However, $\phi_{2,1} = \phi_{2,2} = \phi_{2,3} = \phi_{2,4} = \phi_{2,5} = 1$ are rejected and joint estimation results $\phi_2 = 7.3207$ which is also significant different from 1. Results suggest that the public debt-to-GDP ratio explains the same variations in returns and dividend growth.

[Insert Table 1.6 near here]

In the appendix, we also provide evidence of CDY factor. We find that CDY factor can predict the dividend growth but cannot predict stock returns. Our focus is the common variation therefore we do not discuss CDY further. Moreover, CDY factor is highly correlated to the public debt-to-GDP ratio and controlling for CDY factor will bias the coefficient estimate of $\frac{D}{Y}_t$.

To ensure that the return predictability by the debt-to-GDP ratio comes from the dividend predictability by the debt-to-GDP ratio and to explore further what CAY actually captures, we have the new specification as following

$$(ret_{t,t+H} - \Delta d_{t,t+H}) = \beta_0^{adj} + \beta_1^{adj} \frac{D}{Y}_t + \beta_2^{adj} \widetilde{dp}_t + \beta_3^{adj} CAY_t + \epsilon^r_{t,t+j} \tag{1.16}$$

$$H = 1, \cdots, 5$$

[Insert Table 1.7 near here]

where $(ret_{t,t+H} - \Delta d_{t,t+H})$ is the adjusted returns by dividend growth. We find β_1^{adj} are insignificantly from zero while β_2^{adj} and β_3^{adj} are significantly positive across all horizons. The debt-to-GDP ratio can not explain the variations in adjusted future returns while both $\widetilde{dp_t}$ and CAY can explain the adjusted returns.

1.3.2 Debt-to-GDP Ratio and Macro Variables

In this subsection, we consider macroeconomic variables that are closely related to the firm's behavior, which by sense we expect these macro variables may help predict future stock returns and future dividend growth.

We introduce the macro variables which reflects economic business cycles and expect that those variables can be state variables in pricing the equity. The term spread and default spread has been well documented as state variables in previous literature ([Adrian and Estrella, 2008], [Chen, 2009b], [Gilchrist and Zakrajšek, 2012], [Boons, 2016]). Baa is Moody's seasoned Baa corporate bond yield(FRED: WBAA) to reflect the risky corporate bond returns; Aaa is Moody's Seasoned Aaa Corporate Bond Yield(FRED: AAA) to reflect the safe corporate bond returns; $DefaultSpread$ is defined as the difference of Baa and Aaa; $TermSpread$ is 10-Year treasury constant maturity minus 2-year treasury constant maturity (FRED: T10Y2Y) to reflect term interest risk. CP_t is the bond risk premia factor constructed as [Cochrane and Piazzesi, 2005]. $UnEmloy$ is unemployment rate(aged 15-64: all persons for the United States(FRED: LRUN64TTUSQ156N))([Chen, 2009b]); The rest macroeconomic variables are: $Bankloans$ is annual change ratio of commercial and industrial loans from all commercial banks(FRED: CILACBQ158SBOG) to measure the credit from financial inter-mediation; $FixedInv$ is private nonresidential fixed investment(FRED: PNFI); $MktLev$ is nonfinancial corporate business's credit market debt as a percentage of the market value of corporate equities (FRED: NCBCMDPMVCE); $stInt$ is 3-month or 90-day rates and yields (FRED: IRLTLT01USQ156N) to reflect short-term funding costs; $HHDebt$ is the ratio of household debt over Gross Domestic Product where household debt is measured as debt securities and loans of households and nonprofit organizations (FRED: CMDEBT).

[Insert Table 1.8 near here]

We first run a uni-variate regression to see how each macro variable predicts the return and dividends growth. In table 1.8, we find $UnEmploy$ can predict both stock returns and dividend growth. The high unemployment ratio corresponds to high dividend growth and stock returns. $DefaultSpread$ and $MktLev$ are good return predictor but fail to predict dividend growth while $TermSpread$, $BankLoans$, $StInt$, CP_t, and $HHDebt$ are good candidates to predict dividend growth but not stock returns.

[Insert Table 1.9 near here]

Before we move to control for macro variables in regressions. We do the correlation analysis and find most of the macro variables are highly correlated to the $\frac{D}{Y}_t$. To ensure we have unbiased coefficients of $\frac{D}{Y}_t$, we only control for variables that pass the non-correlation tests. In table 1.9 we find that the debt-to-GDP ratio is still significant in both stock returns and dividends growth regressions after controlling for macro factors. $FixedInv$ is not significant in both. $UnEmploy$ can still predict both stock returns and dividend growth.

$$ret_{t,t+H} = \phi_{0,H} + \phi_{1,H}(\gamma_{1,H}\frac{D}{Y}_t) + \phi_{2,H}(\gamma_{2,H}UnEmploy_t) + \epsilon^r_{t,t+H} \tag{1.17}$$

$$\Delta d_{t,t+H} = \gamma_{0,H} + \gamma_{1,H}\frac{D}{Y}_t + \gamma_{2,H}UnEmploy_t + \epsilon^d_{t,t+H} \tag{1.18}$$

$$H = 1, \cdots, 5$$

We did a similar hypothesis test as in the controlling for the CAY case. We find that the public debt-to-GDP ratio still explains the same variations among the dividend growth and stock returns. Here we did not include the adjusted dividend yields in the GMM system because the dividend yields are correlated to the unemployment ratios. [Hall, 2017] documents that high discount rates and high unemployment because the employee value decreases at higher discount rates. [Lin et al., 2017] also argue that high labor hiring predicts lower stock returns, especially among large firms. To sum, we explore potential state variables that may capture the common component and then we control for the unemployment factor. We find that the debt-to-GDP ratio can still predict the dividend growth after controlling for other macroeconomic factors and coefficient magnitudes of the debt-to-GDP ratio are close.

[Insert Table 1.10 near here]

1.4 A General Equilibrium Model

1.4.1 The Story Behind

The story is about how fiscal uncertainty affects the firm's behaviors and how the cash retention can be regarded as a risk channel. First, high public debt-to-GDP ratio implies higher financing costs and high tax uncertainty for firms. Meanwhile, we introduce costly cash retention, a friction that is ignored in the macro-finance literature but should be counted in the firm's trade-off consideration. The high uncertainty depresses the firm's investment and firms turn to hold more cash and pay higher dividends. Therefore high public debt predicts the high dividend growth. The second point here is the cash-retention friction. Firms borrow costly debt and hold low return liquidity (cash). The proportion of U.S. corporate cash holding over total assets is not negligible ([Bates et al., 2018] document the average U.S. cash holding ratio is 17.6% from 1980 to 2009 except financial firms). Firms with more risky cash flows or higher financial constraints tend to increase their cash holding. Investment and firm bond refinancing would all be related to cash financing. Therefore, the risk of cash holding should also be considered. To rationalize the documented empirical evidence and to explore the potential mechanism, we build a general equilibrium model to incorporate both public debt and dividend payout to study how debt affects both dividend growth and stock returns. We adopt the firm's dynamic trade-off setting and explain the transmission channel through the lens of capital structure, the financing behavior (corporate bond issuance), and firm investment. Cash-retention friction is considered which adds a new risk channel in the economy.

1.4.1.1 Why Introduce the Cash-Retention Friction?

U.S. cash holding accounts for a non-negligible proportion of the firm's total assets. Many papers try to justify why firms tend to hold cash and borrow costly debt. [Acharya et al., 2007] build a model to show that firms that issue debt and hoard cash transfer income from high cash flow states to fund investment in all states, including those states where cash flow is low. [Bates et al., 2009] shows cash ratios increase because firms' cash flows become riskier and the precautionary motive for cash holdings plays an important role in explaining the increase in cash ratios. [Duchin et al., 2010] take the financial crises as the unexplored negative shock to the supply of external finance for non-financial firms and find that the greatest negative effect on investment is for firms with low cash reserves and firms reliant on external capital. [Harford et al., 2014] argue that firms with high refinancing risk tend to hold more cash. Firms use cash reserves to mitigate the under-investment problem. Cash-holding behavior is closely related to the firm's investment. Financial constraints create an inter-temporal trade-off between current and future investments. [Han and Qiu, 2007] show that when future cash flow risk cannot be fully diversified, the inter-temporal trade-off gives constrained firms the incentives of precautionary savings: they increase their cash holdings in response to increases in cash flow volatility. The argument is consistent with what [Minton and Schrand, 1999] documented that investment is negatively related to cash flow volatility and current cash holdings are positively related to cash flow volatility. [Gao et al., 2017] shows that systematic uncertainty increases firm cash holdings and firms with cyclical access to external financing are more affected by systematic uncertainty through the cost-of-capital channel. [Bates et al., 2018] documents that the increase in the value of cash holding is predominantly driven by the investment opportunity set and cash flow volatility.

The feature can also be represented in one way through cash holding and the interaction among capital structure and dividend payment. As [Leland, 1998] argues, the joint determination of capital structure and investment risk should be examined. The optimal capital structure reflects the tax advantages of debt less default costs (Modigliani-Miller) and Modigliani and Miller argue that the optimal amount of debt balances the tax deductions provided by interest payments against the external costs of potential default. This feature is captured in [Croce et al., 2012] where the tax-based risk channel is first investigated. Our story includes another feature where financing frictions and financing constraints are explored through the lens of the firm's cash holding and re-financing. The financing constraints affect firm's financing and payout and a growing number of studies have found that the level of firm leverage (constraint related) negatively affects dividend policy ([Jensen, 1986];[Jensen et al., 1992]; [Agrawal and Jayaraman, 1994]; [Crutchley and Hansen, 1989]; [DeAngelo and DeAngelo, 2007]; [Byoun, 2008]; [Frank and Goyal, 2009]; [Byoun, 2011]). Their studies inferred that highly levered firms look forward to maintaining their internal cash flow to fulfill duties, instead of distributing available cash to shareholders and protect their creditors while mature firms reserve moderate leverage and limit agency costs on free cash flow through large dividend payout. An increase in dividends could be caused either by an increase in the firm's profits (implying higher stock prices) or by the commencement of disinvestment as the firm has fewer profitable opportunities (implying lower stock prices).

Here we introduce the cash-retention friction because it is the precautionary saving behavior of firms and holding low-payoff cash is costly. The cash-retention should be a risk channel and not covered by the previous asset pricing literature. Intuition suggests that they may have an incentive not to pay out all the available cash flows to reduce the chance that the cash flow constraint becomes binding. The emphasis here is on financial-flexibility considerations since the corporate debt issuance in bad economic states is much costly and firms would try to avoid that situation. The financing flexibility can be described as a precautionary saving behavior. Related research by [DeAngelo et al., 2017] study the firms' deleverage process from the retaining financing flexibility point-view. They documented that there exists a counter-cyclical relation between leverage and cash balances at the individual-firm level. Traditional trade-off models of the capital structure take financial distress costs as a motive to affect leverage while the non-distress-related motive for cash-balance accumulation to acquire the flexibility to meet possible future funding needs could also matter in determining the capital structure. [DeAngelo et al., 2017] found that many sample firms effectively trade-off rebuilding flexibility through leverage reductions and cash-balance build ups in order to deliver increasing payouts to shareholders.

1.4.1.2 How to Interpret Public Debt?

To relate the government debt to firm dynamic behavior, we focus on how firms' investment and cash holding behavior would react to future uncertainty. The increase in government leverage raises the uncertainty concerns in the future and firms would react to the increased uncertainty by adjusting firms' investment and financing behavior.

An increasing body of literature investigates the impact of uncertainty on corporate financing and investment decisions besides the previous mentioned [Bloom et al., 2007, Bloom, 2009], [Croce et al., 2012, Croce et al., 2018]. For example, [Chen et al., 2014] find that stock return volatility significantly predicts active leverage adjustment, and falling earning growth appears to be the channel through which increasing volatility predicts leverage reduction and investment contraction. [Gulen and Ion, 2015] find that policy uncertainty can depress corporate investment by inducing precautionary delays due to investment irreversibility. [Chen and Manso, 2016] show that investment and capital structure decisions, as well as debt overhang costs, depend on the cyclicality of cash flows from assets-in-place and growth opportunities. Their study provides the intuition for how macroeconomic risks raise the ex-ante costs of debt overhang and cause larger distortions to investment. More cyclical cash flows from assets-in-place make under-investment more likely in bad times, exacerbating the costs of debt overhang when macroeconomic risk is taken into account. High uncertainty makes both assets in place and investment projects riskier, followed by more severe under-investment problems.

Another way to read the government debt is through the investors' portfolio allocation viewpoint. [Taggart Jr, 1981] points out that aggregate firm leverage is determined by the interaction of the supply of securities by firms and demands for those securities by investors. [Graham et al., 2014] show that U.S. federal government debt issuance significantly affects corporate financial policies and balance sheets. Government debt is strongly negatively correlated with corporate debt and investment, but strongly positively correlated with corporate liquidity. Their results suggest that large, financially healthy corporations act as liquidity providers by supplying relatively safe securities to investors when alternatives are in short supply and that this financial strategy influences firms' capital structures and investment policies. [Graham et al., 2015] also document that when the government reduces debt issuance, corporations increase their use of debt relative to equity, resulting in an increase in corporate leverage.

To sum, we will solve the problem in a dynamic trade-off model through the intersection among investment and cash retention. We would like to introduce cash retention as a risk channel and we would like to see how the firm behaves under fiscal uncertainty and facing costly cash holding. We proceed with the paper in the following: we move to the general equilibrium model relating the dividend payout to the corporate financing and investment behavior in a dynamic trade-off model where firms can issue corporate bonds and hold cash; meantime we incorporate the public debt to introduce the tax uncertainty.

1.4.2 A General Equilibrium Model

For the general equilibrium model, [Croce, 2014] provides the framework for production-based asset pricing and [Croce et al., 2012] introduce public debt into the framework. By introducing the tax channel, the fiscal policy's effect on stock returns can be analyzed and reasonable risk premia can be reproduced from the model. The reason that tax uncertainty should be first-order concern can be listed as i) tax can distort the firm's investment behavior; ii) tax shielding effect plays an important role in determining the corporate bond issuance; iii) high tax rates can depress the productivity in the economy. Another paper to mention is the work did by [Croce et al., 2018], they highlight a novel and distinct mechanism shaping the link between public debt and future growth. They identify innovations to government indebtedness as a risk factor priced in both the cross-section and the time series of stock returns. Empirically, they test these links on the entire cross-section of US stock returns and interpret and quantify them through the lens of a production-based asset pricing model with endogenous innovation and growth. The other two papers by [Bloom et al., 2007], [Bloom, 2009] show that high tax uncertainty or high fiscal policy uncertainty depresses firms' investment which is consistent in the literature.

For corporate behaviors framework, we refer the following several papers [Lintner, 1956], [Easterbrook, 1984], [Andres et al., 2015],[Chen and Manso, 2016] and [Chen et al., 2017]. As [Easterbrook, 1984] augured, any dividend policy (or any other corporate policy) should be designed to minimize the sum of capital, agency, and taxation costs. Besides the trade-off between the corporate debt benefit and expected tax shield, we consider the firm's cash-retention motivations. As explored by [Bates et al., 2009], [Duchin et al., 2010], [Harford et al., 2014], and [Bates et al., 2018], firms that face high cash flow uncertainty or are financially constrained tend to hold cash to mitigate the under-investment in bad states. Meanwhile, holding cash itself could be costly especially when interests rates are high. Apparently, cash holding is closely related to firms' investment and the evidence implies that there is a risk channel we ignore before. When uncertainty increases in the economy, firms may choose under-investment, increase cash holding and pay out more dividends. In previous macro-finance literature, all cash flows are distributed out as dividends and the cash plays no role there. We cover all three effects in our model: (i) introducing the corporate debt shielding for taxation; (ii) distortion of the firm's investment; (iii) introducing the cash retention as a risk channel.

The economy is composed of three sectors: the production sector, the household sector, and the government sector. We start by introducing the production sector with the firm's detailed behavior (e.g. dividend payment, cash holding, and investment). We proceed by describing in detail the government sector and the household sector in our economy, after which we define the general equilibrium solutions.

1.4.2.1 Production Sector

The final consumption good is produced in a competitive sector. There is a representative firm that uses capital K_t, labor L_t to produce the final goods according to production technology

$$Y_t = (K_{t-1})^{\alpha}(\Omega_t N_t)^{1-\alpha} \tag{1.19}$$

where α is the physical capital share, let Ω_t denotes the level of productivity at time t and lowercase letters denote log-units. The decomposition of the productivity growth rate is specified as that $\Omega_t = e^{a_t}$, $\Delta a_t = \mu + z_{t-1} + \epsilon_{a,t}$, with $\epsilon_{a,t} \sim N(0, \sigma_a^2)$, and $z_t = \rho z_{t-1} + \epsilon_{z,t}$, with $\epsilon_{z,t} \sim N(0, \sigma_z^2)$, where z_t refers to the long-run risk (LRR) component in productivity growth, and $\epsilon_{a,t}$ is short-run growth risk (SRR).

The firm's objective is to maximize the shareholder's value. This can be formally stated as

$$\underset{\{I_t, N_t, K_t, B_t^C\}}{max} \; E_0[\sum_{t=1}^{\infty} M_t Div_t] \tag{1.20}$$

where

$$\begin{aligned} CF_t &\leq Y_t - W_t N_t - T_t - I_t + D_t^C - R_{d,t-1} D_{t-1}^C - C_t^E + R_{l,t-1} CH_{t-1} \\ Div_t &= \beta_{d,t} CF_t \\ CH_t &= (1-\beta_{d,t}) CF_t \\ K_t &\leq (1-\delta) K_{t-1} + \Lambda(\frac{I_t}{K_{t-1}}) K_{t-1} \end{aligned} \tag{1.21}$$

where Div_t are the firm's dividends, M_t is the stochastic discount factor, I_t is investment in physical capital, W_t is the wage rate, $\Lambda(I_t)$ is the convex adjustment cost function, D^C is corporate bond, CH_t is cash holding, δ is the depreciation rate of physical capital and $\Lambda(\cdot)$ is the capital adjustment cost function. We specify $\Lambda(\cdot)$ as in [Jermann, 1998], $\Lambda(\frac{I_t}{K_{t-1}}) = \frac{b}{1-a1}(\frac{I_t}{K_{t-1}})^{\zeta} + c$, where $\frac{1}{1-\zeta}$ represents the elasticity of the investment rate with respect to Tobin's Q. The parameters b and c are set so that there are no adjustment costs in the deterministic steady states. Following [Hennessy et al., 2007] and [Livdan et al., 2009], we assume the saving rate is smaller than the borrowing rate so that firms are not indifferent between savings and cash distributions. $R_{l,t}$ is return of cash holding where $R_{l,t} = R_{d,t} - \flat$ where $\flat$ captures the dis-utility of cash holding. The payout ratio is modeled as a mean-reverting process and determined exogenously. The payout ratio follows $\beta_{d,t+1} = (1-\rho_\beta)\bar{\beta_d} + \rho_\beta \beta_{d,t} + \epsilon_{\beta_d,t}$. We model the cash retention(or the dividend payout) is proportional to cash flow which is in support of precautionary savings motives at the firm level being positively driven by expected equity returns([Palazzo, 2012]).

We introduce the costly counter-cyclical agency costs as equation (29). The setting allows the costly debt issuance in bad times than good times.

$$\frac{C_t^E}{\Omega_{t-1}} = \lambda_1 (\frac{D^C}{Y} - \frac{D^C}{Y}_{ss})^2 \tag{1.22}$$

The cash holding costs for each period are

$$C_t^{CH} = \flat CH_t = \flat(1-\beta_d)CF_t \tag{1.23}$$

Here we do not model the firm leverage dynamics directly as [Croce et al., 2012]. Based on the empirical evidence that the debt-to-GDP ratio is negatively correlated to the corporate leverage, we adopt the way to model the dividend process and check the corporate leverage process after that. There are numerous dividend signaling models predict that dividend changes convey information about cash flows; i.e., a dividend increase (decrease) conveys favorable (unfavorable) information about the current and/or future cash flows of the firm (Bhattacharya (1979), [John and Williams, 1985], [Miller and Rock, 1985]). Empirical evidence on earnings behavior following dividend changes provides support for this hypothesis([Denis et al., 1994]). Here for simplicity, we model the payout ratio follows a mean-reverting process and the way we model earning retention proportional to cash flow is in support of precautionary savings motives at the firm level being positively driven by expected equity returns.

Turning to capital structure, we should have the following

$$\frac{\partial(C_t^E + C_t^{CH})}{\partial D_t^C} = E_t[M_{t+1}\tau_{t+1}]r_{f,t} \tag{1.24}$$

The left-hand side of the equation is related to marginal costs from adding one additional unit of corporate debt and the right-hand refers to the marginal benefit from debt(from tax advantage of debt) by adding one additional unit of debt.

1.4.2.2 Household Sector

The representative agent has the Epstein and Zin (1989) preferences defined over the consumption bundle $\tilde{C}_t$:

$$U_t = [(1-\beta)\tilde{C}_t^{1-\frac{1}{\psi}} + \beta(E_t[U_{t+1}^{1-\gamma}])^{\frac{1-\frac{1}{\psi}}{1-\gamma}}]^{\frac{1}{1-\frac{1}{\psi}}} \tag{1.25}$$

The parameters Ψ and γ measure the IES and the RRA of the agent, respectively. The consumption bundle aggregates consumption, C_t, and leisure, L_t, as follows:

$$\tilde{C}_t = C_t^o \cdot (\Omega_{t-1}L_t)^{1-o} \tag{1.26}$$

where Ω_{t-1} denotes aggregate productivity and o is a weight determining the average share of hours worked. Multiplying leisure by productivity guarantees balanced growth, and it is interpreted as an adjustment for the standards of living.

The consumer's budget constraint is

$$C_t + Z_tQ_t + D_t + D_t^C \leq R_{d,t-1}(D_{t-1} + D_{t-1}^C) + Z_{t-1}(Div_t + Q_t) + W_tN_t + G_t \tag{1.27}$$

where Z_t is the number of equity shares, Q_t is the ex-dividend price of stocks, D_t is the number of government bonds and D_t^C is the number of corporate bonds.

The stochastic discount factor takes the following usual form:

$$M_{t+1} = \delta(\frac{C_{t+1}}{C_t})^{-1}(\frac{\tilde{C}_{t+1}}{\tilde{C}_t})^{1-\frac{1}{\psi}}(\frac{U_{t+1}}{E_t[U_{t+1}^{1-\gamma}]^{\frac{1}{1-\gamma}}})^{\frac{1}{\psi}-\gamma} \tag{1.28}$$

The risk free rate is $R_{b,t} = E_t[M_{t+1}]^{-1}$.

The optimality condition for the labor implies that the marginal rate of substitution between consumption and leisure should be equal to the marginal product of labor:

$$1 \geq N_t + L_t$$

$$\frac{\partial \tilde{C}_t}{\partial L} / \frac{\partial \tilde{C}_t}{\partial C_t} = (1-\alpha)\frac{Y_t}{N_t}$$

1.4.2.3 Government Sector

In the model, government debt enhances the liquidity of households by providing an additional means of smoothing consumption (in addition to claims to capital) and by effectively loosening borrowing constraints. With distorting taxes there is a role for government debt as a means of smoothing tax distortions over time. Optimal debt policy in such a model (see Barro, 1979; Chamley, 1985; Chamley, 1986) generally implies that the steady-state level of debt depends on the initial level of debt.

Here the budget constraint follows:

$$D_t = R_{d,t-1}D_{t-1} + G_t - T_t \tag{1.29}$$

Where Government spending and Taxation are represented as G_t and T_t. $R_{b,t-1}$ is the one period bond return and D_t is total public debt at time t.

Here we assume the government expenditure is an exogenous stochastic process. This formulation ensures that the spending ratio is positive for each period and the value of it is less than one.

$$\begin{aligned} \frac{G_t}{Y_t} &= \frac{1}{1+e^{-g_t}} \\ g_t &= (1-\rho_g)\bar{g} + \rho_g g_t + \epsilon_{g,t} \end{aligned} \tag{1.30}$$

Here the tax rate is endogenously determined by the government inter-temporal budget constraint. This setting allows the tax smoothing reflecting the government debt decisions based on macroeconomic conditions. The payments of corporate debt interests are excluded from the tax base to capture the tax-shielding effect by issuing corporate debt.

$$\begin{aligned} \frac{T_t}{Y_t} &= \frac{\tau_t * taxbase_t}{Y_t} \\ taxbase_t &= (Y_t - W_t N_t - r_{d,t-1} D^C_{t-1}) \end{aligned} \tag{1.31}$$

Suppose the public debt policy follows a mean-reverting process which indicates there is not government debt explosion in the model. The residual part reflects the fiscal stance.

$$(\frac{D}{Y})_{t+1} = (1-\rho_{\frac{D}{Y}})(\frac{\bar{D}}{Y}) + \rho_{\frac{D}{Y}}(\frac{D}{Y})_t + \epsilon_{\frac{D}{Y},t} \tag{1.32}$$

For example, the rule can be aimed at stabilizing short-horizon consumption dynamics measured, which is $\epsilon_{\frac{D}{Y}} = \psi_d(\Delta c_{t+1} - \mu_c)$ proposed by [Croce et al., 2012]. The parameter $(\frac{\bar{D}}{Y})$ captures the long-run level of debt, and $\rho_{\frac{D}{Y}}$ is a measure of the speed of repayment of debt: the higher the value of it, the slower the repayment of debt relative to output. In our benchmark model, the policy rule $\epsilon_{\frac{D}{Y}}$ is targeted to smoothing the economic short-run and long-run productivity.

1.4.2.4 Equilibrium Solutions and Asset Prices

We have the market-clearing condition as following. The total output is used for consumption, investment and costs induced from the production process.

$$Y_t = C_t + I_t + C_t^E + C_t^{CH} \tag{1.33}$$

By solving the above defined equilibrium model, we have the optimal investment and financing decision satisfy the following Euler equation:

$$q_t = E_t[M_{t+1}(\beta_{d,t+1}((1-\tau_{t+1})\frac{\partial Y_{t+1}}{\partial K_t} - \frac{\partial C_{t+1}^E}{\partial K_t}) + q_{t+1}(1-\delta-\frac{\Lambda_{t+1}^{'} I_{t+1}}{K_{t+1}} + \Lambda_{t+1}))] \tag{1.34}$$

We can see the future tax rates affect the future marginal product of capital. Uncertainty from the future tax rate changes is priced in equilibrium. We can also tell the payout ratio $\beta_{d,t}$ plays an important role in pricing. If $\beta_{d,t}$ is equal to one, it means all cash flows are distributed to shareholders as dividends and no cash will be held inside the firms. One the other way, if $\beta_{d,t}$ is equal to zero, it indicates that all cash will be held inside the firm and no dividends will be paid out. Later we report simulation results based on two cases. Both two models have the tax uncertainty channel and the only difference is the payout ratio setting. $\beta_{d,t}$ is equal to one in the model without cash holding while the average payout ratio is calibrated to 43.3% in the model with cash holding. We see the quantitative results are quite different from each other when cash is introduced into the model and the model with cash holding can produce more reasonable results.

1.4.3 Quantitative Analysis

In this section, we calibrate our model and explore its predictions regarding key links among debt, investment, dividend payment, and stock returns. In particular, we show that the model predicts a lower investment and higher dividend payout in the case of high government debt, which has been documented empirically.

1.4.3.1 Calibration

We report our baseline calibration in table 1.11. The preference parameters are standard in the literature. The risk aversion γ is calibrated to 10 (see [Mehra and Prescott, 1985], [Bansal and Yaron, 2004] among others). The intertemporal elasticity of substitution ψ is set to 1.5, usual in the long-run risk literature. The household's subjective discount rate β is chosen to target the average historical level of the risk-free rate. For technology, we set the capital share at 37.5% and physical depreciation rate at 0.020. The intensity of corporate debt adjustment λ_1 is set at 0.4 to match the costly debt adjustment ([Croce et al., 2012] among others). The average retention ratio is set at 56.69% which is the average retention ratio of $S\&P$ 500 firms from the year 1966 to the year 2017. For the persistence of the firm's payout ratio is obtained by fitting the AR(1) process at the quarterly frequency and value ρ_{β_d} is equal to 0.905. For the productivity part, the parameter μ is set to have an annual average growth of 2.4% and to obtain annual volatility of output growth of 3.56% under the benchmark calibration. This value for short-run productivity volatility is set at 3.8% annually and the long-run component in productivity is calibrated to 0.4% which is relatively small but persistent. For policy parameters, the persistence of debt is set at 0.96. The parameter ρ_d of debt rule is set to mimic the well-known high persistence of the debt-to-output ratio in the US with the average debt-to-output ratio at 55%. The intensity of debt policy for productivity shocks ψ_{sr} is estimated as -0.18 and ψ_{lr} is estimated as 19.04.

[Place Table 1.11 about here]

For public debt rule, we fit the rule on the short and long-run productivity shocks estimated from a long-run risk model $\Delta a_t = \mu + z_{t-1} + \epsilon_{a,t},\ \epsilon_{a,t} \sim N(0, \sigma_a^2)$, and $z_t = \rho z_{t-1} + \epsilon_{z,t},\ \epsilon_{z,t} \sim N(0, \sigma_z^2)$. The productivity is measured by the Business sector TFP (dtfp) published by the Federal Reserve Bank of San Francisco.

$$\epsilon_{\frac{D}{Y}} = \psi_{sr}\epsilon_{a,t} + \psi_{lr}\epsilon_{z,t} + \epsilon_{by,t} \tag{1.35}$$

where ψ_{sr} is the policy intensity to the short-run productivity shock and ψ_{lr} is the policy intensity to the long-run productivity shock. The estimation results are $\psi_{sr} = -0.177$ with Newey-West t value as -1.81 and $\psi_{lr} = 19.045$ with Newey-West t value as 1.93. Results suggest that public debt rule is negatively corresponding to the short-run productivity shock and positively corresponding to the long-run productivity shock. When negative long-run productivity shock happens, the government would cut tax rates to stimulate the resources reallocation from consumption to investment. Moreover, when positive short-run productivity shock happens, the government would cut tax rates to encourage the resources reallocation from consumption to investment.

1.4.3.2 Unconditional Moments

After calibration, we have our model produce reasonable moments matching what we obtained from data and we report the moments in table 1.12. The upper panel presents the basic moments, the middle panel reports moments related to the asset pricing side and the lower panel reports the moments of dividend growth, tax rates and debt-to-GDP ratio which are crucial to our story. Here the payout ratio is modeled as a mean-reverting process only for the cash holing model while in the model without cash-holding the payout ratio is always equal to one. We find both models can produce reasonable moments related to the macroeconomic side while the model without the firm's cash holding behavior fails to produce several moments in the asset pricing side. First, the mean of excess returns is 1.03% which is much lower than the 5.70% documented in data. Second, the dividend growth 4.85% is much higher than the number 2.40% in data. After introducing the retained earnings, the model can produce reasonable moments matching the moments from the data.

[Place Table 1.12 about here]

1.4.3.3 Predictive Regressions

We first study the effect of the public debt on investment growth and the results indicate high debt dampens the investment growth from one year to five-year horizons based on simulated data from the cash-holding model. Our model with cash holding predicts that the debt-to-GDP ratio has weaker predictive power on investment growth. When the debt-to-GDP ratio increases in the economy, the tax uncertainty increases which can depress the firm's investment. After introducing the cash holding channel, the firm chooses the higher payout with increasing cash on the firm's balance sheet which leads to higher dividend growth.

[Place Table 1.13 about here]

The novel insight of our model points to the existence of a cash-retention friction that plays an important role in determining the firm's dividend payout. When uncertainty increase inside the economy, the held cash can relieve the pressure from costly corporate bond issuance. On the other side, the wait-to-invest behavior lets firms have more cash on their balance sheet which leads to higher dividend payout.

Our model shows that the debt-to-GDP ratio has predictive power for dividend growth and stock returns. Based on the simulated results, we find the factor loadings on both dividend growth and stock returns are on the same scale which is consistent with the common component argument. In figure 1.2 we can see that model implied results replicate the pattern that common component can be captured by the debt-to-GDP ratio. In table 1.14, we also include results from the model where firms have no cash holding and we find that the model can predict the positive stock returns but fail to capture the positive predictability of dividend growth.

[Place Table 1.14 about here]

[Place Figure 1.2 about here]

1.4.3.4 Alternative Public Debt Rules

In our benchmark model, the public debt responds to both long-run and short-run productivity shocks and results show that the debt-to-GDP ratio has predictive power for dividend growth and stock returns. Based on the simulated results, we find the factor loadings on both dividend growth and stock returns are on the same scale which is consistent with the common component argument. In this section, we explore other possibilities that public debt only corresponds to one productivity shock. In the following two tables 1.15, 1.16, we present results when public debt rule is only targeting short-run or long-run productivity shock.

[Place Table 1.15, 1.16 about here]

We find that results are similar when the short-run productivity sensitivity ψ_{sr} in public debt policy is equal to zero. The debt-to-GDP ratio can still drive the co-movement among dividend growth and stock returns when public debt only corresponds to long-run productivity shock, as shown in table 1.16. It suggests the fluctuation of public debt induced by the short-run productivity shock is not going to drive the dividend payout and the stock return in the same direction.

1.5 Out-of-Sample Tests

The previous argument is that the debt-to-GDP ratio can move the dividend growth and stock returns in the same direction and we can validate this by providing the out-of-sample return predictive evidence. If the public debt ratio can instrument the dividend growth and capture the common component, we can better predict stock returns by controlling for variables containing dividend information([Lacerda and Santa-Clara, 2010]). We extend the debt sample back to the 1950s by interpolating the debt data from the annual observations using cubic spline interpolation. The whole sample is from 1950Q1 to 2017Q4 and the training sample length is 20 years. Following [Welch and Goyal, 2007]'s way to construct the OOS statistics, we evaluate the predictive performance at the quarterly frequency.

[Insert Table 1.17 near here]

In this section, we analyze the performance of five specifications from the perspective of a real-time investor. We, therefore, consider out-of-sample evidence for the 1-, 3- and 5-year horizons. We run recursive forecasting regressions for the 1-, 3- and 5-year horizons. Table 1.17 reports the OOS statistics at the quarterly frequency and two indicators we adopt here are OOS R^2 and MSE_F. Both factors help us to compare the predictive performance[3]. The evidence shows that the two-factor model ($\frac{D}{Y}_t$+$\widetilde{dp_t}$) always beats the single-factor model (dp_t or $\widetilde{dp_t}$). It suggests that dividend growth information reflected by the public debt can help us improve the return predictability. Moreover, we find that the two-factor model ($\frac{D}{Y}_t$+$\widetilde{dp_t}$) beats the CAY model for most cases and the three-factor model beats the rest for all cases at the quarterly frequency. We argue that the debt-to-GDP ratios carry information about the co-movement component and results hold in out of sample. Specifically, we can evaluate the role of expected dividend growth in better forecasting the stock returns by comparing the black lines and green lines in figure 2.2. The black line (with debt-to-GDP as a predictor) always beats the green line, which suggests that better prediction on dividend growth can lead to the better prediction on stock returns.

[Insert Figure 2.2 near here]

[3]For OOS R^2, we construct as following: $R^2_{OOS} = 1 - \frac{MSE_A}{MSE_N}$. For MSE_F statistics, we adopt it to evaluate the equal MSE (see McCracken's F statistics): $MSE_F = (T - h + 1) * \frac{MSE_N - MSE_A}{MSE_A}$, where T is observation and h is the overlapping period.

1.6 U.S Cross-Section Evidence

In this section, we also provide cross-sectional evidence on the U.S. market. We test whether the public debt-to-GDP ratio can drive the co-movement between dividend growth and stock returns for value/growth and small/large firms. We use the portfolio data downloaded from the Fama French Data Library. Here we define value firms as the top 30% firms based on book-to-market ratio, growth firms as the bottom 30% firms based on book-to-market ratio, large firms as the top 30% firms based on firm size, and small firms as the bottom 30% firms based on firm size. Our documented results are consistent with [Maio and Santa-Clara, 2015]'s findings. They documented that dividend predictability only exists in small and value firms while most of the price variations of large and growth firms come from the discount rate. The weak cash flow predictability could be due to the co-movement among dividend growth and stock returns. We check whether the debt-to-GDP can capture the common component across firms and we find that public debt drives both the cash flows and stock returns in small, large, and growth firms but not in value firms. In the value portfolio, the magnitudes of common component loadings are not significantly different from 0, which suggests that public debt fails to capture the common component. But in the other three cases, evidence suggests that the weak dividend predictability could be due to the common component driven by public debt.

[Insert Table 1.18 near here]

1.7 International Evidence

The weak predictability of dividend growth is not limited to the U.S. market. [Rangvid et al., 2014] documented that dividend predictability is weaker in large and developed markets where dividends are smoothed more, the average firm size is large, and volatility is lower. We check whether the debt-to-GDP can capture the common component across countries and we find that public debt drives both the cash flows and stock returns in many developed countries. For international data, we collect data on 20 developed countries and 24 developing countries. The stock returns and dividend growth data are obtained from the Datastream. The public debt data are obtained from Oxford Economics. As shown in table 1.19, the estimated ϕ_1 are significantly positive for most of the countries and $\phi_1 = 1$ cannot be rejected for most of the developed countries. The only exception is Japan because the public debt in Japan cannot predict the stock returns. In many developing countries, the magnitudes of common component loadings are significantly not equal to one. Evidence suggests that the weak dividend predictability could be due to the common component driven by public debt.

[Insert Table 1.19 near here]

[Insert Figure 1.4 near here]

1.8 Conclusion

This paper documents the public debt-to-GDP ratio can predict both dividend growth and stock returns. We test the common component hypothesis and the evidence suggests that the debt-to-GDP ratio can capture the common component among stock returns and dividend growth. The finding is consistent with [Lettau and Ludvigson, 2005]'s argument and helps resolve the US asset pricing puzzle ([Cochrane, 2007, Cochrane, 2011]) that dividend price ratio at the market level cannot predict the future dividend growth. The documented puzzle is due to the co-movement among returns and dividend growth and we argue that public debt in one economy is the driving force of the co-movement. Since weak cash flow predictability is not limited to the US aggregate market, e.g. [Maio and Santa-Clara, 2015] documented this pattern for the US large and the

US growth firms, and [Rangvid et al., 2014] documented this pattern at most of the advanced financial countries, we also extend the analysis to the US cross-section and the international financial market level, and we argue the weak cash flow predictability is due to the existence of common component captured by the public debt-to-GDP ratio. To rationalize it, we propose a production-based asset pricing model incorporating firms' trade-off behaviors and the cash-retention friction. The model can produce testable predictions that the increase in public debt moves both dividend payment and the cost of capital in the same direction, resulting in the capture of the common component.

Corporate investment depends on the fiscal policy stance of the government. High government debt leads to high tax uncertainty and the increased uncertainty would depress firms' investment. The theoretical framework is in the spirit of [Croce et al., 2012] and other production-based asset pricing models featuring the recursive preferences and economic uncertainty. The novel insight of our model is that we incorporate the cash-retention friction into the corporate sector, which allows us to study how the firm reacts to the increased uncertainty when cash is held and cash retention is costly. The cash on firms' balance sheet helps them to relieve the pressure from costly corporate debt issuance in bad economic states while it also incurs the cash retention costs and affects firms' dividend payments when the firm's investment is depressed. Since cash retention affects both the firm's financing and investment, we argue cash retention should be considered as a risk channel in the economy. After incorporating the cash-retention friction, the model can rationalize the dividend predictability documented from data. It's also consistent with the finding that firms with high cash flow volatility tend to hold more cash ([Bates et al., 2009, Bates et al., 2018]) and firms facing financial constraints tend to save cash ([Acharya et al., 2007] and [Duchin et al., 2010]). Future work can study how firm investment will interact with cash holding under other uncertainty.

The documented common component is also important in the spirit of better predicting returns by forecasting dividend growth. We documented that controlling for public debt-to-GDP ratio can lead to better out-of-sample performance than using the single dividend-price ratio in return prediction. Besides the predictable component among returns and dividend growth as [Lettau and Ludvigson, 2005], it is consistent with [Lacerda and Santa-Clara, 2010]'s argument that we can better predict stock returns if we can predict the dividend growth, and [Koijen and Van Nieuwerburgh, 2011]'s argument that dividend growth and return predictability are two sides of the same coin. Therefore, by introducing public debt as the cash flow predictor, we can have many asset pricing applications in better predicting future stock returns.

Table 1.1: The table reports regression results in uni-variate setting. The sample period is from 1966Q1 to 2017Q4. Valkanov t statistics of the adjusted dividend-price ratio are reported. Newey-West t-statistics are reported in the square bracket under each coefficient.

$$ret_{t,t+H} = \beta_0 + \beta_1 \widetilde{dp_t} + \epsilon^r_{t,t+j}$$

$$\Delta d_{t,t+H} = \gamma_0 + \gamma_1 \widetilde{dp_t} + \epsilon^d_{t,t+j}$$

$$H = 1, \cdots, 5$$

Panel A

Dep. Var:	$ret_{t,t+1}$	$ret_{t,t+2}$	$ret_{t,t+3}$	$ret_{t,t+4}$	$ret_{t,t+5}$
$\widetilde{dp_t}$	0.3072***	0.2590***	0.1930***	0.1591***	0.1509***
	[3.77]	[3.99]	[3.54]	[3.39]	[3.61]
Valkanov t-test	0.26***	0.28***	0.25***	0.24***	0.25***
Obs.	208	208	208	208	208
R^2	0.155	0.226	0.199	0.180	0.196

Panel B

Dep. Var:	$\Delta d_{t,t+1}$	$\Delta d_{t,t+2}$	$\Delta d_{t,t+3}$	$\Delta d_{t,t+4}$	$\Delta d_{t,t+5}$
$\widetilde{dp_t}$	-0.0150	0.0038	0.0173	0.0172	0.0088
	[-0.31]	[0.11]	[0.71]	[0.90]	[0.53]
Valkanov t-test	-0.02	0.01	0.05	0.06	0.04
Obs.	208	208	208	208	208
R^2	0.003	0.000	0.006	0.008	0.003

*: 10% significance level, **: 5% significance level, ***: 1% significance level.

Table 1.2: In this table, we show the correlations among factors. We report t value for each correlation pair to indicate whether the non-correlation relationship can be rejected and the t values are reported in the square brackets below each coefficients.

Correlation	$\frac{D}{Y}t$	CAY_t	$\widetilde{dp_t}$	dp_t
$\frac{D}{Y}t$	1	-0.037	0.011	-0.628
		[-0.53]	[0.16]	[-11.55]
CAY_t		1	0.020	0.023
			[0.28]	[0.33]
$\widetilde{dp_t}$			1	0.535
				[9.07]
dp_t				1

Table 1.3: The table reports regression results in multi-variate setting. The sample period is from 1966Q1 to 2017Q4. Valkanov t statistics of the debt-to-GDP ratio are reported for both panels. Newey-West t-statistics are reported in the square bracket under each coefficient.

$$ret_{t,t+H} = \beta_0 + \beta_1 \frac{D}{Y}_t + \beta_2 \widetilde{dp_t} + \epsilon^r_{t,t+j}$$

$$\Delta d_{t,t+H} = \gamma_0 + \gamma_1 \frac{D}{Y}_t + \gamma_2 \widetilde{dp_t} + \epsilon^d_{t,t+j}$$
$$H = 1, \cdots, 5$$

Panel A

Dep. Var:	$ret_{t,t+1}$	$ret_{t,t+2}$	$ret_{t,t+3}$	$ret_{t,t+4}$	$ret_{t,t+5}$
$\frac{D}{Y}_t$	0.1463**	0.1457**	0.1512***	0.1558***	0.1547***
	[2.03]	[2.58]	[3.20]	[3.55]	[3.52]
$\widetilde{dp_t}$	0.3019***	0.2670***	0.2083***	0.1753***	0.1673***
	[3.78]	[4.26]	[3.80]	[3.60]	[3.81]
Valkanov t-test	0.14**	0.18***	0.23***	0.26***	0.26***
Obs.	204	200	196	192	188
R^2	0.182	0.285	0.295	0.297	0.307

Panel B

Dep. Var:	$\Delta d_{t,t+1}$	$\Delta d_{t,t+2}$	$\Delta d_{t,t+3}$	$\Delta d_{t,t+4}$	$\Delta d_{t,t+5}$
$\frac{D}{Y}_t$	0.1257***	0.1366***	0.1425***	0.1416***	0.1372***
	[3.46]	[4.33]	[5.33]	[5.74]	[5.61]
$\widetilde{dp_t}$	-0.0127	0.0125	0.0309	0.0314*	0.0266*
	[-0.24]	[0.34]	[1.25]	[1.88]	[1.91]
Valkanov t-test	0.24***	0.31***	0.38***	0.41***	0.41***
Obs.	204	200	196	192	188
R^2	0.193	0.262	0.343	0.394	0.416

*: 10% significance level, **: 5% significance level, ***: 1% significance level.

Table 1.4: Revisit dp_t: i) $ret_{t+j} = f(dp_t, \Delta d_{t+j})$ and ii) Common component argument by [Lettau and Ludvigson, 2005]. The table reports estimation results in GMM setting. The sample period is from 1966Q1 to 2017Q4. In first part we estimate all $\phi_{1,H}$ by GMM. In second part we run the null hypothesis test that $\phi_{1,H} = 1$. The third part reports new results under coefficients specification $\phi_{1,H} = \phi_1$ and corresponding hypothesis tests.

$$ret_{t,t+H} = \phi_{0,H} + \phi_{1,H} E_t[\Delta d_{t,t+H}] + \phi_{2,H} \widetilde{dp_t} + \epsilon^r_{t,t+j}$$

$$\Delta d_{t,t+H} = \gamma_{0,H} + \gamma_{1,H} \frac{D}{Y}_t + \epsilon^d_{t,t+j}$$

Part 1

Dep. Var:	$\Delta d_{t,t+1}$	$\Delta d_{t,t+2}$	$\Delta d_{t,t+3}$	$\Delta d_{t,t+4}$	$\Delta d_{t,t+5}$
$\frac{D}{Y}_t$	0.1290***	0.1365***	0.1404***	0.1390***	0.1347***
	[36.15]	[42.46]	[36.29]	[21.39]	[13.36]
R^2	0.191	0.259	0.323	0.366	0.389
Dep. Var:	$ret_{t,t+1}$	$ret_{t,t+2}$	$ret_{t,t+3}$	$ret_{t,t+4}$	$ret_{t,t+5}$
$E_t[(\sum_{j=1}^{H} \Delta d_{t+j})]$	1.0719***	1.0136***	1.0279***	1.0673***	1.0843***
	[5.21]	[6.19]	[8.80]	[7.70]	[5.82]
$\widetilde{dp_t}$	0.3082***	0.2527***	0.1937***	0.1638***	0.1535***
	[40.37]	[37.68]	[30.72]	[29.49]	[29.10]
R^2	0.181	0.282	0.293	0.293	0.303

Part 2 Wald Test

Null Hypothesis: $\phi_{1,1} = \phi_{1,2} = \phi_{1,3} = \phi_{1,4} = \phi_{1,5} = 1$

Chi-square: 0.7736 p-value: 0.9787

Part 3 Alternative Estimation:

Estimate $\phi_{1,1} = \phi_{1,2} = \phi_{1,3} = \phi_{1,4} = \phi_{1,5} = \phi_1$ and Test $\phi_1 = 1$

ϕ_1=1.0542, Chi-square: 0.2193, p-value: 0.6396

*:10% significance level,**:5% significance level, ***:1% significance level.

Table 1.5: The table reports regression results in multi-variate setting. The sample period is from 1966Q1 to 2017Q4. Newey-West t-statistics are reported in the square bracket under each coefficient.

$$ret_{t,t+H} = \beta_0 + \beta_1 \frac{D}{Y}_t + \beta_2 \widetilde{dp_t} + \beta_3 CAY_t + \epsilon^r_{t,t+j}$$

$$\Delta d_{t,t+H} = \gamma_0 + \gamma_1 \frac{D}{Y}_t + \gamma_2 \widetilde{dp_t} + \gamma_3 CAY_t + \epsilon^d_{t,t+j}$$
$$H = 1, \cdots, 5$$

Panel A

Dep. Var:	$ret_{t,t+1}$	$ret_{t,t+2}$	$ret_{t,t+3}$	$ret_{t,t+4}$	$ret_{t,t+5}$
$\frac{D}{Y}_t$	0.1460**	0.1280***	0.1123***	0.1023***	0.0941***
	[2.26]	[2.99]	[3.42]	[3.28]	[3.15]
$\widetilde{dp_t}$	0.2960***	0.2557***	0.1923***	0.1587***	0.1500***
	[3.64]	[4.48]	[3.83]	[3.39]	[3.51]
CAY_t	2.5395***	2.7724***	2.5043***	2.1069***	1.7673***
	[2.87]	[4.66]	[5.82]	[5.57]	[4.94]
Obs.	204	200	196	192	188
R^2	0.272	0.493	0.542	0.516	0.486
R^2 Debt only:	0.034	0.054	0.075	0.090	0.081
R^2 CAY only:	0.097	0.243	0.319	0.316	0.288

Panel B

Dep. Var:	$\Delta d_{t,t+1}$	$\Delta d_{t,t+2}$	$\Delta d_{t,t+3}$	$\Delta d_{t,t+4}$	$\Delta d_{t,t+5}$
$\frac{D}{Y}_t$	0.1257***	0.1345***	0.1367***	0.1337***	0.1300***
	[3.48]	[4.28]	[4.89]	[4.87]	[4.67]
$\widetilde{dp_t}$	-0.0135	0.0111	0.0285	0.0289*	0.0245*
	[-0.25]	[0.30]	[1.14]	[1.71]	[1.74]
CAY_t	0.3502*	0.3420*	0.3685*	0.3129	0.2118
	[1.68]	[1.86]	[1.89]	[1.44]	[0.96]
Obs.	204	200	196	192	188
R^2	0.206	0.278	0.365	0.414	0.428
R^2 Debt only:	0.191	0.260	0.323	0.367	0.390
R^2 CAY only:	0.013	0.023	0.054	0.080	0.078

*: 10% significance level, **: 5% significance level,***: 1% significance level.

Table 1.6: Revisit dp_t: i) $ret_{t+j} = f(dp_t, \Delta d_{t+j})$ and ii) Common component argument by [Lettau and Ludvigson, 2005]. The table reports estimation results in GMM setting. The sample period is from 1966Q1 to 2017Q4. In first part we estimate all $\phi_{1,H}$ by GMM. In second part we run the null hypothesis test that $\phi_{1,H} = 1$. The third part reports new results under coefficients specification $\phi_{1,H} = \phi_1$ and corresponding hypothesis tests.

$$ret_{t,t+H} = \phi_{0,H} + \phi_{1,H}(\gamma_{1,H}\frac{D}{Y}_t) + \phi_{2,H}(\gamma_{2,H}CAY_t) + \phi_{3,H}\widetilde{dp_t} + \epsilon^r_{t,t+H}$$

$$\Delta d_{t,t+H} = \gamma_{0,H} + \gamma_{1,H}\frac{D}{Y}_t + \gamma_{2,H}CAY_t + \gamma_{3,H}\widetilde{dp_t} + \epsilon^d_{t,t+H}$$

Part 1

Dep. Var:	$\Delta d_{t,t+1}$	$\Delta d_{t,t+2}$	$\Delta d_{t,t+3}$	$\Delta d_{t,t+4}$	$\Delta d_{t,t+5}$
$\gamma_{1,H}$	0.1291***	0.1361***	0.1368***	0.1330***	0.1294***
	[5.22]	[5.90]	[5.72]	[4.78]	[3.76]
$\gamma_{2,H}$	0.3622	0.3813***	0.3947***	0.3051***	0.1772**
	[1.64]	[4.52]	[6.84]	[4.69]	[2.21]
$\gamma_{3,H}$	-0.0066	0.0222	0.0354**	0.03249***	0.0269**
	[-0.13]	[0.80]	[2.47]	[3.52]	[2.11]
R^2	0.206	0.275	0.363	0.412	0.426

Dep. Var:	$ret_{t,t+1}$	$ret_{t,t+2}$	$ret_{t,t+3}$	$ret_{t,t+4}$	$ret_{t,t+5}$
$\phi_{1,H}$	1.1318**	0.9312***	0.8013***	0.7290***	0.6836***
	[2.01]	[2.61]	[3.60]	[3.65]	[2.83]
$\phi_{2,H}$	7.9350	8.0402**	6.8488***	7.4017***	10.5327*
	[1.14]	[2.31]	[3.69]	[2.97]	[1.82]
$\phi_{3,H}$	0.3230***	0.2555***	0.1952***	0.1643***	0.1557***
	[13.40]	[6.43]	[6.61]	[6.80]	[4.95]
R^2	0.269	0.490	0.540	0.514	0.484

Part 2 Wald Test

Null Hypothesis: $\phi_{1,1} = \phi_{1,2} = \phi_{1,3} = \phi_{1,4} = \phi_{1,5} = 1$
Chi-square: 8.8641 p-value: 0.1146

Null Hypothesis: $\phi_{2,1} = \phi_{2,2} = \phi_{2,3} = \phi_{2,4} = \phi_{2,5} = 1$
Chi-square: 30.8020 p-value: 0.0000

Part 3 Alternative Estimation:

Estimate $\phi_{i,1} = \phi_{i,2} = \phi_{i,3} = \phi_{i,4} = \phi_{i,5} = \phi_i$ and Test $\phi_i = 1$
ϕ_1=0.9872, Chi-square: 0.0051, p-value: 0.9433
ϕ_2=7.3207, Chi-square: 48.8255, p-value: 0.0000

*:10% significance level,**:5% significance level, ***:1% significance level.

Table 1.7: The table reports regression results in multi-variate setting. The sample period is from 1966Q1 to 2017Q4. Newey-West t-statistics are reported in the square bracket under each coefficient. Here we define $ret^{adj}_{t,t+H} = ret_{t,t+H} - \Delta d_{t,t+H}$.

$$ret^{adj}_{t,t+H} = \beta^{adj}_0 + \beta^{adj}_1 \frac{D}{Y}_t + \beta^{adj}_2 \widetilde{dp_t} + \beta^{adj}_3 CAY_t + \epsilon^r_{t,t+j}$$

$$H = 1, \cdots, 5$$

Dep. Var:	$ret^{adj}_{t,t+1}$	$ret^{adj}_{t,t+2}$	$ret^{adj}_{t,t+3}$	$ret^{adj}_{t,t+4}$	$ret^{adj}_{t,t+5}$
$\frac{D}{Y}_t$	0.0203	-0.0065	-0.0244	-0.0313	-0.0359
	[0.26]	[-0.13]	[-0.70]	[-0.99]	[-1.10]
$\widetilde{dp_t}$	0.3095***	0.2446***	0.1638***	0.1297***	0.1255***
	[3.41]	[4.59]	[3.79]	[2.94]	[2.94]
CAY_t	2.1893**	2.4304***	2.1357***	1.7940***	1.5555***
	[2.35]	[3.75]	[4.33]	[4.23]	[3.87]
Obs.	204	200	196	192	188
R^2	0.220	0.393	0.400	0.362	0.342

*: 10% significance level, **: 5% significance level,***: 1% significance level.

Table 1.8: The table reports regression results of the macro variables in uni-variate setting. The sample period is from 1966Q1 to 2017Q4. Newey-West t-statistics are reported in the square bracket under each coefficient.

Panel A

Dep. Var:	$ret_{t,t+1}$	$ret_{t,t+2}$	$ret_{t,t+3}$	$ret_{t,t+4}$	$ret_{t,t+5}$
$FixedInv$	0.9572	1.2200	0.8643	0.6813	0.8948
	[0.43]	[0.71]	[0.67]	[0.65]	[0.97]
	0.003	0.011	0.010	0.009	0.019
$UnEmploy$	2.8372***	2.5022***	2.5864***	2.7039***	2.6280***
	[2.65]	[3.31]	[4.96]	[6.91]	[6.76]
	0.078	0.123	0.206	0.300	0.334
$TermSpread$	0.9410	1.9164	2.3801*	2.1470*	1.4092
	[0.51]	[1.21]	[1.91]	[1.93]	[1.10]
	0.003	0.024	0.055	0.058	0.030
$BankLoans$	-0.2707	-0.1243	-0.1445	-0.1830**	-0.1507
	[-1.28]	[-0.98]	[-1.63]	[-2.15]	[-1.57]
	0.020	0.008	0.018	0.038	0.031
$\Delta d_{t-1,t}$	0.2132	0.2248	0.1429	-0.0229	-0.1015
	[0.78]	[1.05]	[0.79]	[-0.14]	[-0.65]
	0.006	0.014	0.008	0.000	0.006
$DefaultSpread$	8.7877**	5.7727**	4.6943**	5.2269**	6.3513***
	[2.12]	[2.17]	[2.19]	[2.54]	[3.64]
	0.051	0.046	0.049	0.080	0.140
$MktLev$	0.2405***	0.2011***	0.1711***	0.1663***	0.1856***
	[2.75]	[3.04]	[3.34]	[3.93]	[5.30]
	0.082	0.116	0.132	0.163	0.241
$StInt$	-0.0960	0.1486	0.1444	0.1549	0.2915
	[-0.18]	[0.44]	[0.51]	[0.51]	[0.88]
	0.000	0.002	0.003	0.004	0.016
CP	-0.0086	-0.0156	-0.0159	-0.0157	-0.0223
	[-0.27]	[-0.72]	[-0.88]	[-0.88]	[-1.21]
	0.001	0.006	0.010	0.013	0.029
$HHDebt$	0.0418	0.0396	0.0429	0.0450	0.0468
	[0.33]	[0.43]	[0.60]	[0.73]	[0.85]
	0.002	0.003	0.006	0.009	0.012

*:10% significance level,**:5% significance level, ***:1% significance level.

Table 1.8: The table reports regression results of the macro variables in uni-variate setting. The sample period is from 1966Q1 to 2017Q4. Newey-West t-statistics are reported in the square bracket under each coefficient.

Panel B

Dep. Var:	$\Delta d_{t,t+1}$	$\Delta d_{t,t+2}$	$\Delta d_{t,t+3}$	$\Delta d_{t,t+4}$	$\Delta d_{t,t+5}$
$FixedInv$	-0.2325	-0.8027	-0.7442	-0.4927	-0.2335
	[-0.33]	[-1.32]	[-1.46]	[-1.17]	[-0.66]
	0.001	0.024	0.029	0.018	0.006
$UnEmploy$	0.5684***	1.1816***	1.3968***	1.3357***	1.2007***
	[1.07]	[2.70]	[3.63]	[3.83]	[3.74]
	0.024	0.134	0.242	0.293	0.312
$TermSpread$	1.6849	2.5725***	3.1760***	3.2458***	2.7849***
	[1.48]	[3.13]	[5.01]	[5.73]	[5.26]
	0.059	0.183	0.371	0.518	0.525
$BankLoans$	0.0246	-0.1334**	-0.1921***	-0.1963***	-0.1860***
	[0.30]	[-2.07]	[-3.82]	[-4.56]	[-4.49]
	0.001	0.047	0.127	0.175	0.209
$\Delta d_{t-1,t}$	0.5456	0.3075	0.1487	0.0472	-0.0541
	[4.20]***	[2.07]**	[0.94]	[0.33]	[-0.42]
	0.301	0.124	0.036	0.005	0.007
$DefaultSpread$	-3.9246*	-1.2046	0.3406	1.2834*	1.9059***
	[-1.69]	[-0.83]	[0.36]	[1.67]	[2.61]
	0.079	0.010	0.001	0.019	0.058
$MktLev$	-0.0557	-0.0321	-0.0153	-0.0075	-0.0069
	[-1.59]	[-0.99]	[-0.52]	[-0.30]	[-0.33]
	0.034	0.015	0.004	0.001	0.002
$StInt$	-0.6062***	-0.6806***	-0.6744***	-0.6007***	-0.5019***
	[-2.63]	[-3.39]	[-3.59]	[-3.26]	[-2.82]
	0.126	0.199	0.247	0.248	0.220
CP	0.0301*	0.0331**	0.0353***	0.0337***	0.0293***
	[1.95]	[2.49]	[3.11]	[3.26]	[2.94]
	0.093	0.140	0.200	0.232	0.221
$HHDebt$	0.1074	0.1054	0.1042*	0.1017**	0.0981***
	[1.50]	[1.65]	[1.92]	[2.28]	[2.74]
	0.095	0.117	0.149	0.187	0.229

*:10% significance level,**:5% significance level, ***:1% significance level.

Table 1.9: In this table, we first describe the correlations among debt-to-GDP and the macroeconomic factors. Then we only include non-correlated factors in the multivariate regressions. Panel A report results after controlling for the non-correlated macro variables and Panel B report regressions excluding FixedInv variable which is not significant in previous regressions. t values are reported in the square brackets below each coefficients.

Correlation Matrix

Corr.	$FixedInv_t$	$UnEmploy_t$	$DFSpread_t$	$BankLoans$	$\Delta d_{t-1,t}$	$TRSpread_t$	$MktLev_t$	$StInt_t$	CP_t	$HHDebt$
$\frac{D}{Y}_t$	0.059	0.065	-0.166	-0.218	0.391	0.533	-0.556	-0.777	0.793	0.796
	[0.86]	[0.94]	[-2.42]	[-3.21]	[6.11]	[8.06]	[-9.61]	[-17.73]	[18.54]	[18.84]

Panel A										
Dep. Var:	$ret_{t,t+1}$	$ret_{t,t+2}$	$ret_{t,t+3}$	$ret_{t,t+4}$	$ret_{t,t+5}$	$\Delta d_{t,t+1}$	$\Delta d_{t,t+2}$	$\Delta d_{t,t+3}$	$\Delta d_{t,t+4}$	$\Delta d_{t,t+5}$
$\frac{D}{Y}_t$	0.1230*	0.1058*	0.0967*	0.0928*	0.0907*	0.1223***	0.1241***	0.1199***	0.1158***	0.1158***
	[1.70]	[1.86]	[1.95]	[1.90]	[1.83]	[3.69]	[5.08]	[6.47]	[6.92]	[7.30]
$FixedInv$	0.5853	0.9994	0.9153	1.0008	1.2766	-0.2664	-0.7836	-0.6226	-0.1888	0.2371
	[0.29]	[0.62]	[0.75]	[1.03]	[1.46]	[-0.44]	[-1.57]	[-1.53]	[-0.54]	[0.78]
$UnEmploy$	2.5453**	2.2824***	2.4055***	2.5404***	2.4662***	0.4268	1.0025***	1.1952***	1.1413***	1.0086***
	[2.24]	[2.75]	[3.77]	[4.96]	[5.46]	[0.95]	[3.26]	[5.02]	[5.61]	[5.75]
Obs.	204	200	196	192	188	204	200	196	192	188
R^2	0.097	0.158	0.252	0.353	0.394	0.206	0.372	0.507	0.572	0.610
Panel B										
Dep. Var:	$ret_{t,t+1}$	$ret_{t,t+2}$	$ret_{t,t+3}$	$ret_{t,t+4}$	$ret_{t,t+5}$	$\Delta d_{t,t+1}$	$\Delta d_{t,t+2}$	$\Delta d_{t,t+3}$	$\Delta d_{t,t+4}$	$\Delta d_{t,t+5}$
$\frac{D}{Y}_t$	0.1240*	0.1071*	0.0963*	0.0893*	0.0834	0.1218***	0.1231***	0.1202***	0.1165***	0.1145***
	[1.71]	[1.82]	[1.87]	[1.75]	[1.54]	[3.70]	[4.94]	[6.15]	[6.83]	[7.56]
$UnEmploy$	2.5449**	2.2847***	2.4147***	2.5576***	2.4866***	0.4270	1.0007***	1.1890***	1.1381***	1.0124***
	[2.23]	[2.73]	[3.77]	[4.92]	[5.29]	[0.96]	[3.10]	[4.64]	[5.51]	[5.94]
Obs.	204	200	196	192	188	204	200	196	192	188
R^2	0.096	0.151	0.243	0.340	0.367	0.204	0.352	0.491	0.570	0.606

*:10% significance level,**:5% significance level, ***:1% significance level.

Table 1.10: The table reports estimation results in GMM setting. The sample period is from 1966Q1 to 2017Q4. In first part we estimate all $\phi_{1,H}$ by GMM. In second part we run the null hypothesis test that $\phi_{1,H} = 1$. The third part reports new results under coefficients specification $\phi_{1,H} = \phi_1$ and corresponding hypothesis tests.

$$ret_{t,t+H} = \phi_{0,H} + \phi_{1,H}(\gamma_{1,H}\frac{D}{Y}_t) + \phi_{2,H}(\gamma_{2,H}UnEmploy_t) + \epsilon^r_{t,t+H}$$

$$\Delta d_{t,t+H} = \gamma_{0,H} + \gamma_{1,H}\frac{D}{Y}_t + \gamma_{2,H}UnEmploy_t + \epsilon^d_{t,t+H}$$

Part 1

Dep. Var:	$\Delta d_{t,t+1}$	$\Delta d_{t,t+2}$	$\Delta d_{t,t+3}$	$\Delta d_{t,t+4}$	$\Delta d_{t,t+5}$
$\gamma_{1,H}$	0.1230***	0.1224***	0.1188***	0.1148***	0.1130***
	[8.07]	[10.62]	[12.75]	[13.64]	[14.88]
$\gamma_{2,H}$	0.8261***	1.3031***	1.3785***	1.2546***	1.0889***
	[3.61]	[7.15]	[9.47]	[10.72]	[11.24]
R^2	0.194	0.343	0.487	0.567	0.603

Dep. Var:	$ret_{t,t+1}$	$ret_{t,t+2}$	$ret_{t,t+3}$	$ret_{t,t+4}$	$ret_{t,t+5}$
$\phi_{1,H}$	0.9932**	0.8579***	0.7839***	0.7403***	0.7047***
	[2.45]	[3.04]	[3.36]	[3.17]	[2.77]
$\phi_{2,H}$	2.8964**	1.7504***	1.8604***	2.1516***	2.3704***
	[2.44]	[4.16]	[5.80]	[6.79]	[7.27]
R^2	0.095	0.149	0.242	0.336	0.365

Part 2 Wald Test
Null Hypothesis: $\phi_{1,1} = \phi_{1,2} = \phi_{1,3} = \phi_{1,4} = \phi_{1,5} = 1$
Chi-square: 1.7206 p-value: 0.8863

Null Hypothesis: $\phi_{2,1} = \phi_{2,2} = \phi_{2,3} = \phi_{2,4} = \phi_{2,5} = 1$
Chi-square: 20.0350 p-value: 0.0012

Part 3 Alternative Estimation:
Estimate $\phi_{i,1} = \phi_{i,2} = \phi_{i,3} = \phi_{i,4} = \phi_{i,5} = \phi_i$ and Test $\phi_i = 1$
ϕ_1=0.7239, Chi-square: 2.3092, p-value: 0.1286
ϕ_2=2.1195, Chi-square: 18.1090, p-value: 0.0000

*:10% significance level,**:5% significance level, ***:1% significance level.

Table 1.11: Calibrated Parameters

Parameter	Symbol	Value
Preferences		
Discount Factor	β	0.984
Relative Risk Aversion	γ	10
Intertemporal Elasticity of Substitution	ψ	1.5
Technology		
Capital Share	α	0.375
Depreciation Rate	δ	0.02
Average Payout Ratio	β_d	0.433
Persistence of Payout Ratio	ρ_β	0.905
Intensity of Debt Adj. Costs	λ_1	0.4
Productivity		
Average Productivity Growth	μ	0.006
Persistence of Productivity	ρ	0.926
Short-Run Productivity Volatility	σ_a	0.019
Long-Run Productivity Volatility	σ_z	0.002
Policy Parameters		
Persistence of Expenditure Shock,	ρ_g	0.96
Expenditure Volatility	σ_g	0.08
Persistence of Debt	ρ_d	0.96
Intensity of SR Productivity Shock	ψ_{sr}	-0.18
Intensity of LR Productivity Shock	ψ_{lr}	19.04

This table reports the benchmark quarterly calibration.

Table 1.12: Simulated Moments and Statistics: The bootstrapped statistics were calculated from 500 simulations, each with 600 observations. All values are annualized. The upper panel reports required variables(moments) in the framework and the lower panel reports variables(moments) we investigated. We compare moments from three cases: Case 0-Data; Case 1-Model with cash holding; Case 2-Model without cash holding.

Variable(Macro)	**Data**	**Case 1**	**Case 2**
$\sigma(\Delta y)$ (%)	3.56	3.42	3.29
$\sigma(\Delta c)/\sigma(\Delta y)$	0.71	0.61	0.56
$ACF_1[\Delta c]$ (%)	0.50	0.30	0.33
$\rho(\Delta c, \Delta i)$	0.39	0.41	0.84
$E[I/Y]$ (%)	17.49	16.25	28.75
$\sigma(\Delta i)/\sigma(\Delta y)$	4.49	4.38	2.74
$\sigma(q)$	0.29	0.20	0.16
$ACF_1[q]$ (%)	0.86	0.99	0.99
$E[\frac{D}{Y}]$ (%)	55.00	54.99	55.22
$\sigma(\frac{D}{Y})$ (%)	22.3	11.00	11.30
$E[\tau]$ (%)	18.20	18.74	17.83
$\sigma(\tau)$ (%)	2.07	5.81	5.45

Variable(Return)	**Data**	**Case 1**	**Case 2**
$E[r_{exr,t+1}]$ (%)	5.70	5.29	0.62
$\sigma(r_{exr,t+1})$ (%)	20.89	8.55	7.17
$ACF_1[r_{exr,t+1}]$ (%)	0.09	-0.00	-0.00
$\rho(\Delta c, r_{exr})$	0.25	0.21	0.35
$E[r_t^f]$ (%)	1.23	1.59	1.15
$\sigma(r_t^f)$ (%)	2.34	0.91	0.68
$ACF_1[r_t^f]$ (%)	0.64	0.67	0.56
$E[\Delta div]$ (%)	1.95	1.54	3.34
$\sigma(\Delta div)/\sigma(\Delta y)$	3.15	4.40	7.10
$E[\beta_d]$ (%)	43.30	43.00	n/a
$\sigma(\beta_d)$ (%)	9.76	8.31	n/a

Table 1.13: Predictive regressions. This table reports statistics obtained from both data and model, where φ are the factor loadings of the debt-to-GDP ratio. We compare results in three cases: Case 0-Data; Case 1-Model with cash holding; Case 2-Model without cash holding. The quarterly data sample is from the period 1966:Q1 to 2017:Q4.

$$\Delta i_{t,t+H} = \varphi_0^{\Delta i} + \varphi_1^{\Delta i} \frac{D}{Y}_t + \epsilon_{t,t+j}^{\Delta i}$$

$$H = 1, \cdots, 5$$

	Data		Case 1		Case 2	
Dep. Var:	$\varphi_1^{\Delta i}$	R^2	$\varphi_1^{\Delta i}$	R^2	$\varphi_1^{\Delta i}$	R^2
$\Delta i_{t,t+1}$	0.0285	0.004	0.3415	0.071	0.5455	0.424
$\Delta i_{t,t+3}$	0.0145	0.003	0.1264	0.047	0.3643	0.309
$\Delta i_{t,t+5}$	0.0117	0.004	0.0080	0.046	0.2315	0.184

Table 1.14: Predictive regressions (benchmark). This table reports statistics obtained from both data and model, where γ and β are the factor loadings of debt-to-GDP in uni-variate regressions. Panel A reports the dividend growth regressions and Panel B reports the stock return regressions. Panel C reports both real data estimated and the model implied common components. We compare results in three cases: Case 0-Data; Case 1-Model with cash holding; Case 2-Model without cash holding. The quarterly data sample is from the period 1966:Q1 to 2017:Q4. ($\beta_{1,H} = \phi_{1,H}\gamma_{1,H}$)

$$ret_{t,t+H} = \phi_{0,H} + \phi_{1,H}(\gamma_{1,H}\frac{D}{Y}_t) + \epsilon^r_{t,t+H}$$

$$\Delta d_{t,t+H} = \gamma_{0,H} + \gamma_{1,H}\frac{D}{Y}_t + \epsilon^d_{t,t+H}$$

$$H = 1, \cdots, 5$$

Panel A	Data		Case 1		Case 2	
Dep. Var:	γ	R^2	γ	R^2	γ	R^2
$\Delta d_{t,t+1}$	0.1257	0.191	0.0785	0.074	-0.2380	0.124
$\Delta d_{t,t+3}$	0.1404	0.323	0.1230	0.193	-0.1803	0.301
$\Delta d_{t,t+5}$	0.1332	0.390	0.1402	0.284	-0.1295	0.278

Panel B	Data		Case 1		Case 2	
Dep. Var:	β	R^2	β	R^2	β	R^2
$ret_{t,t+1}$	0.1470	0.034	0.1774	0.397	0.1502	0.676
$ret_{t,t+3}$	0.1371	0.075	0.1444	0.384	0.1245	0.603
$ret_{t,t+5}$	0.1293	0.080	0.1157	0.310	0.1027	0.485

Panel C	Data		Case 1		Case 2	
Coefficients	est.	s.e.	avg.	[1^{st} Quin, 4^{th} Quin]	avg.	[1^{st} Quin, 4^{th} Quin]
$\phi_{1,1}$	1.1234	(0.0225)	1.1093	[-1.3970, 2.9319]	-0.5379	[-0.5050, -0.3981]
$\phi_{1,3}$	0.9702	(0.0166)	0.9221	[0.3488, 1.8646]	-0.4931	[-0.5000, -0.3600]
$\phi_{1,5}$	0.9426	(0.0378)	0.9258	[0.3800, 1.4279]	-0.4858	[-0.5269, -0.3527]

Table 1.15: Predictive regressions (public debt rule only responding to the short-run productivity). This table reports statistics obtained from both data and model, where γ and β are the factor loadings of debt-to-GDP in uni-variate regressions. Panel A reports the dividend growth regressions and Panel B reports the stock return regressions. Panel C reports both real data estimated and the model implied common components. We compare results in three cases: Case 0-Data; Case 1-Model with cash holding; Case 2-Model without cash holding. The quarterly data sample is from the period 1966:Q1 to 2017:Q4. $(\beta_{1,H} = \phi_{1,H}\gamma_{1,H})$

$$ret_{t,t+H} = \phi_{0,H} + \phi_{1,H}(\gamma_{1,H}\frac{D}{Y}_t) + \epsilon^r_{t,t+H}$$

$$\Delta d_{t,t+H} = \gamma_{0,H} + \gamma_{1,H}\frac{D}{Y}_t + \epsilon^d_{t,t+H}$$
$$H = 1, \cdots, 5$$

Panel A	Data		Case 1		Case 2	
Dep. Var:	γ	R^2	γ	R^2	γ	R^2
$\Delta d_{t,t+1}$	0.1257	0.191	-1.1706	0.107	-0.1014	0.068
$\Delta d_{t,t+3}$	0.1404	0.323	-0.9342	0.146	-0.0711	0.105
$\Delta d_{t,t+5}$	0.1332	0.390	-0.7074	0.157	-0.0888	0.130

Panel B	Data		Case 1		Case 2	
Dep. Var:	β	R^2	β	R^2	β	R^2
$ret_{t,t+1}$	0.1470	0.034	0.0031	0.081	-0.1061	0.085
$ret_{t,t+3}$	0.1371	0.075	0.1089	0.111	-0.0516	0.110
$ret_{t,t+5}$	0.1293	0.080	0.1069	0.127	-0.0051	0.129

Panel C	Data		Case 1		Case 2	
Coefficients	est.	s.e.	avg.	$[1^{st}{}_{\text{Quin}}, 4^{th}{}_{\text{Quin}}]$	avg.	$[1^{st}{}_{\text{Quin}}, 4^{th}{}_{\text{Quin}}]$
$\phi_{1,1}$	1.1234	(0.0225)	0.1136	[-0.3974, 0.6722]	-0.3351	[-0.7135, 0.2443]
$\phi_{1,3}$	0.9702	(0.0166)	0.1129	[-0.5676, 0.8551]	-0.3688	[-0.7265, 0.1416]
$\phi_{1,5}$	0.9426	(0.0378)	0.1536	[-0.4529, 0.8308]	-0.3877	[-0.6826, 0.0470]

Table 1.16: Predictive regressions (public debt rule only responding to the long-run productivity). This table reports statistics obtained from both data and model, where γ and β are the factor loadings of debt-to-GDP in uni-variate regressions. Panel A reports the dividend growth regressions and Panel B reports the stock return regressions. Panel C reports both real data estimated and the model implied common components. We compare results in three cases: Case 0-Data; Case 1-Model with cash holding; Case 2-Model without cash holding. The quarterly data sample is from the period 1966:Q1 to 2017:Q4. ($\beta_{1,H} = \phi_{1,H}\gamma_{1,H}$)

$$ret_{t,t+H} = \phi_{0,H} + \phi_{1,H}(\gamma_{1,H}\frac{D}{Y}_t) + \epsilon^r_{t,t+H}$$

$$\Delta d_{t,t+H} = \gamma_{0,H} + \gamma_{1,H}\frac{D}{Y}_t + \epsilon^d_{t,t+H}$$

$$H = 1, \cdots, 5$$

Panel A	Data		Case 1		Case 2	
Dep. Var:	γ	R^2	γ	R^2	γ	R^2
$\Delta d_{t,t+1}$	0.1257	0.191	0.0648	0.075	-0.2789	0.123
$\Delta d_{t,t+3}$	0.1404	0.323	0.1011	0.192	-0.2514	0.305
$\Delta d_{t,t+5}$	0.1332	0.390	0.1253	0.282	-0.1877	0.281

Panel B	Data		Case 1		Case 2	
Dep. Var:	β	R^2	β	R^2	β	R^2
$ret_{t,t+1}$	0.1470	0.034	0.1974	0.417	0.1561	0.683
$ret_{t,t+3}$	0.1371	0.075	0.1631	0.402	0.1317	0.605
$ret_{t,t+5}$	0.1293	0.080	0.1323	0.322	0.1078	0.480

Panel C	Data		Case 1		Case 2	
Coefficients	est.	s.e.	avg.	$[1^{st}{}_{\text{Quin}}, 4^{th}{}_{\text{Quin}}]$	avg.	$[1^{st}{}_{\text{Quin}}, 4^{th}{}_{\text{Quin}}]$
$\phi_{1,1}$	1.1234	(0.0225)	1.0218	[-1.1981, 2.4285]	-0.5843	[-0.8057, -0.4577]
$\phi_{1,3}$	0.9702	(0.0166)	1.0740	[0.4086, 2.4711]	-0.5247	[-0.7321, -0.3893]
$\phi_{1,5}$	0.9426	(0.0378)	0.9079	[0.3962, 1.8802]	-0.4946	[-0.7060, -0.3489]

Table 1.17: Return Predictive Performance (Recursive Window)

This table reports the return predictive performance under five specifications. Panel A reports one-year return predictive results; Panel B reports three-year return predictive results; Panel C reports five-year return predictive results. The sample period is from 1950Q1 to 2017Q4 and the training length is 20 years. The Out-of-sample benchmark performance is based on average means and the significance level is determined by McCracken F statistics.

	In-Sample		Out-of-Sample	
Panel A (1y)	R^2	RMSE	R^2	RMSE
dp_t	0.197	0.143	0.093***	0.168
$\widetilde{dp_t}$	0.306	0.133	0.146***	0.163
CAY	0.174	0.145	0.149***	0.163
$DGDP+\widetilde{dp_t}$	0.308	0.133	0.216***	0.156
$DGDP+\widetilde{dp_t}+CAY$	0.363	0.127	0.368***	0.140
Panel B (3y)	R^2	RMSE	R^2	RMSE
dp_t	0.570	0.052	0.237***	0.087
$\widetilde{dp_t}$	0.013	0.079	0.255***	0.086
CAY	0.186	0.072	0.374***	0.079
$DGDP+\widetilde{dp_t}$	0.237	0.069	0.413***	0.076
$DGDP+\widetilde{dp_t}+CAY$	0.351	0.064	0.599***	0.063
Panel C (5y)	R^2	RMSE	R^2	RMSE
dp_t	0.696	0.023	0.343***	0.062
$\widetilde{dp_t}$	-0.516	0.051	0.246***	0.066
CAY	0.086	0.040	0.331***	0.062
$DGDP+\widetilde{dp_t}$	0.351	0.064	0.599***	0.063
$DGDP+\widetilde{dp_t}+CAY$	0.243	0.036	0.536***	0.052

*: 10% significance level, **: 5% significance level, ***: 1% significance level.

Table 1.18: The table reports estimation results for U.S. cross-section portfolios in GMM setting. The sample period is from 1966 to 2017. In first part we report the cash flow predictability and $\gamma_{1,H}$ are estimated by GMM. In second part we run the null hypothesis test that $\phi_{1,H} = 1$. The third part reports new results under coefficients specification $\phi_{1,H} = \phi_1$ and corresponding hypothesis tests.

$$ret_{t,t+H} = \phi_{0,H} + \phi_{1,H}(\gamma_{1,H}\frac{D}{Y}_t) + \epsilon^r_{t,t+H}$$

$$\Delta d_{t,t+H} = \gamma_{0,H} + \gamma_{1,H}\frac{D}{Y}_t + \epsilon^d_{t,t+H}$$

Part 1

Small Firms:	$\Delta d_{t,t+1}$	$\Delta d_{t,t+2}$	$\Delta d_{t,t+3}$	$\Delta d_{t,t+4}$	$\Delta d_{t,t+5}$
$\gamma^S_{1,H}$	0.0899	0.1313*	0.1533*	0.1471*	0.1501*
	[1.18]	[1.66]	[1.82]	[1.75]	[1.72]
R^2	0.007	0.042	0.089	0.094	0.112
Large Firms:	$\Delta d_{t,t+1}$	$\Delta d_{t,t+2}$	$\Delta d_{t,t+3}$	$\Delta d_{t,t+4}$	$\Delta d_{t,t+5}$
$\gamma^L_{1,H}$	0.0844***	0.1018***	0.1078***	0.1031***	0.1028***
	[4.17]	[5.11]	[4.31]	[3.74]	[3.23]
R^2	0.022	0.075	0.138	0.144	0.175
Growth Firms:	$\Delta d_{t,t+1}$	$\Delta d_{t,t+2}$	$\Delta d_{t,t+3}$	$\Delta d_{t,t+4}$	$\Delta d_{t,t+5}$
$\gamma^G_{1,H}$	0.1216***	0.1410***	0.1493***	0.1457***	0.1422***
	[3.77]	[5.71]	[6.91]	[6.95]	[6.77]
R^2	0.030	0.090	0.175	0.199	0.238
Value Firms:	$\Delta d_{t,t+1}$	$\Delta d_{t,t+2}$	$\Delta d_{t,t+3}$	$\Delta d_{t,t+4}$	$\Delta d_{t,t+5}$
$\gamma^V_{1,H}$	0.0150	0.0458	0.0581	0.0459	0.0397
	[0.19]	[0.61]	[0.74]	[0.57]	[0.47]
R^2	0.000	0.005	0.014	0.010	0.010

Part 2 Wald Test

Null Hypothesis: $\phi_1 = \phi_2 = \phi_3 = \phi_4 = \phi_5 = 1$

Small Firms:	Chi-square: 1.0518	p-value: 0.9583
Large Firms:	Chi-square: 1.9837	p-value: 0.8514
Growth Firms:	Chi-square: 0.9446	p-value: 0.9669
Value Firms:	Chi-square: 0.4609	p-value: 0.9935

Part 3 Alternative Estimation:

Estimate $\phi_1 = \phi_2 = \phi_3 = \phi_4 = \phi_5 = \phi_i$ and Test $\phi_i = 1$

Small Firms:	ϕ_i=**0.6355**,	s.e. 0.4032,	**t=1.58**,	Chi-square: 0.8169,	p-value: 0.3661
Large Firms:	ϕ_i=**1.2976**,	s.e. 0.3861,	**t=3.36**,	Chi-square: 0.5942,	p-value: 0.4408
Growth Firms:	ϕ_i=**1.1627**,	s.e. 0.3830,	**t=3.04**,	Chi-square: 0.1805,	p-value: 0.6709
Value Firms:	ϕ_i=**0.7415**,	s.e. 0.4992,	**t=1.49**,	Chi-square: 0.2681,	p-value: 0.6046

*:10% significance level,**:5% significance level, ***:1% significance level.

Table 1.19: Predictive regressions - Developed Markets. This table reports statistics obtained from international data, where γ and β are the factor loadings of debt-to-GDP in uni-variate regressions, and ϕ_1 measures the common component loading.

$$ret_{t,t+H} = \phi_{0,H} + \phi_1(\gamma_{1,H}\frac{D}{Y}_t) + \epsilon^r_{t,t+H}$$

$$\Delta d_{t,t+H} = \gamma_{0,H} + \gamma_{1,H}\frac{D}{Y}_t + \epsilon^d_{t,t+H}$$

$$H = 1, \cdots, 5$$

Country	Start Obs	ϕ_1	*s.e.*	t-value	Null $\phi_1 = 1$, p-value
Australia	Q2 1988	0.902	0.439	2.06	0.824
Austria	Q1 1980	0.735	0.256	2.87	0.300
Belgium	Q1 1980	0.356	0.322	1.10	0.046
Canada	Q1 1980	1.644	0.514	3.20	0.210
Denmark	Q1 1980	0.525	0.078	6.72	0.000
Finland	Q2 1988	1.139	0.221	5.15	0.530
France	Q1 1980	0.994	0.205	4.86	0.978
Germany	Q1 1980	1.831	1.039	1.76	0.424
Ireland	Q1 1980	1.195	0.401	2.98	0.627
Italy	Q1 1980	0.382	0.096	3.99	0.000
Japan	Q1 1980	-2.391	5.173	-0.46	0.512
Netherlands	Q1 1980	0.816	0.165	4.93	0.267
Newzealand	Q4 1989	0.666	0.183	3.63	0.069
Norway	Q1 1980	1.485	0.389	3.81	0.213
Poland	Q4 1999	0.239	0.014	17.15	0.000
Portugal	Q2 1990	0.366	0.028	13.25	0.000
Spain	Q1 1987	-0.264	0.143	-1.85	0.000
Sweden	Q2 1982	0.981	0.256	3.83	0.941
Switzerland	Q4 1979	1.371	0.799	1.71	0.643
UK	Q1 1980	1.587	0.245	6.49	0.016

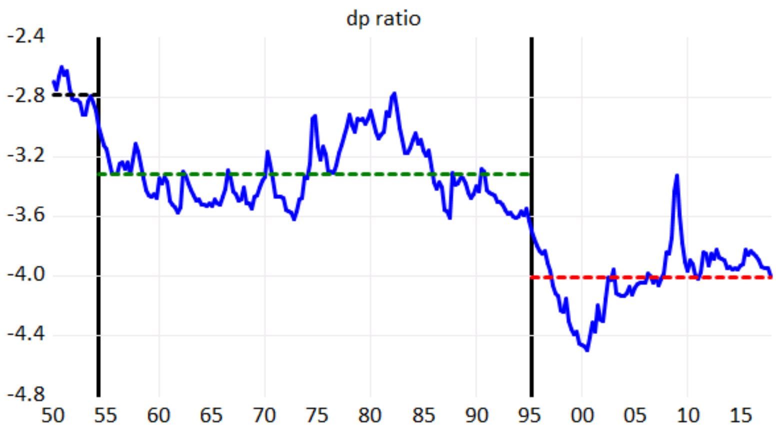
Table 1.19: Predictive regressions - Emerging Markets. This table reports statistics obtained from international data, where γ and β are the factor loadings of debt-to-GDP in uni-variate regressions, and ϕ_1 measures the common component loading.

$$ret_{t,t+H} = \phi_{0,H} + \phi_1(\gamma_{1,H}\frac{D}{Y}_t) + \epsilon^r_{t,t+H}$$

$$\Delta d_{t,t+H} = \gamma_{0,H} + \gamma_{1,H}\frac{D}{Y}_t + \epsilon^d_{t,t+H}$$
$$H = 1,\cdots,5$$

Country	Start Obs	ϕ_1	$s.e.$	t-value	Null $\phi_1 = 1$, p-value
Argentina	Q4 1993	0.184	0.073	2.51	0.000
Brazil	Q3 1994	-0.851	0.691	-1.23	0.007
Chile	Q3 1989	-1.261	0.584	-2.16	0.000
China	Q4 1993	1.332	0.590	2.26	0.574
Colombia	Q4 1996	1.156	0.059	19.51	0.009
CzechRep	Q1 1994	0.253	0.305	0.83	0.014
Egypt	Q3 1996	0.543	0.117	4.65	0.000
Greece	Q4 1989	0.473	0.114	4.14	0.000
Hungary	Q4 1991	0.159	0.382	0.42	0.028
India	Q1 1990	0.626	0.439	1.43	0.394
Indonesia	Q2 1990	0.463	0.211	2.20	0.011
Kuwait	Q1 2004	0.781	0.140	5.59	0.117
Malaysia	Q2 1986	2.088	0.264	7.91	0.000
Mexico	Q3 1989	0.656	0.089	7.34	0.000
Pakistan	Q2 2002	1.341	0.064	21.10	0.000
Peru	Q4 2000	0.673	0.135	5.00	0.015
Philippines	Q1 1989	0.604	0.159	3.78	0.013
Romania	Q4 2000	-22.310	51.946	-0.43	0.654
Russia	Q2 1998	0.424	0.094	4.51	0.000
Slovenia	Q1 1999	-5.289	5.752	-0.92	0.274
SouthAfrica	Q1 1981	-0.924	0.881	-1.05	0.029
SriLanka	Q4 1988	-1.108	1.075	-1.03	0.049
Thailand	Q2 1987	0.249	0.279	0.89	0.007
Turkey	Q2 1989	0.355	0.085	4.17	0.000

Figure 1.1: $\widetilde{dp_t}$: We follow [Lettau and Van Nieuwerburgh, 2007] and apply the structural break method to the quarterly data of dp_t. Here we show the dp_t ratio and the structural breaks. The $\widetilde{dp_t}$ can be obtained by adjusting the dp_t by the steady states values during each break period.



Test statistics employ HAC covariances (Bartlett kernel, Newey -West fixed bandwidth) assuming common data distribution

Sequential F-statistic determined breaks: 2

Break Test	Break	F-statistic	Scaled F-statistic
0 vs. 1 *	1921Q1	15.94486	31.88972
1 vs. 2	1870Q4	2.613803	5.227607
1 vs. 2 *	1966Q2	6.309086	12.61817
2 vs. 3	1870Q4	0.725486	1.450973
2 vs. 3	---	---	---

* Significant at the 0.05 level, Bai-Perron (Econometric Journal, 2003) critical value 11.47.

Break dates:

	Sequential	Repartition
1	1950Q1	1954Q2
2	1995Q2	1995Q2

Figure 1.2: Common Component Coefficients.
The common component coefficients are estimated from the following predictive regression:

$$ret_{t,t+H} = \phi_{0,H} + \phi_{1,H}(\gamma_{1,H}\frac{D}{Y}_t) + \epsilon^r_{t,t+H}$$

$$\Delta d_{t,t+H} = \gamma_{0,H} + \gamma_{1,H}\frac{D}{Y}_t + \epsilon^d_{t,t+H}$$

$$H = 1, \cdots, 5$$

The solid line is the term structure of coefficients estimated from real data and the dotted line is the term structure of coefficients estimated from model simulation data.

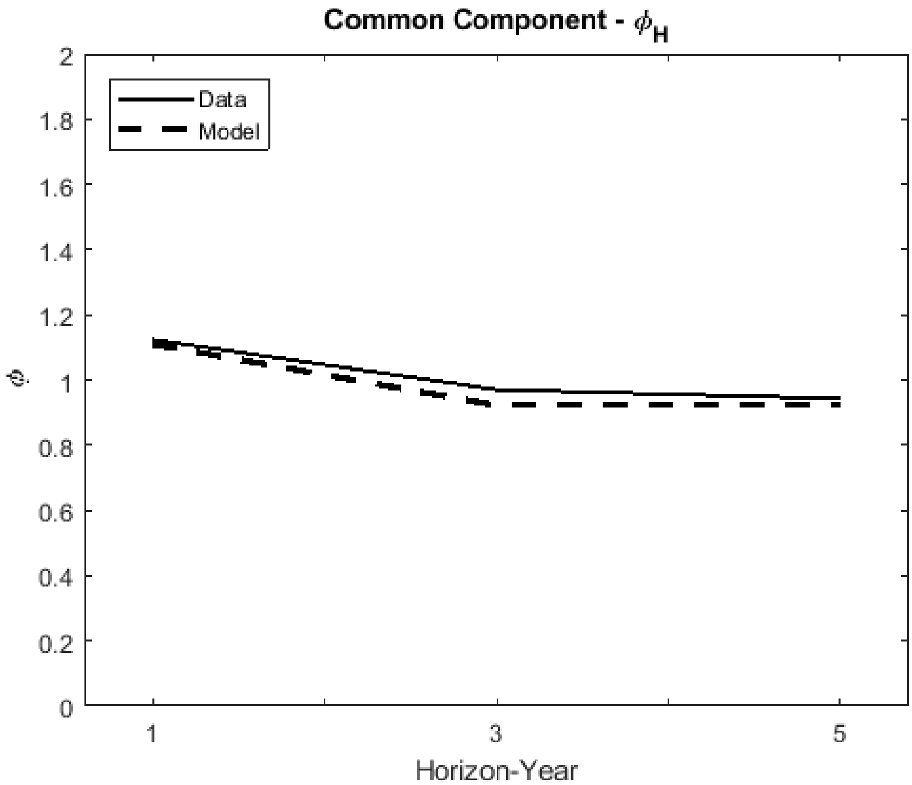
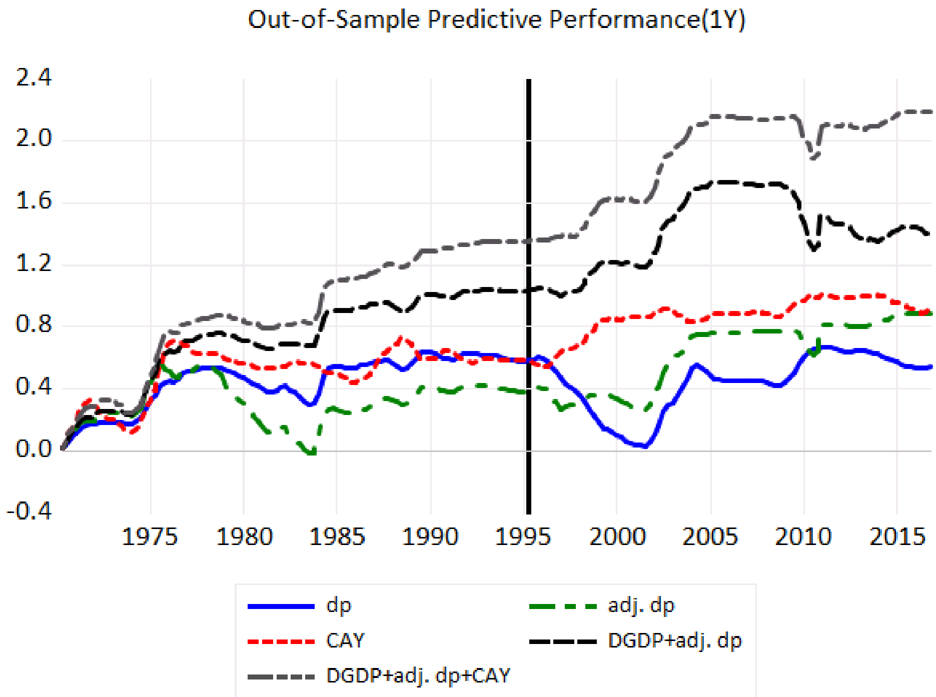
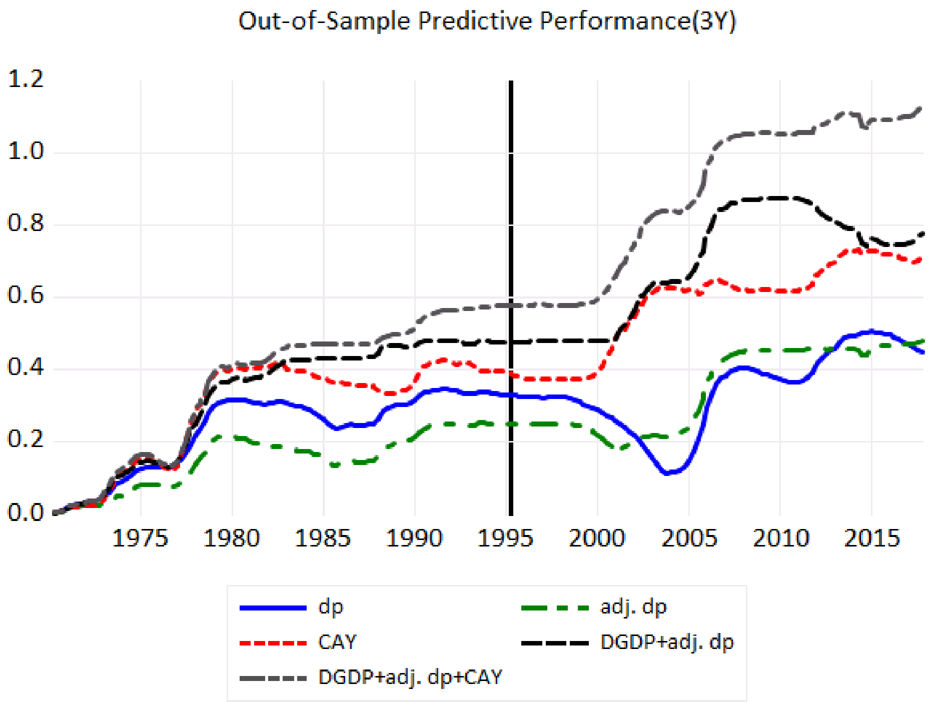


Figure 1.3: Out-of-sample Performance: a) 1-year return, b) 3-year return, c) 5-year return. The above figure plots the cumulative RMSE of forecasts based on five different specifications. The sample period is from 1950Q1 to 2017Q4 and the training length is 20 years.




Out-of-Sample Predictive Performance(3Y)
1.2
1.0
0.8
0.6
0.4
0.2
0.0
1975
1980
1985
1990
1995
2000
2005
2010
2015
dp
adj. dp
CAY
DGDP+adj. dp
DGDP+adj. dp+CAY

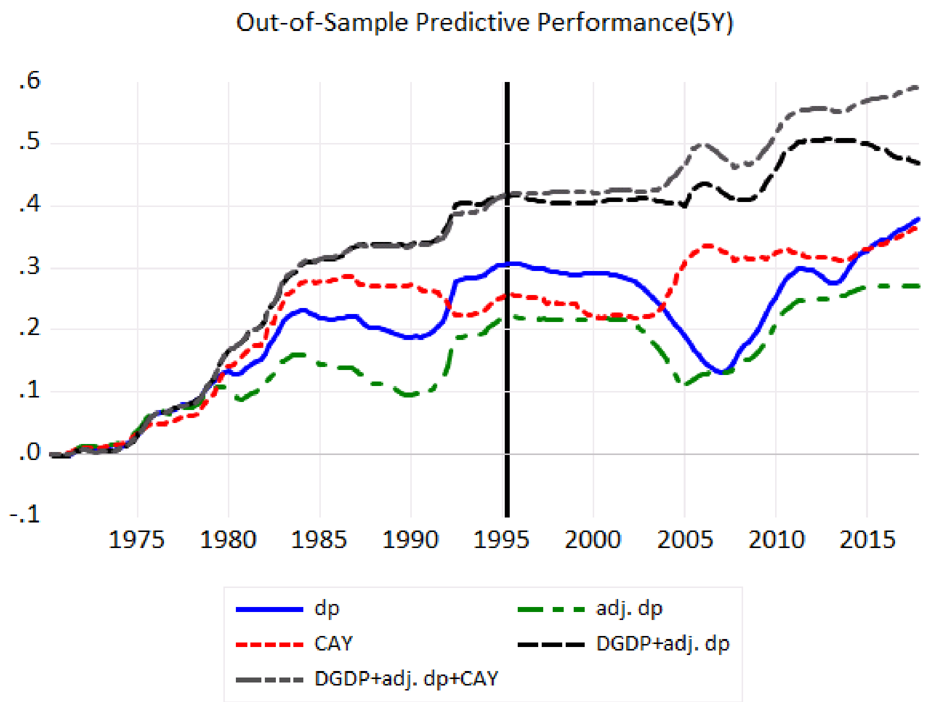
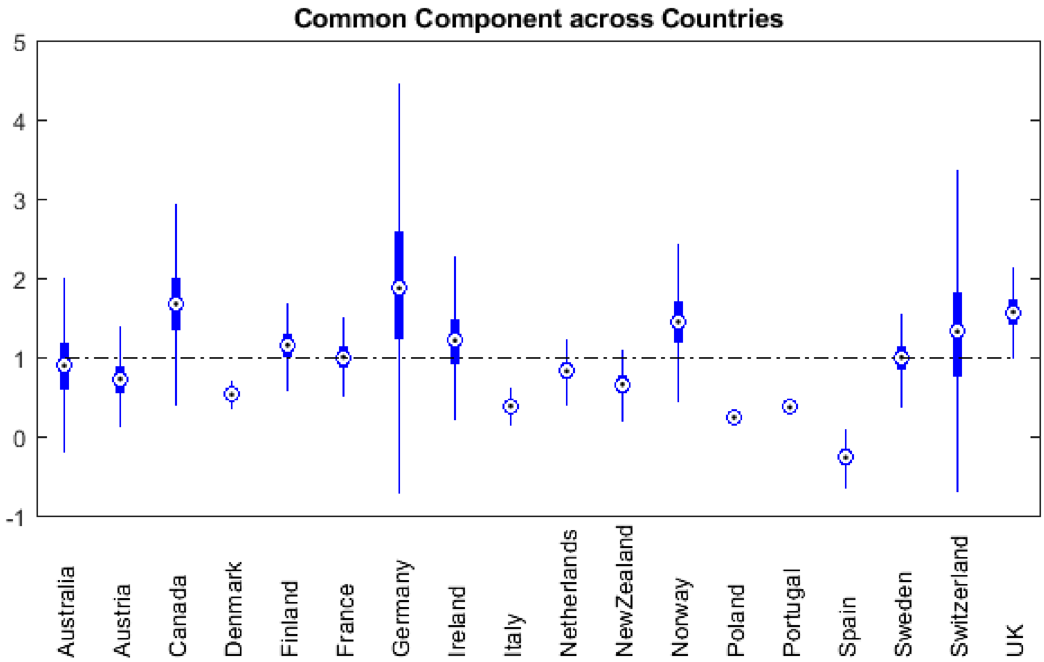

Out-of-Sample Predictive Performance(5Y)
.6
.5
.4
.3
.2
.1
.0
-.1
1975
1980
1985
1990
1995
2000
2005
2010
2015
dp
adj. dp
CAY
DGDP+adj. dp
DGDP+adj. dp+CAY

Figure 1.4: Common Component across Countries: Generate the sample data of common component based on the estimated mean and the standard deviation for each country. The dot represents the median value, the box indicates the 25th and 75th percentiles of the sample data, and the line indicates the approximately 99.3 percent coverage of the sample data.



1.9 Appendix

1.9.1 Data Sources

This Online Appendix reports data description and data sources.

The Debt-to-GDP Ratio. We download Total Public Debt as Percent of Gross Domestic Product (GFDEGDQ188S) from 1966Q1 to 2017Q4 and Federal Debt Held by the Public as Percent of Gross Domestic Product (FYGFGDQ188S) from 1970Q1 to 2017Q4 from St. Louis (FRED). For International public debt data, we use the general government debt series downloaded from the Oxford Economics.

Stock Market Prices. *S&P* 500 index yearly prices from 1950 to 2017 are from Robert Shiller's Web site (see Data Sources at the end of this Appendix); we take December observations. For international data, all prices are downloaded from the Datastream.

Stock Market Dividends. Dividends are 12-month moving sums of dividends paid on the *S&P* 500 index. They are from the Robert Shiller Web site (see Data Sources) for the period 1870-2017. For international data, all dividends data are downloaded and back-outed from the Datastream.

Stock Market Earnings. Earnings are 12-month moving sums of dividends paid on the *S&P* 500 index. They are from the Robert Shiller Web site (see Data Sources) for the period 1870-2017. For international data, all earnings data are downloaded and back-outed from the Datastream.

Stock Market Payout Ratio. Payout ratio is constructed by total dividends over total earnings at each time node.

Stock Market Returns. For the *S&P* 500 index, to construct the continuously compounded return ret_t, we take the ex-dividend price P_t , add dividend D_t over P_{t-1}.

Risk-Free Rate. We download secondary market 3-month T-bill rates from

St. Louis (FRED) from 1966 to 2017.

Log Dividend-Price Ratio (dp_t). The difference between the log of dividends and the log of prices.

Consumption, Wealth, Income Ratio (CAY). The series is taken from Lettau and Ludvigson (2001). Data are available from Martin Lettau's Web site (see Data Sources) at quarterly frequency from 1952 to 2017.

Taxation. We download Federal Government Current Receipts (FGRECPT) from 1966Q1 to 2017Q4 from St. Louis (FRED).

Government Spending. We download Federal government total expenditures (W019RCQ027SBEA) from 1966Q1 to 2017Q4 from St. Louis (FRED).

Corporate Leverage. The corporate leverage is constructed as book leverage of firms in $S\&P$ 500 index. Take the sum of long-term debt and short term debt over firms' book value of total assets as aggregate leverage. The firms' data are downloaded from the WRDS(Compustat Daily Updates-Fundamentals Annual) and matched with the $S\&P$ 500 index list(Compustat - North America-Index Constituents).

Total Factor Productivity (TFP). The quarterly series on total factor productivity (TFP) for the U.S. business sector are downloaded from the San Francisco Fed.

Data Sources

Congressional Budget Office: https://www.cbo.gov/about/products/

Federal Reserve Economic Data: https://fred.stlouisfed.org/

San Francisco Fed: https://www.frbsf.org/economic-research/

Thomson Reuters - Eikon: https://eikon.thomsonreuters.com/index.html

WRDS: https://wrds-web.wharton.upenn.edu/wrds/

Fama-French Data: https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/

Martin Lettau's Web site: http://faculty.haas.berkeley.edu/lettau/

Sydney Ludvigson's Web site: https://www.sydneyludvigson.com/

Robert Shiller's Web site: http://www.econ.yale.edu/ shiller/

1.9.2 CDY and Debt-to-GDP

This Online Appendix reports the additional results of CDY factor.

In [Lettau and Ludvigson, 2005], they also construct the CDY factor which can predict both the stock returns and dividend growth. However the CDY factor only spans from 1948 to 2001 at annual frequency. Here we also considers the situation when we control CDY factor.

[Lettau and Ludvigson, 2005] derive CDY as a trivariate co-integration relation involving three observable variables: c_t, d_t and y_t, where c_t is the log of consumption, d_t is the dividends, and y_t is log labor income.

$$cdy_t \equiv c_t + \upsilon d_t + (1-\upsilon)y_t = E_t \sum_{t=1}^{\infty} \rho_\upsilon^i (\upsilon \Delta d_{t+i} - \Delta c_{t+i} + (1-\upsilon)\Delta y_{t+i})$$

$\Delta d_{a,t}$ is the dividend growth. Under the maintained hypothesis that dividend growth, consumption growth and labor income growth are covariance-stationary and the above equation says that consumption, dividends, and labor income are cointegrated, and that deviations from the common trend in c_t, d_t, y_t summarize expectations of returns to either dividend growth, consumption growth, or labor income growth, or some combination of all three. The wealth shares υ and $1-\upsilon$ are cointegration coefficients.

We provide the correlation matrix and figures from 1948 to 2001 at annual frequency.

Correlation Matrix

Correlation	CDY_t(1948:1996)	CDY_t (1948:2001)
$\frac{D}{Y}_t$	0.577	0.539

Figure 1.6: CDY and $\frac{D}{Y}_t$: both CDY and $\frac{D}{Y}_t$ are from 1948 to 2001 at annual frequency.

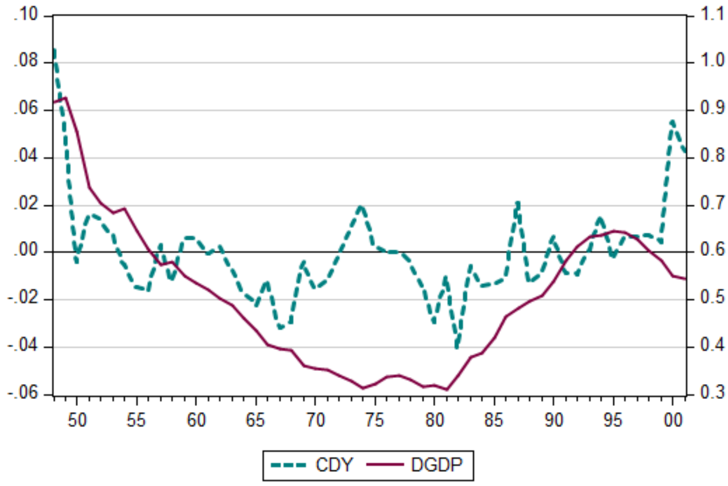


Table 1.20: In this table, we show the results of uni-variate regressions.

Panel A	1948 : (2001-H), LL's Sample				
Dep. Var ($ret_{t,t+H}$)	$ret_{t,t+1}$	$ret_{t,t+2}$	$ret_{t,t+3}$	$ret_{t,t+4}$	$ret_{t,t+5}$
CDY_t	1.0636	2.3295***	1.8189***	1.4268**	1.3361**
	[1.09]	[3.30]	[2.96]	[2.62]	[2.64]
Obs.	53	52	51	50	49
R^2	0.017	0.136	0.154	0.126	0.121

Panel B	1948 : 2001, Extended Sample				
Dep. Var	$ret_{t,t+1}$	$ret_{t,t+2}$	$ret_{t,t+3}$	$ret_{t,t+4}$	$ret_{t,t+5}$
CDY_t	0.4169	1.0097	0.9060	0.6503	0.6293
	[0.32]	[0.90]	[1.07]	[0.92]	[0.99]
Obs.	54	54	54	54	54
R^2	0.003	0.029	0.040	0.027	0.029

*:10% significance level, **: 5% significance level, ***:1% significance level.

1.9.3 Debt-to-GDP and Tax Uncertainty

This Online Appendix reports how tax uncertainty is related to the level of debt-to-GDP ratio.

High debt-to-GDP ratio corresponds to higher tax uncertainty in the economy. We start from the government's inter-temporal budget constraint.

$$D_T = D_{T-1}(1+r) + gY_T - \tau Y_T \tag{1.36}$$

By iterating this equation backward and suppose output grows at constant rate μ ($Y_T = Y_t(1+\mu)^{T-t}$), we have

$$D_T = D_t(1+r)^{T-t} - (\tau - g)Y_t[\sum_{i=t}^{T}(1+r)^{T-i}(1+\mu)^{i-t}] \tag{1.37}$$

Suppose the government will adjust the debt-to-GDP ratio from $\frac{D}{Y}_t$ to $\frac{D}{Y}_T$, which is $\frac{D}{Y}_T = \frac{D}{Y}_t + \Delta\frac{D}{Y}_{t,T}$.

We have the tax rate that can be represented as

$$\tau = g + \frac{\frac{D}{Y}_t(1+r)^{T-t} - \frac{D_T}{Y_T}\frac{Y_T}{Y_t}}{\sum_{i=t}^{T}(1+r)^{T-i}(1+\mu)^{i-t}} \tag{1.38}$$

To simplify the analysis, let $r = 0$ and g is constant, we have the tax rate can be represented as

$$\tau = g + \frac{\frac{D}{Y}_t[1-(1+\mu)^{T-t}] - (1+\mu)^{T-t}\Delta\frac{D}{Y}_{t,T}}{\sum_{i=t}^{T}(1+\mu)^{i-t}} \tag{1.39}$$

Suppose two growth cases where growth rate $\mu_1 > 0$, $\mu_2 < 0$ and $\mu_1 = -\mu_2 =\mid \mu \mid$.

$$(\tau^{\mu_1} - \tau^{\mu_2}) \mid_{T\to\infty} = -(\mu_1 - \mu_2)\frac{D}{Y}_t - \mu_1\Delta\frac{D}{Y}_{t,T} = -\mid \mu \mid (2\cdot\frac{D}{Y}_t + \Delta\frac{D}{Y}_{t,T}) \tag{1.40}$$

Therefore we have

$$|\ \tau^{\mu_1} - \tau^{\mu_2}\ | = |\ \mu\ |\ (2 \cdot \frac{D}{Y}_t + \Delta \frac{D}{Y}_{t,T}) \tag{1.41}$$

and

$$\frac{\partial \mid \tau^{\mu_1} - \tau^{\mu_2} \mid}{\partial \frac{D}{Y}_t} > 0 \tag{1.42}$$

We use the range of implied tax rates $|\ \tau^{\mu_1} - \tau^{\mu_2}\ |$ to measure the tax uncertainty in the economy and we show that the implied tax uncertainty increases with the debt level.

Chapter 2

Prices and Returns: What Is the Role of Inflation?

Abstract: We document that both the dividend yield and earnings yield can predict future inflation across advanced economies. The inflation predictability reinforces the return predictability and reduces the dividend growth predictability. We show that both discount rates and cash flows play an important role in determining prices. We test three hypotheses related to the future growth prospect, risk aversion, and behavior bias to justify the positive correlation among inflation and dividend (earnings) yields. High expected inflation correlates with periods of lower real economic growth and higher discount rates which lead to the drop in today's prices. To rationalize the inflation predictability, we develop and estimate a long-run risk model featuring inflation non-neutrality. The estimated model can reproduce both the inflation predictability and the documented asset pricing facts.

JEL classification: G10, G15.

Keywords: Dividend growth; Dividend yield; Inflation; International equity markets; Money illusion; Stock return.

2.1 Introduction

A fundamental question in asset pricing is to determine whether discount rate news or cash flow news move stock prices. Evidence based on US post-war data suggests most of variations come from the discount rates ([Cochrane, 2007, Cochrane, 2011]) while international evidence shows dividend price ratio can actually predict the cash flows and the contributed variation ratio from cash flows is not negligible ([Engsted and Pedersen, 2010], [Rangvid et al., 2014]). However, predictability results for both returns and dividend growth can be sensitive to the use of nominal or real terms and in this paper we extend the analysis to compare results when nominal term and real term are adopted. Our goal is to assess whether the results obtained in these studies hold when inflation is considered. Indeed we find inflation can change the big picture of return and cash flow predictability.

Inflation can be predicted by the dividend (earnings) yield from one year to twenty year horizon across all seven advanced countries. The interesting implication of this finding is that the apparent strong predictability of nominal stock returns and/or predictability of dividend (earnings) growth are an artifact of inflation predictability by the dividend (earnings) yield. The role of inflation has been rarely explored in previous literature and [Engsted and Pedersen, 2010] claim that they did the first research on this topic. They used data from four countries (US, UK, Denmark and Sweden) and found that inflation predictability can change the US dividend growth predictability. However they failed to draw conclusion on the role of inflation because their inflation predictability results are not robust across forecasting horizons, sub-periods, and countries. A few other papers also have looked at the international dimension of dividend growth predictability. One study by [Ang and Bekaert, 2006] shows that the dividend yield's predictive power to forecast future dividend growth is not robust across sample periods or countries (US, UK, France and Germany). Another international study by [Rangvid et al., 2014] shows that stock returns and dividend growth predictability exist across the world. However both returns and dividend growth in their study are nominal terms. Therefore they did not show whether those results hold in real term or not and furthermore they did not explore the relationship among inflation and the dividend-price ratio.

In our main empirical results, we find that the inflation predictability can reinforce real return predictability and reduce real cash flow predictability. In the equally-weighted global portfolio, the nominal return predictability of the dividend price ratio can be documented while the short-run real return predictability can not be documented. Then the short-run nominal return predictability can be attributed to that the dividend price ratio can positively predict the inflation across different horizons. The same pattern holds when we apply the analysis to earnings yields. The nominal dividend (earnings) growth predictability of the dividend price ratio can be documented while the real dividend growth predictability can not be documented and earnings growth can only be documented in short horizon. A natural explanation is that the dividend (earnings) yield can positively predict the inflation and negatively predict the real dividend (earnings) growth which leads to that the dividend (earnings) yield cannot predict the nominal cash flows. In the value-weighted global portfolio, the dividend price ratio can predict the nominal dividend growth but the signs are in 'wrong direction'. After considering the inflation, the coefficients turn into negative and significant across horizons.

Besides different long-run decomposition and term structure results due to inflation predictability, we are interested in the mechanism behind. We start from exploring why the dividend price ratio can predict the inflation by comparing three main hypothesis. We find that the positive correlation among dividend price ratio and inflation can be backed by the [Fama, 1981]'s growth proxy hypothesis and risk aversion hypothesis ([Brandt and Wang, 2003], [Bekaert and Engstrom, 2010]) but not the money illusion hypothesis ([Modigliani and Cohn, 1979], [Campbell and Vuolteenaho, 2004b]). The [Modigliani and Cohn, 1979]'s money illusion hypothesis has been well documented by [Campbell and Vuolteenaho, 2004b]'s research. They find that in US the dividend-price ratio is positively related to past inflation and they interpret that as evidence of irrational undervaluation of stock prices when inflation is high and irrational overvaluation of stock prices when inflation is low. They propose a decomposition method to study the mispricing error and show that evidence is in accordance with the Modigliani and Cohn (1979)'s hypothesis. This finding has been backed by [Cohen et al., 2005], [Lee, 2010] and [Acker and Duck, 2013]. However it has also been challenged by [Thomas and Zhang, 2007], [Engsted and Pedersen, 2010], [Wei, 2010], [Bekaert and Engstrom, 2010], and [Wei and Joutz, 2011]. [Engsted and Pedersen, 2010]'s results are not consistent with this hypothesis. They find that in US the dividend-price ratio predicts future long-term inflation negatively, i.e. an increase (decrease) in expected inflation leads to an increase (decrease) in stock prices, the opposite of what the Modigliani and Cohn hypothesis implies. [Wei, 2010] finds that a fully rational dynamic general equilibrium model can generate a positive correlation between dividend yields and inflation as observed in the data by introducing a channel where the technology shock moves both inflation and dividend yields in the same direction. The theoretical results are backed by the finding in [Wei and Joutz, 2011]. [Bekaert and Engstrom, 2010] argue that the positive correlations among dividend price ratios and inflation are not due to behavioral bias but due to that inflation reflects future growth prospects or habit-based risk aversion. Our results suggest both the growth proxy hypothesis and the risk aversion hypothesis can help explain the positive relationship among the dividend (earnings) yield and inflation. The high future inflation turns to coincide with periods of lower economic growth and high risk premia. Both lower cash flows and higher discount rates lead to drop in today's price and the dividend(earnings)-price ratio would be higher today, which can justify the positive relationship among inflation and the dividend (earnings) yield.

The hypothesis test results provide a more rational based explanation for the documented facts. To rationalize the inflation predictability and provide further insights, we build a cash flow model with inflation non-neutrality which is high future inflation dampens the economy growth. The framework is built on the long-run risk setup of [Bansal and Yaron, 2004], [Bansal and Shaliastovich, 2013] and [Schorfheide et al., 2018]. We extend [Bansal and Shaliastovich, 2013]'s framework by jointly estimating the consumption growth, dividend growth and inflation. The estimated model can reproduce both the inflation predictability and the documented asset pricing facts. A large number studies have explained that high expected inflation has non-neutral and negative effect on future economic growth. [Piazzesi et al., 2006] highlight the role of inflation non-neutrality in explaining the nominal bond yields. [Bansal and Shaliastovich, 2013] build the long-run risk model featuring that the risk premia are driven by the volatilities of expected growth and expected inflation. [Kung, 2015] develops a stochastic endogenous growth model and argue that the low-frequency negative co-movement of growth and inflation rates is due to the firm production and price-setting decisions. [Engsted and Pedersen, 2018] extend the [Bansal and Shaliastovich, 2013] to explain the disappearance of money illusion during 1970s in U.S.. [Gómez-Cram and Yaron, 2019] build a long-run risk model including the preference shocks to show that the inflation-related factors are not predominant in explaining the term premia component of the nominal yield curves.

The rest of the paper is organized as follows. In the next section, we describe our return, dividend and inflation data on international equity markets and we show that both dividend price ratios and earnings price ratio can predict future inflation. Section 3 contains the main findings of our paper, namely that inflation predictability changes the picture of return and cash flow predictability. In Section 4, we test three main hypothesis to justify the positive correlation among the dividend (earnings) yield and inflation. Section 5 presents the economic model with inflation non-neutrality to rationalize the documented facts. Additional results on dividend predictability and dividend smoothing are shown in Section 6. Section 7 concludes.

2.2 Dividend Yields, Earnings Yields and Inflation

2.2.1 Data and Variables

We analyze a total of seven largest advanced economies for which dividend yields, earnings yields, share prices, total returns and inflation data are available. We employ a quarterly frequency and the total sample period runs from the first quarter of 1973 to the third quarter of 2018. We use the total return indices, dividends and dividend (earnings) yields from Datastream. The advantage of using the Datastream data is that we do not have to back out dividends from time series of total returns and price returns. For all countries the rate of inflation is computed from the price index used to convert nominal variables into real variables. Here we choose the consumer price index as the main price index and use the production price index for robust results. For our empirical analysis below, we form two kinds of aggregate portfolios from our individual country data: an equally-weighted (EW) global portfolio and a value-weighted (VW) global portfolio. We use each market's capitalization (at the end of the previous quarter) as a fraction of total world-market capitalization (at the end of the previous quarter) as weights in the value-weighted portfolio. In other words, in the value-weighted portfolio we use dynamic weights, such that a market that grows in size relative to another market will also be given a larger weight. The value-weighted portfolio is highly dominated by large countries such as the U.S. (roughly 53% market share on average) and Japan (about 23% market share on average) implying that results for the value-weighted portfolio should be expected to closely resemble results from the earlier literature (e.g. [Ang and Bekaert, 2006] find no clear evidence for linear cash-flow predictability in these countries). Results for the EW portfolio, on the other hand, more closely resemble the behavior of the aggregate markets: in the equally-weighted portfolio, the share given to the U.S. is only $1/7 = 14.3\%$ in the whole sample period.

[Insert Table 2.1 near here]

Descriptive statistics for nominal (real) total returns, nominal (real) dividend growth, nominal (real) earnings growth, the average dividend yield, the average earnings yield, and the average inflation for the individual countries are reported in Table 2.1. There are large differences among the real term and the nominal term and there are large differences in inflation across countries. The highest average inflation rate is Italy (6.0%) whereas the lowest average inflation rate is found in Japan (2.1%). For benchmark valuation ratios, the dividend price ratios and earnings price ratios vary across different countries. For instance, among those countries we find the highest average dividend yield is UK (4.17%) whereas the lowest average dividend yield is found in Japan (1.38%) and the highest average earnings yield is France (8.07%) whereas the lowest average earnings yield is found in Japan (3.81%). For the two global portfolios, we see that the equally-weighted portfolio has a higher standard deviation for returns and dividend growth, and a higher dividend yield and earnings yield on average when compared to the value-weighted portfolio.

2.2.2 Dividend Yields, Earnings Yields and Inflation

Turn to the positive correlation among dividend yield, earnings yield and inflation, we document that the higher dividend price ratio and earnings price ratios correspond to the higher inflation rate as shown in figure 4.1. The documented cross-country correlations are 0.67 and 0.45 respectively for sample period 1973Q1 to 2018Q3. The positive relationship among dividend yield and inflation has been widely documented in US post-war data (e.g. [Asness, 2003], [Asness, 2003], [Cohen et al., 2005], [Wei, 2010], [Acker and Duck, 2013]) but has rarely been explored in an international setting.

[Insert Figure 4.1 near here]

The fact that the post-war US dividend yield predicts the future inflation has also been documented by [Engsted and Pedersen, 2010] and they extended the analysis to UK, Denmark and Sweden. However they cannot draw a conclusion on the role of inflation because their inflation predictability results are not robust across forecasting horizons, sub-periods, and countries. Here we find new and robust evidence that dividend price ratios can positively predict future inflation across horizons and across countries, which allows us to explore the mechanism behind this relationship (see Section 2.4). We also extend the analysis to earnings yield and find that the inflation predictability relationship holds.

[Insert Table 2.2 near here]

We report results from regressions of inflation on dividend price ratios and earnings price ratios from one year to twenty year horizon. All coefficients are significant positive from short run to long run for both portfolios. The significance are according to Newey and West (1987) standard errors in brackets. For the cross-section regressions, the R^2 range from 14% to 23% in the dividend yield regressions and range from 23% to 37% in the earnings yield regressions; for the portfolio-based regressions, the R^2 range from 32% to 56% in the dividend yield regressions and range from 26% to 54% in the earnings yield regressions, all suggesting high explanatory power from the financial ratios. Previous evidence suggests the dividend yield positively predicts returns and negatively predicts dividend growth. If we take inflation predictability into consideration, the nominal return predictability may come from the inflation predictability and real dividend growth predictability can be hidden when we use the nominal terms. Therefore, we should pay attention to nominal or real term when dealing with discount rates and cash flow predictability.

2.3 Empirical Results

A fundamental question in asset pricing is whether stock prices move because of news to expected returns or news to expected cash flows. The framework for the dividend yield is based on the decomposition by [Campbell and Shiller, 1988].

$$dp_t \simeq -\frac{\kappa}{1-\rho} + E_t\sum_{j=1}^{\infty}\rho^{j-1}r_{t+j} - E_t\sum_{j=1}^{\infty}\rho^{j-1}\Delta d_{t+j} \tag{2.1}$$

where $\rho = \frac{1}{1+exp(E[dp])}$ is a (log-linearization) discount coefficient that depends on the mean of dp and $\kappa = -log(\rho) + (1-\rho)log(\frac{1}{\rho} - 1)$. Under this present-value relation, the current log dividend-to-price ratio (dp) is positively correlated with future log returns (ret) and negatively correlated with future log dividend growth (Δd).

For earnings yield decomposition, we follow the similar method by [Chen et al., 2012] and [Maio and Xu, 2018]:

$$ep_t \simeq -\frac{\kappa}{1-\rho} - (1-\rho)E_t\sum_{j=1}^{\infty}\rho^{j-1}de_{t+j} + E_t\sum_{j=1}^{\infty}\rho^{j-1}r_{t+j} - E_t\sum_{j=1}^{\infty}\rho^{j-1}\Delta e_{t+j} \tag{2.2}$$

where ep is the log earnings price ratio, de is the log payout ratio and Δe is the earnings growth rate. Under this present-value relation, the current log earnings-to-price ratio (ep) is positively correlated with future log returns (ret) and negatively correlated with future log earnings growth (Δe). The remainder of this section explores empirically how inflation changes the picture of return and cash flow predictability and which of these two drivers dominates in international equity markets. In the following section 2.4 we explore what the underlying economic drivers of inflation predictability are.

2.3.1 Predictive Long-Horizon Regressions

We provide results of the return and cash flow predictability by the dividend (earnings) yield in an international portfolio setting. We run four time-series regressions of future values of cash flows and future values of stock returns on current dividend (earnings) yields:

$$\begin{aligned} ret_{t,t+H} &= a_r^H + b_r^H dp_t + \epsilon_{t,t+H}^r; \\ \Delta d_{t,t+H} &= a_{\Delta d}^H + b_{\Delta d}^H dp_t + \epsilon_{t,t+H}^d; \\ H &= 1, \cdots, 5 \end{aligned} \tag{2.3}$$

and

$$\begin{aligned} ret_{t,t+H} &= {a'}_r^H + {b'}_r^H ep_t + \epsilon_{t,t+H}^r; \\ \Delta e_{t,t+H} &= a_{\Delta e}^H + b_{\Delta e}^H ep_t + \epsilon_{t,t+H}^e; \\ H &= 1, \cdots, 5 \end{aligned} \tag{2.4}$$

where $ret_{t,t+H} \equiv \frac{1}{H}\sum_{j=1}^{H} r_{t+j}$, $\Delta d_{t,t+H} \equiv \frac{1}{H}\sum_{j=1}^{H} \Delta d_{t+j}$ and $\Delta e_{t,t+H} \equiv \frac{1}{H}\sum_{j=1}^{H} \Delta e_{t+j}$. Here we generally work with an annual forecast horizon in order to avoid potential seasonality issues with the dividend growth series. H indexes the forecasting horizon from 1 year to 5 year. Predictability results under both nominal and real terms are reported in table 2.3.

[Insert Table 2.3 near here]

The big picture here is that inflation predictability can affect the return and cash flow predictability a lot (both coefficients' magnitudes and signs). For the cross-sectional results, both nominal and real returns are positively predicted by dividend (earnings) yields and both nominal and real cash flows are negatively predicted by dividend (earnings) yields. However, the coefficients' magnitudes and the R^2 are overestimated in return regressions and are underestimated in cash flow regressions. This can be justified by the fact that the dividend (earnings) yield can positively predict the inflation across all horizons. It suggests that the inflation predictability reinforces real return predictability and reduces the real cash flow predictability.

For the portfolio-based results, the nominal returns can be positively predicted by dividend (earnings) yields from one-year to five-year horizon. However, in real returns regressions, the short-run returns cannot be predicted and long-run predictability holds. Both coefficients' magnitudes and R^2 increase in nominal return regressions. This can be justified by the fact that the dividend (earnings) yield can positively predict the inflation across all horizons. It suggests that the inflation predictability reinforces real return predictability and the short-run nominal returns predictability could come from the inflation predictability. In nominal dividend growth regressions, the dividend growth can not be predicted by the dividend yield in the equally-weighted portfolio and can be predicted in the 'wrong direction' in the value-weighted portfolio. In real dividend growth regressions, the dividend growth can be negatively predicted in equally-weighted portfolio but cannot be predicted in the value-weighted portfolio. In nominal earnings growth regressions, the earnings growth can only be predicted by the earnings yield at one-year horizon in the equally-weighted portfolio and cannot be predicted across all horizons in the value-weighted portfolio. In real earnings growth regressions, the earnings growth can be negatively predicted across all horizons in the equally-weighted portfolio and within two-year horizon in the value-weighted portfolio. It suggests that the inflation predictability reduces (in EW) or changes direction of (in VW) real cash flow predictability. Two points to address here: the first is the changing direction of dividend growth. The reason is that if inflation is sufficiently positively predictable by the dividend-price ratio, it may generate significant predictability of nominal dividend growth in the 'wrong' (i.e. positive) direction. The second is that dividend price ratio cannot predict real dividend growth in value-weighted portfolio. This is simply due to the US account for a large portion in value-weighted setting and US dividend growth cannot be predicted by dividend yields. The losing predictability of dividend yield has been interpreted by [Rangvid et al., 2014] that the failure of dividend predictability is due to the dividend smoothing in large and developed equity markets, which is also the argument made by [Engsted and Pedersen, 2010]. We also provide evidence to justify this argument by showing average firm size and cash volatility matter in determining dividend smoothing. Results are consistent with [Rangvid et al., 2014]'s and presented in section 2.6. Another simple way to resolve this is that the earnings yield can predict the earnings growth even in the value-weighted portfolio which suggests cash flows can be predicted by the financial ratio.

The general impressions are that returns can be predicted by the dividend yield and the dividend growth can not be predicted in the US based literature ([Cochrane, 2007],[Cochrane, 2011]). In the international dimension of return and dividend growth predictability, [Engsted and Pedersen, 2010] investigate long time series for four countries (U.S., U.K., Denmark, and Sweden) and show that dividend yields do not predict returns in Denmark and Sweden but do so in US and dividend yields do not predict dividend growth rates in the U.K. and U.S. but do so in Denmark and Sweden. They also claim that they first analyzed the differences between nominal and real long-horizon predictability but they did not make further conclusion about the role of inflation due to inconsistent inflation predictability evidence. Another paper based on international data is written by [Rangvid et al., 2014]. They used a global sample of fifty stock markets over the period from 1973 to 2009 to show that market-wide dividends are highly predictable by the dividend yield in smaller and medium-sized equity markets, but generally not in large markets such as the U.S. However, their results are based on nominal returns and provide no evidence or theory to emphasize the role of inflation predictability. We adopt a similar setting as [Rangvid et al., 2014] but all returns and dividend growth are measured in both nominal and real terms in our research. The contribution here is that we show that predictability patterns for returns and dividend growth are very sensitive to whether these variables are measured in real or nominal terms. We confirm [Engsted and Pedersen, 2010]'s finding that many of the conclusions for nominal returns and dividend growth are turned upside down when these variables are measured in real terms.

The dividend-price ratio can be a strong signal of future long-term inflation which will bias the estimates of factor loadings. The positive relationship can be potentially related to the future economic prospects, the rising required risk premia or even the behavior bias(e.g. inflation illusion). In section 2.4, we provide evidence that strongly supports the growth proxy hypothesis and the risk aversion hypothesis but rejects the money illusion hypothesis. For results related to earnings yield, [Maio and Xu, 2018] show that most of the price variations come from discount rates but not future earnings growth based on US post-war data while [Myers et al., 2017] show earnings growth expectations are the main driver of earnings yields based on US survey data. Both two studies use the nominal term in determining the earnings growth predictability and our results show the cash flow predictability exists when earnings growths are measured in real terms.

2.3.2 VAR-Based Results

Here we provide the results based on VAR system because [Stambaugh, 1999] argues that the OLS estimator's finite-sample properties can depart substantially from the standard regression setting if the equations' innovations are correlated with the dividend-price ratio. We adopt a way which is firstly proposed by [Cochrane, 2007] and applied by many papers like [Lettau and Van Nieuwerburgh, 2007], [Maio and Santa-Clara, 2015], and [Golez and Koudijs, 2018]. We can formulate in terms of the following three predictive regressions:

$$ret_{t+1} = \alpha_r + \beta_r dp_t + \epsilon^r_{t+1} \tag{2.5}$$

$$\Delta d_{t+1} = \alpha_{\Delta d} + \beta_{\Delta d} dp_t + \epsilon^{\Delta d}_{t+1} \tag{2.6}$$

$$dp_{t+1} = \alpha_{dp} + \beta_{dp} dp_t + \epsilon^{dp}_{t+1} \tag{2.7}$$

By combining the VAR above with the [Campbell and Shiller, 1988] present value relation, we obtain an identity involving the predictability coefficients associated with dp and a relationship which represents the variance decomposition shown in [Cochrane, 2007]:

$$\beta_r - \beta_{\Delta d} + \rho\beta_{dp} = 1 \tag{2.8}$$

Similarly to Cochrane (2008), (2011), we also compute the variance decomposition for an infinite-horizon case:

$$\beta_r^{LR} = \sum_{j=1}^{\infty}(\rho\beta_{dp})^{j-1}\beta_r = \frac{\beta_r}{1-\rho\beta_{dp}} \tag{2.9}$$

$$\beta_{\Delta d}^{LR} = \sum_{j=1}^{\infty}(\rho\beta_{dp})^{j-1}\beta_{\Delta d} = \frac{\beta_{\Delta d}}{1-\rho\beta_{dp}} \tag{2.10}$$

In this long-run decomposition, all the variations in the current dividend yield is tied to either return or dividend growth predictability, since the predictability of the future dividend yield vanishes out at a very long horizon. We have the relationship as

$$\beta_r^{LR} - \beta_{\Delta d}^{LR} = 1 \tag{2.11}$$

For results related to the earnings yield, we follow the same estimation way as the dividend yield by making approximation on the payout ratio term. Compare equation (2.1) and equation (2.2) and we can find the additional component in equation (2.2) is the payout ratio term $E_t\sum_{j=1}^{\infty}\rho^{j-1}de_{t+j}$. Since the payout term's loading $1-\rho$ is close to 0, movements in the future payout ratio do not play a large role in explaining movements in the price-earnings ratio. [Maio and Xu, 2018] documented the long-run variance contribution from payout ratio is less than 1% using US post-war data and our later analysis (table (2.12) suggest the long-run variation contribution from payout ratio is dominated by the other two sources in international portfolios. Therefore we ignore the payout ratio's movements and the equation (2.2) is reduced to equation (2.12).

$$ep_t \simeq -(\frac{\kappa}{1-\rho} + \overline{de}) + E_t\sum_{j=1}^{\infty}\rho^{j-1}r_{t+j} - E_t\sum_{j=1}^{\infty}\rho^{j-1}\Delta e_{t+j} \tag{2.12}$$

where $\overline{de}$ is the mean of log payout ratio. Here we conduct estimation the same way as analyzing dividend yield and provide additional results in section 2.6.2 where the payout ratio variations are considered in estimation.

[Insert Table 2.4 near here]

In table 2.4, we document a clear pattern that the return predictability has been reinforced by the inflation predictability and the cash flow predictability has been reduced by the inflation predictability. For instance, in EW regressions, the R^2 of return regression increase from 3% in real to 8% in nominal (Panel A) and from 1% in real to 5% in nominal (Panel B) while the R^2 of dividend growth regression decrease from 14% in real to 3% in nominal (Panel A) and the R^2 of earnings growth regression decrease from 18% in real to 8% in nominal (Panel B). We also compare coefficients from raw VAR to ones implied from variance constraint and we find magnitudes are quite close which suggest the one-period VAR can fit the variance decomposition quite well and approximation errors are small. An interesting result is that the dividend price ratio can actually predict the dividend growth in the value-weighted setting which suggests there exists correlations among dividend growth innovations and the dividend-price ratio that affect the estimated results. A similar example is that [Engsted and Pedersen, 2010] documented a puzzle that in the post-war period UK long-horizon dividend growth is significantly predictable in the 'wrong' direction. Here we can simply attribute this to correlations among the residuals and the predictor and we can resolve this puzzle by estimating the coefficients in a VAR system by GLS method. For dividend yields predictability, we find the dividend yield of the equally-weighted portfolio is less persistent than the value-weighted with an auto-regressive slope of 0.80 versus 0.86. The R^2 is 0.68 and much lower than the value-weighted case 0.80. For earnings yields predictability, we find the earnings yield of the equally-weighted portfolio is less persistent than the value-weighted with an auto-regressive slope of 0.73 versus 0.83. The R^2 is 0.58 and much lower than the value-weighted case 0.74.

For the long run decomposition, we can see the inflation plays an important role in determining dividend price composition ratio. For the equally-weighted setting in Panel A, we find the discount rates ratio decrease from 76% in nominal to 44% in real while the cash flows ratio increase from 24% in nominal to 56% in real. For the value-weighted setting in Panel A, we find the discount rates ratio decrease from 104% in nominal to 73% in real while the cash flows ratio increase from 4% (positive) in nominal to 27% (negative) in real. For the equally-weighted setting in Panel B, we find the discount rates ratio decrease from 50% in nominal to 25% in real while the cash flows ratio increase from 50%

in nominal to 75% in real. For the value-weighted setting in Panel B, we find the discount rates ratio decrease from 65% in nominal to 42% in real while the cash flows ratio increase from 35% in nominal to 58% in real. After inflation being considered, cash flows become no longer negligible and even account for more than half variations.

2.3.3 The Term Structure of Coefficients

In previous section we discuss the estimation for a one-period VAR system and here we present the variance decomposition results for multi-period. Following Cochrane (2008), (2011), we estimate coefficients of future log returns, log dividend growth, and log dividend-to-price ratio regressions.

$$\sum_{j=1}^{H} \rho^{j-1} r_{t+j} = \alpha_R^H + \beta_r^H dp_t + \epsilon_{t,t+H}^r \tag{2.13}$$

$$\sum_{j=1}^{H} \rho^{j-1} \Delta d_{t+j} = \alpha_{\Delta d}^H + \beta_{\Delta d}^H dp_t + \epsilon_{t,t+H}^{\Delta d} \tag{2.14}$$

$$\rho^{H-1} dp_{t+H} = \alpha_{dp}^H + \beta_{dp}^H dp_t + \epsilon_{t,t+H}^{dp} \tag{2.15}$$

Similarly to Cochrane (2011), by combining the present-value relation with the predictive regressions above, we obtain an identity involving the predictability coefficients associated with dp, at each horizon H.

$$\beta_r^H - \beta_{\Delta d}^H + \rho \beta_{dp}^H = 1 \tag{2.16}$$

which can be interpreted as a variance decomposition for the log dividend yield. The predictive coefficients β_r^H, $-\beta_{\Delta d}^H$, and β_{dp}^H represent the fraction of the variance of current dp attributable to return, dividend growth, and dividend yield predictability, respectively.

[Insert Figure 2.2 near here]

In Figure 2.2 we present both the nominal and real term structure of the equally-weighted portfolio. When we use nominal returns and nominal dividend growth, we will document that most of the price variations come from the discount rates. The contribution from cash flows is insignificant from one year to nine year horizon and significant contribution at 10 year horizon suggesting the 'wrong' predictability direction. When real terms are applied in the framework, we find both discount rates and cash flows significantly contribute to the price variations and contribution ratios from these two sources are comparable.

[Insert Figure 2.3 near here]

In Figure 2.3 we present both the nominal and real term structure of the value-weighted portfolio. When we use nominal returns and nominal dividend growth, we will document that most of the price variations come from the discount rates. The contribution from cash flows is significant from year three but the signs of contribution suggest the 'wrong' predictability direction which is higher dividend yield corresponds to higher dividend growth. When real terms are applied in the framework, we find both discount rates and cash flows contribute to the price variation and the contributions are significant across horizons. The contribution ratios from cash flow sources are not negligible within ten year horizons but discount rates variation dominate in longer horizon.

We consider the earnings growth as an alternative measure of future cash flows and we documented a similar pattern that both the discount rate and cash flows contribute to variations of current financial ratios as we seen in dividend yield case. For the earning yield, we apply the same estimation to the term structure of coefficients and results are presented in Figure 2.4 and Figure 2.5.

In Figure 2.4 we present both the nominal and real term structure of the equally-weighted portfolio. When we use nominal returns and nominal earnings growth, we will document that most of the price variations come from the discount rates especially in the long horizons. The contribution from cash flows become insignificant from three year to nine year horizon and significant contribution at 10 year horizon suggesting the 'wrong' predictability direction. When real terms are applied in the framework, we find both discount rates and cash flows significantly contribute to the price variations and the contribution from cash flows is not negligible.

[Insert Figure 2.4 near here]

[Insert Figure 2.5 near here]

In Figure 2.5 we present both the nominal and real term structure of the value-weighted portfolio. When we use nominal returns and nominal earnings growth, we will document that most of the price variations come from the discount rates. The contribution from cash flows are insignificant from year two to year five. When real terms are applied in the framework, we find both discount rates and cash flows significantly contribute to the price variation across horizons. The contribution ratios from cash flow sources are not negligible within ten year horizons but discount rates variation dominate in longer horizon.

2.4 Why does the Dividend Yield Predict Inflation?

One puzzle in asset pricing literature is that why does the dividend-price ratio predict future inflation. Since the dividend-price ratio is the ratio of price and dividend which is free from the inflation by theoretical construction. [Asness, 2000] and [Sharpe, 2002] find that stock dividend and earnings yields are highly correlated with nominal bond yields. Since stocks are claims to cash flows from real capital and inflation is the main driver of nominal interest rates, this correlation makes little sense, a point made recently by [Ritter and Warr, 2002], [Asness, 2003], and [Campbell and Vuolteenaho, 2004b]. [Engsted and Pedersen, 2010] documented mixed inflation predictability results which are not robust across forecasting horizons, sub-periods, and countries. For example, they find that in the US the dividend-price ratio predicts future long-term inflation negatively, i.e. an increase (decrease) in expected inflation leads to an increase (decrease) in stock prices, the opposite of what the Modigliani and Cohn hypothesis implies. Here we document new international evidence different from [Engsted and Pedersen, 2010] and we find that dividend price ratios can positively predict inflation across countries and across horizons. In this section, our empirical results do not support the hypothesis that the stock market suffers from inflation illusion but provide strong support that high future inflation turns to coincide with periods of worse economic fundamentals and higher risk premia.

Modigliani and Cohn hypothesize that the stock market suffers from money illusion, discounting real cash flows at nominal discount rates. The particular form of money illusion is incorrectly discounting real cash flows with nominal discount rates. An implication of such an mispricing error is that time variation in the level of inflation causes the market's subjective expectation of the future equity premium to deviate systematically from the rational expectation. Thus, when inflation is high (low), the rational equity-premium expectation is higher (lower) than the market's subjective expectation, and the stock market is undervalued (overvalued). If expected long-term growth is constant in real terms, yet the investor expects it to be constant in nominal terms, then in equilibrium stocks will be undervalued when inflation is high and overvalued when inflation is low. Therefore dividend-price ratio positively predicts future inflation. [Campbell and Vuolteenaho, 2004b] find that in the US the dividend-price ratio is positively related to past inflation and they interpret that as evidence of irrational undervaluation of stock prices when inflation is high and irrational overvaluation of stock prices when inflation is low, in accordance with the [Modigliani and Cohn, 1979] hypothesis.

The other two hypothesis made are [Fama, 1981]'s proxy hypothesis and [Brandt and Wang, 2003]'s risk aversion hypothesis. [Fama, 1981] argues that the strong negative relationship between stock returns and inflation is due to stock returns anticipating future economic activity and inflation acting as a proxy for expected real activity; [Brandt and Wang, 2003] argues that high inflation makes investors more risk averse, driving up the equity premium and thus the real discount rate (similar argument made by [Bekaert and Engstrom, 2010]).

We construct the framework as [Campbell and Vuolteenaho, 2004b] and test all three hypothesis. Campbell and Vuolteenaho (2004) derive a mispricing component in the dividend yield by relating the classic Gordon growth model (Gordon, 1962) to the log dividend-price ratio developed by Campbell and Shiller (1988), which allows for time-varying discount rates and dividend growth rates. In relating these two models, they introduce objective and subjective discount rates and growth rates, and capture the mispricing component by the difference between the objective and subjective growth rates. The traditional Gordon growth model states that the dividend-price ratio is equal to discount rate minus growth rate:

$$\frac{D}{P} = R - G \tag{2.17}$$

where R is the long-term discount rate and G is the long-term growth rate of dividends. Subtract the riskless interest rate from both the discount rate and the growth rate of dividends, and define the excess discount rate as $R^e = R - R_f$ and the excess dividend growth rate as $G^e = G - R_f$. Taking into account the possibility that some investors are irrational, Gordon growth model can be rewrote as follows:

$$\frac{D}{P} = R^{e,Obj} - G^{e,Obj} = R^{e,Subj} - G^{e,Subj} = -G^{e,Obj} + R^{e,Subj} + (G^{e,Obj} - G^{e,Subj}) \tag{2.18}$$

Therefore, they decompose the dividend yield into three components: (1) the negative of objective excess dividend growth ($-G^{e,Obj}$), (2) the subjective risk premium ($R^{e,Subj}$), and (3) a mispricing component, which is given by a difference between the objective (i.e., rational) and subjective (i.e., irrational) dividend growth ($G^{e,Obj} - G^{e,Subj}$).

They relate the above Gordon model to the log-linear dynamic valuation model of Campbell and Shiller (1988), which allows for time-varying discount rates and dividend growth rates. The Campbell-Shiller model of the log dividend-price ratio is given by:

$$dp_t \simeq -\frac{\kappa}{1-\rho} + E_t \sum_{j=1}^{\infty} \rho^{j-1}(r_{t+j} - r_{f,t+j}) - E_t \sum_{j=1}^{\infty} \rho^{j-1}(\Delta d_{t+j} - r_{f,t+j}) \tag{2.19}$$

$$= -\frac{\kappa}{1-\rho} + E_t \sum_{j=1}^{\infty} \rho^{j-1} r^e_{t+j} - E_t \sum_{j=1}^{\infty} \rho^{j-1} \Delta d^e_{t+j} \tag{2.20}$$

where Δd^e_{t+j} denotes Δd_{t+j}, log dividend growth, less the log risk-free rate; r^e_{t+j} denotes r_{t+j}, log stock return, less the log risk-free rate.

They note that $E_t \sum_{j=1}^{\infty} \rho^{j-1} r^e_{t+j}$ is analogous to $R^{e,Obj}$ and $R^{e,Subj}$, and $E_t \sum_{j=1}^{\infty} \rho^{j-1} \Delta d^e_{t+j}$ is analogous to $G^{e,Obj}$ and $G^{e,Subj}$, depending on whether the expectations taken are objective or subjective. They estimate the term

$E_t \sum_{j=1}^{\infty} \rho^{j-1} r^e_{t+j}$ objective expectations and backout the negative objective expected growth $-E_t \sum_{j=1}^{\infty} \rho^{j-1} \Delta d^e_{t+j}$ from equation (2.20).

The subjective risk premium is estimated as the fitted value of a regression of $E_t \sum_{j=1}^{\infty} \rho^{j-1} r^e_{t+j}$ on a subjective risk-premium proxy λ_t.

$$E_t \sum_{j=1}^{\infty} \rho^{j-1} r^e_{t+j} = \gamma \lambda_t + \epsilon_t \tag{2.21}$$

A mispricing component given by the difference between objective and subjective expected dividend growth is the residual ϵ_t of this regression. In this model, when stocks are subjectively perceived to be very risky, then the fitted value $\gamma\lambda_t$ is high. In contrast, when stocks are underpriced, the residual ϵ_t is high.

[Insert Table 2.5 near here]

Following [Campbell, 1991], we combine the valuation framework with a vector autoregression (VAR) that predicts stock returns. The first-order VAR includes the excess log stock return over the three-month interest rates (r^e_{t+1}), the excess log dividend growth over the three-month interest rates (Δd^e_{t+1}), the risk premia (λ) constructed as the ratio of standard deviations of stocks returns over ten-year government bond yields as [Asness, 2000] and [Campbell and Vuolteenaho, 2004b] did, the log dividend-price ratio (dp), and the inflation rates (π) are constructed from Consumer Price Indexes (another inflation measure is constructed from Producer Price Indexes as robust). The expected future discount rates and cash flows are predicted from our VAR model as in literature. A recent paper by [Myers et al., 2017] evaluate decomposition using survey data of dividends and earnings. They provide a new perspective in evaluating variation's composition however the survey data is nominal terms rather than real terms which may introduce biases to the estimation. We present the test results in table 2.5 and compare the three hypothesis respectively.

We start from the [Modigliani and Cohn, 1979]'s hypothesis. The money illusion hypothesis assumes that there are significant numbers of irrational investors who incorporate expected inflation into their nominal discount rate but not into future nominal cash flows, thereby there exist undervaluation when inflation is high and we should observe higher mispricing errors ϵ. The coefficient should be positive but the estimate coefficient is -1.709 in the equally-weighted portfolio and -0.677 in the value-weighted portfolio (Panel A). Both coefficients are negative which do not support the money illusion hypothesis. The second hypothesis is [Fama, 1981]'s proxy hypothesis. Fama argues from the quantity theory of money that higher anticipated growth rates of real activity are associated with lower current inflation rates and higher expected future economic activities are more likely corresponding to higher expected dividend growth. Therefore if we use the inflation as future economic fundamental's proxy and we expect that higher inflation should correspond to lower expected cash flows (higher negative series of expected cash flows) which suggest the coefficient of $-E_t \sum_{j=1}^{\infty} \rho^{j-1} \Delta d_{t+j}^{e}$ should be positive. The estimated coefficient is 7.359 in the equally-weighted portfolio and 6.851 in the value-weighted portfolio (Panel A). Both coefficients are significant positive which support the Fama (1981)'s proxy hypothesis. The third hypothesis is risk aversion hypothesis ([Brandt and Wang, 2003], [Bekaert and Engstrom, 2010]) that high inflation makes investors more risk averse, driving up the equity premium and thus the real discount rate. We expect the coefficients of subjective discount rates $\gamma\lambda_t$ and objective discount rates $\gamma\lambda_t + \epsilon_t$ to be positive. The estimated coefficient of $\gamma\lambda_t$ is 0.258 in the equally-weighted portfolio and 2.815 in the value-weighted portfolio (Panel A). The coefficients are significantly positive which means high inflation does correspond to high discount rates. The evidence also lends support to the risk aversion hypothesis. In Panel B, we test each components of the earnings yield and documented consistent evidence as in Panel A. The coefficient of mispricing errors ϵ is -3.132 in the equally-weighted portfolio and -1.500 in the value-weighted portfolio. Both coefficients are insignificant which do not support the money illusion hypothesis. The coefficient of $-E_t \sum_{j=1}^{\infty} \rho^{j-1} \Delta d_{t+j}^{e}$ is 10.973 in the equally-weighted portfolio and 10.050 in the value-weighted portfolio. Both coefficients are significantly positive which support the [Fama, 1981]'s proxy hypothesis.

We also provide 'backed-out' test results in table 2.5 corresponding to [Chen and Zhao, 2009]'s criticism on Campbell-Shiller decomposition's approximation error. They argue that the 'backed-out series' will be acting as a catchall for modelling noise and any inaccuracy in Campbell-Shiller decomposition. [Engsted et al., 2012] have strongly challenged this criticism, arguing that, provided one abstracts from the approximation error in Campbell and Shiller's decomposition and provided the VAR is properly modelled, it should not matter which component is backed out. Therefore we provide the backed-out results and find that the conclusion we made on hypothesis test remain the same. The 'backed-out' results show [Chen and Zhao, 2009]'s criticism plays little role in choosing the hypothesis. The only concern is that the expected inflation corresponds to lower subjective risk premia which is inconsistent with the backed-out results. We argue that the 'wrong' sign of subjective risk premia coefficient is due to the missing variation in payout ratio. After the payout ratio being considered, the signs will turn into positive and suggest higher risk premia required from investors (see table 2.13).

Our international results strongly support the growth proxy hypothesis ([Fama, 1981], [Wei, 2010]) and the risk aversion hypothesis ([Brandt and Wang, 2003], [Bekaert and Engstrom, 2010]) but reject the [Modigliani and Cohn, 1979]'s money illusion hypothesis. [Wei and Joutz, 2011] found that the correlation between inflation and the mispricing component is close to zero in the US post-war period and the evidence does not support the inflation illusion hypothesis. The post-war US data demonstrates a negative relation between rationally expected excess dividend growth rate and inflation, consistent with the rational explanation for the positive correlation between inflation and dividend yields pursued in [Wei, 2010]. We also document consistent evidence that the expected excess dividend growth rate and inflation are negative correlated based on international data which can be interpreted as high inflation implies lower growth prospect. [Brandt and Wang, 2003] propose the time-varying risk aversion hypothesis, which maintains that inflation makes investors more risk averse, driving up the equity premium and thus the real discount rate. Here the documented factor loadings of subjective risk premium are positive which is consistent with their risk aversion hypothesis. Moreover, our evidence here does lend support to [Bekaert and Engstrom, 2010]'s argument that high expected inflation has tended to coincide with periods of heightened uncertainty about real economic growth and high risk aversion. They postulate that in recession times economics uncertainty and risk aversion may increase and lead to high equity premia thus in turn increase the equity yields. We find consistent evidence that high inflation leads to higher required subjective risk premium.

[Insert Table 2.6 near here]

Then we construct the alternative inflation measure from Producer Price Indexes and we find the evidence in table 2.6 still supports the previous argument that high inflation implies lower future cash flows and higher required risk premia. The differences between the PPI and CPI are consistent with the different uses of the two measures. A primary use of the PPI is to deflate revenue streams in order to measure real growth in output. A primary use of the CPI is to adjust income and expenditure streams for changes in the cost of living. In Panel A, the coefficient of mispricing errors ϵ is -0.745 in the equally-weighted portfolio and -2.207 in the value-weighted portfolio. Both coefficients are insignificant which do not support the money illusion hypothesis. The coefficient of $-E_t \sum_{j=1}^{\infty} \rho^{j-1} \Delta d_{t+j}^e$ is 14.018 in the equally-weighted portfolio and 13.218 in the value-weighted portfolio. Both coefficients are significantly positive which support the [Fama, 1981]'s proxy hypothesis. Moreover, we document that inflation can affect the subjective risk premia since all coefficients of $\gamma\lambda_t$ are significantly positive. The coefficient is 4.416 in the equally-weighted portfolio and 8.657 in the value-weighted portfolio. In Panel B, we test each components of the earnings yield and documented consistent evidence as in Panel A. The coefficient of mispricing errors ϵ is 1.152 in the equally-weighted portfolio and 1.904 in the value-weighted portfolio. Both coefficients are insignificant which do not support the money illusion hypothesis. The coefficient of $-E_t \sum_{j=1}^{\infty} \rho^{j-1} \Delta d_{t+j}^e$ is 18.345 in the equally-weighted portfolio and 16.582 in the value-weighted portfolio. Both coefficients are significantly positive which support the [Fama, 1981]'s proxy hypothesis. Moreover, we document that the coefficient of $\gamma\lambda_t$ is 1.882 in the equally-weighted portfolio and 4.650 in the value-weighted portfolio. Therefore, the source of the positive correlation between the US dividend yield and expected inflation is that high expected inflation has tended to coincide with periods of lower real economic growth and higher discount rates.

The conclusion is largely unaffected by the precise definitions of the measures of inflation.

2.5 An Economic Model with Inflation Non-Neutrality

We document that investors do not suffer from the inflation illusion and evidence suggests that high expected inflation has tended to coincide with periods of lower real economic growth and higher discount rates which lead to the drop in today's prices. The hypothesis tests provide a more rational based explanation for the documented facts. To rationalize the inflation predictability and provide further insights, we build a cash flow model with inflation non-neutrality which is high future inflation dampens the economy growth. The estimated model can reproduce both the inflation predictability and the documented asset pricing facts.

A large number studies have explained that high expected inflation has non-neutral and negative effect on future economic growth. [Piazzesi et al., 2006] highlight the role of inflation non-neutrality in explaining the nominal bond yields. [Bansal and Shaliastovich, 2013] extend the long-run risk model ([Bansal and Yaron, 2004]) including preference for early resolution of uncertainty, time-varying volatilities, and non-neutral effects of inflation on growth and in the new model the risk premia are driven by the volatilities of expected growth and expected inflation. [Kung, 2015] develops a stochastic endogenous growth model where the firm production and price-setting decisions drive low-frequency negative co-movement of growth and inflation rates in explaining the bond markets. [Engsted and Pedersen, 2018] extend the [Bansal and Shaliastovich, 2013]'s framework by considering the money illusion in the pricing kernel to explain the disappearance of money illusion during 1970s in US. [Gómez-Cram and Yaron, 2019] build on the long-run risk setup of [Bansal and Shaliastovich, 2013] and [Schorfheide et al., 2018] by including the preference shocks to show that the inflation-related factors are not predominant in explaining the term premia component of the nominal yield curves.

2.5.1 Model

We build on the long-run risk setup of [Bansal and Shaliastovich, 2013] and [Schorfheide et al.,2018]. We include the dividend growth process in economic dynamics and estimate the model jointly to match the consumption, dividend and inflation process. The economic dynamics are joined by z_t and x_t process.

$$z_{t+1} = \mu + \Phi x_t + S_z \eta_{t+1} \tag{2.22}$$

$$x_{t+1} = \Pi x_t + S_x \epsilon_{t+1} \tag{2.23}$$

where $z_t = [\Delta c_t, \Delta d_t, \pi_t]$ are consumption growth, dividend growth and inflation process, $x_t = [x_{c,t}, x_{\pi,t}]$ are the long-run components of expected consumption growth and expected inflation.

$$\Phi = \begin{bmatrix} 1 & 0 \\ \phi & 0 \\ 0 & 1 \end{bmatrix}, \quad \Pi = \begin{bmatrix} \rho_c & \rho_{c\pi} \\ 0 & \rho_\pi \end{bmatrix}$$

In z_t process, ϕ captures the dividend leverage. In x_t process, ρ_c and ρ_π represent the persistence the long-run component process and $\rho_{c\pi}$ measures the non-neutrality of inflation which is negative to dampen the consumption growth.

$$S_z = \begin{bmatrix} \sigma_c & 0 & 0 \\ 0 & \sigma_d & 0 \\ 0 & 0 & \sigma_\pi \end{bmatrix}, \quad S_x = \begin{bmatrix} \sigma_{xc} & 0 \\ 0 & \sigma_{x\pi} \end{bmatrix}$$

η_{t+1} and ϵ_{t+1} represent the normal distributed shocks and S_z and S_x capture the time variation in the uncertainty about expected consumption growth and expected inflation. Both S_z and S_x are diagnol matrix.

In the economy, the representative agent has the Epstein and Zin (1989) preferences defined over the consumption bundle C_t:

$$U_t = [(1-\delta)C_t^{1-\frac{1}{\psi}} + \delta(E_t[U_{t+1}^{1-\gamma}])^{\frac{1-\frac{1}{\psi}}{1-\gamma}}]^{\frac{1}{1-\frac{1}{\psi}}}$$

Therefore the IMRS (Inter-temporal Marginal Rate of Substitution) for this economy is given by

$$m_{t+1} = \theta \cdot log\delta - \frac{\theta}{\psi} \cdot \Delta c_{t+1} + (\theta - 1) \cdot r_{c,t+1}, \quad \theta = \frac{1-\gamma}{1-\frac{1}{\psi}} \tag{2.24}$$

By solving the model, we have the analytic solutions as

$$pc_t = A_0 + A_1 \cdot x_{c,t} + A_2 \cdot x_{\pi,t}, \quad A_1 = \frac{1-\frac{1}{\psi}}{1-\kappa_1 \cdot \rho_c}, A_2 = \frac{\kappa_1 \cdot (1-\frac{1}{\psi}) \cdot \rho_{c\pi}}{(1-\kappa_1 \cdot \rho_c) \cdot (1-\kappa_1 \cdot \rho_\pi)}; \tag{2.25}$$

$$pd_t = B_0 + B_1 \cdot x_{c,t} + B_2 \cdot x_{\pi,t}, \quad B_1 = \frac{\phi-\frac{1}{\psi}}{1-\kappa_1^d \cdot \rho_c}, B_2 = \frac{\kappa_1^d \cdot (\phi-\frac{1}{\psi}) \cdot \rho_{c\pi}}{(1-\kappa_1^d \cdot \rho_c) \cdot (1-\kappa_1^d \cdot \rho_\pi)}; \tag{2.26}$$

$$E_t[r_{d,t+1}] = C_0 + C_1 \cdot x_{c,t} + C_2 \cdot x_{\pi,t}, \quad C_1 = \phi + (\kappa_1^d \rho_c - 1) B_1, C_2 = \kappa_1^d \rho_{c\pi} B_1 + (\kappa_1^d \rho_\pi - 1) B_2; \tag{2.27}$$

The solution coefficients for the effect of expected consumption growth rate $x_{c,t}$ on the price-dividend ratio, B_1, and the effect of inflation rate $x_{\pi,t}$ on the price-dividend ratio, B_2, respectively

$$B_1 = \frac{\phi-\frac{1}{\psi}}{1-\kappa_1^d \cdot \rho_c} > 0; \quad B_2 = \frac{\kappa_1^d \cdot (\phi-\frac{1}{\psi}) \cdot \rho_{c\pi}}{(1-\kappa_1^d \cdot \rho_c) \cdot (1-\kappa_1^d \cdot \rho_\pi)} < 0$$

The economic mechanism is straightforward. B_1 is positive suggesting the substitution effect dominates the wealth effect. When good news on expected consumption growth comes, agents buy more assets which increase the price-dividend ratio. Since $\phi > \frac{1}{\psi}$, B_2 is negative simply due to the negative and non-neutral effect of inflation, $\rho_{c\pi} < 0$.

2.5.2 Estimation

We jointly estimate three processes: consumption growth, dividend growth and inflation. In the model, we calibrate preference parameters before estimation: the risk aversion γ is calibrated to 10 (see [Bansal and Yaron, 2004] among others); the inter-temporal elasticity of substitution ψ is set to 1.5, usual in the long- run risk literature; the household's subjective discount rate δ is set to 0.99 at quarterly frequency. The dividend leverage factor ϕ is calibrated to 3. Here we use the one-year ahead forecast to proxy the expected consumption growth as [Bansal and Shaliastovich, 2013]. The expected inflation data are either the SPF data or the model implied inflation(either choice leads to similar results). We estimate the model using U.S. data for two reasons: one is due to data limitation since U.S. has the longest growth forecast data after 1968Q4 while the other countries' SPF data starts from 1999Q1; the second is that we have better estimated preference parameters based on U.S. data and these parameters are variously applied in many previous studies. We estimate the variable means μ, the transition matrix Π and the variance scale S_z and S_x in the economic dynamics.

[Insert Table 2.7 near here]

The ρ_π is equal to 0.9719 and both scales of σ_π and $\sigma_{x\pi}$ are relatively smaller than the consumption related volatility. Results suggest that the expected inflation is very persistent and with lower variations. The estimated $\rho_{c\pi}$ is equal to -0.0834 and 90% intervals also suggest that $\rho_{c\pi}$ is significantly negative. Evidence suggests that the inflation has negative and non-neutral effect on the consumption growth which is consistent with the argument by [Bansal and Shaliastovich, 2013].

[Insert Figure 2.6 near here]

2.5.3 Model Implications

In table 2.8, we find that the estimated model can match the key features of consumption, asset-pricing related and inflation data. By construction, the model matches the consumption growth, dividend growth and inflation, the model implied price-dividend ratio and implied expected returns can also be matched in the data.

[Insert Table 2.8 near here]

With the calibrated preference parameters and the estimated economic dynamics, we generate 2,000 simulation data each with sample length 180 quarter observations. We re-run the return, dividend, inflation and consumption predictability regressions with independent variable the dividend-price ratio dp_t. As shown in table 2.9, the model can replicate several documented facts. First of all the inflation predictability reinforces the return predictability and reduces the dividend growth predictability. The cash flow predictability decrease if we use the dividend-price ratio to predict the nominal dividend growth. Second, we document that the dividend-price ratio can positively predict future inflation and the predictive significance holds across all horizons. Third, the high expected inflation can dampen the future consumption growth which reflects the inflation non-neutrality by construction.

[Insert Table 2.9 near here]

2.6 Additional Results

2.6.1 Dividend Predictability in VW Portfolio

Why dividend price ratio cannot predict cash flows in the value-weighted portfolio? We documented that the dividend yield can negatively predict the dividend growth in the equal-weighted portfolio but not in the value-weighted portfolio. [Rangvid et al., 2014] argue that dividend growth is significantly more predictable in countries with medium-sized or smaller equity markets and the equally-weighted portfolio puts more weight on smaller markets than the value-weighted portfolio therefore the dividend price ratio can only predict the EW dividend growth. Previous research attribute dividend predictability to dividend smoothing by firms. [Chen et al., 2012] first investigate the relationship among dividend predictability using U.S. data. They documented in the post-war period, dividends are much more smoothed and respond much more to their past levels rather than to the outlook of future cash flows. They argue the dividend smoothing can kill the predictability and reach the conclusion that cash flow news plays a more important role than discount rate news in price variations in the postwar. [Rangvid et al., 2014] documented that dividends are more predictable in countries with smaller equity markets and find that in countries where dividends are smoothed less, dividend predictability by the dividend yield is stronger using international data. They estimate a version of the

Lintner (1956) partial-adjustment model and find that the estimated smoothing parameter is significantly higher in the value-weighted portfolio and even insignificant in the equal-weighted portfolio.

Here we estimate the [Lintner, 1956]'s model using both nominal and real terms and find the results are similar. Here we measure how the earnings growth are disconnected from the dividend growth and how persistent the dividend growth are. δ_1 is slightly higher in equally-weighted setting than the value in value-weighted setting. It suggest that dividends react less to changes in earnings in the value-weighted portfolio compared to the equally-weighted portfolio. δ_2 measures the dividend smoothness and we find the all estimated δ_2 are significant which suggests that firms in those countries do smooth their dividend which may dampens the dividend predictability by the dividend-price ratio.

[Insert Table 2.10 near here]

To measure the smoothness, we construct the smoothing parameter S as [Chen et al., 2012] and [Rangvid et al., 2014] where S is the volatility ratio of dividend and earning growth.

$$S_i = \frac{\sigma(\Delta d_i)}{\sigma(\Delta e_i)} \tag{2.28}$$

Lower value of S means higher degree of the dividend smoothing. For example, the S is equal to zero when there is perfect dividend smoothing $\Delta D_{t-1} = \Delta D_t$. We find that $S = 0.769$ in the EW portfolio and $S = 0.641$ in the VW portfolio, which is consistent with our expectation.

[Insert Table 2.11 near here]

We explore what determines the firms' dividend smoothing pattern as [Rangvid et al., 2014]'s by regressing the smoothing parameter S on potential determinants. [Leary and Michaely, 2011] find that young and small firms and firms with volatile cash flows are less likely to smooth dividend payment. Therefore we construct two factors: $FirmSize$ factor to reflect the effect of average firm capitalization across different countries and $ReturnVolatility$ factor to reflect the effect of firm's fundamentals. We obtain consistent results with the [Rangvid et al., 2014]'s finding that both factors determine the firms dividend smoothing and cash flow predictability. In table 2.11, we find that firm size are negatively correlated with the smoothing parameter which means small firms are less likely to smooth the dividend payment and return volatility are positively correlated with the smoothing parameter which suggests firms with volatile cash flows are less likely to smooth the dividend. We also find the explanatory power of $FirmSize$ become weak when we control for the return volatility factor. Since the sample size is very small, we do not draw conclusion on this.

2.6.2 Time-Varying Payout Ratio in Earnings Yield Test

Here we consider the payout ratio movement in equation (2.2) and the new estimation framework will be

$$\sum_{j=1}^{H}\rho^{j-1}r_{t+j} = \alpha_R^H + \beta_r^H ep_t + \epsilon_{t,t+H}^r \tag{2.29}$$

$$\sum_{j=1}^{H}\rho^{j-1}\Delta e_{t+j} = \alpha_{\Delta e}^H + \beta_{\Delta e}^H ep_t + \epsilon_{t,t+H}^{\Delta e} \tag{2.30}$$

$$(1-\rho)\sum_{j=1}^{H}\rho^{j-1}de_{t+j} = \alpha_{de}^H + \beta_{de}^H ep_t + \epsilon_{t,t+H}^{de} \tag{2.31}$$

$$\rho^{H-1}ep_{t+H} = \alpha_{ep}^H + \beta_{ep}^H ep_t + \epsilon_{t,t+H}^{ep} \tag{2.32}$$

Similarly to Cochrane (2011), by combining the present-value relation with the predictive regressions above, we obtain an identity involving the predictability coefficients associated with ep, at each horizon H.

$$\beta_r^H - \beta_{\Delta e}^H - \beta_{de}^H + \rho\beta_{ep}^H = 1 \tag{2.33}$$

[Insert Table 2.12 near here]

The new estimated results are similar as shown in table 2.4 where the inflation predictability can reinforce the return predictability and decrease the cash flow predictability. We find that the payout ratio can be positively predicted by the dividend (earnings) yield in both global portfolios. The long run variation contribution from payout ratios is limited at 3% in the equally-weighted portfolio and 5% in the value-weighted portfolio. After inflation being considered, the cash flow plays a dominant role in determining today's financial ratios.

[Insert Table 2.13 near here]

The inflation illusion test provide consistent evidence as before. We find the coefficients of $-E_t \sum_{j=1}^{\infty} \rho^{j-1} \Delta e^{e}_{t+j}$ and $\gamma\lambda_t$ are all significantly positive and the coefficients of ϵ_t are insignificant. It suggest higher inflation implies lower cash flows and high discount rates in the economy.

2.6.3 Monte-Carlo Simulation

A part of the return predictability literature has focused on the poor small-sample properties of long-horizon predictability (e.g.[Valkanov, 2003], [Boudoukh et al., 2006]). To address this issue, we conduct a Monte-Carlo simulation of the VAR model associated with both dividend yields and earnings yields.

Following [Cochrane, 2007], the first Monte Carlo simulation is based on the null hypothesis of no return predictability; the data-generating process is simulated under the hypothesis that what drives the variation in the dividend yield is only dividend growth predictability:

$$\begin{array}{rcccccc} ret_{t+1} & = & 0 & \cdot & dp_t & + & (\epsilon^{\Delta d}_{t+1} - \rho\epsilon^{dp}_{t+1}) \\ \Delta d_{t+1} & = & (\rho\beta_{dp} - 1) & \cdot & dp_t & + & \epsilon^{\Delta d}_{t+1} \\ dp_{t+1} & = & \beta_{dp} & \cdot & dp_t & + & \epsilon^{dp}_{t+1} \end{array} \tag{2.34}$$

The second Monte Carlo simulation is based on the null hypothesis of no dividend predictability; the data-generating process is simulated under the hypothesis that what drives the variation in the dividend yield is only discount rates:

$$\begin{array}{rcccccc} ret_{t+1} & = & (-\rho\beta_{dp}+1) & \cdot & dp_t & + & \epsilon^{r}_{t+1} \\ \Delta d_{t+1} & = & 0 & \cdot & dp_t & + & (\epsilon^{r}_{t+1}+\rho\epsilon^{dp}_{t+1}) \\ dp_{t+1} & = & \beta_{dp} & \cdot & dp_t & + & \epsilon^{dp}_{t+1} \end{array} \tag{2.35}$$

We estimate the coefficients using two simulated datasets and compare them to the original ones. In no return predictability case, if the coefficient β_{ret} is greater than the original one, we count it as one rejection observation. In no cash flow predictability case, if the coefficient $\beta_{\Delta d}$ is less than the original one, we count it as one rejection observation. We simulate each data-generating process for 50,000 times and the documented rejection ratios are less than 1% in the two global portfolios when inflation is considered. By using the Monte Carlo simulations presented above, we are able to gauge the statistical significance of the VAR-based return and dividend growth coefficients at multiple horizons. The results suggest that we reject the absence of returns and dividend growth predictability for both two global portfolios.

2.7 Conclusion

In this paper, we explore the fundamental asset pricing question from a new perspective -inflation- using international data. We start from the fact that high inflation corresponds to high dividend yield and high earnings yield across countries and documented the current dividend (earnings) yield can predict future inflation. The inflation predictability brings new implication in assessing the role of discounts rates and cash flows in today's stock prices.

The main finding in this paper is that the inflation predictability reinforces the return predictability but reduces- even changes the direction of- the cash flow predictability. This pattern holds across advanced economies. We also provide fresh evidence to help us understand price movements. We find that the result based on post-War U.S. data pointed out by [Cochrane, 2011] that asset prices move mainly due to variation in expected returns does not uniformly extend to other countries. The new international data allows us to reassess the variance decomposition analysis and find that both discount rates and cash flows play important roles in determining today's equity price.

The consistent inflation predictability evidence across advanced economies allows us to re-evaluate the relationship among dividend price ratio and inflation to see whether the relation is indeed due to inflation illusion. We test three potential hypothesis related to growth prospect, risk aversion and behavior bias and conclude the positive relationship among inflation and dividend (earnings) yields are consistent with [Fama, 1981], [Brandt and Wang, 2003], and [Bekaert and Engstrom, 2010]. It suggests that high inflation implies lower future economic prospects thus lower cash flows and higher discount rates. The prices today will drop and higher yields will be documented. Therefore the inflation and dividend (earnings) yields are positively correlated.

To rationalize the inflation predictability and provide further insights, we build on the long-run risk setup of [Bansal and Yaron, 2004], [Bansal and Shaliastovich, 2013] and [Schorfheide et al., 2018] with inflation non-neutrality which is high future inflation dampens the economy growth. The estimated model can reproduce both the inflation predictability and the documented asset pricing facts.

Our findings have potentially important policy implication. We documented that though investors are not suffering from the money illusion, high inflation does imply lower future cash flows and higher required risk premia. The Federal Reserve's inflation policy does have bearing on the equity market premia and the implications on future economic growth matters. To conclude, we note that the inflation predictability changes the big picture of return and cash flow predictability a lot. Ignorance of inflation will leads us to biased results.

Table 2.1: Descriptive Statistics

This table reports descriptive statistics for the nominal log stock return, nominal log dividend growth, nominal log earnings growth, real log stock return, real log dividend growth, real log earnings growth, dividend yield, earnings yield and inflation. The equity portfolios consist of the equal-weighted index (EW) and value-weighted index (VW). The sample corresponds to quarterly data for the 1973:Q1-2018Q3 period and all statistics are represented in percent(%).

	Ret_{Nom}		Div_{Nom}		$Earn_{Nom}$		Ret_{Real}		Div_{Real}		$Earn_{Real}$		DP		EP		$Inflation$	
Country	*avg*	*std*	*avg*	*std*	*avg*	*std*	*avg*	*std*	*avg*	*std*	*avg*	*std*	*avg*	*std*	*avg*	*std*	*avg*	*std*
Canada	9.5	17.0	12.1	13.8	12.5	24.2	5.7	17.4	8.3	13.3	8.7	23.8	3.00	0.98	7.03	2.67	3.8	3.1
France	10.6	26.3	12.0	17.2	13.1	20.6	6.6	27.1	8.1	17.6	9.2	20.1	3.70	1.32	8.07	2.67	4.0	3.9
Germany	9.3	22.4	8.7	17.0	8.5	22.3	6.9	22.7	6.3	17.5	6.1	22.5	2.67	0.86	6.97	1.68	2.5	1.8
Italy	7.1	30.7	11.3	27.0	8.8	25.1	1.1	31.6	5.2	28.0	6.0	24.9	2.99	1.18	6.23	1.92	6.0	5.7
Japan	7.3	25.4	8.4	13.6	7.1	20.0	5.2	26.1	6.3	14.3	4.9	20.2	1.38	0.65	3.81	1.83	2.1	4.0
UK	11.5	20.2	10.3	8.6	9.7	15.5	6.5	20.4	5.3	8.0	4.7	15.4	4.17	1.24	7.96	3.30	5.0	5.1
US	10.4	17.3	8.1	6.2	8.5	12.6	6.5	17.8	4.3	5.9	4.7	12.0	2.91	1.39	6.85	2.74	3.8	2.9
EW	9.5	18.5	10.1	9.8	9.9	14.6	5.6	19.1	6.3	10.0	6.3	14.3	2.97	0.85	6.81	2.05	3.8	3.5
VW	9.9	17.6	8.9	6.5	8.2	12.4	6.5	18.1	5.6	6.6	4.9	12.0	2.63	0.99	6.13	2.15	3.4	2.9

Table 2.2: Predictive Regressions

This table shows results for predictive regressions of inflation on the log dividend yield or log earnings yield for the CS, EW and VW cases. Panel A reports results about log dividend yield and Panel B reports results about log earnings yield. The forecast horizon is from one year to twenty years. For each case, predictive coefficients are highlighted reported in first row, the t-stat (Newey/West HAC) are reported in second row and the R^2 are reported in the third row.

Panel A	$Inflation$ on dp_t								
Horizon	1	2	3	4	5	7	10	15	20
CS	0.037	0.034	0.032	0.030	0.029	0.027	0.027	0.023	0.020
	[13.22]	[13.21]	[13.09]	[12.67]	[12.59]	[12.59]	[13.96]	[14.26]	[12.44]
	0.14	0.15	0.16	0.16	0.17	0.18	0.21	0.23	0.22
EW	0.074	0.071	0.068	0.064	0.061	0.058	0.055	0.043	0.039
	[5.16]	[5.21]	[5.16]	[4.99]	[4.88]	[4.97]	[6.66]	[6.98]	[7.02]
	0.38	0.40	0.41	0.40	0.41	0.43	0.54	0.56	0.52
VW	0.041	0.038	0.036	0.034	0.032	0.029	0.024	0.019	0.018
	[4.00]	[3.89]	[3.82]	[3.77]	[3.76]	[3.77]	[4.64]	[6.00]	[5.59]
	0.32	0.34	0.34	0.34	0.34	0.35	0.43	0.56	0.53
Panel B	$Inflation$ on ep_t								
Horizon	1	2	3	4	5	7	10	15	20
CS	0.047	0.044	0.041	0.037	0.035	0.032	0.030	0.024	0.018
	[19.08]	[18.79]	[18.38]	[17.26]	[16.85]	[16.43]	[17.19]	[17.30]	[13.38]
	0.23	0.25	0.25	0.25	0.25	0.25	0.31	0.37	0.37
EW	0.078	0.073	0.068	0.063	0.059	0.056	0.052	0.040	0.034
	[5.89]	[5.76]	[5.64]	[5.40]	[5.23]	[5.24]	[6.57]	[6.98]	[5.72]
	0.41	0.41	0.40	0.37	0.37	0.39	0.45	0.49	0.42
VW	0.043	0.039	0.036	0.033	0.031	0.029	0.024	0.021	0.019
	[4.11]	[3.88]	[3.71]	[3.59]	[3.58]	[3.64]	[4.66]	[6.20]	[6.21]
	0.29	0.29	0.28	0.26	0.26	0.28	0.36	0.54	0.52

Table 2.3: Predictive Regressions

This table shows results for predictive regressions of total returns (left panel) and dividend growth or earnings growth (right panel) on the log dividend yield or log earnings yield for the CS, EW, and VW cases. Panel A reports results about log dividend yield and Panel B reports results about log earnings yield. The forecast horizon is from one year to five years. For each case, predictive coefficients are highlighted reported in first row, the t-stat (Newey/West HAC) are reported in second row and the R^2 are reported in the third row.

Panel A: dp_t	*Return*					*Dividend*				
Horizon	1	2	3	4	5	1	2	3	4	5
$CS_{nominal}$	0.127	0.122	0.109	0.101	0.098	-0.075	-0.050	-0.038	-0.032	-0.028
	[7.49]	[10.47]	[12.01]	[13.36]	[15.35]	[-6.37]	[-5.31]	[-4.64]	[-4.31]	[-4.22]
	0.03	0.07	0.09	0.12	0.15	0.00	0.00	0.00	0.00	0.00
CS_{real}	0.090	0.088	0.077	0.071	0.069	-0.112	-0.084	-0.071	-0.062	-0.057
	[5.13]	[7.16]	[8.02]	[8.91]	[10.38]	[-9.47]	[-8.99]	[-8.66]	[-8.58]	[-8.82]
	0.01	0.03	0.03	0.04	0.06	0.03	0.03	0.03	0.03	0.03
$EW_{nominal}$	0.157	0.150	0.141	0.142	0.145	-0.055	-0.021	-0.002	0.013	0.018
	[2.16]	[2.42]	[2.89]	[4.12]	[5.18]	[-1.12]	[-0.55]	[-0.06]	[0.46]	[0.75]
	0.06	0.12	0.17	0.24	0.34	0.03	0.01	0.00	0.00	0.01
EW_{real}	0.083	0.079	0.073	0.079	0.084	-0.129	-0.092	-0.070	-0.051	-0.043
	[1.06]	[1.15]	[1.33]	[1.92]	[2.45]	[-2.78]	[-2.49]	[-2.24]	[-1.85]	[-1.70]
	0.02	0.03	0.04	0.07	0.12	0.14	0.11	0.08	0.06	0.05
$VW_{nominal}$	0.130	0.130	0.128	0.124	0.124	0.010	0.024	0.033	0.036	0.036
	[2.59]	[3.19]	[3.77]	[4.42]	[5.03]	[0.47]	[1.50]	[2.34]	[2.98]	[3.37]
	0.08	0.17	0.25	0.31	0.40	0.00	0.03	0.08	0.13	0.18
VW_{real}	0.089	0.092	0.092	0.091	0.092	-0.031	-0.014	-0.003	0.003	0.004
	[1.61]	[1.99]	[2.34]	[2.68]	[2.99]	[-1.45]	[-0.84]	[-0.20]	[0.20]	[0.29]
	0.04	0.08	0.12	0.16	0.22	0.03	0.01	0.00	0.00	0.00

Panel B: ep_t	*Return*					*Earnings*				
Horizon	1	2	3	4	5	1	2	3	4	5
$CS_{nominal}$	0.131	0.121	0.108	0.098	0.102	-0.152	-0.081	-0.045	-0.028	-0.015
	[7.47]	[10.11]	[11.58]	[12.29]	[15.00]	[-9.48]	[-6.80]	[-4.56]	[-3.31]	[-1.96]
	0.04	0.07	0.10	0.11	0.16	0.03	0.01	0.00	0.00	0.00
CS_{real}	0.084	0.078	0.068	0.061	0.067	-0.199	-0.125	-0.085	-0.066	-0.050
	[4.61]	[6.15]	[6.87]	[7.25]	[9.37]	[-12.91]	[-10.82]	[-8.97]	[-8.03]	[-6.94]
	0.01	0.03	0.03	0.04	0.06	0.07	0.04	0.03	0.02	0.01
$EW_{nominal}$	0.139	0.124	0.114	0.111	0.120	-0.147	-0.067	-0.033	-0.020	-0.009
	[1.90]	[1.97]	[2.29]	[3.02]	[4.06]	[-1.98]	[-1.25]	[-0.77]	[-0.62]	[-0.32]
	0.04	0.08	0.10	0.14	0.22	0.08	0.03	0.01	0.01	0.00
EW_{real}	0.061	0.051	0.046	0.048	0.060	-0.214	-0.129	-0.091	-0.073	-0.058
	[0.79]	[0.75]	[0.83]	[1.15]	[1.75]	[-3.17]	[-2.58]	[-2.18]	[-2.30]	[-2.33]
	0.01	0.01	0.02	0.03	0.06	0.18	0.11	0.09	0.09	0.08
$VW_{nominal}$	0.116	0.111	0.110	0.104	0.107	-0.061	-0.014	0.001	0.003	0.004
	[2.23]	[2.55]	[2.86]	[3.21]	[3.66]	[-1.38]	[-0.45]	[0.04]	[0.13]	[0.24]
	0.05	0.10	0.15	0.18	0.25	0.03	0.00	0.00	0.00	0.00
VW_{real}	0.073	0.072	0.074	0.072	0.076	-0.103	-0.053	-0.034	-0.029	-0.026
	[1.32]	[1.51]	[1.74]	[1.96]	[2.25]	[-2.54]	[-1.79]	[-1.38]	[-1.38]	[-1.40]
	0.02	0.04	0.07	0.08	0.12	0.09	0.04	0.03	0.04	0.04

Table 2.4: VAR-Based Results

This table reports the one-period VAR estimation results for EW and VW cases of real(nominal) returns and real(nominal) dividend(earnings) growth. The variables in the VAR are the log stock return (ret), log dividend growth (Δd) or log earnings growth (Δe), and log dividend-to-price ratio (dp) or log earnings-to-price ratio (ep). Panel A reports results about log dividend yield and Panel B reports results about log earnings yield. β denotes the VAR slopes associated with lagged dp or lagged ep, while t denotes the respective Newey and West (1987) t-statistics. β^{Delta} denotes the slope estimates implied from the variance decomposition constraint, and t denotes the respective asymptotic t-statistics computed under the delta method. R^2 are the coefficient of determination for each equation in the VAR. β^{LR} denotes the long-run coefficients (infinite horizon). The sample corresponds to quarterly data from 1973:Q1 to 2018:Q3.

Panel A: dp_t		β	t	R^2	β^{Delta}	t	R^2	β^{LR}
$EW_{nominal}$	ret	0.17	[3.84]	0.08	0.17	[3.90]	0.08	0.76
	Δd	-0.05	[-2.12]	0.03	-0.05	[-2.23]	0.03	-0.24
	dp	0.80	[19.29]	0.68	0.80	[19.67]	0.68	-
EW_{real}	ret	0.10	[2.16]	0.03	0.10	[2.17]	0.03	0.44
	Δd	-0.13	[-5.26]	0.14	-0.13	[-5.41]	0.14	-0.56
	dp	0.80	[19.25]	0.68	0.80	[19.62]	0.68	-
$VW_{nominal}$	ret	0.14	[4.72]	0.11	0.13	[4.44]	0.11	1.04
	Δd	0.01	[0.79]	0.00	0.01	[0.41]	0.00	0.04
	dp	0.86	[26.00]	0.80	0.89	[31.08]	0.79	-
VW_{real}	ret	0.11	[3.35]	0.06	0.10	[3.02]	0.06	0.73
	Δd	-0.03	[-2.29]	0.03	-0.03	[-2.87]	0.03	-0.27
	dp	0.86	[26.00]	0.80	0.89	[31.08]	0.79	-
Panel B: ep_t		β	t	R^2	β^{Delta}	t	R^2	β^{LR}
$EW_{nominal}$	ret	0.14	[3.01]	0.05	0.14	[3.27]	0.05	0.50
	Δe	-0.14	[-3.90]	0.08	-0.14	[-3.93]	0.08	-0.50
	ep	0.72	[15.53]	0.58	0.73	[15.83]	0.58	-
EW_{real}	ret	0.06	[1.24]	0.01	0.07	[1.61]	0.01	0.25
	Δe	-0.21	[-6.13]	0.18	-0.21	[-6.15]	0.18	-0.75
	ep	0.73	[15.53]	0.58	0.73	[15.85]	0.58	-
$VW_{nominal}$	ret	0.12	[3.47]	0.06	0.12	[3.47]	0.06	0.65
	Δe	-0.06	[-2.46]	0.03	-0.06	[-2.60]	0.03	-0.35
	dp	0.83	[22.53]	0.74	0.83	[22.90]	0.74	-
VW_{real}	ret	0.08	[2.18]	0.03	0.08	[2.19]	0.03	0.42
	Δe	-0.10	[-4.28]	0.10	-0.11	[-4.48]	0.10	-0.58
	ep	0.83	[22.46]	0.74	0.83	[22.84]	0.74	-

Table 2.5: Hypothesis Tests-Consumer Price Indexes (CPI)

Regressions of yield's components on inflation constructed from CPI. Panel A shows results of dividend yield's components and Panel B shows results of earnings yield's components. For each case, coefficients are highlighted reported in first row, the t-stat (Newey/West HAC) are reported in second row and the R^2 are reported in the third row.

Panel A: Dividend Yield (dp)

Dep.	dp_t	$-E_t \sum_{j=1}^{\infty} \rho^{j-1} \Delta d_{t+j}^e$	$\gamma\lambda_t$	ϵ_t	$\gamma\lambda_t + \epsilon_t$
EW	5.891	7.359	0.258	-1.709	-1.449
	[5.84]	[10.22]	[3.98]	[-3.68]	[-3.05]
	0.36	0.69	0.26	0.18	0.13
EW_{backed}	5.891	4.866	1.470	-0.434	1.044
	[5.84]	[9.31]	[3.98]	[-0.97]	[1.90]
	0.36	0.64	0.26	0.02	0.05
VW	8.961	6.851	2.815	-0.677	2.137
	[5.69]	[9.22]	[6.94]	[-0.69]	[2.18]
	0.32	0.62	0.60	0.01	0.06
VW_{backed}	8.961	3.238	6.608	-0.855	5.750
	[5.69]	[14.85]	[6.94]	[-0.66]	[4.05]
	0.32	0.86	0.60	0.01	0.18

Panel B: Earnings Yield (ep)

Dep.	ep_t	$-E_t \sum_{j=1}^{\infty} \rho^{j-1} \Delta e_{t+j}^e$	$\gamma\lambda_t$	ϵ_t	$\gamma\lambda_t + \epsilon_t$
EW	7.015	10.973	-0.825	-3.132	-3.961
	[10.38]	[17.36]	[-4.01]	[-12.04]	[-18.87]
	0.51	0.82	0.26	0.52	0.74
EW_{backed}	7.015	6.994	0.878	-0.864	0.018
	[10.38]	[16.26]	[4.01]	[-4.62]	[0.07]
	0.51	0.75	0.26	0.13	0.00
VW	8.849	10.050	0.303	-1.500	-1.197
	[6.81]	[12.58]	[6.81]	[-2.66]	[-2.08]
	0.36	0.73	0.60	0.06	0.04
VW_{backed}	8.849	6.188	3.761	-1.095	2.665
	[6.81]	[12.57]	[6.81]	[-1.56]	[3.03]
	0.36	0.72	0.60	0.02	0.09

Table 2.6: Hypothesis Robust Tests-Producer Price Indexes (PPI)

Regressions of yield's components on inflation constructed from PPI. Panel A shows results of dividend yield's components and Panel B shows results of earnings yield's components. For each case, coefficients are highlighted reported in first row, the t-stat (Newey/West HAC) are reported in second row and the R^2 are reported in the third row.

Panel A: Dividend Yield (dp)

Dep.	dp_t	$-E_t \sum_{j=1}^{\infty} \rho^{j-1} \Delta d_{t+j}^e$	$\gamma\lambda_t$	ϵ_t	$\gamma\lambda_t + \epsilon_t$
EW	17.419	14.018	4.146	-0.745	3.401
	[2.25]	[2.58]	[3.38]	[-0.46]	[1.40]
	0.19	0.24	0.32	0.01	0.07
EW_{backed}	17.419	10.005	8.201	-0.786	7.414
	[2.25]	[2.47]	[3.38]	[-0.40]	[1.98]
	0.19	0.23	0.32	0.00	0.15
VW	19.639	13.218	8.657	-2.207	6.442
	[2.02]	[2.54]	[3.65]	[-0.76]	[1.39]
	0.14	0.22	0.39	0.01	0.06
VW_{backed}	19.639	4.106	18.764	-3.192	15.554
	[2.02]	[2.08]	[3.65]	[-0.85]	[2.00]
	0.14	0.17	0.39	0.01	0.13

Panel B: Earnings Yield (ep)

Dep.	ep_t	$-E_t \sum_{j=1}^{\infty} \rho^{j-1} \Delta e_{t+j}^e$	$\gamma\lambda_t$	ϵ_t	$\gamma\lambda_t + \epsilon_t$
EW	21.388	18.345	1.882	1.152	3.035
	[2.73]	[2.68]	[3.46]	[1.59]	[2.97]
	0.29	0.28	0.31	0.07	0.29
EW_{backed}	21.388	12.325	6.784	2.268	9.055
	[2.73]	[2.37]	[3.46]	[1.73]	[3.39]
	0.29	0.23	0.31	0.09	0.39
VW	23.139	16.582	4.650	1.904	6.552
	[2.47]	[2.36]	[3.74]	[1.24]	[2.75]
	0.22	0.21	0.39	0.03	0.22
VW_{backed}	23.139	6.977	13.508	2.655	16.158
	[2.47]	[1.62]	[3.74]	[1.13]	[3.15]
	0.22	0.10	0.39	0.02	0.33

Table 2.7: Estimated Parameters

This table reports the estimated parameters. All reported numbers are Bayesian estimated using consumption growth, dividend growth and inflation data. Priors mean, standard deviations and distributions are reported in first three columns. Posterior mean and 90% intervals are reported in last three columns.

Parameters	Prior			Posterior		
	mean	*std*	*dist.*	*mean*	5%	95%
ρ_c	0.900	0.0500	*Beta*	0.8010	0.7357	0.8716
ρ_π	0.900	0.0500	*Beta*	0.9719	0.9558	0.9913
$-\rho_{c\pi}$	0.100	0.0500	*Beta*	0.0834	0.0364	0.1289
μ_c	0.005	0.0015	*Uniform*	0.0050	0.0036	0.0065
μ_d	0.010	0.0030	*Uniform*	0.0104	0.0064	0.0151
μ_π	0.010	0.0030	*Uniform*	0.0093	0.0064	0.0129
σ_c	0.003	*Inf.*	*Inv-Gamma*	0.0014	0.0009	0.0019
σ_{xc}	0.003	*Inf.*	*Inv-Gamma*	0.0024	0.0021	0.0028
σ_d	0.030	*Inf.*	*Inv-Gamma*	0.0214	0.0194	0.0234
σ_π	0.003	*Inf.*	*Inv-Gamma*	0.0007	0.0006	0.0008
$\sigma_{x\pi}$	0.003	*Inf.*	*Inv-Gamma*	0.0011	0.0009	0.0012

Table 2.8: Descriptive Statistics and Simulated Moments

Statistics in Data column are calculated based on quarterly sample data from 1973Q1 to 2018Q3. Statistics in LRR Model column are bootstrapped statistics calculated from 2,000 simulations, each with 180 observations. All values are annualized and standard deviations are reported in brackets.

Variable	**Data**	**LRR Model**
Real Consumption Growth (Δc_{t+1})	0.022	0.020
	[0.021]	[0.009]
Real Dividend Growth (Δd_{t+1})	0.043	0.042
	[0.058]	[0.050]
Real Equity Returns (ret_{t+1})	0.066	0.071
	[0.178]	[0.099]
Log Price Dividend Ratio (pd_t)	3.645	3.480
	[0.464]	[0.341]
Inflation Rate (π_{t+1})	0.035	0.037
	[0.023]	[0.009]

Table 2.9: Predictive Regressions

This table reports results for predictive regressions of stock returns (ret), dividend growth (Δd), inflation (π), and consumption growth (Δc) on the log dividend yield. The forecast horizon is from one year to five years. All reported numbers are taken averages across 2,000 simulations with sample length equal 180. Predictive coefficients are highlighted reported in first row, the t-stat are reported in second row and the R^2 are reported in the third row.

Dep. Var\ Horizon	1	2	3	4	5
$ret_{nom,t+1}$	0.108	0.110	0.110	0.111	0.108
	[1.76]	[2.44]	[2.96]	[3.41]	[3.78]
	0.00	0.00	0.00	0.00	0.01
$ret_{real,t+1}$	0.016	0.025	0.038	0.043	0.051
	[0.49]	[0.75]	[1.06]	[1.48]	[1.74]
	0.00	0.00	0.00	0.00	0.00
$\Delta d_{nom,t+1}$	-0.091	-0.077	-0.063	-0.054	-0.046
	[-2.37]	[-2.41]	[-2.27]	[-2.09]	[-1.88]
	0.00	0.00	0.00	0.00	0.00
$\Delta d_{real,t+1}$	-0.185	-0.159	-0.137	-0.121	-0.106
	[-4.78]	[-5.01]	[-4.82]	[-4.57]	[-4.25]
	0.16	0.19	0.19	0.14	0.09
π_{t+1}	0.092	0.083	0.075	0.067	0.059
	[20.45]	[15.39]	[12.46]	[10.32]	[8.67]
	0.82	0.72	0.62	0.53	0.44
Δc_{t+1}	-0.061	-0.053	-0.047	-0.041	-0.035
	[-7.06]	[-6.62]	[-6.17]	[-5.68]	[-5.30]
	0.34	0.31	0.28	0.24	0.19

Table 2.10: Dividend Smoothing

This table shows results for regressions of dividend growth on the earnings growth and lagged dividend growth for EW and VW where growth are measured in nominal or real term.

$$\Delta D_t = \delta_1 \Delta E_t + \delta_2 \Delta D_{t-1} + \epsilon_t \tag{2.36}$$

δ_1 and δ_2 are coefficients of the earnings growth and lagged dividend growth, respectively. The t-stat (Newey/West HAC) and the R^2 are reported for each cases.

	δ_1	t	δ_2	t	R^2
$EW_{nominal}$	0.37	[7.05]	0.33	[3.63]	0.44
EW_{real}	0.36	[6.98]	0.31	[3.65]	0.42
$VW_{nominal}$	0.28	[3.18]	0.29	[3.67]	0.38
VW_{real}	0.26	[3.24]	0.26	[3.30]	0.34

Table 2.11: Dividend Smoothing, Firm Size, and Volatility

This table shows results for cross-sectional regressions of a country's dividend smoothing parameter S_i on firm size and/or each return volatility. The smoothing parameter is defined as the standard deviation of dividend growth of a country divided by the standard deviation of earnings growth. Numbers in brackets are t-statistics based on White-Hinkley heteroskedasticity consistent standard errors.

	(1)	(2)	(3)
Firm Size	-0.165		-0.068
	[-3.64]		[-1.62]
Return Volatility		2.939	2.529
		[4.03]	[3.11]
constant	0.744	0.059	0.154
	[12.50]	[0.32]	[0.31]
R^2	0.36	0.73	0.78

Table 2.12: VAR-Based Results

This table reports the one-period VAR estimation results for EW and VW cases of real(nominal) returns and real(nominal) earnings growth. The variables in the VAR are the log stock return (ret), log earnings growth (Δe), log payout ratio (de), and log earnings-to-price ratio (ep). β denotes the VAR slopes associated with lagged ep, while t denotes the respective Newey and West (1987) t-statistics. β^{Delta} denotes the slope estimates implied from the variance decomposition constraint, and t denotes the respective asymptotic t-statistics computed under the delta method. R^2 are the coefficient of determination for each equation in the VAR. β^{LR} denotes the long-run coefficients (infinite horizon). The sample corresponds to quarterly data from 1973:Q1 to 2018:Q3.

		β	t	R^2	β^{Delta}	t	R^2	β^{LR}
$EW_{nominal}$	ret	0.14	[3.01]	0.05	0.15	[3.39]	0.05	0.53
	Δe	-0.14	[-3.90]	0.08	-0.14	[-3.89]	0.08	-0.50
	de	0.01	[3.72]	0.07	0.01	[3.56]	0.07	0.03
	ep	0.72	[15.53]	0.58	0.73	[16.06]	0.58	-
EW_{real}	ret	0.06	[1.24]	0.01	0.08	[1.73]	0.01	0.28
	Δe	-0.21	[-6.13]	0.18	-0.21	[-6.09]	0.18	-0.75
	de	0.01	[3.73]	0.07	0.01	[3.42]	0.07	0.03
	ep	0.73	[15.53]	0.58	0.74	[16.08]	0.58	-
$VW_{nominal}$	ret	0.12	[3.47]	0.06	0.12	[3.43]	0.06	0.66
	Δe	-0.06	[-2.46]	0.03	-0.07	[-2.71]	0.03	-0.38
	de	0.01	[4.16]	0.08	0.01	[4.08]	0.09	0.05
	dp	0.83	[22.53]	0.74	0.84	[23.34]	0.74	-
VW_{real}	ret	0.08	[2.18]	0.03	0.08	[2.15]	0.03	0.43
	Δe	-0.10	[-4.28]	0.10	-0.11	[-4.57]	0.10	-0.62
	de	0.01	[4.17]	0.09	0.01	[4.09]	0.09	0.05
	ep	0.83	[22.46]	0.74	0.84	[23.28]	0.74	-

Table 2.13: Hypothesis Tests: Time-Varying Payout Ratio Case

Regressions of earnings yield's components on inflation constructed from both CPI and PPI. Panel A shows results of CPI constructed inflation and Panel B shows results of PPI constructed inflation. For each case, coefficients are highlighted reported in first row, the t-stat (Newey/West HAC) are reported in second row and the R^2 are reported in the third row.

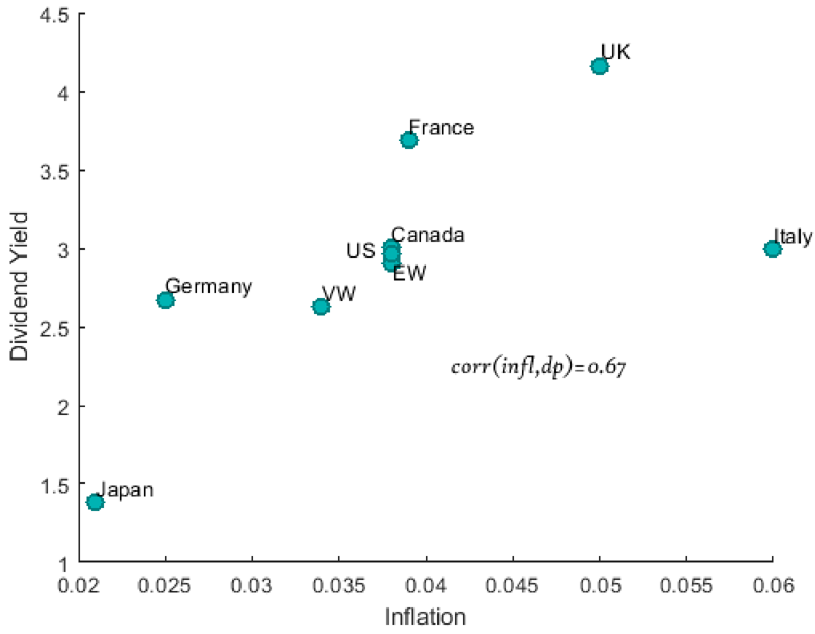
Panel A: CPI Case

Dep.	ep_t	$-E_t \sum_{j=1}^{\infty} \rho^{j-1} \Delta e^e_{t+j}$	$\gamma\lambda_t$	ϵ_t	$\gamma\lambda_t + \epsilon_t$
EW	7.034	8.201	0.567	-1.332	-0.761
	[10.48]	[13.38]	[3.98]	[-2.58]	[-1.46]
	0.52	0.74	0.26	0.13	0.04
EW_{backed}	7.034	4.074	2.527	0.823	3.365
	[10.48]	[9.65]	[3.98]	[1.41]	[4.98]
	0.52	0.55	0.26	0.05	0.29
VW	8.841	7.130	3.155	-0.738	2.416
	[6.76]	[11.74]	[6.92]	[-0.72]	[2.33]
	0.36	0.61	0.60	0.01	0.07
VW_{backed}	8.841	3.040	6.924	-0.416	6.506
	[6.76]	[10.52]	[6.92]	[-0.34]	[4.83]
	0.36	0.35	0.60	0.00	0.25

Panel B: PPI Case

Dep.	ep_t	$-E_t \sum_{j=1}^{\infty} \rho^{j-1} \Delta e^e_{t+j}$	$\gamma\lambda_t$	ϵ_t	$\gamma\lambda_t + \epsilon_t$
EW	21.460	16.911	5.476	0.299	5.780
	[2.74]	[2.88]	[3.47]	[0.17]	[2.19]
	0.30	0.31	0.32	0.00	0.16
EW_{backed}	21.460	9.435	12.302	0.944	13.256
	[2.74]	[2.63]	[3.47]	[0.36]	[2.67]
	0.30	0.23	0.32	0.00	0.24
VW	22.518	16.747	9.617	-2.955	6.651
	[2.54]	[3.31]	[3.81]	[-0.96]	[1.40]
	0.22	0.35	0.38	0.02	0.05
VW_{backed}	22.518	6.641	19.154	-2.375	16.757
	[2.54]	[2.61]	[3.81]	[-0.62]	[2.23]
	0.22	0.17	0.38	0.02	0.15

Figure 2.1: Dividend Yields, Earnings Yields and Inflation: This figure plots inflation of individual countries (horizontal axis) against dividend yield and earnings yield on the vertical axis.



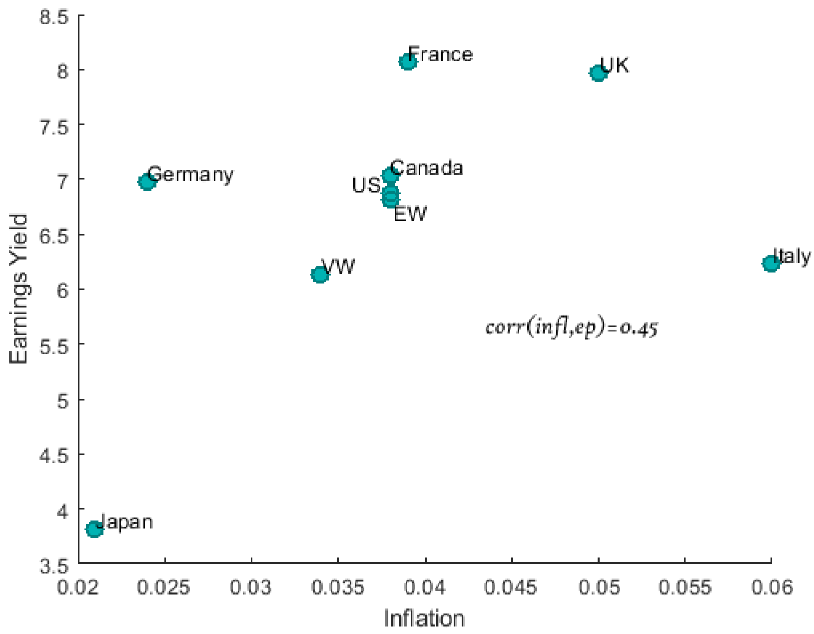
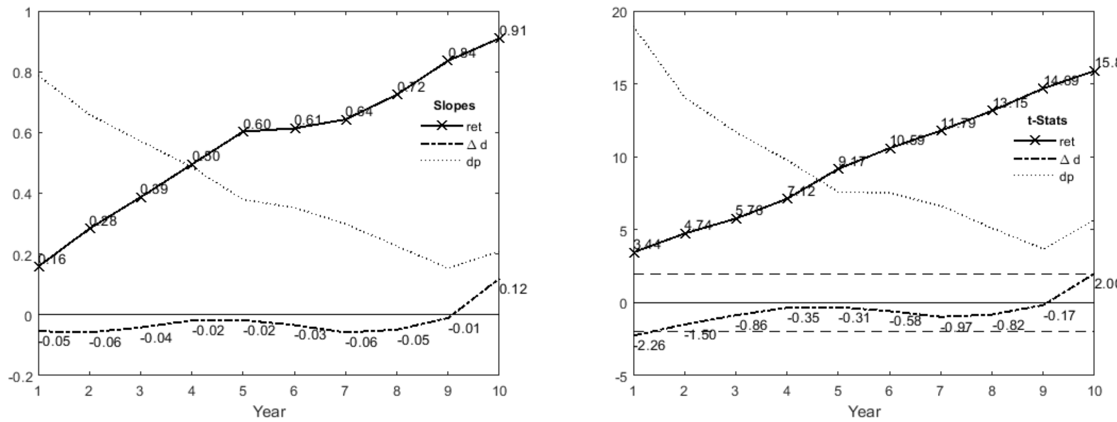
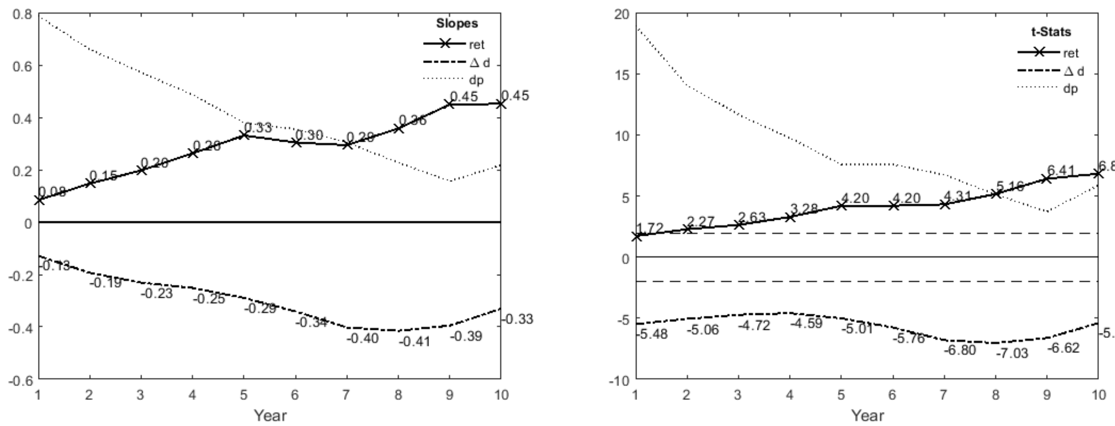


Figure 2.2: Nominal and Real Term Structure of Coefficients of dp: EW. This figure plots the nominal VAR-based term structure of the long-horizon predictive coefficients and respective t-statistics for the equal-weighted case. The predictive slopes are associated with the log return (ret), log dividend growth (Δd), and log dividend-to-price ratio (dp). The forecasting variable is the log dividend-to-price ratio in all three equations. The long-run coefficients are measured in percent, and horizon is 10 years ahead. The horizontal lines in right figures represent the 5% critical values (-1.96, 1.96). The sample is 1973:Q1 to 2018Q3.

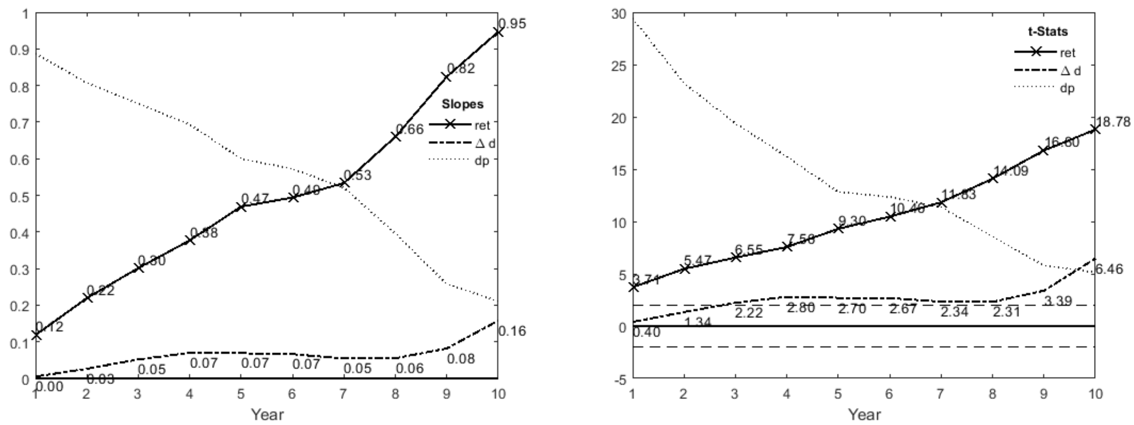


(Nominal-EW: Slopes and t-Stats)

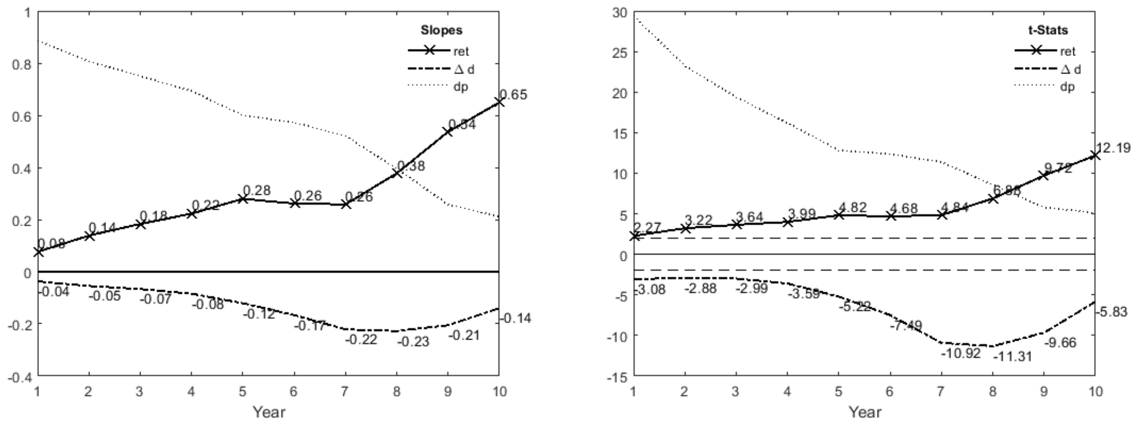


(Real-EW: Slopes and t-Stats)

Figure 2.3: Nominal and Real Term Structure of Coefficients of *dp*: VW. This figure plots the real VAR-based term structure of the long-horizon predictive coefficients and respective t-statistics for the value-weighted case. The predictive slopes are associated with the log return (*ret*), log dividend growth (Δd), and log dividend-to-price ratio (*dp*). The forecasting variable is the log dividend-to-price ratio in all three equations. The long-run coefficients are measured in percent, and horizon is 10 years ahead. The horizontal lines in right figures represent the 5% critical values (-1.96, 1.96). The sample is 1973:Q1 to 2018Q3.

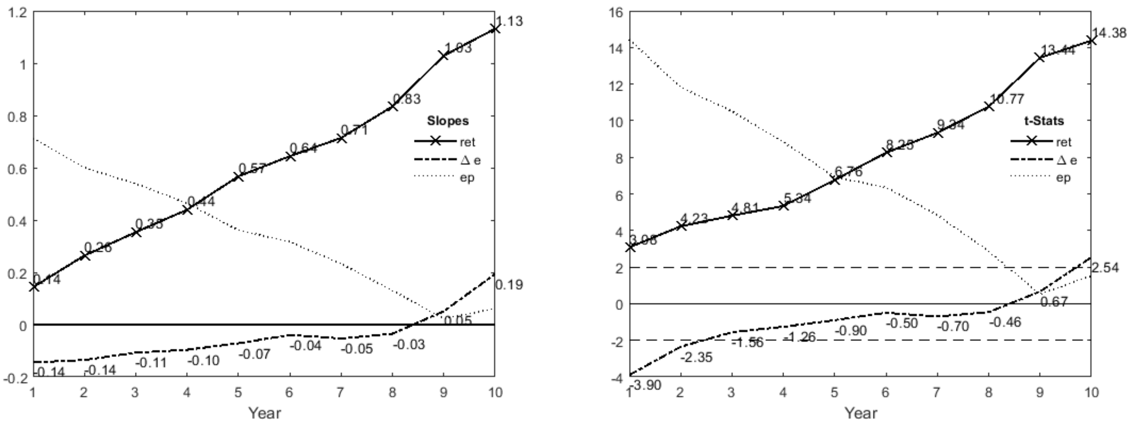


(Nominal-VW: Slopes and t-Stats)

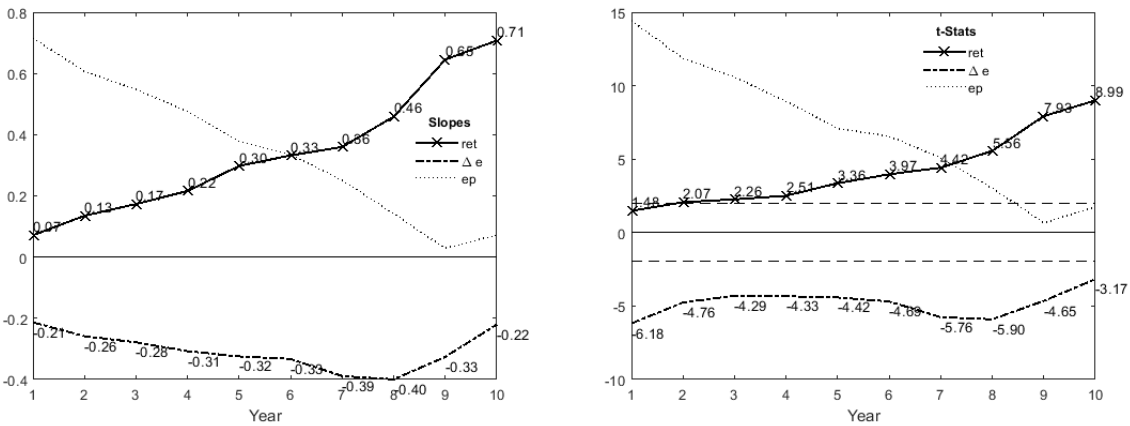


(Real-VW: Slopes and t-Stats)

Figure 2.4: Nominal and Real Term Structure of Coefficients of *ep*: EW. This figure plots the nominal VAR-based term structure of the long-horizon predictive coefficients and respective t-statistics for the equal-weighted case. The predictive slopes are associated with the log return (ret), log earnings growth (Δe), and log earnings-to-price ratio (ep). The forecasting variable is the log earnings-to-price ratio in all three equations. The long-run coefficients are measured in percent, and horizon is 10 years ahead. The horizontal lines in right figures represent the 5% critical values (-1.96, 1.96). The sample is 1973:Q1 to 2018Q3.

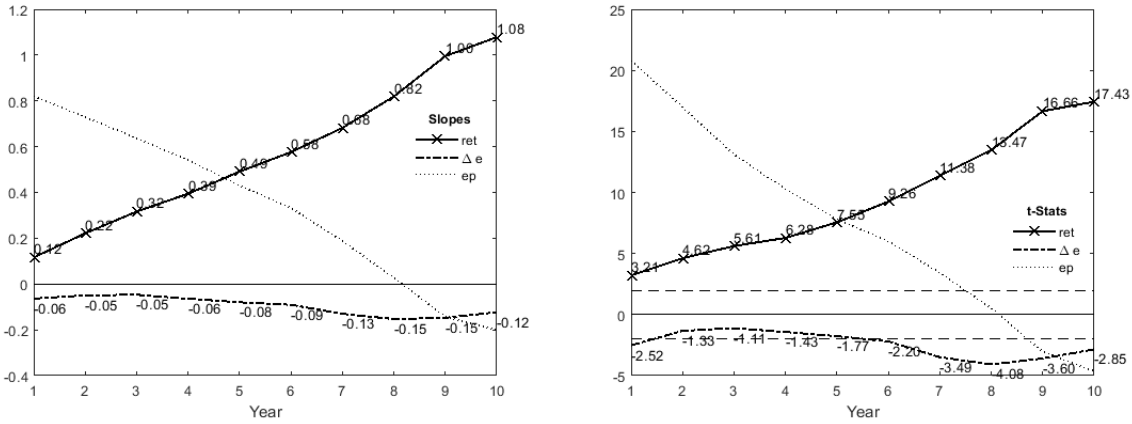


(Nominal-EW: Slopes and t-Stats)

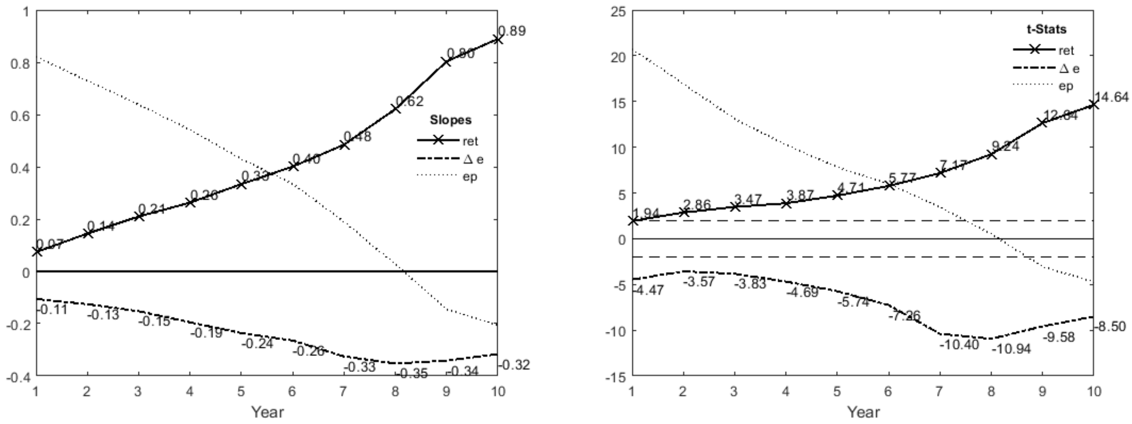


(Real-EW: Slopes and t-Stats)

Figure 2.5: Nominal and Real Term Structure of Coefficients of ep: VW. This figure plots the real VAR-based term structure of the long-horizon predictive coefficients and respective t-statistics for the value-weighted case. The predictive slopes are associated with the log return (ret), log earning growth (Δe), and log earnings-to-price ratio (ep). The forecasting variable is the log earnings-to-price ratio in all three equations. The long-run coefficients are measured in percent, and horizon is 10 years ahead. The horizontal lines in right figures represent the 5% critical values (-1.96, 1.96). The sample is 1973:Q1 to 2018Q3.

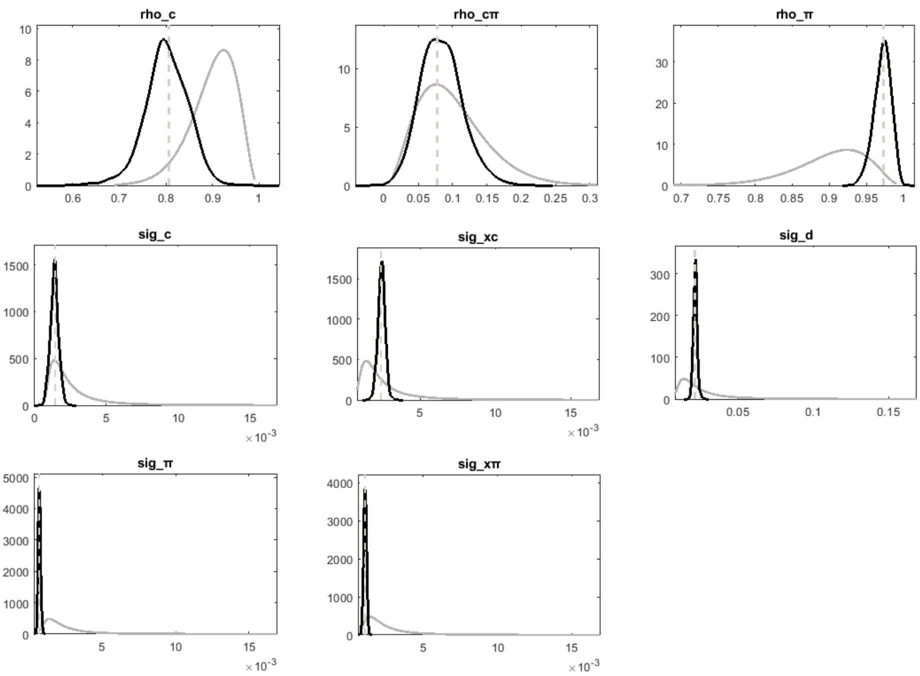


(Nominal-VW: Slopes and t-Stats)



(Real-VW: Slopes and t-Stats)

Figure 2.6: Priors and Posteriors: The vertical lines represent the posterior means, the dark lines represent posteriors and the gray lines represent priors.



2.8 Appendix: Model Solutions

Economic Dynamics:

$$z_{t+1} = \mu + \Phi x_t + S_z \eta_{t+1}$$

$$x_{t+1} = \Pi x_t + S_x \epsilon_{t+1}$$

where

$$z_t = [\Delta c_t, \Delta d_t, \pi_t], \quad x_t = [x_{c,t}, x_{\pi,t}]$$

$x_{c,t}$ and $x_{\pi,t}$ are the long-run components of expected consumption growth and expected inflation.

$$\Phi = \begin{bmatrix} 1 & 0 \\ \phi & 0 \\ 0 & 1 \end{bmatrix}, \quad \Pi = \begin{bmatrix} \rho_c & \rho_{c\pi} \\ 0 & \rho_\pi \end{bmatrix}$$

ϕ captures the dividend leverage and ρ_c, ρ_π represents the persistence the expected process. $\rho_{c\pi}$ measures the non-neutrality of inflation which is negative to dampen the consumption growth.

$$S_z = \begin{bmatrix} \sigma_c & 0 & 0 \\ 0 & \sigma_d & 0 \\ 0 & 0 & \sigma_\pi \end{bmatrix}, \quad S_x = \begin{bmatrix} \sigma_{xc} & 0 \\ 0 & \sigma_{x\pi} \end{bmatrix}$$

η_{t+1} and ϵ_{t+1} represent the normal distributed shocks and S_z and S_x capture the time variation in the uncertainty about expected consumption growth and expected inflation. Both S_z and S_x are diagnol matrix.

In the economy, the representative agent has the Epstein and Zin (1989) preferences defined over the consumption bundle C_t:

$$U_t = [(1-\delta)C_t^{1-\frac{1}{\psi}} + \delta(E_t[U_{t+1}^{1-\gamma}])^{\frac{1-\frac{1}{\psi}}{1-\gamma}}]^{\frac{1}{1-\frac{1}{\psi}}}$$

Therefore the IMRS (Inter-temporal Marginal Rate of Substitution) for this economy is given by

$$m_{t+1} = \theta \cdot log\delta - \frac{\theta}{\psi} \cdot \Delta c_{t+1} + (\theta - 1) \cdot r_{c,t+1}$$

where $\theta = \frac{1-\gamma}{1-\frac{1}{\psi}}$

2.8.1 Price-Consumption Ratio: pc

$$pc_t = A_0 + A_1 \cdot x_{c,t} + A_2 \cdot x_{\pi,t}$$

Proof:

$$1 = E_t[M_{t+1}R_{c,t+1}] = E_t[exp(\theta \cdot log\delta - \frac{\theta}{\psi} \cdot \Delta c_{t+1} + \theta \cdot r_{c,t+1})]$$

where

$$r_{c,t+1} = \kappa_0 + \kappa_1 \cdot pc_{t+1} + \Delta c_{t+1} - pc_t$$

Let $A(\cdot) = \theta \cdot log\delta - \frac{\theta}{\psi} \cdot \Delta c_{t+1} + \theta \cdot r_{c,t+1}$, we have

$$E[A(\cdot)] + \frac{1}{2} Var(A(\cdot)) = 0$$

By the educated guess,

$$pc_t = A_0 + A_1 \cdot x_{c,t} + A_2 \cdot x_{\pi,t}$$

Substitute the guess into $A(\cdot)$ and solve the equation:

$$A_1 = \frac{1 - \frac{1}{\psi}}{1 - \kappa_1 \cdot \rho_c}, \quad A_2 = \frac{\kappa_1 \cdot (1 - \frac{1}{\psi}) \cdot \rho_{c\pi}}{(1 - \kappa_1 \cdot \rho_c) \cdot (1 - \kappa_1 \cdot \rho_\pi)},$$

Q.E.D.

2.8.2 Price-Dividend Ratio: pd

$$pd_t = B_0 + B_1 \cdot x_{c,t} + B_2 \cdot x_{\pi,t}$$

Proof:

$$1 = E_t[M_{t+1}R_{d,t+1}] = E_t[exp(\theta \cdot log\delta - \frac{\theta}{\psi} \cdot \Delta c_{t+1} + (\theta - 1) \cdot r_{c,t+1} + r_{d,t+1})]$$

where

$$r_{d,t+1} = \kappa_0^d + \kappa_1^d \cdot pd_{t+1} + \Delta d_{t+1} - pd_t$$

Let $B(\cdot) = \theta \cdot log\delta - \frac{\theta}{\psi} \cdot \Delta c_{t+1} + (\theta - 1) \cdot r_{c,t+1} + r_{d,t+1}$, we have

$$E[B(\cdot)] + \frac{1}{2}Var(B(\cdot)) = 0$$

By the educated guess,

$$pd_t = B_0 + B_1 \cdot x_{c,t} + B_2 \cdot x_{\pi,t}$$

Substitute the guess into $B(\cdot)$ and solve the equation:

$$B_1 = \frac{\phi - \frac{1}{\psi}}{1 - \kappa_1^d \cdot \rho_c}, \quad B_2 = \frac{\kappa_1^d \cdot (\phi - \frac{1}{\psi}) \cdot \rho_{c\pi}}{(1 - \kappa_1^d \cdot \rho_c) \cdot (1 - \kappa_1^d \cdot \rho_\pi)},$$

Q.E.D.

2.8.3 Returns: $\mathbf{r}_{d,t+1}$

$$r_{d,t+1} = E_t[r_{d,t+1}] + \kappa_1^d B_1 \sigma_{xc} \cdot \epsilon_{c,t+1} + \kappa_1^d B_2 \sigma_{x\pi} \cdot \epsilon_{\pi,t+1} + \sigma_d \cdot \eta_{d,t+1}$$

$$E_t[r_{d,t+1}] = C_0 + C_1 \cdot x_{c,t} + C_2 \cdot x_{\pi,t}$$

Proof:

$$r_{d,t+1} = \kappa_0^d + \kappa_1^d \cdot pd_{t+1} + \Delta d_{t+1} - pd_t$$

By previous proposition,

$$pd_t = B_0 + B_1 \cdot x_{c,t} + B_2 \cdot x_{\pi,t}$$

Submit it and we have

$$C_1 = \phi + (\kappa_1^d \rho_c - 1) B_1, \quad C_2 = \kappa_1^d \rho_{c\pi} B_1 + (\kappa_1^d \rho_\pi - 1) B_2$$

Q.E.D.

Chapter 3

The “In(de-)flated" Value Premium

Abstract: The value premium has disappeared over the last decade and this paper provides a risk-based explanation for its disappearance. I document a positive linear relationship among the value premium and the expected inflation at both high frequency and lower business cycle frequency. A heterogeneous cash flow model featuring inflation non-neutrality is proposed to justify the observed pattern. The estimated results suggest that value firms are more exposed to high-frequency fluctuations in aggregate consumption growth but less exposed to the low-frequency consumption risk. This finding is consistent with the documented inflation-return relationship but it contrasts with the previous findings suggesting that value firms are more sensitive to long-run consumption risk. Simulation-based results show that the positive linear relationship among the value premium and the expected inflation can be recovered when inflation is non-neutral and the relationship turns into uncorrelated when inflation is neutral. Therefore we argue that inflation non-neutrality can justify the positive relationship among inflation and value premium. Meanwhile, value firms tend to underperform growth firms when the inflation is in low range, and it leads to the disappearance of the value premium.

JEL classification: G10.

Keywords: Inflation non-neutrality; Long-run risk model; Value premium.

3.1 Introduction

The most early value premium is proposed by [Graham and Dodd, 1934]. First empirical evidence that value stocks on average outperform growth stocks based on book-to-market ratios are documented by [Stattman, 1980], [Rosenberg et al., 1985], and [Fama and French, 1992]. Then over these years new evidence keeps showing that the value is there. As I quote [Asness et al., 2015] "The existence of the value premium is a well-established empirical fact: it is evident in 87 years of U.S. equity data, in over 30 years of out-of-sample evidence from the original studies, in 40 other countries, in more than a dozen other asset classes*, and even dating back to Victorian age England!†" However, if we focus on sub-sample evidence, we find that the value premium has disappeared for the recent decade and the performance waves over time in the long history. The interesting question can always be asked: what does explain the long-lived component in the value premium and why does it disappear in some sub-sample. In this paper, we answer the question in a heterogeneous cash flow framework and provide a risk-based explanation for the value premium's disappearance.

Two empirical findings motivate this research at the first place. The first finding is that the fisher effect test at industry level suggest that nominal stock returns do not vary in one-to-one correspondence with inflation. Low book-to-market industry has more negative stock returns when inflation is high. A simple consumption-based decomposition suggests that the growth industries are more exposed to the expected consumption growth, which is a fact contrast to previous findings. The second one is that there exists a positive relationship among inflation and value premium. The higher value premium tends to coincide with period of high inflation. The positive relationship holds when the value premium is replaced by the value proxy

*see [Asness et al., 2013]

†see [Chabot et al., 2014] where the value factor is constructed from a monthly high-minus-low portfolio formed on dividend yield.

constructed from industry returns. Therefore, we have the industry returns that can well proxy the value premium in practice and we have the puzzling fact that the value firms are less exposed to long-run consumption risk. We try to rationalize the documented facts in one model to find the causal link behind the positive relationship among inflation and value premium and to answer the question where does the long-lived value component come from. By estimating the heterogeneous cash flow model where inflation non-neutrality is featured, we find the consistent evidence that value industries are less exposed to low-frequency fluctuation in the consumption growth than the value firms. The positive relationship among inflation and value premium is replicated when the model features the inflation non-neutrality and the relationship turns into uncorrelated when the inflation is neutral in the economy.

The paper is related to several literature and one major literature is how to justify the quantity of risk premium. [Asness et al., 2015] argues that no model of value is so compelling that a consensus exists for its explanation, especially when it comes to risk-based or behavioral-based theory. The other literature is to study the relationship among inflation and the economy where higher inflation could be bad news for the economy and asset prices in financial markets would reflect the risk.

We start from introducing the risk-based literature to show how value firms are compensated by higher risk exposures. There are many different explanations in resolving the value premium and here we can only briefly summarize several papers in each explanation. The first explanation is long-run consumption risk based. Long-run risk framework has been applied in explaining the cross-section of stock returns by [Bansal et al., 2005], [Kiku, 2006], and [Hansen et al., 2008]. [Bansal et al., 2005] show that co-variances among cash flow growth rates and past consumption growth help explain the value premium. High book-to-market portfolio's dividend growth rates demonstrate a close pro-cyclical movements with the smoothed consumption growth rates and thus the portfolio investors require higher risk premium. Similar pattern shown by [Hansen et al., 2008] is that the cash flow growth of portfolios of growth stocks has negligible co-variation with consumption in the long run whereas the cash flow growth of value portfolios has positive co-variation with consumption. [Kiku, 2006] developed a heterogeneous cash flow model based on [Bansal and Yaron, 2004]. She documented that value firms are more exposed to the long-run consumption growth and carry higher risk compensation. [Parker and Julliard, 2005] also show that contemporaneous consumption risk cannot explain the cross-section of average returns while the ultimate consumption risk (measured by the consumption growth cumulated over many quarters following the returns) can explain a large fraction of the variation. A closely related to the long-run consumption risk literature is the cash flow duration explanation for the value premium. Studies suggest that the shorter cash flow duration of the value firms can potentially account for the higher subsequent returns for value firms while growth firms have higher cash flow duration are less risky which account for the lower growth returns and the observed value premium. [Dechow et al., 2004] construct the equity duration measure and find that high-duration firms have lower returns. They argue that the Fama and French (1993) book-to-market factor can be interpreted as a noisy duration factor. In this literature, we specifically introduce the duration-based value premium model by [Lettau and Wachter, 2007, Lettau and Wachter, 2011] where the value firm is short-horizon equity, more exposed to short-run consumption risk and compensated in the economy while the growth firms is long-horizon equity, more exposed to un-priced preference shock which has no compensation. Hence a value premium is obtained by letting the value firms co-vary more with the short-run cash flows. [Da, 2009] developed a two-factor cash flow model to show that a long-run consumption based factor and a duration factor can explain 82% of the cross-section return variations. [Van Binsbergen et al., 2012] decompose the equity premium by using dividend strips data and find that short-duration dividends carry higher premium. [Croce et al., 2014] shows the downward equity term structure under bounded rationality in a long-run risk framework. When investors cannot distinguish the shock on persistent consumption growth, the required risk premium on the long-duration equity would be lower. [Marfe, 2015] introduce the labor-share as a risk-sharing channel and find that the labor-share can predict both the duration premium and the value premium, and the labor-share does not forecast the component of the value premium orthogonal to the duration premium. [Gormsen and Lazarus, 2019] propose a duration factor and the factor explains most of the cross-section of stock returns in both the U.S. and global sample. They document that firms that have higher expected returns also have a short cash-flow duration and lower cumulative future dividend growth. Therefore, empirical evidences are consistent with the argument that assets with shorter cash flow duration tend to have higher expected returns and firms in the value group tend to have a lower cash flow duration. For the operating leverage explanation, with the fixed costs of investment, assets in place are more riskier and value firms tend to have higher leverage and carry more premium (e.g. [Carlson et al., 2004], [Novy-Marx, 2010]). [Novy-Marx, 2010] documents that the value premium are from the intra-industry book-to-market differences which are mainly driven by the differences in operating leverage while the cross-industry differences in book-to-market ratios are driven by differences in the capital intensity of production and unrelated to value premium. Related to the operating leverage, another explanation focuses on firm's profitability. [Zhang, 2005] shows that value firms face higher adjustment costs by scaling down capital in bad times and growth firms face higher adjustment costs by expanding their capital in good times. The asymmetry of adjustment costs leads to the result that value firms are more riskier in bad times and the high book-to-market firms tend to have lower profitability. A similar mechanism proposed by [Cooper, 2006] shows that shock on the profitability decreases the market value and increases the book-to-market ratio, therefore value firms are riskier and investors are compensated more. Empirical evidence by [Novy-Marx, 2013] shows that the gross-profits-to-assets ratio has roughly the same power as the book-to-market ratio predicting the cross section of average returns. However, [Clementi and Palazzo, 2015] shows that though value firms command higher expected returns in the one-factor neoclassical investment model with mean-reverting idiosyncratic productivity, the premium is from the riskier cash flows accruing far in the future. They find that value premium becomes lower when large value firms divest capital facing the negative profitability shock.

Many researchers try to justify the value premium from different risk-based standpoints. However, a recent paper by [Golubov and Konstantinidi, 2018] casts doubts on several value premium theories including the operating leverage theory, the cash-flow duration theory, and the theory about investment specific technology risk. They decompose the book-to-market ratio into the book-to-“value" ratio and the “value"-to-market ratio, where the fitted “value" is an estimate of fundamental value based on industry valuations. Evidence suggests that most of the value premium are from the “value"-to-market ratio while the operating leverage, the cash-flow duration, and the exposure to investment specific technology shocks are related to the book-to-“value" ratios. They claim that the possible theories to justify the value premium could include expectation errors theory, limits to arbitrage theory, and certain types of cash flow risk and consumption risk exposure theory, where the market-to-“value" component plays a role. There are still other mixed evidence. e.g. [Chen and Zhao, 2009] document that the cash flow betas for value firms are not higher than the growth firms’ cash flow betas for most cases; [Chen, 2017] documented there exist look-back bias in first year cash flow growth which biases the cash flow duration estimation.

The other literature is the behavioral-based theory to explain the value premium. [Lakonishok et al., 1994] did not find that higher book-to-market firms and high cash-flow-to-price firms are riskier based on conventional notions of the systematic risk and they argue there are several behavioral and institutional reasons to justify it. They claimed unsophisticated investors may prefer “safer" firms with stable cash flows and perceive those firms as less risky while sophisticated institutional investors over-invested in glamour stocks and under-invested in value stocks.‡ LSV (1994) argued that investors may extrapolate firm’s past earning growth into the future. [Porta et al., 1997] examine the market reactions to the earnings growth to explore the role of market mis-pricing and find that the expectation errors made by investors can contribute to the value premium. Related papers including [De Bondt and Thaler, 1985] and [Daniel et al., 1998] explore that investors “over-react" to unexpected news and the mis-pricing contributes to the value premium by under-valuing the value stocks and over-valuing the growth stocks. [Golubov and Konstantinidi, 2018] shows investors are negatively surprised by the realization of fundamentals of growth firms and positively surprised by the news of value firms, which is consistent with the expectation errors theory. [Griffin and Lemmon, 2002] documents that firm with distress risk experience larger return reversals around earnings announcement, which suggests that more mis-pricing exists in the high distressed group. Other theory by [Golubov and Konstantinidi, 2018] shows that the value premium concentrates in stocks where arbitrages are constrained, the evidence is also documented by [Wang and Yu, 2014] where they find the risk-based theory can justify the value premium only in the low limits-to-arbitrage group and mispricing dominates in explaining the value premium in the high limits-to-arbitrage group. Moreover when [Weber, 2018] explores the duration explanation, he finds that the return predictability comes from stocks that are difficult to arbitrage especially in periods following high investor sentiment and the premium can also be attributed to the analysts’ forecast errors.

Our paper is also related to the inflation non-neutrality literature. It starts from

‡see [Lettau et al., 2018]’s recent evidence that even the “value" funds hold high proportion of low-book-to-market stocks.

testing whether the high inflation would be bad news for the economy and how asset returns would be related to inflation in a Fisherian (or Non-Fisherian) world. A long list in this literature includes [Modigliani and Cohn, 1979], [Boudoukh et al., 1994], [Fama, 1981], [Brandt and Wang, 2003], [Bekaert and Engstrom, 2010], [Wei, 2010], [Bansal and Shaliastovich, 2013], and [Eraker et al., 2015]. Previous papers document that there exists a negative relationship among returns and inflation. The first cross-sectional evidence at industry level is [Boudoukh et al., 1994]'s paper where they captures the cross-industry negative relations among inflation and stock returns. They propose a simple model to justify the documented negative relationship in short run and positive relationship in the long run. They study the relations in a Fisherian framework but did not attempt to argue the inflation neutrality or explore the relationship among inflation and real activities. The intuition behind their model is based on [Fama, 1981]'s “Proxy" argument as they claimed. In the original papers by Fama, he argues that the inflation is a proxy for future economic growth and high inflation is bad news for the future economy. However one drawback of the “Proxy" hypothesis is that it is a qualitative framework but does not provide a quantitative way to measure the effect of inflation on economy and financial markets. Later the inflation non-neutrality is introduced into the long-run risk framework where the role of inflation can be quantified at certain cases. [Bansal and Shaliastovich, 2013] extend the long-run risk framework of [Bansal and Yaron, 2004] by introducing the inflation non-neutrality to study the currency and bond markets. [Eraker et al., 2015] build up a two-good economy where high inflation is bad news for future consumption growth. They find the durable good sector is more affected by the high inflation than the non-durable sector. Our framework here is to feature the cash flow process at industry level where the inflation's effect on each industry can be evaluated and the relationship among inflation and returns can be replicated. By combining it to the value premium literature, we show that the positive relationship among value premium and inflation is driven by the inflation non-neutrality.

There are several advantages of our method to explore the data at industry level. One is that industry level proxy let us free from the concern of distress risk. Financial distress firms are more likely be classified as value firms in practice. Therefore the value premium could be driven by the distress risk ([Bhamra et al., 2018]) or driven by the behavioral concern for distress risk ([Lakonishok et al., 1994]). However, [Campbell et al., 2008] show that financial distressed firms can deliver lower returns but have higher loadings on the value factor than stocks with lower failure risk, which is inconsistent with the argument that value premium is the compensation for the financial distress risk. [Novy-Marx, 2013] proposes that the profitability has roughly same explanation power as book-to-market ratio in predicting the average stock returns. Profitable firms tend to have high average returns but tend to be less prone to be distressed, which puts doubts on the argument that value premium is associated with distress risk. Another contribution is that the measure is more easy to interpret and more stable and persistent than measures from sorting the book-to-market ratio in the whole universe of individual stocks. [Lev and Srivastava, 2019]'s paper shows that the length of stay in value or growth group is around 2.5 years at individual stock level. While value and growth group's compositions at industry level are much more stable in the last fifty years. [Golubov and Konstantinidi, 2018] also fitted the long-run industry "value" in the book-to-market decomposition. Among many other papers in the literature on industry-relative[§] market-to-book ratios are [Cohen and Polk, 1996], [Lewellen, 1999], [Asness, 2000], [Cohen et al., 2003], [Novy-Marx, 2010], and [Golubov and Konstantinidi, 2018]. Therefore our method provides a new perspective to understand the value premium using industry level book-to-market data in a long-run risk framework.

The rest of the paper is organized as follows. In the next section, we show

[§]see also [Houthakker, 1979], [Jarrett and Selody, 1982], among the earlier analysis on the negative relationship among inflation and growth at industry level.

that fisher effect does not hold at industry level and the positive relationship exists among value premium and inflation. A simple decomposition suggests that value industry should be less exposed to the expected consumption risk. Section 3 introduces the value proxy constructed from the industry returns and proxy tests are provided to show that value premium is well proxyed. In Section 4, we present the economic model with inflation non-neutrality to rationalize the documented facts. Heterogeneous cash flows processes are considered in the model to reflect the cross-industry dynamics. The model is Bayesian estimated and empirical patterns are recovered based on the simulated data. Long-run projections of value premium are shown in Section 5. Section 6 provides two additional robust test results, and Section 7 concludes the paper.

3.2 Empirical Results

In this section, we show the documented empirical findings that motivate our heterogeneous cash model in section 4. The first finding is that the fisher effect test at industry level suggests that nominal stock returns do not vary in one-to-one correspondence with inflation. Low book-to-market industry has more negative stock returns when the inflation is high. The second finding is that there exists a positive relationship among inflation and value premium. The higher value premium tends to coincide with period of high inflation and the several disappearances of value premium in history happen to coincide with the low inflation period.

For the Fisher effect test at industry level, we find that nominal stock returns do not vary in one-to-one correspondence with inflation. [Fisher, 1930] hypothesized that the nominal return can be decomposed into the real return and the expected inflation. If inflation is uncorrelated with the real return, we expect that nominal stock returns vary in one-to-one correspondence with inflation. Start from the most simple econometric framework where returns are regressed on the contemporaneous expected inflation.

$$E_t[ln(R_{t+1})] = \alpha_i + \beta_i \cdot E_t[\pi_{t+1}] + \epsilon^i_{t+1} \tag{3.1}$$

By Fisher hypothesis, the inflation β_i should be equal to one. However, evidence shows that β_i are less than 1 for all the cases and are negative for most cases, which is contrast to the convention that nominal returns should move one-to-one with the inflation. As shown in table 1, we run hypothesis tests whether $\beta = 1$ and the null hypothesis are rejected for most industries. For regressions that cannot reject null hypothesis $\beta = 1$, we find most of the industry have high book-to-market ratio in the long-run, e.g the usually conceived value industry like energy and utility. We proceed with the simple decomposition

$$E_t[ln(R_{t,t+1})] = E_t[\pi_{t.t+1}] + E_t[\Delta d_{t+1}] + E_t[(\Delta pd_{t+1})] \tag{3.2}$$

where expected nominal returns are represented by three components: the expected inflation, the expected dividend growth and the expected changes in price-dividend ratios. Therefore we can have inflation beta represented as following as first developed by [Boudoukh et al., 1994].

$$\begin{aligned}\beta &= \frac{cov(E_t[ln(R_{t,t+1})], E_t[\pi_{t,t+1}])}{var(E_t(\pi_{t,t+1}))} \\ &= \frac{cov(E_t[\pi_{t.t+1}] + E_t[\Delta d_{t+1}] + E_t[(\Delta pd_{t+1})], E_t[\pi_{t,t+1}])}{var(E_t(\pi_{t,t+1}))} \\ &= 1 + \frac{cov(E_t[\Delta d_{t+1}] + E_t[(\Delta pd_{t+1})], E_t[\pi_{t,t+1}])}{var(E_t(\pi_{t,t+1}))}\end{aligned} \tag{3.3}$$

Since the pd_{t+1} is highly persistent, we have the Δpd_{t+1} of small magnitudes at high frequency and further suppose that Δpd_{t+1} is not correlated to the current expected inflation (evidence later shows results are robust across the frequency). The above equation is reduced to the following equation

$$\beta = 1 + \frac{cov(E_t[\Delta d_{t+1}], E_t[\pi_{t,t+1}])}{var(E_t(\pi_{t,t+1}))} \tag{3.4}$$

Let $cov(E_t[\Delta d_{t+1}], E_t[\pi_{t,t+1}]) = \rho_{\Delta d,\pi}\sigma_{\Delta d}\sigma_\pi$, we have β represented as

$$\beta = 1 + \rho_{\Delta d,\pi}\frac{\sigma_{\Delta d}}{\sigma_\pi} \tag{3.5}$$

where $\rho_{\Delta d,\pi}$ is the correlation among inflation and dividend growth, $\sigma_{\Delta d}$ is the standard deviation of dividend growth, and σ_π is the standard deviation of expected inflation. The magnitudes of β less than one can be justified by the negative correlations $\rho_{\Delta d,\pi}$ among dividend growth and expected inflation and the higher the variation ratio $\frac{\sigma_{\Delta d}}{\sigma_\pi}$, the lower the inflation beta β.

We motivate our paper by first showing that the nominal stock returns do not move one-to-one with the inflation in the economy. Cross-section evidence suggests that the Fisher model is rejected for both post 1926 sample and post 1968 sample as shown in table 1. For most industries, the inflation betas are negative and the growth firms tend to have the most negative inflation betas than value firms. We find that all industries have the negative inflation betas except one industry labeled as *"other"*. Moreover, for cases that cannot reject $\beta = 1$, most of them are industries with high book-to-market ratios, like the energy industry. The evidence is robust by using equally weighted returns or value-weighted returns.

We intend to quantify the observed patterns by relating the economy to the financial market. By taking one step further, we try to relate the individual cash flow growth to the aggregate consumption growth in the economy. We extend the previous equation in a consumption based asset pricing framework. For example, we assume the firm's cash flow is linear with the aggregate consumption growth in the economy, a setting consistent with the long-run risk framework and variously applied in many papers.

$$E_t[\Delta d_{i,t+1}] = \phi_i E_t[\Delta c_{t+1}] \tag{3.6}$$

where ϕ_i is the consumption leverage (or long-run consumption risk exposure) for each individual stock. By substitution, we have the consumption-based measure of β_i as

$$\beta_i = 1 + \phi_i \cdot \rho_{\Delta c,\pi} \frac{\sigma_{\Delta c}}{\sigma_\pi} \tag{3.7}$$

By construction, we introduce the cash flow heterogeneity into the model and we relate the firm fundamental to the aggregate economy. In the above equation, β_i

for each stock will be determined by two variables: the first one is the correlation among inflation and aggregate consumption growth $\rho_{\Delta c,\pi}$ and the second one is the long-run leverage ϕ_i. The negative $\rho_{\Delta c,\pi}$ will make the magnitudes of β_i less than one and the negative signs of $\rho_{\Delta c,\pi}$ are also consistent with the inflation non-neutrality documented by various papers. The ϕ_i will reflect how the stock is loaded on the consumption growth in the economy and will determine magnitudes of β_i for each individual.

[Insert Table 3.1 near here]

To test the positive relationship among inflation and value premium, in a simplified setting, letting the ϕ_v be the long-run leverage of value firms and letting the ϕ_g be the long-run exposure of growth firms, we have the following equation holds:

$$E_t[r_v - r_g] = (\phi_v - \phi_g) \cdot \rho_{\Delta c,\pi} \frac{\sigma_{\Delta c}}{\sigma_\pi} \cdot E_t[\pi_{t+1}] \tag{3.8}$$

The equation suggests that there exists a linear relationship among expected inflation and value premium. For example, high inflation in the economy should correspond to high value premium if $(\phi_v - \phi_g) \cdot \rho_{\Delta c,\pi}$ is positive.

We first provide the evidence on correlations among inflation and value premium at different time frequency. As suggested by table 2, correlations are always positive and increase with the time frequency. The correlation increases to 0.653 at ten-year frequency in full sample period and increases to 0.734 at ten-year frequency in post 1968 period, which suggests that inflation becomes more correlated with value premium in the long run.

[Insert Table 3.2 near here]

To better show the relationship, we regress the value premium on the inflation at multiple frequency and results are reported in table 3. We find that betas are significantly positive and consistent with our linear relationship argument. The magnitudes of betas are 0.87 at 10 year frequency in full sample period and 0.90 at 10 year frequency in post 1968 period. The R^2 also increase with horizons and reach 43% and 57% for the two samples respectively. By zooming in the statistics at each decade shown in table 4, we can find that the value premium actually waves across the decades and have disappeared in 1990s and in 2010s, meanwhile high inflation periods coincide with high value premium periods in 1940s, 1970s and 1980s.[¶] The more intuitive way to show the pattern is to see how the inflation and *hml* premium share the slow-moving trend as in figure 1. We find the correlation is equal to 0.653 at ten year frequency.

The positive correlations among value premium and inflation shown in table 3 suggest that $(\phi_v - \phi_g) \cdot \rho_{\Delta c,\pi}$ should be positive. The $\rho_{\Delta c,\pi}$ is negative due to inflation non-neutrality, therefore we should have the following relationship holds

$$\phi_v - \phi_g < 0$$

It suggests that the long-run leverage of value firms should be less than the growth firms. By the conventional wisdom, growth firms should be firms with higher growth rates and therefore the leverage ϕ_g on the consumption growth should be higher than the long-run leverage ϕ_v of value firms. The relationship is also consistent with [Lettau and Wachter, 2007]'s argument that growth firms are more exposed to long-run consumption risk. However this result is contrast to previous findings obtained from the long-run risk framework by [Kiku, 2006]. She studies the value premium in a long-run risk framework and argues that the value premium exists because value firms have larger long run exposure to the consumption growth

[¶][Kok et al., 2017] document that the value premium is insignificant from zero in sample period from 1926 to 1962 and sample period from 2002 to 2015. [Lev and Srivastava, 2019] document the value loses its edge since 2007 and they claimed the google search “death of value investing" and related terms yields hundreds of articles, including in Forbes, Barrons, The Wall Street Journal, Bloomberg, Financial Times, and The Economist.

in the economy.

[Insert Table 3.3 near here]

Therefore, our main focus here is to rationalize the documented facts in a asset pricing framework to show: value firms are less exposed to the consumption growth and the positive relationship among the value premium and inflation can be justified. We are also interested in explaining the persistent component of the value premium in a more clear and economic way. A risk-based theory is proposed in section 4 where the model is estimated based on real data and the estimated model implied results help us to justify the value premium and the positive relationship among value and inflation.

[Insert Table 3.4 near here]

[Insert Figure 3.1 near here]

3.3 Value Proxy

In the second empirical finding, we find that there exists a positive relationship among inflation and value premium. The higher value premium tends to coincide with period of high inflation. Further evidence shows that the positive relationship holds when the value premium is replaced by the value proxy constructed from industry returns. Therefore, we have the industry returns that can well proxy the value premium in practice.

Previous papers choose the value/growth portfolio dynamic balanced at monthly frequency. The dynamic balanced way can reproduce the value premium but there are no economic meaning behind since the composition of each portfolio keep changing. Since we need to reproduce the value premium in our later model and therefore in the empirical evidence we need to show that the value proxy constructed at industry level can well fit the value premium constructed from all stock universe. We find the value premium can be proxy-ed by the industry-level returns and later evidence shows that the value proxy capture all inflation related risk embedded inside the value premium. By sorting the average book-to-market ratio of each industry, we construct six proxy for the value premium and find that the value premium is highly correlated with the proxy and it shares the same inflation risk property with the proxy.

By sorting each industry's long-run book-to-market ratio, we construct each proxy by taking the difference of high book-to-market (value) returns and low book-to-market (growth) returns. For example, proxy3 ($rep3$) is constructed as average returns of three industries in the most high book-to-market ratios group minus average returns of three industries in the most low book-to-market ratios group. Firms are classified into 12 industry as Fama-French suggested way and thus total six proxy are constructed here.

[Insert Figure 3.2 near here]

We present the evolving pattern of value premium and all six value proxy from 1968 in figure 2. The striking evidence suggest that the value premium can be well replicated by the industry proxy. Table 5 shows that the value premium are highly correlated with the proxy and correlations are robust both from high frequency - monthly - to very low business cycle frequency - ten years and the relationship holds across all six value proxy. [Lakonishok et al., 1994] argue that the value premium may not persist in the long run therefore we provide the detailed analysis from high frequency to the very low frequency to show a more complete picture.

[Insert Table 3.5 near here]

We next proceed to see the relationship among each proxy and inflation. We expect the value proxy can well reflect the inflation risk same as the original value premium. Magnitudes of inflation betas and the in-sample R-squares in the proxy regressions are close to the corresponding ones in the original value premium regressions. The inflation betas are significantly positive in most proxy regressions and magnitudes of inflation betas are close especially at frequency lower than 10 years.

[Insert Table 3.6 near here]

To further validate the proxy, we construct a simple tests to see that most of the inflation-related variations in value premium are explained by the proxy based on variance decomposition point-view. Suppose the value proxy captures all the inflation related variance and the unexplained part is inflation irrelevant. Suppose the value premium is a function of value proxy $hml = f(proxy)$, then we have following relationship holds:

$$hml = f(\widehat{proxy}) + \widehat{\epsilon} \tag{3.9}$$

Where $\widehat{\epsilon}$ is the residual for fitted regressions and the residuals are supposed to be uncorrelated to the inflation. We conduct the test in two steps by fitting the regression in the first step and testing the non-correlations in the second step. We show that the value proxy can significantly fit the value premium in a linear relationship in the first stage. In the second stage, we regress the fitted residuals obtained from the first stage on the inflation.

$$\widehat{\epsilon} = \beta_{inf} \cdot Inflation + \eta \tag{3.10}$$

If the inflation risk is well captured by the value proxy, then we expect the β_{inf} estimated in second stage regressions should be indifferent from zero. As shown in table 7, the first stage results suggest that the proxy can significantly fit the value premium across all six constructions. The betas are increasing with the frequency and are insignificantly from one at lower frequencies from year three to year ten. Meanwhile the explained R-squares increase with frequency and range from 34% to 68% at five year frequency and from 30% to 71% at ten year frequency. With the fitted regressions, we can prepare the residuals and test the relationship among residuals and the inflation in the second stage. By the theoretical construction, the residuals should be non-correlated to the inflation. Therefore we expect the betas are insignificantly from zero and the explained R-squares should be lower compared to the R-squares obtained by simply regress value premium on inflation. The second stage results in table 7 suggest that the inflation are uncorrelated to the residuals across six specifications and across multiple frequencies except at the ten-year frequency. For frequency from one quarter to three years, the magnitudes of betas and the R-squares are almost equal to zeros. For frequency at one month and at five year, magnitudes of betas decrease and the R-squares reduce sharply compared to the original R-squares. By passing the test, we show that the proxy constructed from industry returns can robustly replicate the value premium at both high frequency and at low frequency.

[Insert Table 3.7 near here]

3.4 Model

In this section, we build up the heterogeneous cash flow model to rationalize the documented empirical facts. We argue the inflation non-neutrality leads to the causality behind the positive relationship among inflation and value premium. Moreover we try to provide a risk-based explanation to answer the question where does the long-lived value component come from. By estimating the heterogeneous cash flow model where inflation non-neutrality is featured, we find the consistent evidence that value industries are less exposed to low-frequency fluctuations in the consumption growth than the value firms. The positive relationship among inflation and value premium is replicated when the model features the inflation non-neutrality and the relationship turns into uncorrelated when the inflation is neutral in the economy. Variance decomposition and impulse response figures are consistent with our argument and results are shown in the last subsection.

3.4.1 Economic Dynamics

We build on the long-run risk setup of [Bansal and Shaliastovich, 2013] and [Schorfheide et al., 2018]. The initial economic dynamics only include the consumption growth and inflation while here we include the heterogeneous dividend growth process at industry level. We estimate the model to match the consumption, dividend and inflation process by Bayesian MCMC. The economic dynamics are joined by z_t and x_t process.

$$z_{t+1} = \mu + \Phi x_t + S_z \eta_{t+1} \tag{3.11}$$

$$x_{t+1} = \Pi x_t + S_x \epsilon_{t+1} \tag{3.12}$$

where $z_t = [\Delta c_t, \Delta d_{i,t}, \pi_t]$ are consumption growth, dividend growth and inflation process, $x_t = [x_{c,t}, x_{\pi,t}]$ are the long-run components of expected consumption growth and expected inflation.

$$\Phi = \begin{bmatrix} 1 & 0 \\ \phi_i & 0 \\ 0 & 1 \end{bmatrix}, \quad \Pi = \begin{bmatrix} \rho_c & \rho_{c\pi} \\ 0 & \rho_\pi \end{bmatrix}$$

In z_t process, ϕ_i captures the dividend leverage at industry level. In x_t process, ρ_c and ρ_π represent the persistence the long-run component process and $\rho_{c\pi}$ measures the non-neutrality of inflation which is negative to dampen the consumption growth.

$$S_z = \begin{bmatrix} \sigma & 0 & 0 \\ 0 & \varphi_{d,i}\sigma & 0 \\ 0 & 0 & \varphi_\pi \sigma \end{bmatrix}, \quad S_x = \begin{bmatrix} \sigma_{xc} & 0 \\ 0 & \sigma_{x\pi} \end{bmatrix}$$

η_{t+1} and ϵ_{t+1} represent the normal distributed shocks and S_z and S_x capture the time variation in the uncertainty about expected consumption growth and expected inflation. S_x is diagonal matrix. Later we allow the short-run consumption shock η_c to be correlated with the dividend growth shock η_d and $\alpha_i = corr(\eta_c, \eta_{d,i})$.

In the economy, the representative agent has the Epstein and Zin (1989) preferences defined over the consumption bundle C_t:

$$U_t = [(1-\delta)C_t^{1-\frac{1}{\psi}} + \delta(E_t[U_{t+1}^{1-\gamma}])^{\frac{1-\frac{1}{\psi}}{1-\gamma}}]^{\frac{1}{1-\frac{1}{\psi}}}$$

Therefore the IMRS (Inter-temporal Marginal Rate of Substitution) for this economy is given by

$$m_{t+1} = \theta \cdot log\delta - \frac{\theta}{\psi} \cdot \Delta c_{t+1} + (\theta - 1) \cdot r_{c,t+1}, \quad \theta = \frac{1-\gamma}{1-\frac{1}{\psi}} \tag{3.13}$$

We also have consumption return and stock returns as

$$r_{c,t+1} = \kappa_{c,0} + \kappa_{c,1} \cdot pc_{t+1} + \Delta c_{t+1} - pc_t$$

$$r_{d,t+1} = \kappa_{d,0} + \kappa_{d,1} \cdot pd_{t+1} + \Delta d_{t+1} - pd_t$$

The stock will be priced in the economy as

$$E_t[r_{d,t+1} - r_f] + \frac{\sigma^2}{2} = -cov_t(m_{t+1}, r_{d,t+1}) \tag{3.14}$$

For the analytical expressions of the pricing kernel, we present it by showing the difference of the realized and conditional stochastic discount factor on the left hand side and the economic shocks on the right hand side. There are three economic shocks priced in the economy and each of them is compensated.

$$m_{t+1} - E_t[m_{t+1}] = -\lambda_c \sigma \eta_c - \lambda_{xc} \sigma_{xc} \epsilon_{xc,t+1} - \lambda_{x\pi} \sigma_{x\pi} \epsilon_{x\pi,t+1} \tag{3.15}$$

where λ_c, λ_{xc} and $\lambda_{x\pi}$ are market price of risk for short-run consumption risk, expected consumption risk and expected inflation risk. The market price of short-run inflation is zero and we do not include it here. The short-run consumption risk is positively compensated ($\lambda_c > 0$) and the expected consumption risk is also positively compensated due to early resolution of uncertainty ($\lambda_{xc} > 0$). The market price of expected inflation risk is negatively compensated ($\lambda_{x\pi} < 0$) if the inflation is non-neutral ($\rho_{x\pi} < 0$) and high expected inflation leads to lower consumption growth.

By solving the model, we have the analytic solutions for the equity premium as

$$\begin{aligned} E_t[r_{d,t+1} - r_f] + \frac{\sigma^2}{2} &= B_1 + B_2 + B_3 \\ &= \beta_c \lambda_c \sigma^2 + \beta_{xc} \lambda_{xc} \sigma_{xc}^2 + \beta_{x\pi} \lambda_{x\pi} \sigma_{x\pi}^2 \end{aligned} \tag{3.16}$$

We represent the expected stock returns by three components with each corresponding to one risk source in the economy. B_1 corresponds to the short-run consumption risk, B_2 corresponds to the expected consumption risk, and B_3 corresponds to the expected inflation risk.

$$B_1 = \beta_c \lambda_c \sigma^2 = \varphi \alpha \gamma \sigma^2; \quad B_2 = \beta_{xc} \lambda_{xc} \sigma_{xc}^2 = (\phi - \frac{1}{\psi})(\gamma - \frac{1}{\psi}) \frac{1}{\frac{1}{\kappa_{c,1}} - \rho_c} \frac{1}{\frac{1}{\kappa_{d,1}} - \rho_c} \sigma_{xc}^2;$$

$$B_3 = \beta_{x\pi} \lambda_{x\pi} \sigma_{x\pi}^2 = (\phi - \frac{1}{\psi})(\gamma - \frac{1}{\psi}) \frac{1}{\frac{1}{\kappa_{c,1}} - \rho_c} \frac{1}{\frac{1}{\kappa_{d,1}} - \rho_c} \frac{1}{\frac{1}{\kappa_{c,1}} - \rho_\pi} \frac{1}{\frac{1}{\kappa_{d,1}} - \rho_\pi} \rho_{c\pi}^2 \sigma_{x\pi}^2;$$

For short-run consumption risk compensation, the sign of B_1 is determined by the short-run correlations $\alpha_i = corr(\eta_c, \eta_{d,i})$. If the short-run consumption growth is positively correlated with the firm's cash flow, then holding the stock would be compensated. If α is negative, the firm provides a hedge against the short-run consumption risk and β_c should be negative. For both expected consumption risk compensation and expected inflation risk compensation, signs are positive as along as the leverage factor $\phi > \frac{1}{\psi}$ which suggests that investor's high exposures to the long-run risk should be compensated.

3.4.2 Estimation

We jointly estimate the economic dynamics: consumption growth, dividend growth of all industries and the inflation. In the model, we calibrate preference parameters as: the risk aversion γ is calibrated to 10 (see [Bansal and Yaron, 2004] among others); the inter-temporal elasticity of substitution ψ is set to 1.5, usual in the long-run risk literature; the household's subjective discount rate δ is set to 0.993 at monthly frequency. Here we use the one-year ahead forecast to proxy the expected consumption growth in the economy as [Bansal and Shaliastovich, 2013]. The expected inflation data is the SPF inflation data. We use the median earnings growth forecast as the proxy for each industry's cash flow growth. The rest of the parameters are jointly estimated by Bayesian MCMC using the quarterly observation on consumption growth rates, cash flow rates, and inflation spanning from 1968Q1 to 2018Q4. We report all parameters including the macroeconomic estimates and the long-run leverage factor ϕ_i estimate for each industry, as shown in the following table 8.

In the main context, three models with different specifications are estimated: inflation neutrality ($\rho_{c\pi} = 0$) case with short-run consumption correlations ($\alpha \neq 0$), inflation non-neutrality ($\rho_{c\pi} \neq 0$) case without short-run consumption correlations ($\alpha = 0$), and the benchmark specification - inflation non-neutrality ($\rho_{c\pi} \neq 0$) case with short-run consumption correlations ($\alpha \neq 0$).

In the benchmark case, the ρ_π is equal to 0.921 and the scale of σ_π is relatively smaller than the consumption volatility σ. Results suggest that the expected inflation is very persistent and of lower variations. The estimated $\rho_{c\pi}$ is equal to -0.048 and 90% intervals also suggest that $\rho_{c\pi}$ is significantly negative. Evidence suggests that the inflation has negative and non-neutral effect on the consumption growth which is consistent with the argument by [Bansal and Shaliastovich, 2013]. Compared to the case with inflation neutrality, we find the ρ_c increases from 0.927 to 0.985 while ρ_π decreases from 0.921 to 0.896. The consumption growth becomes more persistent in the inflation neutral economy and more risk compensation comes from the expected consumption growth by construction.

[Insert Table 3.8 near here]

For the long-run exposures to the expected consumption risk, we find industries with high average book-to-market ratios are less exposed to the expected consumption risk. The estimated leverages are quite close in cases with or without inflation non-neutrality as suggested by figure 3. All three estimations suggest that there exists a negative relationship among the book-to-market ratios BM and the long-run leverages ϕ_i. More specifically, the fitted lines are stable after controlling the short-run consumption correlations. The finding shows growth industry has higher expected growth rates in the economy as suggested with conventional wisdom. It is also consistent with the duration argument that growth firms have longer cash flow duration than the value firms and the future cash flows of growth firms are more exposed to the long-run consumption risk. [Gormsen and Lazarus, 2019] propose a duration factor and document that firms that have lower expected returns also have a long cash-flow duration and higher cumulative dividend growth. Moreover, results here are also consistent with findings estimated from the unexpected news term. [Chen and Zhao, 2009] estimate the CF news and DR news contained in returns and document that value stocks do not have higher cash flow betas for most cases. However, directly use the value portfolio and growth portfolio data to estimate the long run risk model and contrasting results might be documented, e.g. [Kiku, 2006] documented that the value portfolios are more exposed to the long-run risk and have higher leverage on the expected consumption risk (low-frequency fluctuations). She justifies the documented facts by the growth option theory which is value firms are more mature and well-established thus exposed to long-run risk. One advantage of our method is that our proxy for the value premium can be easily constructed and has stable and clear compositions over the past century (industry in the value group minus industry in the growth group). One possible drawback of sorting method at individual firm level is that firm compositions in value portfolio and growth portfolio may keep changing with higher possibility while the pattern at industry level is more stable and robust.

[Insert Figure 3.3 near here]

For the short-run consumption correlations α, we find that high book-to-market industry's short-run cash flows tend to less correlated with the short-run consumption growth, e.g. the utility industry. Industry with the lower book-to-market ratio tends to have negative correlations among the short-run cash flows and consumption growth, e.g. the health industry can provide a hedge against the short-run consumption risk. Figure 4 shows the estimated correlations in two specifications and the linear relationship holds in both cases. Two fitted lines suggest that the short-run correlations estimation is less affected by introducing the inflation non-neutrality. In our later simulation, the fitted short-run correlations of each industry would be used in the benchmark model. However the replication results would be robust in cases adopting the raw correlations or adopting the fitted correlations.

[Insert Figure 3.4 near here]

3.4.3 Model Simulation Results

Our simulation is based on parameters estimated in both the benchmark specification and the inflation neutral specification. All parameters are reported in table 8. The estimated benchmark model can reproduce patterns we documented based on real data.

[Insert Table 3.9 near here]

The first test is the fisher effect test at industry level. Our results provide solid evidence that the inflation beta less than one is due to the inflation non-neutrality. The inflation betas are significantly less than one except the utility industry in the benchmark specification while betas are close to one in the inflation neutral specification as shown in table 9. This suggests that the negative relationship among inflation and stock returns are not just statistical correlations but are due to the causal effects of inflation. The estimated model here shows that the inflation beta should be equal to one if inflation is neutral. The documented evidence supports that inflation non-neutrality should be considered in the asset pricing model. By our knowledge, it is the first replication of the inflation-return pattern from an estimated asset pricing model.

Further evidence in figure 5 also suggests our heterogeneous cash flow model is well estimated and can reproduce the documented pattern. As we shown previously, the inflation betas are less than one and magnitudes are determined by the long-run leverage ϕ_i on the expected consumption risk - $\beta_i = 1 + \phi_i \cdot \rho_{\Delta c,\pi} \frac{\sigma_{\Delta c}}{\sigma_\pi}$.

Letting $\rho_{\Delta c,\pi} \frac{\sigma_{\Delta c}}{\sigma_\pi} = -c$ where c is a positive constant and rearrange the equation, we have

$$(1 - \beta_i) = c * \phi_i \tag{3.17}$$

By construction, the adjusted inflation beta $(1 - \beta_i)$ is linear in the the long-run leverage ϕ_i. Figure 5 suggests the linear relationship can be applied among the adjusted inflation beta $(1 - \beta_i)$ and the long-run leverage ϕ_i, and furthermore, the two series' correlation is as high as 0.714.

[Insert Figure 3.5 near here]

In table 10, we show that the significantly positive relationship among value premium and inflation is due to the inflation non-neutrality. In case 1, the inflation betas are positive while the inflation betas are around zero in case 2. It suggests that inflation non-neutrality is the driving force of this positive relationship. When high inflation is bad news for the consumption growth, the high value premium would be documented as suggested by results in case 1 and case 2.

[Insert Table 3.10 near here]

3.4.4 Variance Decomposition

We propose the variance decomposition to evaluate the contribution from each risk sources. The framework is based on the equilibrium solutions in the benchmark model. Suppose there exists value and growth two group in the economy, then taking the difference we have the proxy-ed value premium. We compare contributions from the short-run consumption risk, the expected consumption risk and the expected inflation risk sources, and results are reported in table 11. Table 11 reports the benchmark results in case (1) and six other decomposition results under different specifications. We find that inflation contributes to 21.2% to the value proxy in the benchmark case and the inflation's contribution compared to the long-run consumption risk contribution is relative stable, which is consistent with the previous documented empirical evidence. For example, suppose the 1% increase in inflation corresponds to 1% increase in the value premium and the standard deviations for inflation and value premiums are 3.5% and 8.0% respectively, then the variance decomposition suggests $19.1\% = (\frac{3.5\%}{8.0\%})^2$ variance of the value premium are contributed from the inflation. We also compare results for changes in long-run risk exposures (case (2) and (3)), change in short-run correlations (case (4)), changes in long-run risk persistence (case (5) and (6)), and change in the inflation non-neutrality (case (7)). The contribution from the inflation is stable unless the persistence of expected inflation ratio (ρ_π) or the relationship among inflation and expected consumption ($\rho_{c\pi}$) changes.

$$E_t[r_v - r_g] = D_1 + D_2 + D_3 \tag{3.18}$$

where

$$\text{SR consumption risk:} \quad D_1 = (\varphi_v \alpha_v - \varphi_g \alpha_g)\gamma\sigma^2$$

$$\text{LR consumption risk:} \quad D_2 = (\phi_v - \phi_g)(\gamma - \frac{1}{\psi})\frac{1}{\frac{1}{\kappa_{c,1}} - \rho_c}\frac{1}{\frac{1}{\kappa_{d,1}} - \rho_c}\sigma_{xc}^2$$

$$\text{LR inflation risk:} \quad D_3 = (\phi_v - \phi_g)(\gamma - \frac{1}{\psi})\frac{1}{\frac{1}{\kappa_{c,1}} - \rho_c}\frac{1}{\frac{1}{\kappa_{d,1}} - \rho_c}\frac{1}{\frac{1}{\kappa_{c,1}} - \rho_\pi}\frac{1}{\frac{1}{\kappa_{d,1}} - \rho_\pi}\rho_{c\pi}^2\sigma_{x\pi}^2$$

[Insert Table 3.11 near here]

For example, in case (6), the inflation contributes to 49.6% of the total premium's variation and accounts for 79.4% of variation from the expected consumption risk if inflation's persistence increases from 0.92 to 0.97. It suggests the inflation risk effect become more severe when inflation becomes more persistent. Similar results are documented if we change the relationship among the expected consumption risk and the expected inflation. In case (7), we increase the magnitude of $\rho_{c\pi}$ from 0.048 to 0.096 and the inflation contribution ratio increases from 21.2% to 51.8%. It suggests that the inflation plays more important role in value premium when inflation has more negative effect on the long-term economic growth.

3.4.5 Model Implications

Besides the variance decomposition, we provide the impulse responses analysis for each risk source. We find consistent results that value premium more corresponds to the expected consumption risk and expected inflation risk. When there is a negative shock on the expected inflation, it would be good news for the consumption growth, and growth firms would benefit more due to higher leverage to the expected consumption growth which leads to the decrease in value premium. While there is a positive shock on the expected consumption growth, value firms benefit less than the growth firms which also leads to the drop in value premium. Comparing there risk sources, we find that only the shock on the expected inflation leads to the drop of both inflation and value premium at the same time, and causes the co-movement among inflation and value premium.

[Insert Figure 3.6 near here]

3.5 Long-Run Projections of Value Premium

In this section, we first document the co-integrated relationship between value factor and inflation by running a co-integration test in a two-variate VAR system. Then we project the long-run value premium using the long-run inflation forecast data and the estimated equations.

[Insert Table 3.12 near here]

In equilibrium, value premium and inflation are co-integrated because inflation is a proxy for future economy growth and this information is priced in the value premium. Equilibrium relationship from both post 1968 sample and full sample suggest that high inflation is corresponding to high value premium in equilibrium. We also find that the co-integration relationship is a strong predictor of value premium change across different sample specifications but are not significant in predicting changes in future inflation. Later we use the estimated co-integration system to project the long-run value premium based on the inflation forecasts and results are shown in figure 3.7.

[Insert Figure 3.7 near here]

We provide three projections based on different inflation projections. Black line is the projection based on long-run inflation forecast released by OECD and the spanning horizon is from 2019 to 2060; gray line is the projection based on long-run inflation rates at constant 8% and light gray line is the projection based on inflation rates simulated from a normal process with 8% mean and 3% standard deviation. We find that the long-run projected value premium would keep to be at low level based on the OECD inflation forecasts unless we have inflation move back to higher level as the counterfactual simulations suggest. The average value premium would be at 1.67% for the period 2019-2060 as pointed out by the benchmark simulation.

3.6 Additional Results

3.6.1 Value and Growth Portfolio Data

In this section, we provide results when value and growth portfolio data are used in the estimation. In the model, there are three cash flow processes from value, neutral, and growth portfolio. The three portfolios are constructed at monthly basis as in Fama and French (1993), using data from CRSP/Compustat Merged Database. We construct the value, neutral, and growth portfolio as top 30%, middle 40%, and bottom 30% firms based on the book-to-market ratio. The dividend growth are constructed from the value-weighted method. The estimation results are reported in table 3.13 for sample from 1950 to 2018 at annual frequency. The results are similar if we use the sample from 1926 to 2018.

[Insert Table 3.13 near here]

We find that value portfolio is more exposed to the long-run expected consumption growth as documented by Kiku (2006). However, the positive correlation among inflation and the value premium is gone under this estimation. As shown in table 3.14, high inflation would correspond to lower value premium because value firms underperform growth firms when inflation is high. The consistent result is that the correlation is near zero when inflation is neutral in the economy.

[Insert Table 3.14 near here]

Why would results be different at portfolio level? Our explanation is that we use the realised dividend growth for each portfolio rather than expected (or forecast) dividend growth. The average realised dividend growth is 11.9% for value portfolio and 5.6% for growth portfolio. Based on the realised dividend growth, the value portfolio seems to have high growth rates while the growth portfolio has lower growth rates. Growth portfolio is supposed to have higher growth rates and we also expect higher forecast-ed dividend growth for growth portfolio. If we can construct dividend growth forecast data at portfolio level, we can estimate the economic dynamics and have similar patterns as documented in our previous benchmark case. However, we do not have dividend forecast for each stock in CRSP/Compustat Merged Database and we do not know whether the same stock would remain in the value/growth portfolio in next month or not. Therefore, it is impractical to have forecast dividend growth at portfolio level. At industry level, we have the forecast cash flow growth and high market-to-book industry tends to have higher growth rates forecast. Therefore, we choose to conduct analysis at industry level in this paper.

3.6.2 Post 1926 Data

Firm characteristics data and the earnings forecast data are available after the 1968 and we choose the post 1968 period data to estimate our benchmark model to reproduce the documented patterns. However, for robust check, we provide the evidence based on the full sample which spans from 1926m7 to the most recent day. The full sample evidence suggests that the constructed proxy can still proxy the value premium at higher frequency within three years. The correlation table suggests the value premium and the proxy are highly correlated across different frequency and across six proxy. In table 13, we regress the value proxy on inflation and find that the pattern that high inflation corresponds to high value premium still holds at higher frequency within three years. For frequency lower than three years, both the explanation power and magnitudes of inflation betas decrease.

[Insert Table 3.15 near here]

[Insert Table 3.16 near here]

We move to the proxy test in table 14. First stage results suggest that the value proxy can significantly fit the value premium and magnitudes of betas increase with frequency and are close to one in lower frequency. In the second stage, we find that magnitudes of betas are positive but insignificant at higher frequency within three years. At lower frequency, betas become significantly positive, which suggest that the residuals still contain inflation risk premium and the constructed value proxy can not well proxy the value premium at five year and ten year horizons.

There are several explanations to justify that the value proxy behaves relatively worse in the full sample than in the post 1968 sample. One explanation is that the proxy is constructed based on nearly one hundred year's book-to-market ranking. There is part of inflation variations are related to the short-run changes in valuation ratios (e.g. industry compositions in the value or growth group could change in short run). At higher frequency the constructed value proxy can fit the value premium. But at lower frequency (e.g. ten years), the noise part would accumulate and make the proxy fail in the long run. The second explanation is that there exists the book value mis-measurement. The book-to-market ratios for industries are quite volatile in the pre-1950 period, which might bias the way of constructing proxy. The accounting standards for the book value evaluation also changes during the long-run, e.g. details on how to state the intangibles or tangible assets‖. The third explanation is that the proxy is constructed by ranking the industry's book-to-market ratio in the nearly one hundred years while the value-growth pattern may have changed. It could be due to technology innovations at heterogeneous speed, changes in industry structure (e.g. input-output network) or it could be due to changes in macro environment (e.g. government industry policy, wars). All those factors can lead the value proxy to fail at the lower frequency over the nearly one-hundred years.

Therefore we show that our value proxy can well proxy the value premium in the post 1968 sample and it can still proxy the value premium at higher frequency within three years in the post 1926 sample.

[Insert Table 3.17 near here]

3.7 Conclusion

In the data, we document that the high value premium corresponds to high inflation and the value premium disappeared during the low inflation period. Is this pattern just a coincidence or is there a causal link behind? We answer this question by first showing that there exists a heterogeneous relationship among industry stock returns and inflation. Growth industries are more exposed to the inflation risk and value premium can be obtained by holding a long position in the value industry and a short position in the growth industry. Then we bring the data to the long-run risk model featuring both inflation non-neutrality and heterogeneous cash flows. The estimated results suggest that value firms are more exposed to high-frequency fluctuations in aggregate consumption growth but less exposed to the low-frequency consumption

‖see [Lev and Srivastava, 2019] in explaining how accounting standards may introduce the mismeasurement into the book value.

risk, a finding consistent with the documented inflation-return relationship but in contrast to previous papers.

The positive linear relationship among the value premium and the expected inflation can be recovered when inflation is non-neutral and the relationship turns into uncorrelated when inflation is neutral. We also find that inflation would play a major role in the variance contribution of value premium if inflation process becomes more persistent or effects of the inflation non-neutrality become more severe. Therefore we argue that the inflation non-neutrality can justify the positive relationship among inflation and value premium, meanwhile, value firms tend to underperform growth firms when the inflation is in low range, which leads to the disappearance of the value premium.

In the last, we provide the long-run projections of value premium based on long-run inflation forecast provided by OECD. Results show the value premium would remain at low level (with average value premium at 1.67%) from 2019 to 2060.

Table 3.1: The Non-Fisher Effect

This table reports the inflation beta for each industry using both equally weighted returns and value weighted returns. The full sample case spans from 1926m7 to 2018m12 and the Post 1968 case spans from 1968m1 to 2018m12. For each panel, we rank industries by their average book-to-market ratios and the order is from growth to value. Both inflation betas and the corresponding standard errors are reported and estimated by GMM. For each inflation beta, we test whether it equals to one and Y is marked if the null hypothesis is rejected.

Post 1968	BM	β_{ew}	std	β_{vw}	std	$\beta_{ew} \neq 1$	$\beta_{vw} \neq 1$
$HLTH$	0.29	-1.42	0.82	-1.17	0.75	Y	Y
$BUSEQ$	0.45	-3.16	1.11	-2.81	0.85	Y	Y
$NODUR$	0.49	-0.88	0.75	-0.29	0.73	Y	N
$SHOPS$	0.50	-0.91	0.90	-1.35	0.83	Y	Y
$CHEMS$	0.53	-1.18	0.74	-1.03	0.59	Y	Y
$TELCM$	0.59	-1.47	0.88	-0.74	0.61	Y	Y
$DURBL$	0.60	-2.27	1.02	-1.45	0.94	Y	Y
$MANUF$	0.67	-1.85	0.92	-1.94	0.79	Y	Y
$OTHER$	0.67	-1.11	0.92	0.11	0.82	Y	N
$ENRGY$	0.73	-0.39	1.18	-0.70	0.89	N	N
$MONEY$	0.87	-1.89	1.02	-0.73	0.92	Y	N
$UTILS$	1.04	-0.26	0.69	0.01	0.68	N	N
Full Sample	BM	β_{ew}	std	β_{vw}	std	$\beta_{ew} \neq 1$	$\beta_{vw} \neq 1$
$HLTH$	0.32	-1.05	0.74	-0.91	0.58	Y	Y
$BUSEQ$	0.42	-2.08	1.00	-1.67	0.84	Y	Y
$CHEMS$	0.44	-1.25	0.78	-1.10	0.63	Y	Y
$SHOPS$	0.54	-1.49	0.87	-0.87	0.66	Y	Y
$NODUR$	0.56	-1.80	0.73	-0.64	0.49	Y	Y
$DURBL$	0.67	-2.05	1.05	-1.87	0.95	Y	Y
$MANUF$	0.78	-2.08	0.95	-1.34	0.79	Y	Y
$TELCM$	0.78	-1.28	0.76	-0.18	0.46	Y	Y
$ENRGY$	0.82	-0.49	0.94	-0.16	0.65	N	N
$MONEY$	0.85	-1.16	0.83	-0.69	0.75	Y	Y
$UTILS$	0.89	-0.50	0.78	-0.16	0.62	N	N
$OTHER$	1.36	-1.78	0.96	-0.61	0.78	N	Y

Table 3.2: Correlations at different frequency

This table reports the correlations among the value premium and the inflation at multiple frequency. The full sample case spans from 1926m7 to 2018m12 and the Post 1968 case spans from 1968m1 to 2018m12. The results are reported at one month, one quarter, one year, three year, five year and ten year, respectively.

	1m	1q	1y	3y	5y	10y
Corr(inflation, HML), Post 1968	0.067	0.117	0.075	0.205	0.355	0.734
Corr(inflation, HML), Full Sample	0.089	0.095	0.112	0.280	0.400	0.653

Table 3.3: Value on Inflation

This table reports the relationship among value premium and inflation. The full sample case spans from 1926m7 to 2018m12 and the Post 1968 case spans from 1968m1 to 2018m12. For each panel, the results are reported at one month, one quarter, one year, three year, five year and ten year, respectively. Betas, standard errors, and the corresponding R^2 are reported.

Post 1968	β	std	R^2	Full Sample	β	std	R^2
$1M$	0.61	0.36	0.00	$1M$	0.61	0.23	0.01
$1Q$	0.83	0.41	0.01	$1Q$	0.54	0.29	0.01
$1Y$	0.35	0.43	0.01	$1Y$	0.39	0.32	0.01
$3Y$	0.52	0.29	0.04	$3Y$	0.59	0.18	0.08
$5Y$	0.74	0.22	0.13	$5Y$	0.75	0.15	0.16
$10Y$	0.90	0.08	0.57	$10Y$	0.87	0.08	0.43

Table 3.4: Value Premium Waves

This table reports the average value premium and average inflation for each decade. The full sample case spans from 1926m7 to 2018m12.

	Full	$1920s$	$1930s$	$1940s$	$1950s$	$1960s$	$1970s$	$1980s$	$1990s$	$2000s$	2010-
HML	0.04	-0.03	0.02	0.10	0.04	0.04	0.08	0.06	-0.01	0.04	0.00
$Infla.$	0.03	-0.01	-0.02	0.06	0.02	0.02	0.07	0.06	0.03	0.03	0.02

Table 3.5: Correlations: Premium and Proxy

This table reports the correlations among the value premium and the value proxy at multiple frequency. The sample case spans from 1968m1 to 2018m12. The results are reported at one month, one quarter, one year, three year, five year and ten year, respectively.

Freq.	$rep1$	$rep2$	$rep3$	$rep4$	$rep5$	$rep6$
1M	0.600	0.445	0.464	0.462	0.368	0.340
1Q	0.621	0.462	0.482	0.470	0.348	0.310
1Y	0.531	0.496	0.481	0.460	0.316	0.264
3Y	0.568	0.721	0.542	0.504	0.521	0.651
5Y	0.640	0.826	0.610	0.583	0.595	0.645
10Y	0.297	0.590	0.626	0.632	0.486	0.367

Table 3.6: Value Proxy on Inflation

This table reports the relationship among the value premium, the value proxy and the inflation. The sample case spans from 1968m1 to 2018m12. For each panel, the results are reported at one month, one quarter, one year, three year, five year and ten year, respectively. Betas are reported in the first row, standard errors are reported in the second row, and the corresponding R^2 are reported in the third row.

Freq.	hml	$rep1$	$rep2$	$rep3$	$rep4$	$rep5$	$rep6$
1M	0.61	0.45	0.39	1.00	0.83	0.61	0.34
	(0.36)	(0.48)	(0.39)	(0.35)	(0.31)	(0.26)	(0.24)
	0.00	0.00	0.00	0.01	0.01	0.01	0.00
1Q	0.83	0.68	0.65	1.52	1.33	1.10	0.88
	(0.41)	(0.45)	(0.39)	(0.34)	(0.28)	(0.24)	(0.24)
	0.01	0.01	0.01	0.06	0.06	0.06	0.04
1Y	0.35	0.47	0.22	0.94	1.01	0.91	0.61
	(0.43)	(0.41)	(0.35)	(0.24)	(0.22)	(0.20)	(0.20)
	0.01	0.01	0.00	0.07	0.10	0.10	0.05
3Y	0.52	0.53	0.30	0.57	0.65	0.65	0.40
	(0.29)	(0.31)	(0.23)	(0.15)	(0.14)	(0.14)	(0.11)
	0.04	0.03	0.02	0.09	0.15	0.17	0.09
5Y	0.74	0.75	0.49	0.52	0.56	0.62	0.37
	(0.22)	(0.22)	(0.14)	(0.13)	(0.14)	(0.14)	(0.11)
	0.13	0.15	0.11	0.12	0.17	0.22	0.12
10Y	0.90	0.45	0.43	0.26	0.30	0.37	0.20
	(0.08)	(0.08)	(0.07)	(0.07)	(0.07)	(0.07)	(0.05)
	0.57	0.25	0.36	0.11	0.18	0.28	0.13

Table 3.7: Value Proxy Tests

This table reports test results of the value proxy. The sample case spans from 1968m1 to 2018m12. The top panel reports the relationship among inflation and value proxy. The lower panel reports the relationship among first stage residuals and inflation. For each panel, the results are reported at one month, one quarter, one year, three year, five year and ten year, respectively. Betas are reported in the first row, standard errors are reported in the second row, and the corresponding R^2 are reported in the third row.

1st Stage	*hml*	(1)	(2)	(3)	(4)	(5)	(6)
1M	-	0.26	0.46	0.45	0.51	0.64	0.71
	-	(0.04)	(0.07)	(0.08)	(0.09)	(0.11)	(0.12)
	-	0.14	0.31	0.22	0.19	0.21	0.24
1Q	-	0.32	0.56	0.55	0.62	0.75	0.83
	-	(0.45)	(0.39)	(0.34)	(0.28)	(0.24)	(0.24)
	-	0.16	0.36	0.27	0.25	0.26	0.29
1Y	-	0.43	0.73	0.70	0.71	0.83	1.05
	-	(0.05)	(0.08)	(0.11)	(0.12)	(0.14)	(0.15)
	-	0.23	0.49	0.31	0.23	0.25	0.37
3Y	-	0.49	0.84	0.71	0.76	0.82	1.24
	-	(0.06)	(0.07)	(0.11)	(0.12)	(0.12)	(0.14)
	-	0.32	0.52	0.29	0.25	0.27	0.42
5Y	-	0.67	1.18	0.83	0.89	0.93	1.27
	-	(0.09)	(0.08)	(0.15)	(0.16)	(0.16)	(0.18)
	-	0.41	0.68	0.37	0.34	0.35	0.44
10Y	-	0.85	1.30	0.84	0.86	0.94	1.11
	-	(0.10)	(0.09)	(0.13)	(0.14)	(0.15)	(0.19)
	-	0.48	0.71	0.34	0.30	0.35	0.30
2nd Stage	*hml*	ϵ_1	ϵ_2	ϵ_3	ϵ_4	ϵ_5	ϵ_6
1M	0.61	0.49	0.43	0.16	0.18	0.22	0.37
	(0.36)	(0.38)	(0.36)	(0.38)	(0.38)	(0.37)	(0.34)
	0.00	0.00	0.00	0.00	0.00	0.00	0.00
1Q	0.83	0.61	0.46	-0.01	-0.00	0.01	0.10
	(0.41)	(0.39)	(0.36)	(0.41)	(0.40)	(0.39)	(0.37)
	0.01	0.01	0.01	0.00	0.00	0.00	0.00
1Y	0.35	0.15	0.18	-0.31	-0.37	-0.40	-0.29
	(0.43)	(0.35)	(0.30)	(0.37)	(0.39)	(0.38)	(0.38)
	0.01	0.00	0.00	0.01	0.01	0.01	0.01
3Y	0.52	0.26	0.27	0.11	0.03	-0.02	0.02
	(0.29)	(0.21)	(0.18)	(0.23)	(0.25)	(0.24)	(0.23)
	0.04	0.02	0.02	0.00	0.00	0.00	0.00
5Y	0.74	0.23	0.16	0.30	0.23	0.16	0.26
	(0.22)	(0.15)	(0.11)	(0.17)	(0.17)	(0.17)	(0.16)
	0.13	0.02	0.02	0.03	0.02	0.01	0.03
10Y	0.90	0.48	0.30	0.64	0.60	0.51	0.64
	(0.08)	(0.06)	(0.06)	(0.07)	(0.09)	(0.09)	(0.09)
	0.57	0.35	0.25	0.50	0.41	0.32	0.47

Table 3.8: Estimated Parameters

This table reports the estimated macroeconomic and leverage parameters of the benchmark model specification. All reported numbers are estimated by Bayesian MCMC using the quarterly observation on consumption growth rates, dividend growth rates, and inflation. Benchmark model priors mean, standard deviations and distributions are reported in first three columns. Posterior mean and 90% intervals are reported in last six columns. Posteriors are reported for both models with inflation risk (Posterior-1) or without inflation risk (Posterior-2). The quarterly data are from 1968Q1 to 2018Q4.

Macro	Prior			Posterior-1			Posterior-2		
	mean	*std*	*dist.*	*mean*	5%	95%	*mean*	5%	95%
ρ_c	0.90	0.050	*Beta*	0.927	0.921	0.934	0.985	0.980	0.990
ρ_π	0.90	0.050	*Beta*	0.921	0.914	0.926	0.896	0.892	0.899
$-\rho_{c\pi}$	0.05	0.025	*Beta*	0.048	0.046	0.051	-	-	-
σ_c	0.003	$Inf.$	*Inv-Gamma*	0.0065	0.0059	0.0071	0.0076	0.0070	0.0081
σ_{xc}	0.003	$Inf.$	*Inv-Gamma*	0.0016	0.0014	0.0018	0.0014	0.0012	0.0017
σ_π	0.003	$Inf.$	*Inv-Gamma*	0.0008	0.0006	0.0009	0.0007	0.0006	0.0009
$\sigma_{x\pi}$	0.003	$Inf.$	*Inv-Gamma*	0.0014	0.0013	0.0016	0.0016	0.0014	0.0017
Leverage	Prior			Posterior-1			Posterior-2		
	mean	*std*	*dist.*	*mean*	5%	95%	*mean*	5%	95%
ϕ_1	3.00	3.00	*Beta*	6.26	5.90	6.59	6.55	6.29	6.75
ϕ_2	3.00	3.00	*Beta*	3.93	3.59	4.26	3.49	3.23	3.77
ϕ_3	3.00	3.00	*Beta*	3.89	3.53	4.37	3.90	3.67	4.16
ϕ_4	3.00	3.00	*Beta*	2.43	2.07	2.79	2.82	2.59	3.04
ϕ_5	3.00	3.00	*Beta*	4.73	4.16	5.18	4.25	4.04	4.49
ϕ_6	3.00	3.00	*Beta*	4.83	4.50	5.12	5.00	4.81	5.16
ϕ_7	3.00	3.00	*Beta*	2.99	2.74	3.23	2.37	2.21	2.54
ϕ_8	3.00	3.00	*Beta*	2.80	2.59	3.00	2.47	2.29	2.66
ϕ_9	3.00	3.00	*Beta*	5.78	5.40	6.13	5.64	5.22	5.98
ϕ_{10}	3.00	3.00	*Beta*	2.57	2.28	2.83	2.03	1.88	2.16
ϕ_{11}	3.00	3.00	*Beta*	4.30	3.98	4.57	3.12	2.87	3.39
ϕ_{12}	3.00	3.00	*Beta*	0.91	0.67	1.12	0.92	0.59	1.24

Table 3.9: Inflation Beta

This table reports the inflation beta for each industry in both inflation neutral and non-neutral economy. For each panel, both inflation betas and the corresponding standard errors are reported. All reported numbers are taken averages across 2,000 simulations with sample length equal 200.

Industry	BM	β_{ew}	β_{vw}	$\beta_{nonfisher}$	std	β_{fisher}	std
$HLTH$	0.29	-1.42	-1.17	-2.57	1.67	1.01	1.59
$BUSEQ$	0.45	-3.16	-2.81	-3.80	2.26	1.10	2.14
$NODUR$	0.49	-0.88	-0.29	-1.05	0.94	0.89	0.91
$SHOPS$	0.50	-0.91	-1.35	-0.87	0.88	0.87	0.84
$CHEMS$	0.53	-1.18	-1.03	-1.95	1.45	0.98	1.39
$TELCM$	0.59	-1.47	-0.74	-2.28	1.57	1.01	1.51
$DURBL$	0.60	-2.27	-1.45	-1.96	1.42	0.98	1.38
$MANUF$	0.67	-1.85	-1.94	-2.66	1.75	1.07	1.67
$OTHER$	0.67	-1.11	0.11	-3.47	2.19	0.97	2.09
$ENRGY$	0.73	-0.39	-0.70	-0.66	1.10	0.96	1.07
$MONEY$	0.87	-1.89	-0.73	-1.14	1.25	0.99	1.21
$UTILS$	1.04	-0.26	0.01	0.63	0.81	0.91	0.83

Table 3.10: Value on Inflation

This table reports the relationship among value premium and inflation. The left panel reports results based on real data, the middle panel reports results based on simulated data from the inflation non-neutral economy, and the right panel reports results based on simulated data from the inflation neutral economy. For each panel, the results are reported at one quarter, one year, three year, five year and ten year, respectively. Betas, standard errors, and the corresponding R^2 are reported. For Case 1 and Case 2, all reported numbers are taken averages across 2,000 simulations with sample length equal 200.

Data	β	std	R^2	Case-1	β	std	R^2	Case-2	β	std	R^2
$1Q$	0.54	0.29	0.01	$1Q$	0.99	0.61	0.02	$1Q$	0.02	0.61	0.00
$1Y$	0.39	0.32	0.01	$1Y$	0.58	0.50	0.03	$1Y$	0.00	0.51	0.00
$3Y$	0.59	0.18	0.08	$3Y$	0.52	0.35	0.08	$3Y$	0.02	0.36	0.00
$5Y$	0.75	0.15	0.16	$5Y$	0.48	0.29	0.12	$5Y$	0.02	0.30	0.00
$10Y$	0.87	0.08	0.43	$10Y$	0.54	0.22	0.20	$10Y$	0.02	0.23	0.01

Table 3.11: Variance Decomposition

This table reports the variance decomposition of the premium. The first three rows reports variance contributions from the short run consumption risk, long run consumption risk and long run inflation risk. The fourth row reports the contribution ratio of long run inflation over long run consumption risk. Case 1 is the benchmark specifications with the other cases by modifying one parameter each. The parameters in the benchmark specifications are reported as $\gamma = 10, \psi = 1.5, \phi_v = 3.025, \phi_g = 4.088, \varphi_v = 4, \varphi_g = 2, \alpha_v = 0.1, \alpha_g = -0.3, \sigma_c = 0.0065, \sigma_{xc} = 0.0016, \sigma_{x\pi} = 0.0014, \rho_c = 0.927, \rho_\pi = 0.921, \rho_{c\pi} = -0.048, \overline{pc} = 3.4519,$ and $\overline{pd} = 4.0704$.

Total Premium = SR Consump + LR Consump + LR Inflation

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	-	$\phi_g = 5.00$	$\phi_g = 3.50$	$\alpha_g = -0.50$	$\rho_c = 0.97$	$\rho_\pi = 0.97$	$\rho_{c\pi} = -0.096$
SR.Consump (%)	-18.86	-9.34	-55.06	-38.44	-5.14	-12.06	-11.53
LR.Consump (%)	97.69	89.87	127.44	113.79	86.41	62.48	59.75
LR.Inflation (%)	21.17	19.47	27.61	24.65	18.72	49.58	51.78
$\frac{LR.Inflation}{LR.Consumption}$ (%)	21.67	21.67	21.67	21.67	21.67	79.35	86.67

Table 3.12: Co-integrated VAR Estimates

This table reports the co-integration test results. In panel A, we reports the co-integration vector about inflation and value premium. The co-integration relationship is estimated as no trend and no intercept. Panel B reports the results of error correction model and no co-integration tests are provided following. The VAR lag is selected based on lag exclusion tests and the sample period is from 1968 to 2018, from 1950 to 2018, and from 1926 to 2018 respectively.

Panel A: Sample	Cointegration	hml	$infla.$
1968 - 2018	β	1.00	-0.95
	(s.e.)		(0.27)
1950 - 2018	β	1.00	-0.95
	(s.e.)		(0.24)
1926 - 2018	β	1.00	-1.10
	(s.e.)		(0.24)

Panel B-1: Sample 1968 - 2018

Error Correction Model		$\Delta(hml)$	$\Delta(infla.)$
	α	-1.47	0.06
	(s.e)	(0.34)	(0.05)
	Adj. R^2	0.57	0.26
Hypothsis Test: NO CE		Trace-p	Max eigen-p
	None	0.00	0.00
	At Most 1	0.38	0.38

Panel B-2: Sample 1950 - 2018

Error Correction Model		$\Delta(hml)$	$\Delta(infla.)$
	α	-1.39	0.07
	(s.e)	(0.28)	(0.04)
	Adj. R^2	0.59	0.33
Hypothsis Test: NO CE		Trace-p	Max eigen-p
	None	0.00	0.00
	At Most 1	0.34	0.34

Panel B-3: Sample 1926 - 2018

Error Correction Model		$\Delta(hml)$	$\Delta(infla.)$
	α	-1.15	0.13
	(s.e)	(0.25)	(0.05)
	Adj. R^2	0.53	0.39
Hypothsis Test: NO CE		Trace-p	Max eigen-p
	None	0.00	0.00
	At Most 1	0.19	0.19

Table 3.13: Estimated Parameters

This table reports the estimated macroeconomic and leverage parameters. All reported numbers are estimated by Bayesian MCMC using the annual observation on consumption growth rates, dividend growth rates, and inflation. Model priors mean, standard deviations and distributions are reported in first three columns. Posterior mean and 90% intervals are reported in last six columns. Posteriors are reported for both models with inflation risk (Posterior-1) or without inflation risk (Posterior-2). The annual data are from 1950 to 2018.

Macro	Prior			Posterior-1			Posterior-2		
	mean	*std*	*dist.*	*mean*	5%	95%	*mean*	5%	95%
ρ_c	0.90	0.050	*Beta*	0.886	0.822	0.959	0.858	0.765	0.952
ρ_π	0.90	0.050	*Beta*	0.890	0.831	0.944	0.905	0.846	0.966
$-\rho_{c\pi}$	0.05	0.025	*Beta*	0.035	0.008	0.063	-	-	-
σ_c	0.020	*Inf.*	*Inv-Gamma*	0.0115	0.0079	0.0151	0.0115	0.0078	0.0152
σ_{xc}	0.020	*Inf.*	*Inv-Gamma*	0.0133	0.0082	0.0172	0.0132	0.0085	0.0175
σ_π	0.003	*Inf.*	*Inv-Gamma*	0.0019	0.0008	0.0031	0.0020	0.0008	0.0033
$\sigma_{x\pi}$	0.030	*Inf.*	*Inv-Gamma*	0.0169	0.0146	0.0194	0.0172	0.0146	0.0196
Leverage	Prior			Posterior-1			Posterior-2		
	mean	*std*	*dist.*	*mean*	5%	95%	*mean*	5%	95%
ϕ_g	3.00	3.00	*Beta*	1.34	-0.31	3.16	1.92	-0.57	4.21
ϕ_m	3.00	3.00	*Beta*	1.53	-0.05	3.07	2.20	0.15	4.06
ϕ_v	3.00	3.00	*Beta*	3.18	1.22	5.30	3.83	1.10	6.54

Table 3.14: Value on Inflation

This table reports the relationship among value premium and inflation. The left panel reports results based on real data, the middle panel reports results based on simulated data from the inflation non-neutral economy, and the right panel reports results based on simulated data from the inflation neutral economy. For each panel, the results are reported at one year, three year, five year and ten year, respectively. Betas, standard errors, and the corresponding R^2 are reported. For Case 1 and Case 2, all reported numbers are taken averages across 2,000 simulations with sample length equal 68.

Data	β	*std*	R^2	Case-1	β	*std*	R^2	Case-2	β	*std*	R^2
$1Y$	0.39	0.32	0.01	$1Y$	-0.34	0.39	0.02	$1Y$	0.04	0.38	0.01
$3Y$	0.59	0.18	0.08	$3Y$	-0.18	0.34	0.05	$3Y$	0.04	0.33	0.04
$5Y$	0.75	0.15	0.16	$5Y$	-0.17	0.30	0.07	$5Y$	0.05	0.29	0.06
$10Y$	0.87	0.08	0.43	$10Y$	-0.14	0.22	0.13	$10Y$	0.06	0.23	0.12

Table 3.15: Correlations: Premium and Proxy

This table reports the correlations among the value premium and the value proxy at multiple frequency. The full sample case spans from 1926m7 to 2018m12. The results are reported at one month, one quarter, one year, three year, five year and ten year, respectively.

Freq.	$rep1$	$rep2$	$rep3$	$rep4$	$rep5$	$rep6$
1M	0.380	0.559	0.465	0.440	0.459	0.489
1Q	0.401	0.602	0.519	0.496	0.507	0.543
1Y	0.478	0.703	0.553	0.480	0.503	0.607
3Y	0.390	0.440	0.458	0.429	0.232	0.142
5Y	0.379	0.485	0.509	0.485	0.279	0.188
10Y	0.693	0.844	0.582	0.545	0.592	0.544

Table 3.16: Value Proxy on Inflation

This table reports the relationship among the value premium, the value proxy and the inflation. The full sample case spans from 1926m7 to 2018m12. For each panel, the results are reported at one month, one quarter, one year, three year, five year and ten year, respectively. Betas are reported in the first row, standard errors are reported in the second row, and the corresponding R^2 are reported in the third row.

Freq.	hml	$rep1$	$rep2$	$rep3$	$rep4$	$rep5$	$rep6$
1M	0.61	0.53	0.39	0.18	0.62	0.48	0.45
	(0.23)	(0.46)	(0.25)	(0.19)	(0.22)	(0.16)	(0.14)
	0.01	0.00	0.00	0.00	0.01	0.01	0.01
1Q	0.54	0.43	0.26	0.00	0.53	0.41	0.37
	(0.29)	(0.42)	(0.25)	(0.22)	(0.20)	(0.16)	(0.13)
	0.01	0.00	0.00	0.00	0.01	0.01	0.01
1Y	0.39	-0.16	-0.30	-0.31	0.18	0.19	0.22
	(0.32)	(0.49)	(0.20)	(0.17)	(0.19)	(0.15)	(0.13)
	0.01	0.00	0.01	0.01	0.00	0.01	0.01
3Y	0.59	-0.38	-0.23	-0.12	0.13	0.16	0.14
	(0.18)	(0.36)	(0.14)	(0.12)	(0.10)	(0.10)	(0.10)
	0.08	0.01	0.01	0.00	0.01	0.01	0.01
5Y	0.75	-0.41	-0.05	0.03	0.13	0.19	0.15
	(0.15)	(0.27)	(0.14)	(0.12)	(0.10)	(0.09)	(0.08)
	0.16	0.02	0.00	0.00	0.01	0.03	0.02
10Y	0.87	-0.20	0.09	0.12	0.14	0.19	0.15
	(0.08)	(0.14)	(0.08)	(0.08)	(0.07)	(0.06)	(0.05)
	0.43	0.01	0.01	0.02	0.03	0.07	0.07

Table 3.17: Value Proxy Tests

This table reports test results of the value proxy. The sample case spans from 1926m1 to 2018m12. The top panel reports the relationship among inflation and value proxy. The lower panel reports the relationship among first stage residuals and inflation. For each panel, the results are reported at one month, one quarter, one year, three year, five year and ten year, respectively. Betas are reported in the first row, standard errors are reported in the second row, and the corresponding R^2 are reported in the third row.

1st Stage	*hml*	(1)	(2)	(3)	(4)	(5)	(6)
1M	-	0.43	0.36	0.48	0.53	0.55	0.57
	-	(0.04)	(0.06)	(0.08)	(0.09)	(0.10)	(0.12)
	-	0.36	0.20	0.22	0.21	0.14	0.12
1Q	-	0.46	0.41	0.53	0.57	0.54	0.54
	-	(0.06)	(0.06)	(0.09)	(0.10)	(0.12)	(0.15)
	-	0.39	0.21	0.23	0.22	0.12	0.10
1Y	-	0.35	0.44	0.51	0.54	0.45	0.42
	-	(0.05)	(0.06)	(0.08)	(0.09)	(0.11)	(0.13)
	-	0.28	0.25	0.23	0.21	0.10	0.07
3Y	-	0.22	0.38	0.48	0.54	0.33	0.22
	-	(0.06)	(0.05)	(0.07)	(0.10)	(0.11)	(0.11)
	-	0.15	0.19	0.21	0.18	0.05	0.02
5Y	-	0.22	0.48	0.62	0.72	0.47	0.35
	-	(0.06)	(0.07)	(0.08)	(0.11)	(0.12)	(0.12)
	-	0.14	0.23	0.25	0.24	0.08	0.04
10Y	-	0.21	0.77	0.88	0.97	0.94	0.84
	-	(0.07)	(0.09)	(0.09)	(0.11)	(0.15)	(0.17)
	-	0.09	0.35	0.39	0.40	0.24	0.13
2nd Stage	*hml*	ϵ_1	ϵ_2	ϵ_3	ϵ_4	ϵ_5	ϵ_6
1M	0.61	0.38	0.47	0.52	0.28	0.34	0.35
	(0.23)	(0.17)	(0.21)	(0.22)	(0.18)	(0.21)	(0.21)
	0.01	0.00	0.01	0.01	0.00	0.00	0.00
1Q	0.54	0.34	0.44	0.54	0.23	0.32	0.34
	(0.28)	(0.23)	(0.27)	(0.27)	(0.25)	(0.27)	(0.27)
	0.01	0.01	0.01	0.01	0.00	0.00	0.00
1Y	0.39	0.45	0.52	0.55	0.29	0.31	0.30
	(0.32)	(0.21)	(0.27)	(0.27)	(0.27)	(0.31)	(0.30)
	0.01	0.02	0.03	0.03	0.01	0.01	0.01
3Y	0.59	0.67	0.68	0.65	0.52	0.54	0.56
	(0.18)	(0.16)	(0.15)	(0.16)	(0.17)	(0.18)	(0.19)
	0.08	0.12	0.13	0.12	0.08	0.07	0.07
5Y	0.75	0.84	0.78	0.74	0.66	0.66	0.70
	(0.15)	(0.14)	(0.10)	(0.12)	(0.12)	(0.14)	(0.15)
	0.16	0.23	0.22	0.21	0.16	0.13	0.14
10Y	0.88	0.92	0.80	0.77	0.74	0.70	0.75
	(0.08)	(0.08)	(0.05)	(0.05)	(0.05)	(0.07)	(0.07)
	0.43	0.51	0.55	0.54	0.51	0.36	0.36

Figure 3.1: Value premium and the expected inflation (annualized at 10-year level)

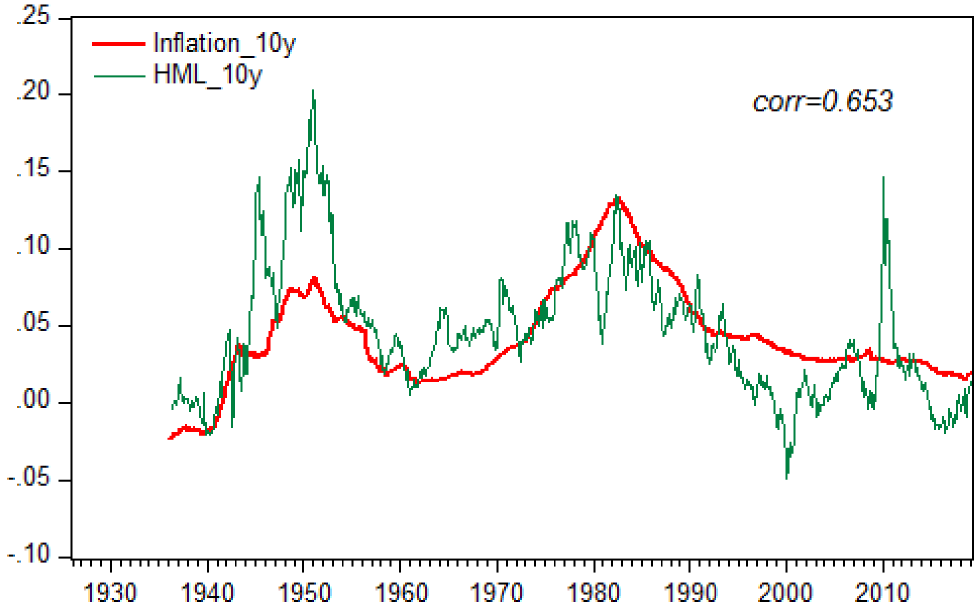


Figure 3.2: Value Premium and Value Proxy

This figure shows the relationship among the value premium and the multiple value proxy constructed from industry returns. The data here spans from 1968m1 to 2018m12.

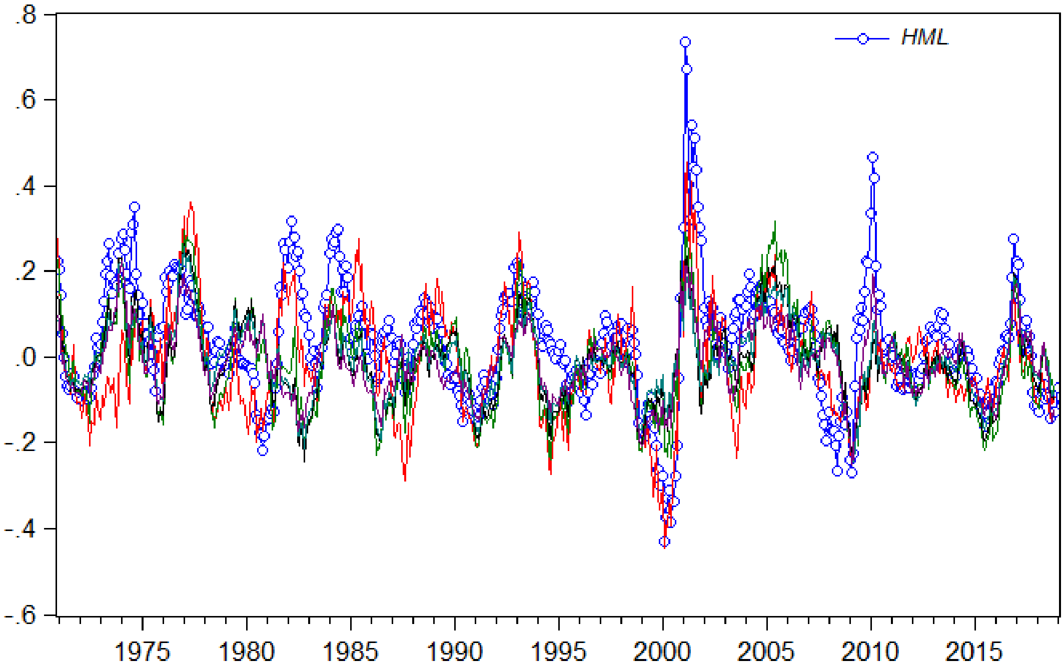


Figure 3.3: Long-Run Leverage & Book-to-Market Ratio

This figure shows the relationship among long run exposures and means of the industry's book-to-market ratios. Three cases are reported: the inflation neutral economy with short-run correlations α_i, the inflation non-neutral economy, and the inflation non-neutral economy with short-run correlations α_i. The fitted linear relationship and R^2 are shown for each case.

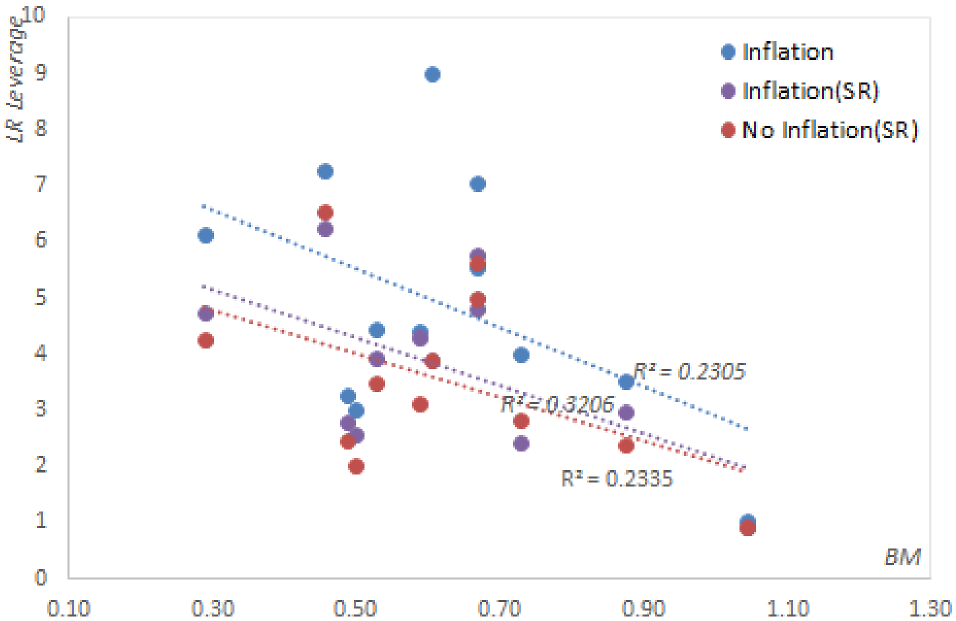


Figure 3.4: Short-Run Correlations α_i & Book-to-Market Ratio

This figure shows the relationship among short-run correlations and means of the industry's book-to-market ratios. Two cases are reported: the inflation neutral economy with short-run correlations α_i and the inflation non-neutral economy with short-run correlations α_i. The fitted linear relationship and R^2 are shown for each case.

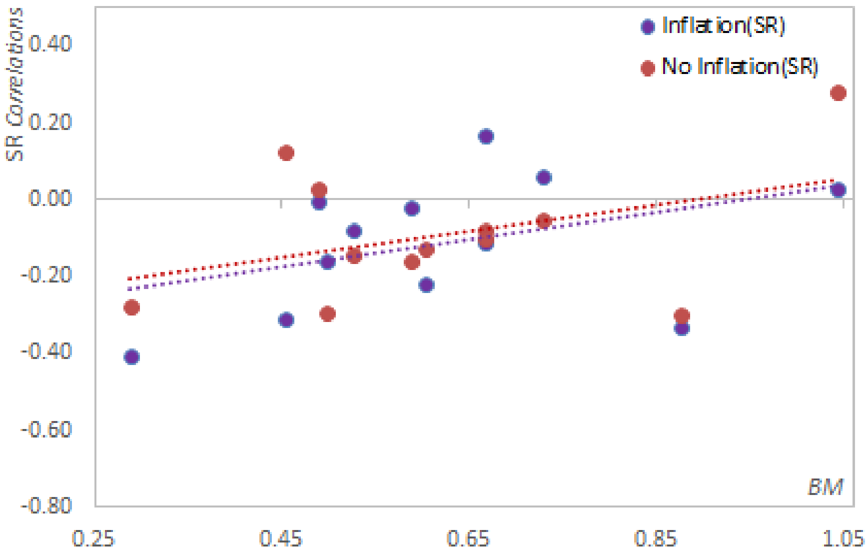


Figure 3.5: Inflation Beta & Long-Run Leverage

This figure shows the relationship among inflation betas and the long-run leverages. By theoretical construction, there is a linear relationship among the negative inflation betas and industry's exposures to the consumption risk.

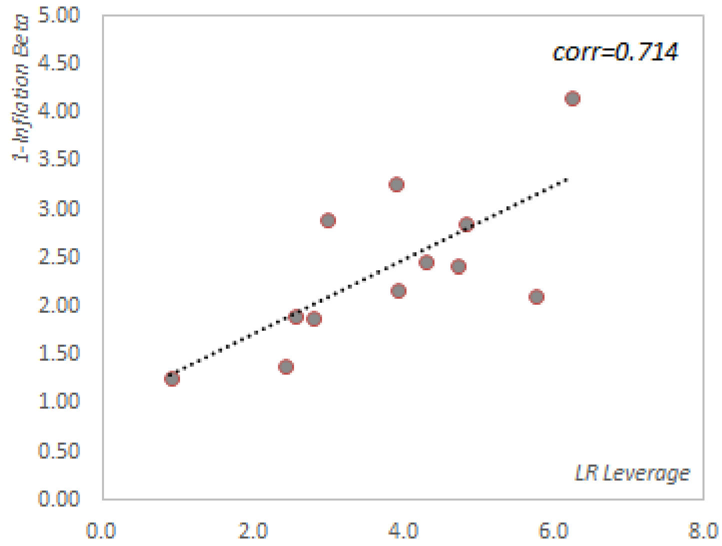


Figure 3.6: Impulse Responses of the Priced Shocks

This figure shows quarterly log-deviations from the steady state. All the parameters are same as the ones in benchmark specification reported in table 8.

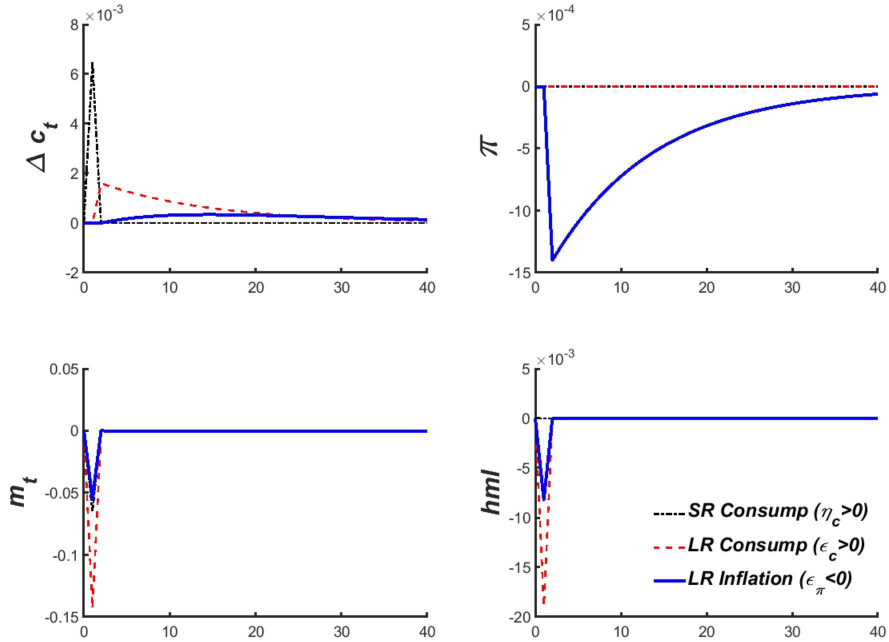
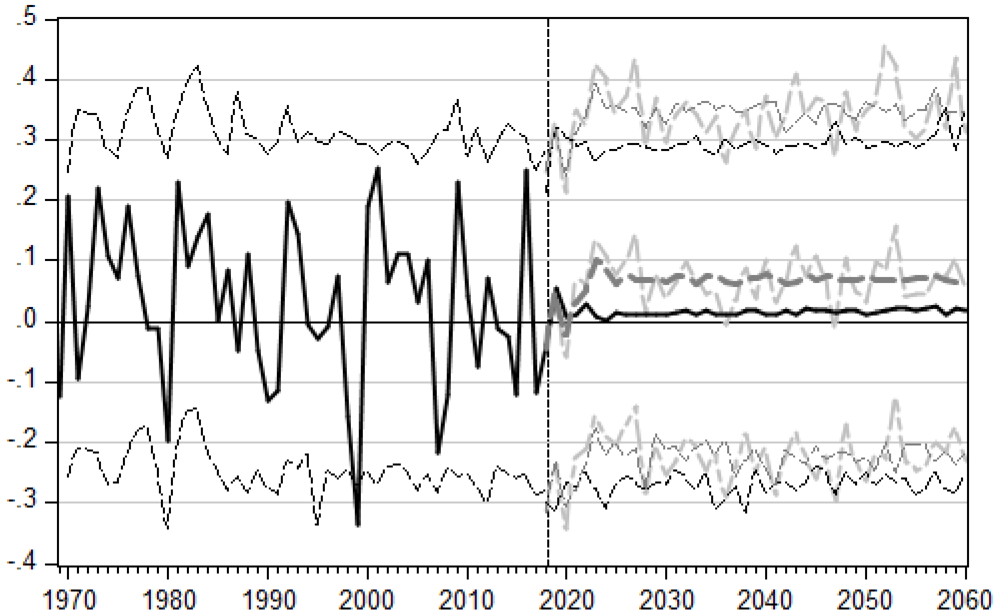


Figure 3.7: Long-Run Projections of Value Premium

This figure shows the long-run projections of value premium. Three projections are provided: black line is the projection based on long-run inflation forecast by OECD; gray line is the projection based on long-run constant inflation rates at 8% and light gray line is the projection based on inflation rates simulated from a normal process with mean at 8% and std at 3%.



Chapter 4

History Doesn't Repeat, But It Rhymes. - Cash Flow Risk and Expected Returns

Abstract: Chava, Hsu, and Zeng (2019) find that investors don't fully incorporate business cycle variation in cash flow growth and thus conditional Sharpe ratio can be informative for future industry returns. It suggests that cash flow risk at the idiosyncratic level is not fully incorporated into the prices by investors. I develop a stochastic volatility framework to evaluate the unexpected cash flow news through the variance decomposition perspective and apply the method to U.S. industry data. I find that i) The common cash flow volatility estimated from unexpected industry-level cash flow news is highly correlated to Uncertainty index constructed by Jurado, Ludvigson, and Ng (2015); ii) the idiosyncratic cash flow risk is robustly priced and the explanation power cannot be consumed by current well-known risk factors and firm characteristics; iii) stocks with high conditional Sharpe ratios tend to have higher idiosyncratic cash flow volatility and higher compensated returns, which is consistent with Chava, Hsu, and Zeng (2019)'s finding. A strategy that goes long the decile portfolio with the largest idiosyncratic cash flow volatility and short the decile portfolio with the smallest idiosyncratic cash flow volatility yields a Fama-French-Five-Factor alpha of 37 bps per month (t-stat: 6.90) in long sample (1931-2018) and 64 bps per month (t-stat: 12.28) in the modern sample (1963-2018).

JEL classification: G10.

Keywords: Cash flow risk, Idiosyncratic volatility, Cross-section of stock returns, factor models, ICAPM.

4.1 Introduction

The fundamental question in empirical asset pricing is the determinants of the cross-sectional stock returns. While a large body of recent research proposing new factors based on a host of empirically motivated economic or financial characteristics, we address this question from a new perspective, offering evidence that the idiosyncratic cash flow risk - the unexpected cash flow news at individual level - is important for understanding the cross-sectional stock returns.

In this paper, I argue that cash flow risk at the idiosyncratic level is not fully incorporated into the prices by investors. The cash flow risk and discount rates risk have been well defined in the pioneer work of [Campbell, 1991]. [Campbell and Vuolteenaho, 2004a] apply the technique and use the market level unexpected news to explain the cross-section of stock returns and following their “Bad Beta, Good Beta” work, many papers have explored the role of the unexpected news risk in asset pricing. However, most of them focus on the cash flow risk at the market level and cash flow risk at individual level has been rarely explored. A recent paper by [Chava et al., 2019] shows that there is significant variation in cash flow growth across industries over the business cycle and they find investors do not fully incorporate business cycle fluctuations into the industry level cash flows. If the business cycle information is not reflected in each industry’s cash flow, then conditional Sharpe ratio can be informative for future industry returns. In their paper, sector rotation strategy based on history-dependent Sharpe ratio can produce significant returns. It suggests that cash flow risk at the idiosyncratic level is not fully incorporated into the prices by investors. However, no theoretical model is provided to rationalize the documented Sharpe ratio premium and the role of idiosyncratic cash flows should be re-highlighted. In this paper, I develop a stochastic volatility framework to evaluate the unexpected cash flow news through the variance decomposition perspective, and I relate the conditional Sharpe ratio to the firm's cash flow volatility - especially the idiosyncratic cash flow volatility - to justify the premium.

[Campbell and Vuolteenaho, 2004a] apply the technique in [Campbell, 1991] and use the market level unexpected news to explain the cross-section of stock returns. Following their "Bad Beta, Good Beta" work, many papers have explore the unexpected news risk like [Da and Warachka, 2009], [Botshekan et al., 2012], [Maio, 2013], [Chen et al., 2013], [Campbell et al., 2013], [Cooper and Maio, 2018], and [Campbell et al., 2018]. [Da and Warachka, 2009] show that stock returns are partially driven by the unexpected cash flows by using data of analysts' earnings forecast revisions on market earnings. [Botshekan et al., 2012] construct a four-factor model to reflect the cash flow and discount rates risk under downside market and upside market. They find the downside cash flow risk is robust priced across different specifications and the downside cash flow risk premium is mainly attributable to small stocks. [Maio, 2013] extend the [Campbell and Vuolteenaho, 2004a]'s model and allow the price of aggregate cash flow to be time-varying by setting the conditional cash-flow beta to be linear in a state variable. [Chen et al., 2013] show that cash flow news plays significant roles in determining stock returns and the importance increases with the investment horizon by using direct cash flow forecasts data. A most recent paper by [Campbell et al., 2018] introduces the stochastic volatility into the initial homoskedastic ICAPM model and show that the volatility of future expected returns is negatively priced in the cross-sectional of stock returns. Different from their research, I find that the cash flow news and discount rates news at individual level tend to move together, which suggests the existence of common factors behind the big picture. Therefore I apply the stochastic volatility model to disentangle the common and idiosyncratic volatility from the individual-level news. To the best of my knowledge, however, no one has tried to disentangle the pricing properties of cash flow and discount rate news from the variance decomposition perspective.

To motive the empirical results, I build up a cash flow model where each firm's dividend growth is driven by two independent stochastic volatility processes - the common cash flow shock and the idiosyncratic cash flow shock - and the equilibrium solutions imply that the idiosyncratic and common cash flow risk are priced in the cross-sectional stock returns.

My main intention is simple. I argue that the unexpected cash flow volatility could carry additional information besides current risk factors and firm characteristics. To verify my proposition, I apply the method to U.S. industry portfolios. In the main empirical results, I find that the common cash flow volatility estimated from unexpected industry-level cash flow news is highly correlated to Uncertainty index constructed by [Jurado et al., 2015]. The idiosyncratic cash flow risk is robustly significant in explaining the cross-section of stock returns. The explanation power can not be consumed by current risk factors and firm characteristics. A strategy that goes long the decile portfolio with the largest idiosyncratic cash flow volatility and short the decile portfolio with the smallest idiosyncratic cash flow volatility can produce robust alpha across different specifications. The alpha significantly exists with respect to asset pricing models like Fama-French three factor model, Carhart four factor model and Fama-French five factor model. For example, the single-sorted strategy yields a Fama-French five factor alpha of 0.37% per month (t-stat: 6.90) in long sample (1931-2018) and 0.64% per month (t-stat: 12.28) in modern sample (1963-2018). By the double sorting, we find the abnormal alpha is mainly driven by the growth industries. I also build a theoretical connection between conditional Sharpe ratio and idiosyncratic cash flow volatility. I find that stocks with high conditional Sharpe ratios tend to have higher idiosyncratic cash flow volatility and higher compensated returns, which is consistent with [Chava et al., 2019]'s finding.

One related literature is to study the role of the idiosyncratic and common stock return volatility in cross-sectional stock return literature. Their focus is the realized return volatility while my focus is the unexpected cash flow volatility. These two are closely connected and could help to understand the mechanism behind. In the realized return volatility literature, [Ang et al., 2006] document that high exposure to systematic return volatility or higher idiosyncratic return volatility corresponds to lower stock returns. The negative coefficients of common stock return volatility have been widely accepted while the negative role of idiosyncratic return volatility is controversial. For the common stock volatility, the negative association can be justified by the leverage theory of [Black, 1976] and [Christie, 1982] and the risk premia theory of [French et al., 1987]. The leverage hypothesis argues that the firms become more levered when the stock prices fall which increase the aggregate volatility. The risk premium hypothesis argue investors demand higher risk premia when market volatility increase which depresses the firms' value and results in the negative relationship. Both two explanation can justify the negative relationship among stock returns and aggregate return volatility. For the idiosyncratic return volatility, [Ang et al., 2006] document that portfolios with high realized idiosyncratic volatility deliver low value-weighted average returns in the subsequent month while [Bali and Cakici, 2008] document no robustly significant relationship among stock returns and the idiosyncratic return volatility. [Huang et al., 2009] find that the negative relationship is due to the short-term reversal and confirm the positive relationship among expected returns and the idiosyncratic volatility. Similar explanation is made by [Fu, 2009] where he uses the exponential GARCH models to estimate expected idiosyncratic volatility and find a significantly positive relation between the estimated conditional idiosyncratic volatility and expected returns. [Fu, 2009] argue that [Ang et al., 2006]'s findings are largely explained by the return reversal of a subset of small stocks with high idiosyncratic volatility. These can go back the initial puzzle documented by [Duffee, 1995]. [Duffee, 1995] documented the positive relationship among stock returns and the idiosyncratic volatility and argue that the positive contemporaneous relationship cannot be justified by the leverage hypothesis or the risk premium hypothesis. [Grullon et al., 2012] resolve this puzzle by showing that the positive relation between firm-level stock returns and firm-level return volatility is due to firms' real options. Here the documented positive relationship among idiosyncratic cash flow volatility and stock returns which can also be backed up by the argument of [Grullon et al., 2012]. They take the firm's future investment as potential growth options and the value of the growth options increase with the idiosyncratic return volatility which justifies the positive relationship among volatility and stock returns. Our evidence on cash flow volatility support their argument on the amplified effect of good news on growth options.

Different from current discussions on the volatility of stock returns, my focus is the cash flow volatility estimated from the unexpected news. Since the basic economic theory tells us that prices should fully reflect the future cash flows and the future cash flow news should price today's financial ratios, a direct approach to identify the role of cash flow can be helpful.

The aim of this paper is three-fold. First I build up a cash flow model where the firm's cash flow is driven by a common factor and an idiosyncratic factor and I argue that the cash flow news will be priced in the cross-section stock returns. The model provides a clear closed-form solution to show the relationship among idiosyncratic and common cash flow risk, cross-section stock returns and the conditional Sharpe ratio. For the corresponding identification method, I propose a stochastic volatility econometric method to extract the common and idiosyncratic cash flow volatility from cross-section observed data. Second I apply the method to the U.S. industry portfolios and results suggest that the common cash flow volatility is closely to the whole economy uncertainty (see [Jurado et al., 2015]) and the idiosyncratic cash flow volatility is not fully consumed by the current well-known risk factors and firm characteristic factors. The idiosyncratic cash flow volatility is positively related to the stock returns. Third, I relate the conditional Sharpe ratio to the idiosyncratic cash flow risk. Firms with higher idiosyncratic cash flow volatility tend to have higher Sharpe ratio and higher stock returns, which justifies the Sharpe ratio premium (see [Chava et al., 2019]).

The rest of the paper is organized as follows. In the next section, I introduce the cash flow model that motives my empirical analysis and derive the equilibrium solution to show the relationship among idiosyncratic and common cash flow risk, cross-section stock returns and the conditional Sharpe ratio. Section 3 contains the estimation method to extract the volatility measures from the cash flow news. In section 4 I apply the method to US industry portfolio data and provide the main findings of this paper, namely that the common cash flow volatility is closely to the whole economy uncertainty and the idiosyncratic cash flow news volatility cannot be fully explained by the well-known risk factors and firm characteristics. Strategy based on the idiosyncratic cash flow volatility can produce alpha in both long and modern samples. Section 5 concludes.

4.2 Theory

4.2.1 Motivation

In the influential "Bad Beta, Good Beta" paper, [Campbell and Vuolteenaho, 2004a] break the CAPM beta into two components: the bad one reflecting the future market cash flow news and the good one reflecting the future discount rates news. The economically motivated two-factor model is well applied to explain the size and value "anomalies". They decompose unexpected market returns into the discount rate and cash flow components by using the return decomposition technique of [Campbell and Shiller, 1988] and [Campbell, 1991]. The Campbell and Shiller's technique is using a log-linear approximation of the present relation for stock prices that allows for time-varying discount rates. In Campbell and Vuolteenaho's paper, the market return is decomposed into

$$\begin{aligned} r_{m,t+1} - E_t r_{m,t+1} &\simeq (E_{t+1} - E_t) \sum_{j=0}^{\infty} \rho^j \cdot \Delta d_{m,t+1+j} - (E_{t+1} - E_t) \sum_{j=1}^{\infty} \rho^j \cdot r_{m,t+1+j} \\ &= N_{m,CF,t+1} + N_{m,DR,t+1} \end{aligned} \tag{4.1}$$

where $\rho = 1/(1 + exp(\overline{dp}))$ is a (log-linearization) discount coefficient that depends on the mean of log dividend-price ratio dp, $r_{m,t+j}$ is the log market return and $\Delta d_{m,t+j}$ is the log market dividend growth. N_{CF} denotes news about future market cash flows and N_{DR} denotes news about future market expected returns.

The technique allows the unexpected market returns to be represented as the sum of cash flow news and discount rates news. By the construction, they can estimate each stock's beta by looking at the co-variance of the individual stock returns and market level news. The fitting two-beta ICAPM greatly improves the poor performance of the standard CAPM, which suggests that information is hidden in the unexpected cash flow and discount rates news.

Rather than look at market level news, I explore the information that might be hidden at individual level news. In this paper, the work is not limited to the market level decomposition since the return decomposition also works at the individual stock level. For example, the log-linearization formulation works at individual stock level, which is

$$\begin{aligned} r_{i,t+1} - E_t r_{i,t+1} &\simeq (E_{t+1} - E_t) \sum_{j=0}^{\infty} \rho^j \cdot \Delta d_{i,t+1+j} - (E_{t+1} - E_t) \sum_{j=1}^{\infty} \rho^j \cdot r_{i,t+1+j} \\ &= \tilde{N}_{i,CF,t+1} + \tilde{N}_{i,DR,t+1} \end{aligned} \tag{4.2}$$

where $N_{i,CF}$ denotes news about future cash flows of stock i and $N_{i,DR}$ denotes news about future expected returns of stock i. If I bring this thought to real data, I find that cash flow news or discount rates news at individual level are driven by a common factor besides their idiosyncratic exogenous shocks. For example, I show the cash flow news and the discount rates news of each 30 industry (defined as Fama and French)* in figure 4.1. I find that the individual news move together which is consistent with our argument.

[Insert Figure 4.1 near here]

The [Campbell and Vuolteenaho, 2004a]'s cash flow and discount rates decomposition at aggregate market level has became an important contribution to the ability of the CAPM model in explaining the cross-sectional differences in average returns. Following this framework, a large number of papers have shown that the cash flow and discount rates news are priced in the stock prices like [Da and Warachka, 2009], [Botshekan et al., 2012], [Maio, 2013], [Chen et al., 2013], [Campbell et al., 2013], [Cooper and Maio, 2018], and [Campbell et al., 2018]. To the best of my knowledge, however, no one has tried to disentangle the pricing properties of cash flow and discount rate news from the variance decomposition - the idiosyncratic and common factor - perspective. To economically motive the empirical evidence, I provide a cash flow model where the individual firm's dividend growth is driven by the common shock and its own idiosyncratic shock and I derive the proposition showing that the individual stock returns are determined by both two risk sources.

4.2.2 A Cash Flow Model

I start the theoretical framework from the pricing kernel as [Constantinides, 1992]. In a no-arbitrage world, I always have the following condition holds as

$$1 = E_t[M_{t+1}R_{t+1}]$$

Here I assume the state pricing kernel at $t+1$ in this economy follows

*Results are robust when other industry definitions are applied. e.g. 48 industry.

$$m_{t+1} = -r_f - \frac{1}{2} \cdot \sigma_{m,t}^2 + \epsilon_{m,t+1}, \quad \epsilon_{m,t+1} \sim N(0, \sigma_{m,t}^2) \tag{4.3}$$

where m_{t+1} is the state pricing density at time $t+1$, r_f is the constant risk free rates and $\sigma_{m,t}^2$ are exogenously determined. The pricing kernel form has been applied by previous researchers (e.g. [Amin and Ng, 1993], [Wu, 2001]) and here I adopt this functional form to easily derive the closed-form equilibrium solutions.

For the cash flow model, I allow the heterogeneous cash flow shocks on individual stocks. In my model, the cash flow is driven by two independent stochastic volatility processes - the common cash flow shock $\epsilon_{d,t+1}^c$ and the idiosyncratic shock $\epsilon_{d,t+1}^i$ - for each stock.

$$\Delta d_{i,t+1} = \alpha_0 + \alpha_1 \cdot \Delta d_{i,t} + \epsilon_{d,t+1}^c + \epsilon_{d,t+1}^i; \tag{4.4}$$

$$(\sigma_{d,t+1}^c)^2 = \beta_0^c + \beta_1^c \cdot (\sigma_{d,t}^c)^2 + \sigma_{d,t}^c \cdot \upsilon_{t+1}^c; \tag{4.5}$$

$$(\sigma_{d,t+1}^i)^2 = \beta_0^i + \beta_1^i \cdot (\sigma_{d,t}^i)^2 + \sigma_{d,t}^i \cdot \upsilon_{t+1}^i; \tag{4.6}$$

where

$$\epsilon_{d,t+1}^c | I_t \sim N(0, (\sigma_{d,t}^c)^2), \quad \epsilon_{d,t+1}^i | I_t \sim N(0, (\sigma_{d,t}^i)^2);$$

$$\upsilon_{t+1}^c \sim N(0, (\eta_\upsilon^c)^2), \quad \upsilon_{t+1}^i \sim N(0, (\eta_\upsilon^i)^2);$$

I price the cash flow risk by the following way where $\rho_m^{c(i)}$ reflects the relationship among the cash flow growth and the value of dividends regarding different states. The positive sign of ρ_m implies the period of more valuable of dividend coincides with period of higher cash flow growth while the negative sign of ρ_m implies the period of more valuable of dividend coincides with period of lower cash flow growth.

As long as ρ_m is not equal to zero, we have the cash flow risk being priced.

$$cov_t(\epsilon^c_{d,t+1}, \epsilon_{m,t+1}) = \rho^c_m \cdot (\sigma^c_{d,t})^2, \quad cov_t(\epsilon^i_{d,t+1}, \epsilon_{m,t+1}) = \rho^i_m \cdot (\sigma^i_{d,t})^2;$$

I also allow the shock to the dividend and the shock to its volatility to be correlated which captures the leverage effect as argued by [Black, 1976] in explaining the asymmetric volatility of individual stock returns.

$$corr(\epsilon^c_{d,t+1}, \upsilon^c_{t+1}) = \rho^c_l, \quad corr(\epsilon^i_{d,t+1}, \upsilon^i_{t+1}) = \rho^i_l;$$

I further assume that the two stochastic volatility processes are uncorrelated which allows us to derive a simple closed form solution.

$$corr(\epsilon^c_{d,t+1}, \upsilon^i_{t+1}) = 0, \quad corr(\epsilon^i_{d,t+1}, \upsilon^c_{t+1}) = 0;$$

$$corr(\upsilon^c_{t+1}, \upsilon^i_{t+1}) = 0, \quad corr(\epsilon_{m,t+1}, \upsilon^{c(i)}_{t+1}) = 0;$$

I build up the house foundation step by step. The first three propositions show the formulations of the price-dividend ratio, stock returns and unexpected news. Then the fourth proposition shows how the cash flow volatility is related to the conditional Sharpe ratios and the cross-section of stock returns.

Proposition 1: The log price-dividend ratio in the economy can be represented as

$$(p_t - d_t)_i = c_0 + c_1 \cdot \Delta d_{i,t} + c_2 \cdot (\sigma^c_{d,t})^2 + c_3 \cdot (\sigma^i_{d,t})^2 \tag{4.7}$$

where

$$c_0 = \frac{-r_f + \kappa + (\rho \cdot c_1 + 1)\alpha_0 + \rho \cdot c_2 \cdot \beta^c_0 + \rho \cdot c_3 \cdot \beta^i_0}{1 - \rho}, \quad c_1 = \frac{\alpha_1}{1 - \rho \cdot \alpha_1};$$

$$c_2 = \frac{(1-\rho\alpha_1)\cdot(1-\rho\beta_1^c) - \rho\cdot\eta_v^c\rho_l^c \pm \sqrt{[(1-\rho\alpha_1)\cdot(\rho\beta_1^c - 1) + \rho\cdot\eta_v^c\rho_l^c]^2 - \rho^2\cdot(\eta_v^c)^2\cdot[1+2\cdot\rho_m^c\cdot(1-\rho\alpha_1)]}}{(1-\rho\alpha_1)\cdot\rho^2\cdot(\eta_v^c)^2};$$

$$c_3 = \frac{(1-\rho\alpha_1)\cdot(1-\rho\beta_1^i) - \rho\cdot\eta_v^i\rho_l^i \pm \sqrt{[(1-\rho\alpha_1)\cdot(\rho\beta_1^i - 1) + \rho\cdot\eta_v^i\rho_l^i]^2 - \rho^2\cdot(\eta_v^i)^2\cdot[1+2\cdot\rho_m^i\cdot(1-\rho\alpha_1)]}}{(1-\rho\alpha_1)\cdot\rho^2\cdot(\eta_v^i)^2};$$

Proof: See Appendix.

Note for c_2 and c_3, each of them has two roots. The root selection actually depends on where does the volatility feedback come from. At aggregate level, the negative volatility feedback effect requires the sign of the volatility to be negative. However, I cannot conclude the signs at individual stock level.

Proposition 2: The realized return of each stock can be represented as

$$r_{i,t+1} = \lambda_0\cdot\Delta d_{i,t} + \lambda_1^c\cdot(\sigma_{d,t}^c)^2 + \lambda_1^i\cdot(\sigma_{d,t}^i)^2 + \lambda_2^c\cdot\epsilon_{d,t+1}^c + \lambda_2^i\cdot\epsilon_{d,t+1}^i + \lambda_3^c\cdot\upsilon_{d,t+1}^c + \lambda_3^i\cdot\upsilon_{d,t+1}^i \tag{4.8}$$

where

$$\lambda_0 = (\rho\cdot c_1)\cdot\alpha_1 - c_1; \quad \lambda_1^c = \rho\cdot c_2\cdot\beta_1^c - c_2; \quad \lambda_1^i = \rho\cdot c_3\cdot\beta_1^i - c_3;$$

$$\lambda_2^c = \lambda_2^i = \frac{1}{1-\rho\cdot\alpha_1}; \quad \lambda_3^c = \rho\cdot c_2\cdot\sigma_{d,t}^c; \quad \lambda_3^i = \rho\cdot c_3\cdot\sigma_{d,t}^i$$

Proof: See Appendix.

Note that the return will be positively related to cash flow shock $\epsilon_{d,t+1}^{c(i)}$and negatively related to the volatility shock $\upsilon_{d,t+1}^{c(i)}$.

The cash flow news framework is first proposed by [Campbell and Hentschel, 1992] that any unexpected returns can be decomposed into a cash flow news term and a discount rates news term. The derived shock to dividend level and to its volatility can be well fitted into the expected cash flow news and discount rates news framework ([Campbell and Vuolteenaho, 2004a], [Campbell et al., 2009], [Botshekan et al., 2012]). By the model construction, I can represent the expected news term in the formulation of common and idiosyncratic shocks.

Proposition 3:

CF News:

$$(E_{t+1} - E_t) \sum_{j=0}^{\infty} \rho^j \cdot \Delta d_{i,t+1+j} = \lambda_2^c \cdot \epsilon_{d,t+1}^c + \lambda_2^i \cdot \epsilon_{d,t+1}^i \tag{4.9}$$

DR News:

$$-(E_{t+1} - E_t) \sum_{j=1}^{\infty} \rho^j \cdot r_{i,t+1+j} = \lambda_3^c \cdot \upsilon_{d,t+1}^c + \lambda_3^i \cdot \upsilon_{d,t+1}^i \tag{4.10}$$

Proof: See Appendix.

Therefore I have the unexpected cash flow news are reflected by the shock to dividend and the unexpected discount rates news are reflected in the shock to the dividend volatility. The second derivation is a powerful justification of volatility feedback effect because it indicates the increase in volatility will decrease the expected returns which lead to drop in today's stock prices.

Proposition 4:

Conditional Sharpe ratio increase with idiosyncratic cash flow volatility.

Proof: See Appendix.

Stocks with higher idiosyncratic cash flow risk tend to have higher conditional Sharpe ratio. This proposition relates the conditional Sharpe ratio to the cash flow risk, which provide a risk-based explanation why stocks with high conditional Sharpe ratio have higher risk premia.

4.3 Estimation Methodology

4.3.1 Analytic Framework

In this section, I relate the economic dynamics to the cross-sectional asset pricing. I argue cash flow risk should be priced and the idiosyncratic cash flow risks can be priced in the cross section. The classical CAPM model may fail to reflect the role of idiosyncratic cash flow risk. In the traditional CAPM, the systematic market risks are considered. The systematic risks in standard CAPM are abstract and hard to interpret while the common cash flow risk corresponds to the market risk premia in our framework. The new perspective is to provide a risk framework where idiosyncratic cash flow risk determines the asst prices conditional on common cash flow risk. In sum, the CAPM model may fail to explain the idiosyncratic cash flow risk since the market betas only reflect the systematic risk.

The cash flow and discount rates risks are first explored by [Campbell and Vuolteenaho, 2004a]'s paper. [Campbell and Vuolteenaho, 2004a] estimate the unexpected market-level news and show aggregate level risks are priced in the cross-section stock returns. By the the novel cash flow setting, we manage to show that idiosyncratic cash flow risk is also priced in the cross section. For the economic dynamics, the cash flow framework is actually inspired by [Wu, 2001]'s earlier work. However, his paper focus on the market level cash flow and provide no insights on heterogeneous cash flow risks while our interests mainly lie in the cross-sectional stock pricing. My framework allows us to take one step further to study the determinants of cross sectional returns.

4.3.2 Stochastic Volatility Model Estimation

The priced volatility terms are estimated from the stochastic volatility model as below. Let $X_{i,t}$ be the individual cash flow news $\tilde{N}_{i,CF,t}$ and we can estimate the common factor from all individual news term, which can lead to the estimated common volatility and idiosyncratic volatility.

$$X_{i,t} = B_i^c \cdot F_t^c + e_{i,t}; \tag{4.11}$$

$$F_t^c = \alpha + \sum_{j=1}^{p} \rho_j^c \cdot F_{t-j}^c + \Omega^{0.5} \cdot \upsilon_t; \tag{4.12}$$

$$\Omega^{0.5} = A_t^{-1} \cdot diag(\gamma_t) \cdot A_t^{-1\prime}; \tag{4.13}$$

$$e_{i,t} = \sum_{j=1}^{p} \rho_j^i \cdot e_{t-j} + h_{i,t}^{0.5} \cdot \epsilon_t; \tag{4.14}$$

Therefore we have the variance decomposition of the unexpected news term $X_{i,t}$.

$$var(X_{i,t}) = var(B_i^c F_t^c) + var(e_{i,t}) \tag{4.15}$$

by which we have the cash flow news variance decomposition as follows where the total variations are equal to the sum of common and idiosyncratic volatility.

$$var(\tilde{N}_{i,CF}) = (\sigma_{CF}^c)^2 + (\sigma_{CF}^i)^2 \tag{4.16}$$

4.4 Application

In this section, I mainly study the asset pricing property at U.S. industry level. Evidence suggests that the idiosyncratic cash flow risk is robust priced at different specifications.

4.4.1 Data

I choose the U.S. industry portfolio data to test our framework where Fama-French Industry 30 data are explored here. I choose the industry specification (30 industries) due to the long documented data history than other industry specifications. The sample spans from 1926m6 to 2018m12 at monthly frequency.

The cash flow news and discount rates news are estimated as [Campbell and Vuolteenaho, 2004b] where the state variables are chosen as term spread, default spread and the adjusted PE ratios.

The term spread (TS) is defined as the difference between the ten-year yield and the three-month yield. The default spread (DS) is defined as the difference between Moody's Seasoned Aaa and Baa bond yields. The $CAPE$ is cyclically adjusted Price Earnings ratio downloaded from Robert Shiller's website.

The $-(E_{t+1} - E_t)\sum_{j=1}^{\infty}\rho^j \cdot r_{i,t+1+j}$ is estimated from the VAR system while the $(E_{t+1} - E_t)\sum_{j=0}^{\infty}\rho^j \cdot \Delta d_{i,t+1+j}$ is backed from the unexpected returns $r_{i,t+1} - E_t[r_{i,t+1}]$. I present the calculated news term in Figure 4.1. A fact that can be documented here is that either cash flow news or discount rates news are driven by a common factor and they tended to move in the same direction. Therefore it is consistent with our argument that each news term is driven by a common shock sources and their volatility can be decomposed into two parts - a common part and an idiosyncratic part.

4.4.1.1 Volatility

I apply the estimation framework discussed in the methodology part. I estimate the cash flow volatility where the cash flow volatility follows an AR(1) process. I also run robust check letting the cash flow volatility follows an stationary AR(p) process and the main conclusion holds in our U.S industry portfolio application.

For cash flow volatility, I estimate it by letting the volatility term follows an AR(1) process. The AR(1) framework is consistent with the economic model and reflects the stationary property of volatility updating process.

$$ln(\gamma_t) = \bar{a} + \bar{b} \cdot ln(\gamma_{t-1}) + Q^{0.5}\bar{\eta}_t; \tag{4.17}$$

$$ln(h_{i,t}) = a + b \cdot ln(h_{i,t-1}) + q^{0.5}\eta_{i,t}; \tag{4.18}$$

The stochastic volatility model is estimated via Gibbs sampling. Detailed procedures to carry out the estimation are introduced in the technical appendix. In the benchmark specifications, we use 20,000 replications and base our inference on the last 5000 replications. The lag in cash flow estimation is equal to four. Detailed processes are introduced in the technical appendix. I find that the idiosyncratic volatility varies across different industries. Each industry has its idiosyncratic cash flow volatility evolving pattern. It could be attributed to its industry's life cycle and other industry characteristics.

[Insert Figure 4.2 near here]

[Insert Figure 4.3 near here]

4.4.2 Common Cash Flow Volatility

The common cash flow volatility is estimated from the U.S. whole industry's cross-sectional cash flows. It is the common source that drive each industry's dividend growth. Compared to the economic uncertainty index constructed by [Jurado et al., 2015], I find that the common cash flow volatility is highly correlated to both financial uncertainty and macroeconomic uncertainty at 82% and 73%, respectively.

[Insert Figure 4.4 near here]

In Jurado, Ludvigson, and Ng (2015)'s construction, it takes 132 macro series to construct the macroeconomic uncertainty UNC^{macro} and it takes 147 financial time series to construct the financial uncertainty UNC^{fin}. The macro data represents broad categories of macroeconomic time series including real output and income, employment and hours, different economic sector orders, inventories, and sales, consumer spending, compensation and labor costs, capacity utilization measures, price indexes, bond and stock market indexes, and foreign exchange measures while the financial data-set includes valuation ratios such as the dividend-price ratio and earnings-price ratio, growth rates of aggregate dividends and prices, default and term spreads, yields spreads of private and public bond, and a broad cross-section of portfolio equity returns. Here I simply use the unexpected cash flow news from thirty industry portfolios and the estimated common cash flow volatility is tightly co-moves with [Jurado et al., 2015]'s macroeconomic and financial uncertainty.

4.4.3 Idiosyncratic Cash Flow Volatility

4.4.3.1 ICFV in the Cross-Section

I first investigate how the idiosyncratic cash flow volatility (ICFV) is related to the industry characteristics. Monthly cross-sectional regressions are run for the modern sample (1963-2018):

$$Y_t = \alpha + \gamma \cdot F_t + \epsilon_t$$

where $Y_t = \{ICFV_i\}$, $ICFV_i$ is the idiosyncratic cash flow volatility and F_t are firm characteristics including the operating profitability ROE, the book-to-market ratio BM, the average firm size $Size$, leverage LEV as Johnson (2004), idiosyncratic stock volatility $IVOL$ constructed as Ang, Hodrick, Xing, and Zhang (2009) and risk factors such as the economic uncertainty UNC from Jurado, Ludvigson, and Ng (2015), lottery demand factor $FMAX$ from Bali, Brown, Murray, and Tang (2017) and liquidity factor $ILLIQ$ from Pastor and Stambaugh (2003). In order to control for the potential economic explanation of the estimated volatility measures, we include these industry characteristics and risk factors in the cross-sectional regressions. In table 4.1, the intercepts $Cons$ remain significant across different specifications and the explained R^2 are less than 5% except specification (5) and (7). Results suggest that the idiosyncratic cash low volatility can not be fully explained by firm's characteristics. We find that $IVOL$, LEV and UNC factors can increase the explanatory power R^2 a lot. For industry characteristics, evidence suggests that value firms and large firms tend to have larger idiosyncratic cash flow volatility.

High firm leverage corresponds to high idiosyncratic cash flow volatility which is consistent with findings of [Ang et al., 2009]. The interesting finding is that high past idiosyncratic stock return volatility $IVOL$ corresponds to high idiosyncratic cash low volatility and it has the largest explanatory power on the idiosyncratic cash flow risk. For the risk factors, the high economic uncertainty UNC indicates high idiosyncratic cash flow volatility. Both $ILLIQ$ and $FMAX$ factors are significant but the explanatory power is trivial.

[Insert Table 4.1 near here]

Results in table 4.2 suggest the coefficients of idiosyncratic cash flow volatility are positive across all specifications while the magnitudes range from 0.075 to 0.150. We find that the idiosyncratic cash flow volatility can explain 15% in the first column. The positive magnitudes implies that a portfolio buying stocks with the highest idiosyncratic cash flow volatility and short-selling stocks with the lowest cash flow volatility can generate returns in the following month controlling for all else. The β_{mkt} coefficients are positive and insignificant. We find that the coefficients of BM are positive across all specifications which is consistent with the value effect. The coefficients of $SIZE$ are negative but insignificant. The leverage and the lagged idiosyncratic stock volatility are negatively priced which is consistent with [Ang et al., 2009]. The economic uncertainty is significantly priced as documented by [Bali et al., 2017] and investors get compensated by economic uncertainty exposure. The liquidity factor by [Stambaugh, 1999] is negatively priced in the industry cross section. As shown in Column 5, 6 and 7, including UNC, $ILLIQ$ and $FMAX$ do not affect the power of the idiosyncratic cash flow volatility and other firm characteristic variables.

Here we study the role of idiosyncratic cash flow volatility which is related to the idiosyncratic and common stock return volatility covered in previous cross-sectional stock return literature. [Ang et al., 2006] document that high exposure to systematic return volatility or higher idiosyncratic return volatility corresponds to lower stock returns. The negative coefficients of common return volatility have been widely accepted while the negative role of idiosyncratic return volatility is controversial. For the common return volatility, the negative association can be justified by the leverage theory of [Black, 1976] and [Christie, 1982] and the risk premia theory of [French et al., 1987]. The leverage hypothesis argues that the firms become more levered when the stock prices fall which increase the aggregate volatility. The risk premium hypothesis argue investors demand higher risk premia when market volatility increase which depresses the firms' value and results in the negative relationship. Both two explanation can justify the negative relationship among stock returns and aggregate volatility. For the idiosyncratic volatility, [Ang et al., 2006] document that portfolios with high realized idiosyncratic volatility deliver low value-weighted average returns in the subsequent month while [Bali and Cakici, 2008] document no robustly significant relationship among stock returns and idiosyncratic volatility. [Huang et al., 2009] find that the negative relationship is due to the short-term reversal and confirm the positive relationship among expected returns and idiosyncratic volatility. Similar explanation is made by [Fu, 2009] where he use the exponential GARCH models to estimate expected idiosyncratic volatility and find a significantly positive relation between the estimated conditional idiosyncratic volatility and expected returns. [Fu, 2009] argue that [Ang et al., 2006]'s findings are largely explained by the return reversal of a subset of small stocks with high idiosyncratic volatility. These can go back the initial puzzle documented by [Duffee, 1995]. [Duffee, 1995] documented the positive relationship among stock returns and idiosyncratic volatility and argue that the positive contemporaneous relationship cannot be justified by the leverage hypothesis or the risk premium hypothesis. [Grullon et al., 2012] resolve this puzzle by showing that the positive relation between firm-level stock returns and firm-level return volatility is due to firms' real options. Here the documented positive relationship among idiosyncratic cash flow volatility and stock returns which can also be backed up by the argument of [Grullon et al., 2012]. They take the firm's future investment as potential growth options and the value of the growth options increase with the idiosyncratic volatility which justifies the positive relationship among volatility and stock returns. Here the amplified effect of good news on growth options is closely related to the cash flow volatility we estimated from each stock's unexpected cash flows. Later we double sort the industry stocks by the idiosyncratic cash flow uncertainty and the book-to-market ratios. Results suggest the pricing of idiosyncratic cash flow risk is mainly driven by the growth industry. There are other hypothesis to explain the relationship among idiosyncratic volatility and stock returns. [Stambaugh et al., 2015] argue the negative relationship of some stocks is due to the relatively higher constraint on short selling.

[Insert Table 4.2 near here]

Due to extensive data mining in research on cross-sectional expected returns, [Harvey et al., 2016] argue that we should raise the threshold for accepting empirical results as evident of true economic phenomena. Their results suggests that today a newly discovered factor needs to clear a much higher hurdle, with a t statistics greater than 3.0. As shown in table 4.2, the Fama-MacBeth cross-sectional regression indicates that the industry level cash flow volatility passes this test with a t statistic above the threshold 3.0 when firm's characteristics are considered.

4.4.3.2 Sorted Portfolios

Uni-variate Sorted Portfolios: At the end of each month, I sort all stocks into five groups based on the estimated idiosyncratic cash flow volatility. A strategy that goes long the decile portfolio with the largest idiosyncratic cash flow volatility and short the decile portfolio with the smallest idiosyncratic cash flow volatility can produce robust alpha across different specifications. The alpha significantly exists with respect to asset pricing models like Fama-French three factor model, Carhart four factor model and Fama-French five factor model. For example, the single-sorted strategy yields a Fama-French five factor alpha of 0.37% per month (t-stat: 6.90) in long sample (1931-2018) and 0.64% per month (t-stat: 12.28) in modern sample (1963-2018).

[Insert Table 4.3 near here]

Double-Sorted Portfolios: I show that the abnormal returns can be obtained by sorting stocks into different idiosyncratic cash flow volatility groups. Here I proceed to evaluate the role of idiosyncratic cash flow volatility by further sorting the stocks into different industry characteristic groups. I consider the well-known characteristics like the book-to market ratio BM, the debt-to-asset ratio LEV and the average market capitalization $Size$. At the end of each month, we sort all stocks into three groups based on the estimated idiosyncratic volatility and sort stocks in each volatility group into two groups based on an ascending sort of the industry characteristics. The intersections of the two industry characteristics groups and the three volatility groups generate six portfolios. Therefore we obtain the cash flow volatility premium by taking difference of high volatility and low volatility. Panel A of Table 4.4 shows that the equally-weighted volatility factor generates an average monthly return of 0.50% with a Newey-West t-statistic of 2.88 in Growth group and an insignificant average monthly return of 0.21% in Value group. It suggest the industry cash flow volatility is more likely priced in the growth industry which is supposed to have high cash flow volatility. The finding here is consistent with [Grullon et al., 2012]'s argument that the value of firms' growth options increases with the idiosyncratic volatility which results in the positive relationship among stock returns and idiosyncratic volatility. Panel B of Table 4.4 shows that the equally-weighted uncertainty factor generates an average monthly return of 0.45% with a Newey-West t-statistic of 2.65 in High leverage group and an average monthly return of 0.26% with a Newey-West t-statistic of 1.82 in Low leverage group. Panel C of Table 4.4 shows that the equally-weighted uncertainty factor generates an average monthly return of 0.32% with a Newey-West t-statistic of 1.90 in Small firm group and an average monthly return of 0.40% with a Newey-West t-statistic of 2.84 in Large firm group. These results indicate that the idiosyncratic cash flow volatility is more likely to be priced in the growth industries.

[Insert Table 4.4 near here]

4.4.4 Conditional Sharpe Ratio

As argued by [Chava et al., 2019]. investors fail to incorporate the business cycle information into the cash flow growth and it affect the cross-sectional returns. If the pattern holds, then the price ratio during the similar history regime should predict the future returns. In their paper, they showed that firms with higher conditional (regime-dependent) Sharpe ratios correspond to higher stock returns and they find those firms have stronger fundamentals and more upward analyst forecast revisions. Here I argue that higher idiosyncratic cash flow volatility leads to higher conditional Sharpe ratio and brings higher risk compensation as shown in proposition 4.

[Insert Table 4.5 near here]

Table 4.5 shows that portfolio with higher idiosyncratic cash flow risk has higher conditional Sharpe ratio and higher average stock returns. The result provides empirical support for the previous proposition. Figure 4.5 shows how the conditional Sharpe ratios of top quintile and bottom quintile evolve during 1963 to 2018. The conditional Sharpe ratio of top quintile is larger than the bottom Sharpe ratio for most of the time.

[Insert Figure 4.5 near here]

4.4.5 Further Discussions

I apply the method to the US industry portfolios. Results suggest that the common cash flow volatility represents the economic uncertainty while the idiosyncratic cash flow volatility is persistent priced in the cross sectional stock returns. Investors are compensated by holding a diversified portfolios. Results suggest that the volatility measure estimated from the unexpected stock returns are not fully explained by the current risk factors and the firm characteristics. My argument here is that there are information embedded in the unexpected return news at individual level and we can extract new factors from the individual cash flow news. It can also help to better understand the role of cash flows in pricing the current stocks.

The method can also be applied to other situations. For example, we can study the cross-country stock returns to evaluate the role of idiosyncratic and common cash flows, the analysis which may complement our understanding in global investment. It is also possible to extend the sample to the individual stocks in a larger sample and to evaluate the role of current risk factors and the well-known firm characteristics by the newly estimated volatility measures.

4.5 Conclusion

The fundamental question in empirical asset pricing is the determinants of the cross-sectional stock returns. While a large body of recent research proposing new factors based on a host of empirically motivated economic or financial characteristics, I address this question from a new perspective, offering evidence that idiosyncratic and common cash flow volatility is important for understanding stock returns. My main intention is simple. I argue that the unexpected cash flow news should carry additional information besides current risk factors and firm characteristics. In particular, drawing on classic work of [Campbell and Vuolteenaho, 2004a] and the insightful framework of [Wu, 2001], I link uncertainty to cross-sectional stock returns through the common and idiosyncratic volatility perspective.

A recent paper by [Chava et al., 2019] shows that there is significant variation in cash flow growth across industries over the business cycle and they find investors do not fully incorporate business cycle fluctuations into the industry level cash flows. If the business cycle information is not reflected in each industry's cash flow, then conditional Sharpe ratio can be informative for future industry returns. In their paper, sector rotation strategy based on history-dependent Sharpe ratio can produce significant returns. It suggests that cash flow risk at the idiosyncratic level is not fully incorporated into the prices by investors. However, no theoretical model is provided to rationalize the documented Sharpe ratio premium and the role of idiosyncratic cash flows should be re-highlighted. In this paper, I develop a stochastic volatility framework to evaluate the unexpected cash flow news through the variance decomposition perspective, and I relate the conditional Sharpe ratio to the firm's cash flow volatility - especially the idiosyncratic cash flow volatility - to justify the premium.

I propose a method to estimate common and idiosyncratic cash flow volatility from Campbell and Vuolteenaho (2004a)âs cs cash flow news. Papers have been developed based on the aggregate unexpected news but the individual dimension has been less explored. Moreover, the pure news shock has less been connected to the macroeconomic business cycles. I am inspired by a previous work of Wu (2001) where they explored the cash flow model and connected the unexpected stock returns to the model implied shock on cash flow and on its volatility term. I extend the aggregate level cash flow model by allowing a common factor and an idiosyncratic factor driving each firm's cash flow growth. The setting allows us to have a new perspective and able to study the cross-sectional pricing from the volatility perspective and to provide a theoretical justification for [Chava et al., 2019]'s findings on Sharpe ratios.

I apply the method to the U.S. industry portfolios and to study the role of newly estimated volatility measure. I find that the common cash flow volatility estimated from unexpected industry-level cash flow news is highly correlated to Uncertainty index constructed by Jurado, Ludvigson, and Ng (2015). I also documented that the idiosyncratic cash flow volatility is positively priced in the cross-sectional stock returns. I control for well-known risk factors and firm characteristics to see the economic mechanism behind and results suggest the idiosyncratic cash flow volatility is not consumed by the current factors. I do the double sorting by the book-to-market ratio, the industry leverage and the average capitalization and find that the abnormal alphas are main driven by the growth industries. A strategy that goes long the decile portfolio with the largest idiosyncratic cash flow volatility and short the decile portfolio with the smallest idiosyncratic cash flow volatility yields a Fama-French-Five-Factor alpha of 37 bps per month (t-stat: 6.90) in long sample (1931-2018) and 64 bps per month (t-stat: 12.28) in the modern sample (1963-2018). The results suggest the idiosyncratic cash flow risk is not fully reflected by current risk factors. The results may not be limited to U.S. industry portfolios. Our method can also be applied to other situations, for example the cross-country asset returns and the cross-section individual firm returns.

Table 4.1: Comparison with Firm Characteristics: $ICFV_i$

This table shows results from regressing the idiosyncratic cash flow volatility on firm characteristics. The variables are economic uncertainty factor UNC from Jurado, Ludvigson, and Ng (2015), lottery demand factor $FMAX$ from Bali, Brown, Murray, and Tang (2017), liquidity factor $ILLIQ$ from Pastor and Stambaugh (2003), operating profitability ROE, book-to-market ratio BM, average firm size $Size$, leverage LEV as Johnson (2004) and idiosyncratic stock volatility $IVOL$ constructed as Ang, Hodrick, Xing, and Zhang (2009). Newey-West adjusted t statistics are reported in brackets. The sample period is from 1963 to 2018.

$ICFV_i$	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
BM	0.004	-	-	-	-	-	-	-	0.001
	[3.04]	-	-	-	-	-	-	-	[1.14]
SIZE	-	0.199	-	-	-	-	-	-	0.219
	-	[25.11]	-	-	-	-	-	-	[25.82]
ROE	-	-	-0.001	-	-	-	-	-	0.000
	-	-	[-1.19]	-	-	-	-	-	[-0.55]
LEV	-	-	-	2.410	-	-	-	-	3.142
	-	-	-	[11.15]	-	-	-	-	[16.15]
IVOL	-	-	-	-	0.183	-	-	-	0.114
	-	-	-	-	[54.15]	-	-	-	[33.00]
ILLIQ	-	-	-	-	-	1.288	-	-	2.093
	-	-	-	-	-	[3.68]	-	-	[6.63]
UNC	-	-	-	-	-	-	0.063	-	0.054
	-	-	-	-	-	-	[54.98]	-	[43.71]
FMAX	-	-	-	-	-	-	-	-0.011	-0.006
	-	-	-	-	-	-	-	[-4.75]	[-2.86]
$Cons$	3.733	2.317	3.739	3.079	3.391	3.720	-0.531	3.634	-2.396
	[14.55]	[10.58]	[14.54]	[12.36]	[18.35]	[14.96]	[-2.16]	[15.55]	[-11.50]
R^2	0.00	0.06	0.00	0.05	0.14	0.00	0.08	0.00	0.25

Table 4.2: Fama-MacBeth Cross-Section Regressions

This table reports the time-series averages of the slope coefficients obtained from regressing monthly excess returns (in percentage) on the cash flow volatility and a set of factors. The control variables are the β_{mkt} of market risk factor ($MktRf$) from Fama and French (1993 & 2015), economic uncertainty factor UNC from Jurado, Ludvigson, and Ng (2015), lottery demand factor $FMAX$ from Bali, Brown, Murray, and Tang (2017), liquidity factor $ILLIQ$ from Pastor and Stambaugh (2003), operating profitability ROE, book-to-market ratio BM, average firm size $Size$, leverage LEV as Johnson (2004) and idiosyncratic stock volatility $IVOL$ constructed as Ang, Hodrick, Xing, and Zhang (2009). Newey-West adjusted t -statistics are reported in brackets. The sample period is from 1963 to 2018.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$ICFV_i$	0.105	0.105	0.075	0.148	0.150	0.148	0.150
	[2.67]	[2.87]	[1.93]	[3.71]	[3.75]	[3.71]	[3.75]
β_{mkt}	-	-0.001	0.038	0.150	0.148	0.150	0.148
	-	[-0.01]	[0.22]	[0.81]	[0.79]	[0.81]	[0.79]
BM	-	-	0.021	0.163	0.172	0.163	0.172
	-	-	[0.12]	[0.95]	[1.00]	[0.95]	[1.00]
$SIZE$	-	-	0.042	0.054	0.050	0.054	0.050
	-	-	[0.72]	[0.94]	[0.86]	[0.94]	[0.86]
ROE	-	-	-	-0.149	-0.139	-0.149	-0.139
	-	-	-	[-0.45]	[-0.42]	[-0.45]	[-0.42]
LEV	-	-	-	-1.807	-1.801	-1.807	-1.801
	-	-	-	[-3.26]	[-3.21]	[-3.26]	[-3.21]
$IVOL$	-	-	-	-0.242	-0.244	-0.242	-0.244
	-	-	-	[-2.47]	[-2.46]	[-2.47]	[-2.46]
$ILLIQ$	-	-	-	-	-0.225	-	-
	-	-	-	-	[-1.10]	-	-
UNC	-	-	-	-	-	-0.212	-
	-	-	-	-	-	[-1.35]	-
$FMAX$	-	-	-	-	-	-	1.447
	-	-	-	-	-	-	[8.08]
$Cons$	0.424	0.439	0.154	0.310	0.151	0.533	0.248
	[1.45]	[1.78]	[0.26]	[0.50]	[0.64]	[0.89]	[1.33]
R^2	0.15	0.24	0.37	0.51	0.51	0.51	0.51

Table 4.3: Uni-variate Sorted Portfolios

This table shows results of real equally-weighted returns of industry portfolios sorted according to their industry-level cash flow volatility. Return data are monthly over the long sample from 1931 to 2018 and over the modern sample from 1963 to 2018. Industry definitions are from Kenneth French's website. CAPM (FF3, Carhart4, and FF5) denotes average excess returns unexplained by the CAPM (Fama-French three-factor model, Carhart four-factor model and Fama-French five-factor model). The numbers in parentheses are t statistics according to Newey and West (1987). One, two, and three asterisks denote significance at the 10%, 5%, and 1% levels, respectively.

Long Sample	(1)	(2)	(3)	(4)	(5)	$H-L$
$CAPMAlpha$	0.63	0.64	0.63	0.82	1.02	0.39***
	(7.75)	(8.07)	(8.05)	(10.52)	(11.00)	(7.41)
$FF3Alpha$	0.64	0.65	0.63	0.83	1.03	0.39***
	(7.80)	(8.09)	(8.08)	(10.57)	(11.12)	(7.54)
$Carhart4Alpha$	0.60	0.59	0.58	0.79	0.96	0.37***
	(6.96)	(7.19)	(7.19)	(9.60)	(10.18)	(6.90)
Modern Sample	(1)	(2)	(3)	(4)	(5)	$H-L$
$CAPMAlpha$	0.09	0.11	0.09	0.30	0.44	0.36***
	(1.86)	(2.55)	(2.23)	(7.20)	(7.79)	(6.95)
$FF3Alpha$	-0.18	-0.17	-0.16	0.05	0.28	0.46***
	(-6.15)	(-6.08)	(-5.98)	(1.76)	(5.73)	(8.91)
$Carhart4Alpha$	-0.02	-0.01	-0.02	0.17	0.42	0.44***
	(-0.72)	(-0.20)	(-0.69)	(5.49)	(7.69)	(8.13)
$FF5Alpha$	-0.23	-0.25	-0.19	0.00	0.42	0.64***
	(-6.76)	(-8.58)	(-6.04)	(0.14)	(7.94)	(12.28)

Table 4.4: Double-Sorted Portfolios

This table shows results of real equally-weighted returns of industry portfolios sorted according to their industry-level cash flow volatility and their industry characteristics. Return data are monthly over the modern sample from 1970 to 2018. Industry definitions are from Kenneth French's website. Industry characteristics include the book-to-market ratio BM, the industry leverage LEV and the average firm size factor $Size$. The numbers in parentheses are t statistics according to Newey and West (1987). One, two, and three asterisks denote significance at the 10%, 5%, and 1% levels, respectively.

BM/$ICFV_i$	(1)	(2)	(3)	$H-L$
Growth	0.58	0.66	1.08	0.50***
	(2.02)	(2.46)	(3.50)	(2.88)
Value	0.66	0.62	0.88	0.21
	(2.32)	(2.30)	(2.95)	(1.33)
LEV/$ICFV_i$	(1)	(2)	(3)	$H-L$
High	0.64	0.65	1.10	0.45***
	(2.26)	(2.35)	(3.47)	(2.65)
Low	0.60	0.63	0.86	0.26*
	(2.10)	(2.43)	(3.18)	(1.82)
SIZE/$ICFV_i$	(1)	(2)	(3)	$H-L$
Small	0.61	0.63	0.92	0.32*
	(2.04)	(2.15)	(2.81)	(1.90)
Large	0.63	0.65	1.03	0.40***
	(2.32)	(2.67)	(3.99)	(2.84)

Table 4.5: Conditional Sharpe Ratio

This table shows results of real equally-weighted returns of industry portfolios sorted according to their industry-level cash flow volatility. Return data are monthly over the modern sample from 1963 to 2018. Industry definitions are from Kenneth French's website. The numbers in parentheses are t statistics according to Newey and West (1987). One, two, and three asterisks denote significance at the 10%, 5%, and 1% levels, respectively.

Modern Sample	(1)	(2)	(3)	(4)	(5)	$H-L$
Average Ret	0.67	0.69	0.66	0.87	1.09	0.42***
	(8.27)	(8.69)	(8.60)	(11.27)	(11.71)	(7.96)
Sharpe Ratio	0.423	0.433	0.438	0.447	0.469	0.046***
						(4.92)

Figure 4.1: Cash Flow News - Industry Portfolios

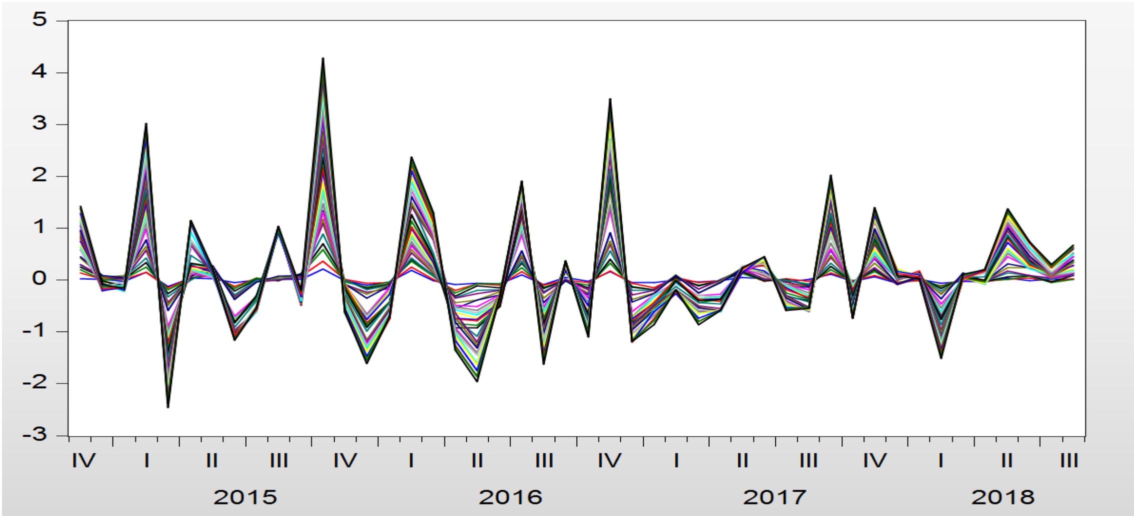


Figure 4.2: Common Cash Flow Volatility

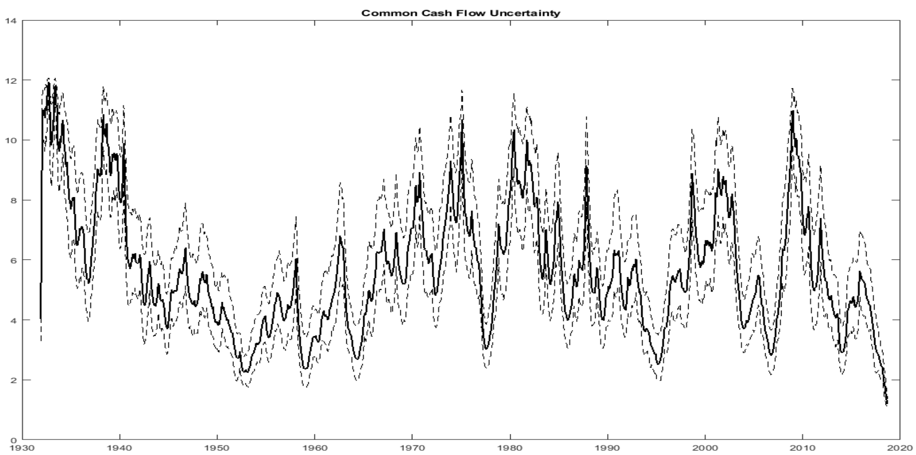


Figure 4.3: Idiosyncratic Cash Flow Volatility

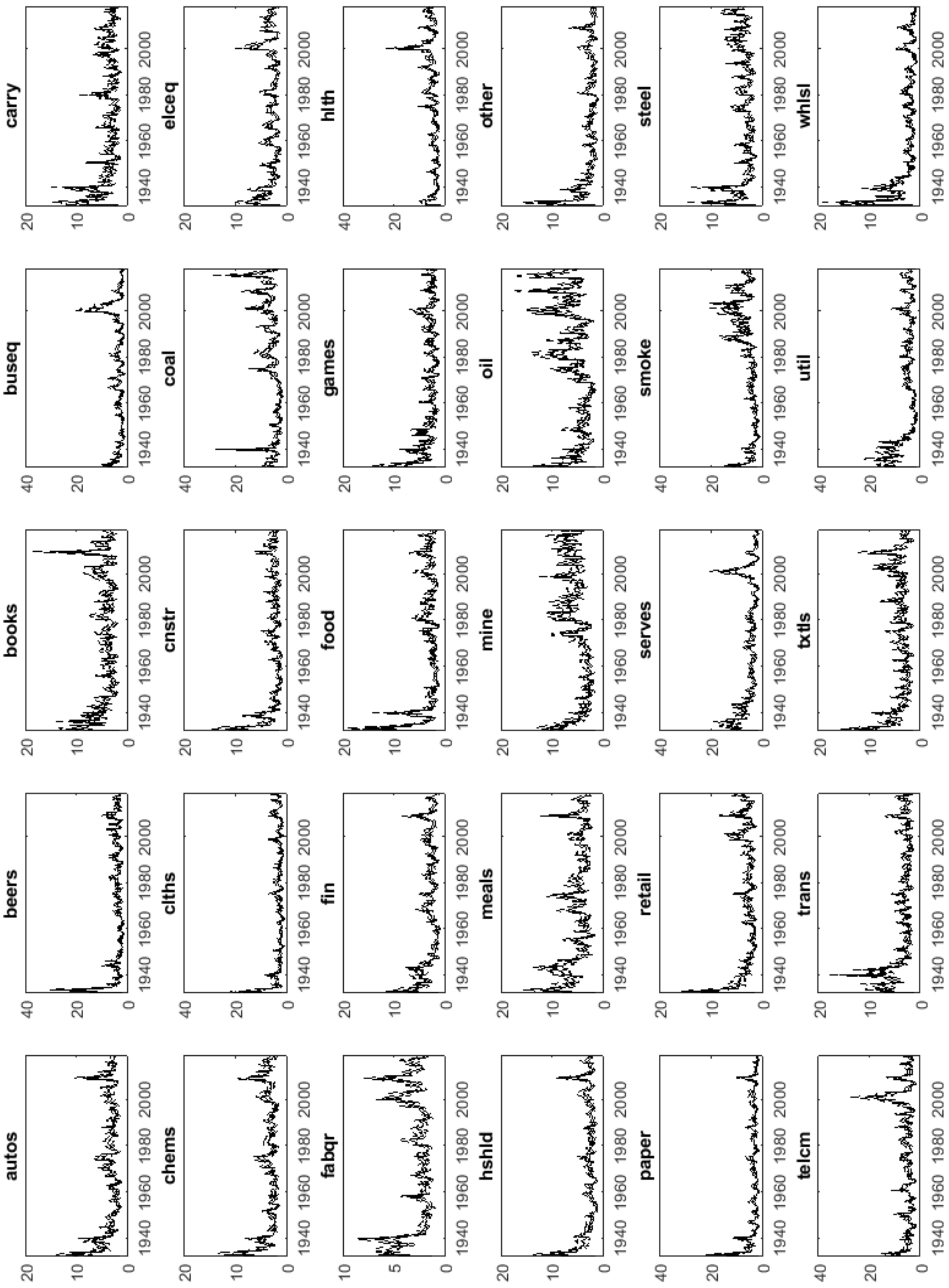


Figure 4.4: Common Cash Flow Volatility and Uncertainty Index of Jurado, Ludvigson, and Ng (2015)

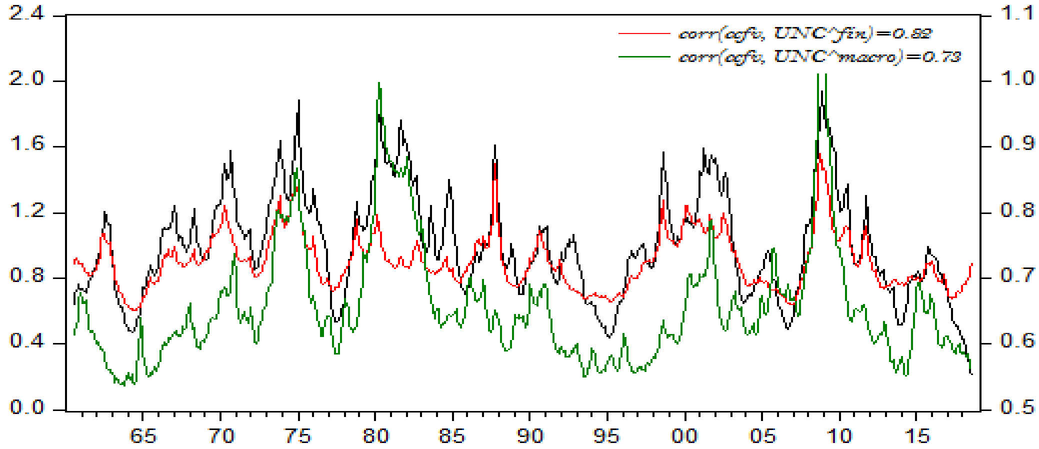
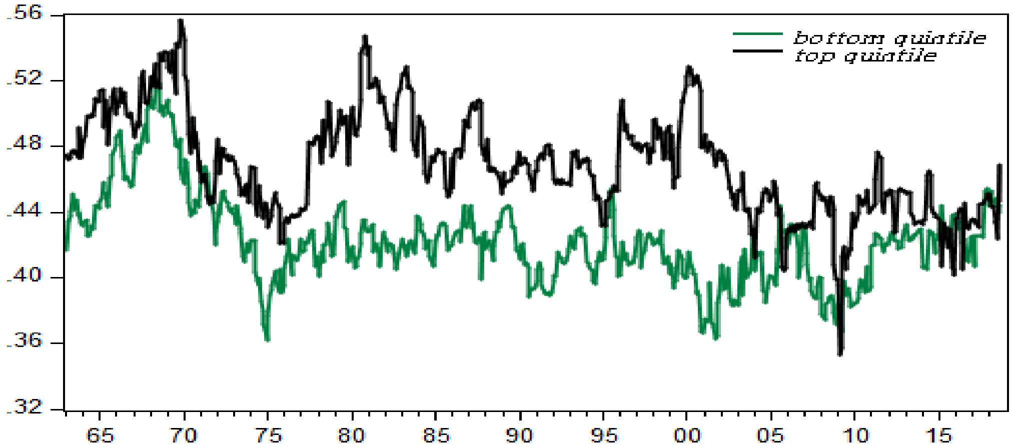


Figure 4.5: Conditional Sharpe Ratios Sorted by Idiosyncratic Cash Flow Volatility



4.6 Appendix

4.6.1 A Cash Flow Model

$$\Delta d_{i,t+1} = \alpha_0 + \alpha_1 \cdot \Delta d_{i,t} + \epsilon^c_{d,t+1} + \epsilon^i_{d,t+1}$$

$$(\sigma^c_{d,t+1})^2 = \beta^c_0 + \beta^c_1 \cdot (\sigma^c_{d,t})^2 + \sigma^c_{d,t} \cdot \upsilon^c_{t+1}$$

$$(\sigma^i_{d,t+1})^2 = \beta^i_0 + \beta^i_1 \cdot (\sigma^i_{d,t})^2 + \sigma^i_{d,t} \cdot \upsilon^i_{t+1}$$

4.6.1.1 Proposition 1

$$(p_t - d_t)_i = c_0 + c_1 \cdot \Delta d_{i,t} + c_2 \cdot (\sigma^c_{d,t})^2 + c_3 \cdot (\sigma^i_{d,t})^2$$

Proof:

$$1 = E_t(M_{t+1}R_{t+1}) = E_t(exp(-r_{f,t+1} - \frac{1}{2}\sigma^2_{m,t} + \epsilon_{m,t+1} + r_{t+1}))$$

where

$$r_{t+1} = \kappa + \rho \cdot (p_{t+1} - d_{t+1}) + \Delta d_{t+1} - (p_t - d_t)$$

Let $A(\cdot) = -r_{f,t+1} - \frac{1}{2}\sigma^2_{m,t} + \epsilon_{m,t+1} + r_{t+1}$, we have

$$E[A(\cdot)] + \frac{1}{2}Var(A(\cdot)) = 0$$

By the educated guess,

$$(p_t - d_t)_i = c_0 + c_1 \cdot \Delta d_{i,t} + c_2 \cdot (\sigma^c_{d,t})^2 + c_3 \cdot (\sigma^i_{d,t})^2$$

Substitute the guess into $A(\cdot)$ and the corresponding equation:

- For the constant term:

$$-r_f + \kappa + \rho \cdot c_0 + (\rho \cdot c_1 + 1)\alpha_0 + \rho \cdot c_2 \cdot \beta^c_0 + \rho \cdot c_3 \cdot \beta^i_0 - c_0 = 0$$

$$\Rightarrow c_0 = \frac{-r_f + \kappa + (\rho \cdot c_1 + 1)\alpha_0 + \rho \cdot c_2 \cdot \beta^c_0 + \rho \cdot c_3 \cdot \beta^i_0}{1 - \rho}$$

- For the Δd corresponding term:

$$(\rho \cdot c_1) \cdot \alpha_1 - c_1 = 0$$

$$\Rightarrow c_1 = \frac{\alpha_1}{1-\rho \cdot \alpha_1}$$

- For the $(\sigma^c_{d,t})^2$ corresponding term:

$$\frac{1}{2}\rho^2 \cdot c_2^2 \cdot (\eta_v^c)^2 + (\rho \cdot \beta_1^c - 1) \cdot c_2 + \frac{1}{2}(\rho \cdot c_1 + 1)^2 + (\rho \cdot c_1 + 1) \cdot \rho_m^c + (\rho \cdot c_1 + 1) \cdot (\rho c_2 \cdot \eta_v^c)\rho_l^c = 0$$

$$\Rightarrow c_2 = \frac{(1-\rho\alpha_1)\cdot(1-\rho\beta_1^c) - \rho \cdot \eta_v^c \rho_l^c \pm \sqrt{[(1-\rho\alpha_1)\cdot(\rho\beta_1^c - 1) + \rho \cdot \eta_v^c \rho_l^c]^2 - \rho^2 \cdot (\eta_v^c)^2 \cdot [1 + 2 \cdot \rho_m^c \cdot (1-\rho\alpha_1)]}}{(1-\rho\alpha_1)\cdot \rho^2 \cdot (\eta_v^c)^2}$$

- For the $(\sigma^i_{d,t})^2$ corresponding term:

$$\frac{1}{2}\rho^2 \cdot c_3^2 \cdot (\eta_v^i)^2 + (\rho \cdot \beta_1^i - 1) \cdot c_3 + \frac{1}{2}(\rho \cdot c_1 + 1)^2 + (\rho \cdot c_1 + 1) \cdot \rho_m^i + (\rho \cdot c_1 + 1) \cdot (\rho c_3 \cdot \eta_v^i)\rho_l^i = 0$$

$$\Rightarrow c_3 = \frac{(1-\rho\alpha_1)\cdot(1-\rho\beta_1^i) - \rho \cdot \eta_v^i \rho_l^i \pm \sqrt{[(1-\rho\alpha_1)\cdot(\rho\beta_1^i - 1) + \rho \cdot \eta_v^i \rho_l^i]^2 - \rho^2 \cdot (\eta_v^i)^2 \cdot [1 + 2 \cdot \rho_m^i \cdot (1-\rho\alpha_1)]}}{(1-\rho\alpha_1)\cdot \rho^2 \cdot (\eta_v^i)^2}$$

Q.E.D.

4.6.1.2 Proposition 2

$r_{i,t+1} = \lambda_0 \cdot \Delta d_{i,t} + \lambda_1^c \cdot (\sigma^c_{d,t})^2 + \lambda_1^i \cdot (\sigma^i_{d,t})^2 + \lambda_2^c \cdot \epsilon^c_{d,t+1} + \lambda_2^i \cdot \epsilon^i_{d,t+1} + \lambda_3^c \cdot \upsilon^c_{d,t+1} + \lambda_3^i \cdot \upsilon^i_{d,t+1}$

Proof:

$$r_{t+1} = \kappa + \rho \cdot (p_{t+1} - d_{t+1}) + \Delta d_{t+1} - (p_t - d_t)$$

By proposition 1,

$$(p_t - d_t)_i = c_0 + c_1 \cdot \Delta d_{i,t} + c_2 \cdot (\sigma^c_{d,t})^2 + c_3 \cdot (\sigma^i_{d,t})^2$$

We have

$$r_{i,t+1} = \lambda_0 \cdot \Delta d_{i,t} + \lambda_1^c \cdot (\sigma_{d,t}^c)^2 + \lambda_1^i \cdot (\sigma_{d,t}^i)^2 + \lambda_2^c \cdot \epsilon_{d,t+1}^c + \lambda_2^i \cdot \epsilon_{d,t+1}^i + \lambda_3^c \cdot \upsilon_{d,t+1}^c + \lambda_3^i \cdot \upsilon_{d,t+1}^i$$

where

$$\lambda_0 = (\rho \cdot c_1) \cdot \alpha_1 - c_1;$$

$$\lambda_1^c = \rho \cdot c_2 \cdot \beta_1^c - c_2; \quad \lambda_1^i = \rho \cdot c_3 \cdot \beta_1^i - c_3;$$

$$\lambda_2^c = \lambda_2^i = \frac{1}{1 - \rho \cdot \alpha_1};$$

$$\lambda_3^c = \rho \cdot c_2 \cdot \sigma_{d,t}^c; \quad \lambda_3^i = \rho \cdot c_3 \cdot \sigma_{d,t}^i$$

Q.E.D.

4.6.1.3 Proposition 3

CF News:

$$(E_{t+1} - E_t) \sum_{j=0}^{\infty} \rho^j \cdot \Delta d_{i,t+1+j} = \lambda_2^c \cdot \epsilon_{d,t+1}^c + \lambda_2^i \cdot \epsilon_{d,t+1}^i$$

DR News:

$$-(E_{t+1} - E_t) \sum_{j=1}^{\infty} \rho^j \cdot r_{i,t+1+j} = \lambda_3^c \cdot \upsilon_{d,t+1}^c + \lambda_3^i \cdot \upsilon_{d,t+1}^i$$

Proof:

CF News:

$$
\begin{aligned}
(E_{t+1}-E_t)\sum_{j=0}^{\infty}\rho^j\cdot\Delta d_{i,t+1+j} &= \sum_{j=0}^{\infty}\rho^j\cdot[E_{t+1}[\Delta d_{i,t+1+j}]-E_t[\Delta d_{i,t+1+j}]] \\
&= \sum_{j=0}^{\infty}\rho^j\cdot\alpha_1^j(\epsilon^c_{d,t+1}+\epsilon^i_{d,t+1}) \\
&= \frac{1}{1-\rho\cdot\alpha_1}(\epsilon^c_{d,t+1}+\epsilon^i_{d,t+1}) \\
&= \lambda_2^c\cdot\epsilon^c_{d,t+1}+\lambda_2^i\cdot\epsilon^i_{d,t+1}
\end{aligned}
$$

DR News:

$$
\begin{aligned}
-(E_{t+1}-E_t)\sum_{j=1}^{\infty}\rho^j\cdot r_{i,t+1+j} &= -\rho\sum_{j=1}^{\infty}\rho^{j-1}\cdot[E_{t+1}[r_{i,t+1+j}]-E_t[r_{i,t+1+j}]] \\
&= \text{-}\rho\textstyle\sum_{j=1}^{\infty}\rho^{j-1}\cdot[E_{t+1}[\lambda_1^c\sigma^c_{d,t+1+j}+\lambda_1^i\sigma^i_{d,t+1+j}]-E_t[\lambda_1^c\sigma^c_{d,t+1+j}+\lambda_1^i\sigma^i_{d,t+1+j}]] \\
&= -\rho\sum_{j=0}^{\infty}(\rho\beta_1^c)^j\cdot(\lambda_1^c\sigma^c_{d,t}\upsilon^c_{t+1})-\rho\sum_{j=0}^{\infty}(\rho\beta_1^i)^j\cdot(\lambda_1^i\sigma^i_{d,t}\upsilon^i_{t+1}) \\
&= \rho\frac{-\lambda_1^c}{1-\rho\cdot\beta_1^c}\sigma^c_{d,t}\upsilon^c_{t+1}+\rho\frac{-\lambda_1^i}{1-\rho\cdot\beta_1^i}\sigma^i_{d,t}\upsilon^i_{t+1} \\
&= \rho\cdot c_2\cdot\sigma^c_{d,t}\cdot\upsilon^c_{t+1}+\rho\cdot c_3\cdot\sigma^i_{d,t}\cdot\upsilon^i_{t+1} \\
&= \lambda_3^c\cdot\upsilon^c_{d,t+1}+\lambda_3^i\cdot\upsilon^i_{d,t+1}
\end{aligned}
$$

Q.E.D.

4.6.1.4 Proposition 4

Proof:

In proposition 2, we have

$$
r_{i,t+1}=\lambda_0\cdot\Delta d_{i,t}+\lambda_1^c\cdot(\sigma^c_{d,t})^2+\lambda_1^i\cdot(\sigma^i_{d,t})^2+\lambda_2^c\cdot\epsilon^c_{d,t+1}+\lambda_2^i\cdot\epsilon^i_{d,t+1}+\lambda_3^c\cdot\upsilon^c_{d,t+1}+\lambda_3^i\cdot\upsilon^i_{d,t+1}
$$

The conditional Sharpe ratio using log returns can be represented as

$$
\begin{aligned}
SR_t &= \frac{E_t[r_{i,t+1}] + \frac{1}{2}Var_t[r_{i,t+1}]}{\sqrt{Var_t[r_{i,t+1}]}} \\
&= \frac{\lambda_0 \cdot \Delta d_{i,t} + \lambda_1^c \cdot (\sigma_{d,t}^c)^2 + \lambda_1^i \cdot (\sigma_{d,t}^i)^2 + \frac{1}{2}[(\lambda_2^c \cdot \sigma_{d,t}^c)^2 + (\lambda_2^i \cdot \sigma_{d,t}^i)^2 + (\lambda_3^c \cdot \eta_v^c)^2 + (\lambda_3^i \cdot \eta_v^i)^2]}{\sqrt{(\lambda_2^c \cdot \sigma_{d,t}^c)^2 + (\lambda_2^i \cdot \sigma_{d,t}^i)^2 + (\lambda_3^c \cdot \eta_v^c)^2 + (\lambda_3^i \cdot \eta_v^i)^2}}
\end{aligned}
$$

Conditional Sharpe Ratio increases with idiosyncratic cash flow volatility $\sigma_{d,t}^i$.

Q.E.D.

4.6.2 Bayesian Estimation

Here we provide detailed procedure to estimate the common and idiosyncratic cash flow uncertainty ($X_{i,t}$ is $\tilde{N}_{i,CF,t}$)

$$X_{i,t} = B_i^c \cdot F_t^c + e_{i,t};$$

$$F_t^c = \alpha + \sum_{j=1}^{p} \rho_j^c \cdot F_{t-j}^c + \Omega^{0.5} \cdot \upsilon_t;$$

$$\Omega^{0.5} = A_t^{-1} \cdot diag(\gamma_t) \cdot A_t^{-1\prime};$$

$$e_{i,t} = \sum_{j=1}^{p} \rho_j^i \cdot e_{t-j}^c + h_{i,t}^{0.5} \cdot \epsilon_t;$$

$$ln(\gamma_t) = \bar{a} + \bar{b} \cdot ln(\gamma_{t-1}) + Q^{0.5}\bar{\eta}_t;$$

$$ln(h_{i,t}) = a + b \cdot ln(h_{i,t-1}) + q^{0.5}\eta_{i,t};$$

4.6.2.1 Gibbs

- Draw common volatility γ given the coefficients F^c, and the parameters of the volatility transition equation Q.

- Draw idiosyncratic stochastic volatility h_i conditional on a draw for the factors F^c, the parameters of the transition equation q and the factor loadings B_i^c and the auto-regression coefficients derived error terms.

- Draw factor F^c using the algorithm of Carter and Kohn (2004) given a draw for all other parameters.

- Draw α and ρ_j^c conditional a draw of γ. First the left and the right hand side variables of the models can be transformed to remove the heteroscedasticity by the newly drawn $\sqrt{\gamma}$, then we can obtain the standard conditional posterior distribution for the coefficients.

- Draw A given the draw of α and ρ_j^c in common factor equation and given the draw of common stochastic volatility γ.

- Draw ρ_j^i conditional on a draw for the factors F^c and the factor loadings B_i^c. First re-scale the left and the right hand side by $\frac{1}{\sqrt{h_i}}$ to remove heteroscedasticity and then we can obtain the conditional posterior of ρ_j^i which is normal with mean and variance given by the standard formula for the linear regression model.

- Draw $\bar{a}$, $\bar{b}$ and Q conditional on the draw of $ln(\gamma)$. By the re-written transition equation $ln(\gamma_t) - \overline{ln(\gamma)} = \bar{b} \cdot (ln(\gamma_{t-1}) - \overline{ln(\gamma)}) + \eta_t$, we can derive the Q, $\bar{b}$ and $\bar{a}$ in order.

- Draw a, b and q conditional on the draw of h_i. Similar way as in previous step to derive the q, b and a in order.

4.6.2.2 Priors

Parameters of the common volatility transition equation The prior for the off-diagonal elements A_t is assumed to be normal and derived from the inverse of the Cholesky decomposition of volatility with each row scaled by the corresponding element on the diagonal. The OLS estimates are obtained using the VAR method by introducing a natural conjugate prior for the VAR parameters via dummy observations following [Bańbura et al., 2010] and [Mumtaz and Theodoridis, 2017]. The prior means are chosen as the OLS estimates of the coefficients of an AR(1) regression estimated for each endogenous variable using a training sample.

The prior for log γ_t is that the process is driven by normal shocks and the unconditional mean is equal to zero. The prior for Q is inverse-gamma where the mean is equal to the average of the variances of the shocks to the transition equations using the initial uni-variate stochastic volatility estimates. Parameters of the idiosyncratic volatility transition equation The prior for log h_t is that the process is driven by normal shocks and the unconditional mean is equal to zero. The prior for q is inverse-gamma where the mean is equal to the average of the variances of the shocks to the transition equations using the initial uni-variate stochastic volatility estimates. Factor loadings The priors on factor loadings are assumed to be normal with variance equal to one. The means of the prior are the loadings obtained using principal component estimates of F_t^c.

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