EMPIRICAL ANALYSIS OF RISKS AND RETURNS OF SHORT-TERM DIVIDEND STRIPS

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Abstract

In this thesis, I examine the risk and return properties of individual dividend strips, which are claims to short-term dividends from individual companies. First, contrary to the conventional assumption that quarterly dividend payments from individual companies are sticky and certain, I document considerable variability in short-term dividends at the firm level. Uncertainty in dividends of individual stocks in the next quarter can give rise to short-term dividend risk premium at the firm level, which affects the pricing of claims on quarterly dividend payments. Then, I use exchange-traded options on individual stocks to create synthetic dividend strips and use the put-call parity relation to compute prices of dividend strips. During the sample period from 1996 to 2017, the dividend strip aggregated from all individual firms earns an average return of 4.62% per quarter, higher than the average quarterly return of the S&P 500 index during the same period. The high average return on the aggregate dividend strip is consistent with an average downward-sloping term structure of equity premium documented by prior studies using index derivatives. There are substantial cross-sectional differences in returns on dividend strips among individual firms sorted by average normalized dividend premium in the previous four quarters, which is a measure of ex-ante dividend risk premium. Average

value-weighted returns on dividend strip portfolios in the highest and lowest quintiles of dividend premiums are 11.91% and −2.87% per quarter, and the spread in return is highly statistically significant. Differences in dividend strip returns are not driven by potential measurement errors in options prices, as option-implied dividends are strong predictors of future dividend payments, and are not driven by differences between dividend payers and non-payers, as the results hold for the subsample of stocks that have ever paid regular cash dividends in the past five years. Variations in returns of claims on short-term dividends do not diminish after controlling for short-sale constraints of underlying stocks and adjusting early exercise premiums in prices of American-style options. In addition, results of both the Fama and MacBeth (1973) cross-sectional regressions and the multivariate test of Gibbons, Ross and Shanken (1989) indicate that the Fama and French (2015) five-factor model can well describe average returns on dividend strips sorted by the ex-ante dividend risk premium. In contrast, the Capital Asset Pricing Model, the Fama and French (1993) three-factor model, and the Carhart (1997) four-factor model seem to be incomplete models. I also use four well-known stock return predictors, book-to-market ratio (BM), operating profitability (OP), total asset growth rate (ATG), and cumulative stock return in the previous six months (RET(−1,−6)) as alternative sorting variables. The four stock return predictors can predict subsequent dividend strip returns in the same direction of prediction on stock returns. The five-factor model performs the best in explaining variations in dividend strips of stocks with different characteristics, which indicates that the superior performance of the model is not specific to dividend strips sorted by historical dividend premium. Dividend strip returns associated with different sorts share common exposures to risk factors other than the market risk which are well captured by the profitability factor and the investment factor.

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Chapter 1

Introduction

This thesis examines the risk and return properties of individual companies' short-term dividend strips synthetically replicated from individual equity options in the U.S. market.

Studying the pricing of dividends is important in light of the essential roles that dividends play in the financial market. Cash dividend is an essential way for companies to distribute cash flows to stockholders despite the growing popularity of alternative payout policies like stock repurchases (Julio and Ikenberry, 2004; Michaely and Moin, 2019). For investors in the U.S., dividends contribute to over one-third of the total return on equity (Fama and French, 2007) and account for a large and growing proportion of personal incomes (Lu and Karaban, 2009).

According to the present value model, a stock's price is equal to the sum of present values of all future dividends from that stock (Gordon, 1962). A stock can be considered as a portfolio of dividend strips, which entitle investors to dividends paid during some finite periods. Analogous to zero-coupon bonds, dividend strips contain information about the discount rate of equity at different horizons. Therefore, studying how dividend strips are priced can improve our understanding of how stock price is formed.

Studying risk and return properties of dividend strips is a straightforward practice if prices of equity cash flows at different horizons are available. Due to the lack of such data in the past, the literature on equity valuation has been focusing on studying the dynamics of the value of a stock as a whole. Recently, with the development of the equity derivative market and the introduction of new financial assets like dividend derivatives, investors can trade dividends directly in the market, and researchers have access to prices of dividend strips with different maturities. To better understand how stock price is formed, the literature moves towards to investigate the pricing of individual dividends paid over different horizons. van Binsbergen, Brandt and Koijen (2012) use options on the S&P 500 index to calculate prices of dividend strips that pay dividends only in the near future and show that the short-term asset earns a higher return than the underlying index on average. They find that though the short-term index dividend strip has a positive market beta, its average return is still too high to be explained by the Capital Asset Pricing Model (CAPM). Introducing the size factor (SMB) and the value factor (HML) as in Fama and French (1993) hardly helps to explain the high average near-term equity risk premium. van Binsbergen, Brandt and Koijen (2013) use index dividend futures and Cejnek and Randl (2016) use index dividend swaps to examine the pricing of short-term index dividend strips and find similar results.

The current literature about dividend strips focuses on the market level. To better understand how short-term equity cash flows are priced, it also stands to examine dividend strips of individual stocks. First, dividends paid by individual stocks can be uncertain and risky in the short run. Since the seminal paper of Lintner (1965) which uses a partial adjustment model to study corporate payout policies and documents that managers prefer to maintain a stable dividend policy, the literature has assumed that companies' dividend policies are conservative and there is little uncertainty about dividends paid by individual companies in the short run. However, several recent studies challenge this dividend stickiness assumption by showing that managers will cut dividends when faced with dividend constraints (Kim, Lee and Lie, 2017) and will increase dividends as earnings increase substantially (Lie, 2005). Besides, Bilinski and Bradshaw (2015) document an increasing availability of analyst forecasts of quarterly dividends, which indicates investors' growing demands for explicit forecasts on dividends due to variable dividend payments of individual firms in recent years. To measure the degree of uncertainty of dividend payments from quarter to quarter, I compute the root mean squared error of quarterly dividend surprises proxied by actual quarterly dividend growth rate or by analyst dividend forecast error of dividends in the next fiscal quarter. Contrary to the assumption of dividend stickiness, the variability of dividend payments is high on average, suggesting that there are significant deviations between realized dividends in the next quarter and anticipated levels. The high average quarterly dividend uncertainty at the firm level may command a dividend premium, which will affect the pricing of claims on quarterly dividend payments from individual stocks. Second, the market of single stock dividend futures is growing rapidly, suggesting increasing interests in trading individual dividends independent of underlying stocks and greater exposures to dividend risks of investors (Manley and Mueller-Glissmann, 2008). Studying how individual dividends are priced can help investors make better portfolio decisions and manage dividend risks. Third, studying risk and return properties of short-term cash flows of individual stocks is essential for understanding how prices of individual stocks are formed. Cash flows at different horizons of individual companies should be discounted at appropriate discount rates reflecting risk profiles of cash flows with different maturities. Discounting short-term cash flows of individual stocks at the same discount rate will result in misvaluation if there are cross-sectional differences in risk exposures of near-term dividend payments from individual firms (Ang and Liu, 2004). Finally, Manley and Mueller-Glissmann (2008) suggest that the high risk premium of short-term dividend strips synthetically replicated by index dividend derivatives may be due to the excess supply of dividend risk as banks issue high volumes of structured products most often linked to equity index to retail and institutional investors and need to buy index dividend swaps to hedge their long index dividend risk exposures. Claims on index dividends can be replicated by a weighted portfolio of dividend strips of individual stocks, which are less likely to be affected by selling pressures. Thus, studying the pricing of the aggregate dividend strip made up of individual dividend strips can help us understand whether the high average return of near-term dividend strip at the market level is due to imbalanced demand and supply of dividend risk.

Studies on how individual dividends are priced in the cross section of companies are very few. This thesis contributes to the literature by investigating the risk and return properties of claims on near-term dividends at the firm level and aims to answer three research questions. First, is there a difference between the return of market dividend strips and the return of dividend strip aggregated from dividend strips of individual stocks? Second, do returns on near-term dividend strips vary across individual stocks? And third, if there are cross-sectional variations in returns on dividend strips, whether the variations in returns can be explained by rational asset pricing. Several recent papers also examine the pricing of single cash flows with different maturities separately at the firm level. To estimate returns on short-term cash flows of individual stocks, prior studies usually use historical accounting or equity market data and have to make assumptions on processes of expected dividend growth rates and/or stochastic discount factors. This paper differs from other studies in the computation of prices of claims on near-term single cash flows. I use data on individual equity options to calculate prices of individual dividend strips, so the identification of returns on short term cash flows does not rely on additional assumptions but only requires the absence of arbitrage opportunities. Another advantage of using options data is that options prices contain forward-looking information about underlying stocks. Besides, options written on individual stocks have relatively high liquidity, and a large and growing fraction of listed stocks have options traded on them over time.

As in van Binsbergen, Brandt and Koijen (2012), I use equity options to create dividend strips of individual stocks synthetically. One can replicate the payoff of a dividend strip by trading a portfolio made up of the underlying stock, put and call options written on the stock and risk-free bonds. Specifically, a strategy of selling a put option, buying a call option and buying a risk-free bond (with the face value equal to the strike price of the pair of options) replicates the ex-dividend payoff of the underlying stock at the maturity date of the options. Since an investment in the strategy above is not entitled to dividends paid during the life of the options, while an investment in the actual stock is, the difference between the value of the actual stock and the value of the strategy is the price of the future dividend. According to the put-call parity no-arbitrage relation (Stoll, 1969), the price of the future dividend, or option-implied dividend (DI) as the price is inferred from options prices, is given by:

$$\mathrm{DI} = S + P - C - Ke^{R^f \tau}, \tag{1.1}$$

where S is the price of the stock, P and C are prices of put and call options with strike price K and time to maturity τ, and R^f is the continuously compounding risk-free rate. One thing to note is that the put-call parity relation only holds exactly for European-style options, while individual equity options in the U.S. market are American-style options. Therefore, the option-implied dividend is biased by the differences between early exercise premiums (EEP) of put and call options. As discussed later, I adjust the early exercise premiums in the options-implied dividends and find that adjusting EEP does not change the empirical results.

I examine the how prices of short-term dividend strips are formed both at the aggregate level and in the cross section of individual firms. For the marker level, I construct a dividend strip of the market by aggregating dividend strips of individual stocks and find that the aggregate dividend strip has risk and return properties similar to those of index dividend strips documented by prior studies. Average quarterly return of the aggregate dividend strip is 4.62%, higher than the average quarterly return on the S&P 500 index (2.53%) during the sample period from January 1996 to December 2017, indicating that the high average return on short-term equity cash flows is not specific to indexes and cannot be fully explained by index-linked structured products issuers' demands for hedging dividend risk. The CAPM cannot explain the high average return of the aggregate dividend strip, as the CAPM beta of the near-term asset is low and the CAPM-alpha is significantly positive. I also examine whether multi-factor asset pricing models, including the Fama and French (1993) three-factor model (FF3), the Carhart (1997) four-factor model (FFM4), and the Fama and French (2015) five-factor model (FF5), which introduce portfolio-based risk factors other than the market risk, can help improve the description of the high near-term risk premium at the aggregate level. The aggregate dividend strip has positive loadings on the value, investment, and profitability factors. The alphas relative to the FF3 and the FFM4 are still significantly positive, while the alpha relative to the FF5 becomes insignificant, suggesting that the FF5 performs the best in explaining returns on the short-term asset at the market level.

Then I examine dividend strip returns across individual stocks. The average return on individual dividend strip is 3.12% per quarter, with a first quartile of −13.07% and a third quartile of 19.69%, indicating significant cross-sectional variations in returns on dividend strips among individual firms. I further study what may explain the cross-sectional variations in returns on individual dividend strips. To mitigate the noises in the returns of dividend strips based on individual equity options prices, I use a portfolio-based approach. Specifically, at the end of each quarter, dividend strips are sorted into five portfolios by the average price-normalized dividend premium in the previous four quarters ($\overline{\mathrm{DP}}$), where the price-normalized dividend premium is defined as the difference between the present value of the realized dividend and the option-implied dividend divided by current stock price. $\overline{\mathrm{DP}}$ is an ex-ante measure of dividend risk premium. A high normalized dividend premium indicates that investors pay a low price and ask for a high premium for the right to get a stock's dividend. The portfolio with the highest and lowest historical normalized dividend premium earns a quarterly value-weighted average return of 11.91% and −2.87%. The spread between the quarterly returns of the two portfolios is 14.78% and is highly statistically significant.

In a rational asset pricing framework, cross-sectional variations in asset returns should be associated with different exposures to systematic risks. I aim to explain the cross-sectional variations in returns on individual short-term assets by differences in risk exposures to asset pricing factors under the four asset pricing models. To this end, I use a rolling window of five-year quarterly returns to estimate the beta coefficients with respect to different risk factors. Portfolios sorted by historical dividend premium have very different exposures to risk factors. Portfolios with high (low) returns on dividend strips are associated with high (low) market betas. For the characteristic-based risk factors other than the market risk, returns on portfolios with high $\overline{\mathrm{DP}}$ behave more like returns on stocks with high book-to-market ratio, large firm size, high profitability, conservative investment and high past return, and vice versa for portfolios with low $\overline{\text{DP}}$. The results from the Fama and MacBeth (1973) cross-sectional regressions show that the market risk is significantly positively priced in the cross section of individual dividend strips. However, the average regression intercept of the CAPM is still significantly positive. The GRS (Gibbons, Ross and Shanken, 1989) test rejects the CAPM model to describe average returns of the five portfolios sorted by $\overline{\text{DP}}$ with a p-value of 0.003. Introducing the size, value, and momentum factor improves the description of dividend strip returns, as suggested by the higher p-values of the GRS (1989) test on the three-factor and the four-factor model. Adding RMW and CMA produces less significant regression intercepts with smaller absolute values, and the GRS (1989) test fails to reject the five-factor model with a p-value of 0.123. The superior performance of the FF5 is also supported by the fact that the FF5-alpha has the smallest magnitude and least statistical significance for the aggregate short-term dividend strip.

In addition to dividend risk premium, other factors like short-sale constraints of underlying stocks and early exercise premiums in American-style options prices can make the actual stock price and the American-style option-implied ex-dividend stock price different. Option-implied dividends can be overestimated and returns on dividend strips can be underestimated if stocks are subject to short-sale constraints, resulting in a positive relation between normalized dividend premium and future dividend strip return. To address this issue, I do a double-sorting analysis by first sorting stocks based on the percentage of institutional holding (PIH), which is a proxy for short-sale constraint, and then sorting stocks based on historical dividend premium. Within each PIH group, average returns on dividend strips still increase with historical dividend premium and portfolios in the fifth quintiles of $\overline{\text{DP}}$ significantly outperform portfolios in the first quintiles of $\overline{\text{DP}}$, while return differences across PIH groups are not significant, suggesting that short-sale constraints do not drive the variations in returns on dividend strips. The results of the cross-sectional regressions and the GRS (1989) test indicate that the FF5 is superior in explaining variations of dividend strips returns, similar to results for the portfolios sorted by historical dividend premium only. Using the 25 double-sorted portfolios as testing portfolios in the Fama and MacBeth (1973) cross-sectional regressions, I find that the market risk, HML, RMW, and CMA carry significantly positive risk premium in the cross section of individual short-term dividend strips.

I conduct a battery of robustness checks and additional analysis on the main results. First, since DI is obtained from market options prices, it may be subject to measurement errors or microstructure noises in the market. To investigate the information contents of option-implied dividends (DI), I look at the dynamics of DI around announcement dates of four significant changes in dividend policies of Apple Inc. and General Motor Company. I find that changes in dividend payments have been picked up by dividends implied from options prices before the changes in dividend policies are announced. Before Apple Inc. publicly announced its decision to initiate dividends in 2012 and the decision to increase dividends in 2013, DI has been increasing higher than historical dividends, which suggests that option traders have anticipated the dividend initiation and the dividend increase in light of the company's high profitability and large cash holding. Before General Motors Company cut quarterly dividends in 2006 and suspended dividends in 2008, DI has been decreasing lower than historical levels, as option traders expected dividends to decrease in view of the company's deteriorating financial performances. The four examples provide preliminary evidence that option-implied dividends incorporate information about future dividends. I also use a regression approach to examine the predictability of DI for future dividends formally. For a given stock, I regress its dividend change (normalized by quarter-end stock price) in the next quarter on normalized option-implied dividend change at the end of this quarter. For over 70% of individual stocks in the sample, the coefficient on the option-implied dividend change is significantly positive, suggesting that option-implied dividends significantly predict actual dividend changes and that option-implied dividends indeed contain information about future dividends.

Second, I do the empirical analysis for a subsample of dividend payers, which are companies that have ever paid a positive regular cash dividend in the previous five years. Companies that paid dividends in the past are likely to continue dividend payments in the future, and vice versa for dividend nonpayers. Thus, the cross-sectional variations in dividend strip returns may be driven by differences between dividend payers and nonpayers. I find that average returns on dividend strips also vary substantially among dividend payers and the five-factor model can well describe average dividend strip returns of this subsample of stocks, so the main empirical results are not merely driven by differences in dividend policies of companies.

Third, regarding the issue of early exercise premium, the American-style option implied dividend is underestimated (overestimated) if EEP of a call option is higher (lower) than EEP of a put option. To deal with this issue, I use a simple method to adjust for EEP in prices of American-style options. OptionMetrics uses the Cox, Ross and Rubinstein (1979) binomial tree model and the most recent announced dividend to compute the implied volatility of American options. Since the binomial tree takes the possibility of early excise of options into account, the implied volatility calculated by OptionMetrics has been adjusted for EEP. I substitute the implied volatility from OptionMetrics and the most recent historical dividend into the Black and Scholes (1973) option-pricing formula to calculate prices of options as if they were European-style options and calculate dividends implied from the hypothetical European options prices. The main results do not change after DI is adjusted by EEP. I also use an alternative simulation-based approach under the Heston (1993) stochastic volatility model and use the average option-implied dividend as a proxy for expected dividend to deal with the concerns that the Black and Scholes (1973) model may misprice options and that historical dividends may not incorporate investors' most recent expectations for future dividends. This more sophisticated approach gives very similar estimates of EEP of call and put options, and the differences in differences of EEP of calls and puts are not correlated with prices of individual dividend strips, the ex-ante measure of short-term dividend risk premium or short-sale constraints of underlying stocks, suggesting that the results of sorting portfolio analysis will be similar under the two approaches to estimate EEP.

Finally, I examine the cross-sectional differences in returns on dividend strips of stocks sorted by four equity characteristics, book-to-market ratio (BM), operating profitability (OP), total asset growth rate (ATG) and cumulative return in the previous six months (RET(−1,−6)), which are documented by prior studies to predict subsequent cross-sectional stock returns (Fama and French, 1992, 2015; Titman, Wei and Xie, 2004; Jegadeesh and Titman, 1993). Dividend strips of value stocks, profitable stocks, stocks with conservative investments, and past winners earn significantly higher returns than dividend strips of growth stocks, unprofitable stocks, stocks with aggressive investments and past losers, and the differences in portfolio returns are not driven by short-sale constraints of underlying stocks. The five-factor model can well explain cross-sectional variations in dividends strips with different sorts, as evidenced by the small and insignificant average regression intercepts from the cross-sectional regressions and the high p-values of the GRS (1989) test on the model. The results indicate that the superior performance of the FF5 is not specific to portfolios sorted by ex-ante dividend risk premiums. Dividend strip returns associated with different sorting variables seem to share common exposures to risks in addition to the market risk, which are well captured by the profitability factor (RMW) and the investment factor (CMA).

The rest of this thesis is organized as follows. Chapter 2 gives a review of related literature. Chapter 3 presents data sources and summary statistics of the characteristics of stocks in the sample. Chapter 4 examines whether dividends paid from individual firms are uncertain in the short run. In Chapter 5, I discuss how to estimate prices and returns of individual dividend strips from market options prices. Chapter 6 and Chapter 7 examine risk and return properties and asset pricing implications of the dynamics of values of the near-term claims at the aggregate level and across individual stocks. Chapter 8 conducts robustness tests. The final chapter concludes.

Chapter 2

Literature Review

2.1 Aggregate Dividends

2.1.1 Importance of Dividends

Investigating how dividends are priced is an important research question in light of the essential roles that dividends play in the financial market and the real economy. In the U.S., dividends make a great contribution to the total return on equity investment and are important sources of income for investors. Since 1926, dividends have represented approximately one-third of the total return of the S&P 500 index (Fama and French, 2007). Over time, dividend incomes increase in proportion to increasing equity market capitalization and account for a larger fraction of personal incomes in the U.S. market (Lu and Karaban, 2009). Cash dividend is an important way for companies to distribute cash flows to stockholders. The literature has documented the 'disappearing dividends' phenomenon in the U.S. market, which refers to the empirical findings of a dramatic decline in the percentage of firms paying cash dividends (Fama and French, 2001) and of the substitution of stock repurchases for dividends (Grullon and Michaely, 2002). However, recent studies find that the declining trend of dividends reverses significantly since the 21st century. Julio and Ikenberry (2004) find that after reaching its lowest level of 36% in 1999, the percentage of dividend payers climbed back to 46% at the end of 2004, as more U.S. companies initiated dividend payments. Michaely and Moin (2019) examine the fraction of dividend payers in a more recent sample period and also find a rebound of cash dividends starting around 2000 and continuing throughout 2016. Figure 1 shows the time-series plot of the percentage of dividend-paying stocks of all firms listed on NYSE, AMEX and NASDAQ (the black line) and of stocks traded on the three stock exchanges with exchange-traded options (the blue line) in each quarter from 1996 to 2017. From 1996 to 2000, the fraction of dividend payers of all listed firms decreased from 34% to 30%, and the decline was more dramatic for stocks with options (from 48% to 32%). After 2000, for both samples, the proportion of dividend payers grew steadily. During the subprime crisis from 2007 to 2009, a large number of firms omitted dividend payments, but the percentage of dividend payers recovered soon after the crisis and reached to about 45% at the end of 2017. The disappearing and reappearing of cash dividends over time suggest uncertainty in aggregate dividends and that cash dividend remains an important payout policy for companies.

2.1.2 The Pricing of Index Dividend Strips

Dividends are essential constitutes of equity. Studying the pricing and return of dividend strips can provide information about the way the total value of equity is formed. How to discount future cash flow is an important question in finance. The present value model says that the current price of a financial asset is equal to the sum of present values of all future cash flows generated by the asset at different horizons. For example, the price of a bond is equal to the sum of present values of coupons paid at different dates and the principal of the bond repaid at the bond maturity date. According to the law of one price, the price of a bond should be equal to the sum of the value of bond strips which are zero-coupon bonds with various time-to-maturities. Any mispricing should be arbitraged away quickly. Similarly, a stock's price is equal to the sum of present values of all future dividends from that stock paid at different times. Analogous to a bond, a stock can be considered as a portfolio of dividend strips, which are claims on single dividends paid during finite periods. Dividends paid at different horizons contain information about the term structure of expected dividend growth rate and equity risk premium. Therefore, studying separate cash flow strips of financial assets can help us understand investors' risk preferences and the endowment process at different horizons (van Binsbergen, Brandt and Koijen, 2012) and provide information incremental to those contained in prices and returns of aggregate equity cash flows.

Returns of fixed income securities with different time-to-maturities, often referred to as the term structure of interest rate, have been extensively studied in the bond pricing literature. In contrast, the equity valuation literature has been focusing on studying the dynamics of the value of a stock or an equity index as a whole. One reason for the lack of research about dividend strips is a lack of relevant data in the past. Unlike treasury strips with various time-to-maturities, there is not a spot market to trade dividends directly, so current prices of future dividends are not observable. Early studies about the term structure of equity use cross-sectional returns of stocks with different cash flow growth rates or risk exposures to examine properties of short-term and long-term equity cash flows. This indirect approach to inferring properties of cash flows at different horizons is subject to the problem that the results depend on the assumptions made about cash flow growth rates. Recently, with the development of the equity derivative market and the introduction of dividend derivatives, researchers can obtain prices of dividend strips directly. There are two ways to trade dividends in the market. First, dividend derivatives (i.e., dividend futures and dividend swaps) allow investors to trade dividends directly. Since around 2000, there emerged an over-the-counter market of dividend derivatives, and later some contracts became exchange-traded.[1] Alternatively, dividend strips can be replicated using equity options or futures. van Binsbergen, Brandt and Koijen (2012) are the first to use options on the S&P 500 index to replicate short-term dividend strips that pay dividends in the near future and examine properties of the short-term assets. They find that compared to the underlying index, the short-term assets earn higher average returns and have higher volatility. Though the short-term assets have positive loadings on market excess returns, suggesting that short-term equity cash flows share general information with long-term equity cash flows, alphas relative to the Capital Asset Pricing

[1] Dividend derivatives have been traded over-the-counter since early 2000, and the most popular dividend contracts are index dividend swaps. Dividend derivatives were first traded on exchange in 2002 in South-Africa. Eurex launched dividend futures on the Dow Jones Euro index in 2008. NYSE Liffe launched futures on the FTSE100 dividend index in 2009. According to the factbook of Eurex, open interests and trading volumes of the Dow Jones Euro index dividend futures have been increasing significantly since the launch, and the success of this product led to the subsequent launch of dividend derivatives based on major equity indexes of various markets, including the FTSE 100, the S&P 500, the Nikkei 225 and other equity indexes.

Model (CAPM) is still significantly positive. The Fama and French (1993) three-factor model which adds the size factor (SMB) and the value factor (HML) slightly helps explain the high average risk premium of near-term cash flows, mainly due to a positive slope coefficient on HML. However, the improvement is limited as the FF3-alpha remains significantly positive. van Binsbergen, Brandt and Koijen (2013) use dividend futures of major equity indexes to study near-term dividend strips in the U.S., Europe and Japan market and have similar findings. Cejnek and Randl (2016) use index dividend swaps to construct short-duration assets in four markets. They also find that the short-duration investment strategy outperforms the equity index on a risk-adjusted basis.

2.2 Dividends Paid by Individual Firms

2.2.1 Dividend Stickiness

Existing literature on the pricing of short-term equity cash flows usually focus on index dividends, while only a few papers examine properties of separate cash flows for individual firms. One reason for the lack of such studies is that the literature generally believes that dividends paid by individual companies are sticky in the short run. Lintner (1965) observes that managers believe that investors put a premium on stocks with stable dividend payments. When setting dividends in a quarter, managers use the dividend of the previous quarter as a benchmark and try to avoid dividend changes. He proposes a partial adjustment model in which managers set a target payout ratio and adjust dividends continuously towards this target ratio. Since the seminal work of Lintner (1965), the literature has assumed that dividends are sticky and that such a conservative dividend policy will result in little uncertainty about dividends paid by individual companies in the short run. Several recent papers challenge this view by showing that dividend policies are more flexible in recent years. For example, Brav, Graham, Harvey and Michaely (2005) adopt the partial adjustment model of Lintner (1965) on a cross section of individual companies and find that the median target ratio and adjusted-R^2 of the regression model decreases over time, indicating a deterioration of performances of the model and that target payout ratios no longer play a central role in making dividend policies. Among the 384 financial executives surveyed in the study, 45% of them claim that they are flexible in pursuing dividend goals and 12% of them do not have a target dividend at all, suggesting that dividend policies are more flexible in recent years. Some papers show that companies will change dividends in response to changes in earnings quickly. In his paper, Lintner (1965) concedes that "stockholders would understand and accept the cut in dividends in the face of any substantial or continued decline in earnings." Consistent with this view, Lie (2005) finds that companies cut dividends when there is a substantial concurrent decline in earnings in a fiscal year and increase dividends when there is a concurrent positive shock to operating incomes. Kim, Lee and Lie (2017) find that when facing dividend constraints, companies are more likely to cut dividends than to manipulate earnings to avoid dividend cuts. Guttman, Kadan and Kandel (2010) find that the probability that a company keeps dividends constant in the next year conditional on the company changed dividends in the last year is 16%, and they conclude that a large proportion of dividend payers do not engage in the dividend smoothing practice. Bilinski and Bradshaw (2015) find that during the sample period from 2000 to 2012, 62% of U.S. dividend payers increase dividends and 11% of them cut dividends from last fiscal year. They argue that the variability of dividend payments can reduce investors' reliance on historical dividends as a benchmark for future dividends and can increase their demands for explicit dividend forecasts. Consistent with this conjecture, they document that from 2001 to 2012, the percentage of dividend payers with analyst dividend forecasts increase from 3% to 96%, suggesting that analysts provide more information about future dividends in response to increasing demands on such information of investors. The uncertainty about dividend payments in the short-run from individual stocks may comprise dividend risk premium at the firm level, which will affect the pricing of short-term dividend strips of individual companies.

2.2.2 The Market for Trading Individual Dividends

Investigating the pricing of claims on dividends at the firm level is of interest as investors have increasing interests in trading dividends of individual stocks. In addition to the rising of the market for index dividend derivatives, single stock dividend derivatives also gain popularity among investors as attractive investment vehicles. Major investment banks have traded single stock dividend risk since 2015. Trading individual dividend strips expands investment opportunities and can provide further diversification opportunities for investors (Manley and Mueller-Glissmann, 2008). Besides, individual dividend strips enable investors to have exposures to individual cash flows linked directly to a company's income statement of a specific maturity without having exposures to the underlying risk, which should appeal for fundamental investors who can forecast future cash flows at specific horizons and for institutional investors with a stream of liabilities at specified times like pension funds. Eurex introduced single stock dividend futures in 2010. At the end of 2018, the products are traded on around 150 largest companies in Europe and the U.S. market, with an average daily volume of over 27,092 contracts. As trading claims on single cash flows of individual companies becomes popular, investors have growing exposures to uncertain dividend payments of individual firms caused by time-varying capabilities and propensities to pay dividends. Studying the pricing of individual dividend strips can help investors better manage dividend risk down to a corporate level.

Studying the pricing of individual dividend strips can help us understand whether the high average return of index dividend strip documented by prior studies is due to an imbalance in demand and supply of dividend risk. The empirical finding that risk premium is higher in the short run than in the long run is puzzling since many leading asset pricing models suggest the opposite. There is a rapidly growing literature that aims to explain the high near-term risk premium.[2] Manley and Mueller-Glissmann (2008) suggest that a possible reason for the high average return on index dividend strip is the excess supply of dividend risk of banks, which have started issuing high volumes of structured products often linked to an equity index since 2000 and need to sell index dividend strips to hedge their exposures to dividend risks. Dividend strips of equity indexes can also be replicated

[2]van Binsbergen and Koijen (2017) comprehensively summarizes potential explanations for an average downward-sloping term structure of equity.

by a weighted portfolio of individual dividend strips, which are less likely affected by such selling pressures. Investigating the pricing of the dividend strip aggregated from individual dividend strips can provide a robustness check on whether the high dividend premium at the market level is due to the excess selling pressure of dividend risk.

2.2.3 The Pricing of Individual Dividend Strips

The growing popularity in dividend stripping among investors and increasing interest in studying the pricing and return of single cash flows of index equity at different maturities in the equity pricing literature spur recent studies to estimate and examine returns of dividend strips of individual stocks. Studying how single cash flows at different maturities of individual stocks is essential to understand the formation of prices of equity at the firm level. Ang and Liu (2004) show that using constant discount rates of near-term and long-term cash flows when the term structure of equity is actually not flat can lead to severe misvaluations of individual stocks.

Several recent papers examine the pricing of near-term cash flows of individual firms. To study separate cash flows of individual stocks, some papers use historical financial statements information or equity market data and usually make assumptions about the cash flow process and discount rate process. For instance, assuming that both returns on equity and expected stock returns follow mean-reverting processes and using a log-linearization approach, Lyle and Wang (2015) develop a stock price valuation model in which expected return is a function of book-to-market ratio and return on equity. Using historical accounting and stock return data, they estimate the expected holding period return of individual firms at different horizons and find the expected returns can predict cross-sectional future stock returns. A potential problem of such an approach to estimate return on single cash flows is that results depend on the assumptions made about the cash flow process and discount rate process. More recently, several papers use derivative data to examine the risks and returns of claims on near-term cash flows of individual companies. Callen and Lyle (2019) use options written on individual stocks in the U.S. market to estimate the term structure of implied cost of capital at the firm level, and they find that option-implied cost of capital can predict future stock return and earnings announcement premium. They document cross-sectional differences in the term structure of implied cost of capital: firms that have higher beta, lower profitability and more growth opportunity have a more upward-sloping term structure. Their estimation of the term structure of equity needs specifying a functional form for the stochastic discount factor and thus is not fully model-free. Besides, they not only use options data but also use historical equity market data to estimate the expected correlation between individual stock return and market portfolio return. In a recent paper by Gormsen and Lazarus (2019), they use single stock dividend futures to examine returns on dividend strips of individual firms up to five years during a sample period from 2010 to 2018. Although the market for single stock dividend futures is developing rapidly, the market is still young and their sample only covers about 150 firms with very large market capitalization.They do not find significant cross-sectional variations on near-term dividend strips among their sample of stocks. Clara (2018) uses individual equity options in the U.S. market to estimate near-term and long-term market betas of individual stocks. He finds that the slope of the term structure of beta can positively predict future stock return and is a priced factor in the cross section of stock returns, even after controlling for the level of term structure and for Fama and French (1993) three risk factors.

2.3 Incremental Contributions

This thesis is different from prior studies and contributes to the literature in several ways. First, contrary to the assumption made by prior literature, I document considerable variability in dividends from quarter to quarter of individual stocks. The uncertainty of dividend payments at the firm level suggests that in addition to studying the pricing of near-term dividend strips at the aggregate level, it also stands to examine the pricing of claims in dividends at the corporate level.

Second, this study provides a model-free approach to calculate prices and returns of near-term dividend strips of individual firms. To calculate prices of individual dividend strips, I only use individual equity options data but not historical data on firm fundamentals or past equity market data. Using options data has the advantage that options prices contain forward-looking information about the underlying stocks. Another advantage of using options data is that the market of exchange-traded individual equity options is more developed and liquid than the market of other derivatives in the U.S., and the proportion of listed stocks with options traded is large and growing over time. Besides, the approach to compute dividend strip prices from options data only requires no-arbitrage relations.

It does not rely on a specific model and is free from assumptions on the process of cash flows or discount rates. This model-free approach presents its own issues that the estimated prices of dividend strips can be contaminated by early exercise premiums (EEP) of American-style options and short-sale constraints of underlying stocks (Ofek, Richardson and Whitelaw, 2004). I do robustness checks to alleviate the effects of these issues and find that the main empirical results are not significantly affected after controlling for short-sale constraints and adjusting for EEP. In short, this paper provides a model-free approach to directly and reliably estimate price and return on cash flow at a particular maturity date for individual stocks.

Third, the option-implied dividend is the present value of the expected future dividend and is determined by the expected dividend growth rate and dividend risk premium. Prior studies estimate expected dividends from options prices and find that option-implied dividends can predict realized dividends (Bae-Yosef and Sarig, 1992; Fodor, Stowe and Stowe, 2017; Kragt, 2017). However, no existing study has considered individual option-implied dividend as a measure of the price of dividend. This paper complements the literature by showing that individual equity options prices also contain information about near-term dividend risk premiums of individual firms.

Next, this study is the first to document that returns on near-term dividend strips vary across stocks and that the variations in returns are driven by differences in risk exposures of near-term cash flows. The findings suggest that variations in returns on the short-end of the term structure of equity across stocks may also contribute to cross-sectional variations in stock returns and that it is important to estimate a term structure of equity at the firm level.

Finally, this thesis confirms and provides a possible explanation for the high average return on index dividend strips documented by prior studies. The dividend strip aggregated from individual dividend strips also earns an average return higher than that of the equity index, ruling out the possibility that the high average return on the short-term asset synthetically created from equity derivatives is simply driven by selling pressure of dividend risk. Prior studies about the pricing of dividend strips at the market level find that the CAPM has difficulty in explaining the average return on short-term assets, and that introducing the size factor (SMB) and the value factor (HML) as in the Fama and French (1993) three-factor model (FF3) does not produce improvements, leaving the high average return on short-term claims a puzzle. Consistent with the finding of prior studies, I also find that the CAPM and the FF3 are incomplete descriptions of returns on short-term dividend strips, both at the aggregate level and in the cross section of individual stocks. I investigate whether the Carhart (1997) four-factor model which adds the momentum factor (UMD) and the Fama and French (2015) five-factor model which adds the profitability factor (RMW) and the investment factor (CMA) are better descriptions of average returns on near-term dividend strips. The results from asset pricing tests indicate that the five-factor model can well explain the average return on the aggregate dividend strip and the cross-sectional differences in returns on dividend strips of individual stocks, suggesting that RMW and CMA may help explain the high near-term equity premium at the market level. Besides, if an asset pricing model is correctly specified, the model should be able to describe returns on all assets at all maturities. Using the individual dividend strips as testing portfolios for asset pricing models complements existing studies about the performances of models in describing asset returns.

Chapter 3

Data and Sample

The sample of this study includes common stocks listed on NYSE, AMEX or NASDAQ during the sample period from January 1996 to December 2017 with options traded on the stocks. Stocks that have prices lower than $5 at the quarter end are excluded from the sample. Monthly data of individual companies are obtained from the Center for Research in Security Prices (CRSP). CRSP also provides data on the amount, frequency of payments, ex-dividend date and announcement date of cash dividends. However, CRSP does not provide information about dividend announcement date if a firm does not pay a cash dividend in a given quarter. In this case, I use the earnings announcement date as the dividend announcement date for the firm in that quarter. Annual and quarterly information about financial statements is obtained from CRSP/Compustat Merged database. Daily option data, including closing bid and ask options price, open interest, trading volume, strike price, maturity date and implied-volatility, are obtained from OptionMetrics. OptionMetrics also provides continuously compounded risk-free interest rates at different maturities.[3] Data on institutional holdings are obtained from the Thomson Financial Institutional Holdings (13F) database. Stocks that cannot be matched with the companies in the database are assumed to have zero institutional holdings.

[Insert Table 1 here]

During the sample period, in total, there are 8,355 unique individual stocks that can be matched with exchange-traded options. On average, in a quarter, there are 2,385 stocks in the sample. The upper part of Panel A of Table 1 reports summary statistics of characteristics of underlying stocks with options traded. For easy comparison with the full sample of stocks listed on the three major stock exchanges, the lower part of Panel A reports summary statistics of characteristics for the full sample of stocks. Statistics are computed across stocks in each quarter, and the table reports time-series averages of statistics. Equity characteristics are computed following prior literature. Firm size is the product of stock price per share and total number of shares outstanding at the end of June in a year. Stocks in the sample have an average logarithm of firm market capitalization (LogSIZE) of 20.97, higher than the average firm size of the full sample of stocks (average LogSIZE is 19.55), indicating that stocks with options traded tend to be large firms. Book-to-market ratio (BM) is the ratio of the book value of common stocks for the fiscal year ending in the last year over the market value of equity at the end of December of last year. Stocks in the sample have an average BM of 0.57, which is lower

[3]The interest rate provided by OptionMetrics is a zero curve derived from LIBOR rates of the British Bankers' Association (BBA) and settlement prices of Chicago Mercantile Exchange (CME) Eurodollar futures.

than the mean value of BM (0.69) for the full sample of stocks. The lower mean value of BM suggests that stocks with options tend to be growth firms. Investment is measured as the annual growth rate in total assets (ATG) from the fiscal year ending in the year before last year to the fiscal year ending in the last year. Stocks with options traded have an average ATG of 24%, higher than the average ATG of 19% for the full sample of stocks. Operating profitability (OP) is equal to annual revenues minus cost of goods sold, interest expense, and selling, general, and administrative expenses divided by the book value of equity for the fiscal year ending in the last year. Stocks in the sample are on average more profitable (average OP is 31%) than the full sample of stock (average OP is 17%). Average compounding return in the past six months (RET(−1,−6)) of stocks with options traded is 7.66%, higher than mean RET(−1,−6) of all listed stocks (6.79%), indicating that stocks in the sample tend to be past winners. As in Nagel (2005), I use the percentage of institutional holdings (PIH), which is equal to the sum of stock holdings of all reporting institutions for a stock in a quarter divided by the stock's total number of shares outstanding at the end of that quarter, as a proxy for short-sale constraint. The lower the PIH, the greater the short-sale constraint is. On average, 66% of shares of stocks in the sample are held by institutional investors, while the full sample of stocks have an average PIH of 46%, suggesting that stocks with options traded have lower short-sale constraints.

At the end of each quarter, I compute cross-sectional Pearson correlations between each pair of stock characteristics and report time-series averages of the correlations in

Panel B of Table 1. Average correlations between all pairs of variables for the sample with options traded (reported in the upper part) have the same signs with the counterparts for the full sample of listed stocks (reported in the lower part). For both samples, stock characteristics have strong correlations with each other, except for the correlation between ATG and OP for the full sample of stocks, which is insignificantly negative. The results show that LogSIZE is on average positively correlated with ATG, OP, RET(−1,−6) and PIH, while is on average negatively correlated with BM, consistent with the results reported in Panel A that stocks with options with larger firm sizes have higher ATG, OP, RET(−1,−6), PIH and lower BM than the full sample. Consistent with the finding in Fama and French (2015), BM has negative associations with OP and ATG, suggesting that value stocks tend to have weaker profitability and more conservative investments than growth stocks. The negative relation between BM and RET(−1,−6) indicates that value stocks tend to be past losers. On average, ATG is negatively correlated with OP and RET (−1,−6), suggesting that firms with aggressive investments tend to have weaker profitability and earn lower historical returns. Profitable stocks tend to outperform unprofitable stocks in the last few months, as evidenced by the positive correlation between OP and RET(−1,−6). Institutional holdings are strongly correlated with equity characteristics. PIH is positively correlated with LogSIZE, ATG, OP and RET(−1,−6) and is negatively correlated with BM, indicating that institutional holders tend to hold stocks with large market capitalization, high asset growth rate, robust profitability, high historical return and low book-to-market ratio.

Chapter 4

Uncertainty of Individual Dividends

Empirical findings of recent studies suggest that contrary to the widespread belief of smoothing dividends in the short run, there is considerable variability in dividend payments at the corporate level. In this section, I examine how uncertain quarterly dividends of individual companies are. The uncertainty of quarterly dividends is measured by the degree of deviation of realized dividends from expected dividends. Investors' expectations of dividends in the next quarter are not directly observable. I use either historical dividend or analyst consensus forecast on dividend as a proxy for expected dividends.

4.1 Variability of Dividends: Naive Model

The 'Naive Model', which assumes that investors expect the dividend to be paid in the next quarter to remain the same as the dividend paid in the last quarter, is commonly used by the literature to measure dividend surprises. I first follow the literature and use the historical dividend to measure the expected dividend.

During the sample period from January 1996 to December 2017, 9,182 stocks listed on the three stock exchanges have ever paid a positive regular cash dividend,[4] among which 4,796 stocks have options traded. Among 608,729 quarterly cash dividends of the full sample of dividend payers, 29.75% of quarterly dividends represent an increase compared to the dividend paid in the same quarter of last fiscal year, and quarterly dividends are reduced in 13.61% cases. For the sample of dividend payers with options traded, the frequency of quarterly dividend changes is higher while the frequency of dividend cut is lower. For the stocks with options, 46.12% of the 287,319 quarterly dividend payments constitute a change in the amount of dividend, with dividend increase nearly four times (35.23%) as often as dividend decrease (10.90%). The results indicate that dividend changes are not rare events for individual companies.

I use the root mean squared error (RMSE) of quarterly dividend growth rate to measure the extent of variability of dividend payments. In a quarter q, for a stock i that has ever paid a positive cash dividend during the sample period, I calculate its quarterly dividend growth rate, $g_q^{d,i}$, as the percentage change of quarterly dividend:

$$g_q^{d,i} = \frac{D_q^i}{D_{q-4}^i} - 1, \tag{4.1}$$

where D_q^i is the dividend per share of stock i in quarter q and D_{q-4}^i is the dividend per share of stock i in the previous fourth quarter.[5] Quarterly dividends are compared with quarterly dividends paid in the same fiscal quarter in the previous year to diminish

[4] To reduce effects of extreme values, special dividends, which account for less than 0.5% of all dividend announcements, are excluded from the sample.

[5] In case of monthly dividend frequency, the quarterly dividend D_q^i is equal to the sum of monthly dividends paid in that quarter. In case of semi-annual or annual dividend frequency, D_q^i is equal to half of the semi-annual dividend or a quarter of the annual dividend.

seasonality in quarterly dividend payments. Note that the equation only applies to cases when the historical dividend D^i_{q-4} is positive. In case that both the current dividend D^i_{q-4} and the historical D^i_{q-4} are zero, the quarterly dividend growth rate is equal to zero.[6] For stocks with at least 12 quarters of observations, I compute the root mean squared error (RMSE) of quarterly dividend growth rate, RMSE($g^{d,i}$), which is the square root of the time-series average squared dividend growth rate,[7] to measure the uncertainty of quarterly dividends of the stock i.

[Insert Table 2 here]

Panel A.1 and A.2 of Table 2 report the summary statistics of quarterly dividend growth rate and its root mean squared error across all stocks listed on NYSE, AMEX and NASDAQ (8,571 stocks in total) and the sample of stocks with options traded (4,388 stocks in total). For the quarterly dividend growth rate, I first compute its time-series average for each stock, and the table reports cross-sectional distributions of the average dividend growth rate. The quarterly dividend growth rate (g^d) is on average positive for both samples of stocks. Quarterly dividend payments of the sample with options grow faster (mean value of g^d = 2.02%) than the full sample of stocks (mean value of g^d = 1.17%). On average, individual stocks' variability of quarterly dividend growth rate (RMSE(g^d)) is 31.85%. There is cross-sectional dispersion in dividend uncertainty. The

[6] The dividend growth rate cannot be calculated in cases of dividend initiations since the actual dividend is positive while the last dividend is zero. Excluding dividend initiations will lead to underestimation of the variability of dividend payments.

[7] I assume that investors' expected dividend growth rate is zero. I also use average quarterly dividend growth rate in the previous three years as an alternative proxy for expected dividend growth rate and find qualitatively similar results.

stock in the 25$^{\text{th}}$ percentile has a RMSE(g^d) of 16.33% while the stock in the 75$^{\text{th}}$ percentile has a RMSE(g^d) of 52.10%. Distributions of RMSE(g^d) are similar among stocks with options traded, with the mean value of RMSE of dividend growth rate slightly lower (mean value of RMSE(g^d) = 28.64%) than that of the full sample. The high average variability of quarterly dividend growth rate indicates large magnitudes of changes in dividend payments from quarter to quarter and suggests considerable uncertainty in quarterly dividend payments of individual companies.

4.2 Variability of Dividends: Analyst Forecast

While the 'Native model' is commonly used in the literature, some studies find that historical dividend is not a good proxy for investors' expected dividends because the model does not incorporate the market's most recent expectations since the last dividend payment (Yoon and Starks, 1995). Bae-Yosef and Sarig (1992) show that actual changes in dividends are not correlated with the market's responses to dividend announcements. Another estimate of expected dividend is the average analyst dividend forecast. Andres, Betzer, van den Bongard, Haesner and Theissen (2013) document significant stock price reactions to dividend surprises measured as the difference between the actual dividend and consensus analyst dividend forecast. After controlling for analyst dividend surprise, they find no significant relation between actual dividend changes and abnormal stock returns around dividend announcements, suggesting that analyst dividend forecast is a better measure of expected dividend than historical dividend. In the U.S. market, analyst forecasts for quarterly dividends have been available since 2001, and the proportion of companies with dividend forecast is growing rapidly over time. Data on actual dividends and analyst consensus forecasts are obtained from the Institutional Brokers' Estimate System (I/B/E/S). From 2001 to 2017, analysts provide forecasts on quarterly dividends for 4,867 stocks in total. Since the number of stocks with dividend forecasts is too small in 2001, I use a sample period from 2002 to 2017.

For a firm i that announces an actual dividend per share in a fiscal quarter q, D_q^i, I use the last consensus[8] forecast on dividend per share for the next fiscal quarter[9] made by analysts prior to the announcement of dividend payments to measure expected dividend, $E_{q-1}(D_q^i)$. Analyst dividend forecast error, $e_q^{d,i}$, is measured as:

$$e_q^{d,i} = \frac{D_q^i - E_{q-1}(D_q^i)}{E_{q-1}(D_q^i)}. \tag{4.2}$$

The equation only applies when a forecast dividend per share is positive. In case that both the actual dividend and the forecast dividend are zero, the dividend forecast error is zero. To ensure that dividend forecasts reflect the most recent information, I exclude observations when no analyst forecasts are available one month preceding dividend announcements. The sample only includes stocks covered by analysts for at least 12 quarters. The requirements reduce the final sample to 4,655 stocks, among which 3,984 have options traded. For each stock i meeting the requirements, I calculate the root mean squared analyst dividend forecast error, RMSE($e^{d,i}$), which is the square root of time series average

[8] Consensus forecast is a simple average of dividend forecasts made by all analysts. I also use the median of dividend forecast and find similar results.

[9] Forecast Period Indicator is 6.

squared dividend forecast error, to measure its variability of dividend payments.

Prior studies find that firm size is an important determinant of analyst following (Barth, Kasznik and McNichols, 2001). To compare the sample with and without analyst following, I compute summary statistics of the mean and RMSE of quarterly dividend growth rate for the sample of stocks covered by analysts during the sample period from 2002 to 2017 and report the results in Panel A.3 and A.4 of Table 2. Compared with the full sample of listed stocks, stocks followed by analysts have a higher average dividend growth rate (mean value of $g^d = 2.26\%$). The average RMSE of dividend growth rate for listed stocks with analysts following is 29.82%, lower than the counterpart value for the all listed stocks, suggesting that analysts on average tend to cover stocks with relatively less variable dividend policies.

Panel B of Table 2 reports distributions of time-series average of analyst dividend forecast error and root mean squared analyst dividend forecast error across all stocks covered by analysts and for the subsample of stocks with options traded. For both samples, the mean values of dividend forecast errors are positive, suggesting that on average, analysts make conservative estimates of future dividends. The average root mean squared dividend forecast error, RMSE(e^d), is 26.31%, for the full sample. The first and third quartiles of RMSE(e^d) are 9.44% and 45.43%, respectively, which indicates that the accuracy of dividend forecast varies across stocks. Results are similar when the sample is reduced to stocks with options traded, with the average RMSE(e^d) slightly lower that of all stocks covered by analysts. The high average variability of dividend forecast error demonstrates difficulty in accurately forecasting dividend payments in the next quarter.

In short, I find that on average there is considerable uncertainty in quarterly dividend payments at the firm level when the expected dividend is measured either by historical dividend or by consensus analyst dividend forecast and that there is cross-sectional dispersion of dividend uncertainty among individual stocks. Investors' exposures to uncertain dividend payments in the next quarter should be compensated by dividend risk premium, which will affect the pricing of claims on near-term dividends of individual stocks. In the following chapters, I use the put-call parity relation to compute prices of individual dividend strips from individual equity options and examine the risk and return properties of the short-term assets at both the aggregate level and the firm level.

Chapter 5

Research Methodology

5.1 Option-Implied Dividend

Suppose that a stock i pays quarterly dividends at the end of each quarter. Let D^i_{q+1} be the cash dividend of the stock i to be paid in the next quarter $q+1$ and DI^i_q is the price of the dividend in the next quarter at the end of this quarter q. 97.5% of dividend payers in the sample pay quarterly dividends. In case that a stock pays monthly dividends (0.64% of the sample), the unknown dividend in the next quarter is defined as the sum of the three nearest unknown monthly dividend payments. In case that a stock pays semi-annual or annual dividends (0.97% and 0.88% of the sample, respectively), quarterly dividends in fiscal quarters with no dividends are assumed to be announced as zero on earnings announcement dates in that quarter. Special dividends (0.02% of the sample) are excluded. Since the Options Clearing Corporation (OCC) adjusts options strike prices for extraordinary dividends,[10] options prices should not contain information about special

[10] Before February 1$^{\mathrm{st}}$ 2009, dividends greater than 10% of the value of the underlying stock triggers an option contract adjustment, so dividends with an amount higher than 10% of stock prices are excluded. After February 1$^{\mathrm{st}}$ 2009, ordinary dividends are defined as "cash dividends declared pursuant to a policy or practice of paying such dividends on a quarterly or other regular basis". From then on, the OCC

dividends.

Prices of dividend strips can be calculated either from futures or options on underlying stocks. I use individual equity options because the options market of individual stocks is more developed and liquid than the futures market in the U.S.. In the absence of arbitrage opportunities, the put-call parity relation for European-style options should hold (Stoll, 1969), and the price of the dividend strip at the end of quarter q is given by:

$$\mathrm{DI}_q^i = P_q^i(T, K) + S_q^i - C_q^i(T, K) - Ke^{R_q^f \tau}, \tag{5.1}$$

where $P_q^i(T, K)$ and $C_q^i(T, K)$ are mid prices of put and call options written on the underlying stock i with strike price K and maturity date T at the end of quarter q, S_q^i is quarter-end closing price of the stock i, R_q^f is the continuously compounding risk-free rate at the quarter end, and $\tau = T - q$ is the time to maturity of options. For a pair of options which mature on a given date, the appropriate risk-free rate should be the one of the risk-free bond with a maturity date equal to that of the options. In case that the risk-free rate for a given option maturity is not available, I linearly interpolate between the two risk-free rates with closest maturities. The no-arbitrage relation shows that a dividend strip can be synthetically replicated by buying a put option, writing a call option, buying an underlying stock, and borrowing cash.

For a stock i at the end of a quarter q, I select pairs of call and put options that meet the following criteria. To ensure that options have relatively high liquidity, only near the

adjusts extraordinary cash dividends with an amount of at least \$12.50 per contract. After the new dividend adjustment policy is adopted, I exclude dividends with a CRSP dividend code 1272 and with a size of at least \$0.125.

money ($0.8 \leqslant K/S \leqslant 1.2$) and short-to-intermediate time-to-maturity options ($20 \leqslant \tau \leqslant 180$) options are used. Closing bid and ask prices of options should be at least \$0.5, and closing bid price should be positive. I also require options to have positive open interests and valid implied-volatility. Besides, options should not violate the no-arbitrage bounds for American-style options (Guo and Su, 2006):

$$C_q^i(T,K) + Ke^{R_q^f \tau} \leqslant P_q^i(T,K) + S_q^i \leqslant C_q^i(T,K) + K + \mathrm{PV}_q(D_{q+1}^i). \tag{5.2}$$

The left inequality imposes that the option-implied dividend is non-negative. The right inequality ensures that the option-implied dividend is bounded from above to avoid arbitrage opportunities.[11] The choice of the maturity date of options is important. For a stock at the end of a quarter, I use the stock's cash dividend history to forecast its ex-dividend dates of future dividends. Options should mature after the expected ex-dividend date of the first unknown quarterly dividend but before the expected ex-dividend date of the second unknown quarterly dividend. Thus, during the life of the options, the underlying stock only has one cash dividend payment, and the synthetic dividend strip created from the options entitles investors to and only to the nearest uncertain dividend. In case that an option expires after ex-dividends of announced dividends, present values of announced dividends are subtracted from the option-implied dividend. The option pricing date should

[11]Since the dividend to be paid in the next quarter $q+1$ is unknown at the end of this quarter q, I simply use the most recently announced dividend to estimate it. Other approaches to estimate D_{q+1}^i for calculating the upper no-arbitrage bound do not change the empirical findings. The estimated price of an individual dividend strip can be close to zero, and return on a dividend strip can be very high. To mitigate noises in the estimation of prices of individual dividend strips, I only use the prices of synthetic dividend strips with a quarterly return lower than or equal to 300%. Increasing the upper bound of return to 500% or 1000% does not change the empirical results.

be earlier than the dividend announcement date for the next not yet announced dividend so that the actual dividend amount is uncertain, and the option-implied dividend at the quarter end contains dividend risk premium information. Among options that meet all the filtering criteria above, I select the most at-the-money pair of put and call options (i.e., K/S ratio closest to 1). The most at-the-money options have relatively high liquidity. Besides, individual equity options traded in the U.S. market are American-style options, so the option-implied dividend is biased by the difference between early exercise premium (EEP) of put and call options. Using the most at-the-money options mitigate errors in the price of dividend strip due to EEP because EEPs of at-the-money put and call options have similar magnitudes and tend to offset each other. In case that multiple pairs of the most at-the-money options are available, I choose the pair of options with time-to-maturities closest to 90 days.

[Insert Table 3 here]

Table 3 reports characteristics of individual equity options used to replicate claims on near-term dividend payments of individual companies in the sample. As I restrict options to near-the-money and short-to-intermediate maturity options, the average K/S ratio is close to 1.00 and options have an average time to maturity (τ) of 90 days. The average implied volatility (IV) is 49%. Open interest (OI) and daily trading volume (VOL) are on average 911 contracts and 45 contracts, respectively, and both variables are right skewed. Though the mean values are not low, quite a portion of options have zero daily trading volumes or low open interests. The low liquidity of some options presents the issue that option-implied dividend may be contaminated by errors and noises in the options market and may not reflect option traders' most recent expectations about future dividends. To address this concern, I use specific examples to examine information contents of option-implied dividends.

5.2 Examples of Changes in Dividend Policies and Information Contents of Option-Implied Dividends

Option-implied dividend (DI) is equal to the present value of the expected dividend and is determined by options traders' expectations on the future dividend and dividend risk premium. I take four specific dividend events, (1) the dividend initiation in 2012 and (2) the dividend increase in 2013 of Apple Inc., and (3) the dividend cut in 2006 and (4) the dividend omission in 2008 of General Motors Company, as examples to show that dividends implied from options prices contain investors' anticipations for future dividends before announcements.

Apple Inc.'s Dividend Initiation in 2012

Apple Inc. began to pay quarterly dividends since 1987 while stopped dividend payments in 1995. During the past two decades, the company has a rapidly growing business and a record of continuous profitability over the years. At the end of 2011, Apple Inc. has become one of the largest firms with a market capitalization of $377 billion and a giant estimated cash holding of $80 billion, and the rumor was around that the company would restart to pay cash dividends. On March 19$^{\text{th}}$ 2012, Apple Inc. stated its intention to initiate quarterly dividends from the fourth quarter of that year. On July 24th 2012, the company announced that it would pay a quarterly dividend of $2.65 per share with an ex-dividend date on August 9th 2012. For each day from the last quarter in 2011 until the last quarter in 2012, I calculate option-implied dividends from prices of pairs of options which expired on July 20th 2012 or on Oct 19th 2012, and take a simple average of option-implied dividends across strike prices to get a daily average option-implied dividend. Then for each week, I calculate an average option-implied dividend by averaging daily option-implied dividends in that week. Figure 2(a) shows the time-series plot of weekly average option-implied dividends calculated from options with two different expiration dates 25 weeks before and after the date of the public statement of dividend initiation in March 2012. Before the company publicly stated its intention to initiate dividends, average implied dividend had already increased from close to zero at the end of 2011 to about $0.5 per share from options which expired on July 24th 2012 and to about $1 per share from options which expired on October 19th 2012 as the statement date approached. The increasing tendency of DI suggests that as new information arrived, investors' anticipation for the future dividend increased. Note that the dividend implied from options that matured in the fourth quarter of 2012 is generally higher than it is implied from options that mature in the third quarter of 2012 because investors expect more dividends to be paid during a more extended time length. After the company publicly stated its intention to initiate dividends from the fourth fiscal quarter, dividend implied from the option expiring on July 24th 2012 decreased to nearly zero, indicating that investors were aware that dividend strips synthetically created from options expiring in July 2012 would not be entitled to the cash dividend with an ex-dividend date in the fourth quarter of 2012. In contrast, dividend implied from options expiring in late October 2012 gradually increased from about \$1 on the initial statement date to about \$2.5 before the company announced on July 24th 2012 that the exact ex-dividend date of the first cash dividend was August 9th 2012. After the announcement date, the option-implied dividend was near the realized amount of \$2.65 per share and decreased to near zero after the ex-dividend date. The results suggest that options prices had reflected investors' anticipations of the dividend initiation before Apple Inc. publicly stated it. The different patterns of dividends implied from options with different maturity dates suggest that investors consider not only the amount but also the timing of future dividends.

Apple Inc.'s Dividend Increase in 2013

After its dividend initiation in late 2012, Apple Inc. maintained a quarterly cash dividend of \$2.65 per share for three quarters. On April 23th 2013, the company announced that starting from the second quarter in 2013, its quarterly dividend would increase to \$3.05 per share, with the first ex-dividend on May 9th 2013. Figure 2(b) plots the time series of implied dividends from prices of options which expired on July 19th 2013 from the last ex-dividend date February 7th 2013 to one week after the ex-dividend date May 9th 2013. The plot shows that the option-implied dividend was initially around the level of the last cash dividend (\$2.65 per share), while about two weeks before the announcement of dividend increase, the option-implied dividend gradually increased to about \$3 per share, suggesting that option-traders anticipated the dividend increase. Once the new quarterly dividend was announced, there is a jump in option-implied dividend on the announcement date, and the implied dividend remained close to the realized amount until the ex-dividend date in May 2013.

The two examples of Apple Inc. show that options traders anticipate dividends to increase when the company has robust profitability, and options prices incorporate investors' expectations for future dividend increases.

General Motors' Dividend Cut in 2012

Next, I examine whether options prices reflect decreases in dividends before announcements, taking two dividend events of General Motors Company as examples. General Motors is one of the largest automakers in the U.S.. From 1997 to 2005, the company paid a steady quarterly dividend of \$0.5 per share. However, since 2003, General Motors was haunted by several recall scandals and was burdened by huge health costs for retired employees, and its stock price dwindled from over \$60 in early 2003 to under \$20 in early 2006. After years of financial losses and market share losses to Japanese automakers, since 2006, General Motors began to carry out bold restructures of operations, which would require massive investments. To save costs, on February 7$^{\text{th}}$ 2006, the company announced that it would reduce quarterly dividends by half to \$0.25 per share. Figure 3(a) shows daily average dividend implied from options which expired on March 17$^{\text{th}}$ 2006 from the last ex-dividend date (November 8$^{\text{th}}$ 2005) of the original dividend to one week after the ex-dividend date (February 14$^{\text{th}}$ 2006) of the reduced dividend. The option-implied dividend remained close to the \$0.5 per share since the last dividend was declared. On January 28th 2006, General Motors announced a net loss of \$4.8 billion in the fourth quarter of 2005, which was its fifth consecutive quarterly loss, and a net loss of \$8.6 billion for the entire fiscal year of 2005, which was its first unprofitable year since 1992. After the earnings announcement, the option-implied dividend dropped to lower than \$0.3 per share, suggesting that option-traders lost faith in the company's ability to maintain the historical dividend in light of its substantial financial losses. General Motors finally announced to cut its quarterly dividend by half on February 7th 2006, and the dividend implied from options were close to the realized dividend until the ex-dividend date.

General Motors' Dividend Omission in 2012

General Motors maintained a quarterly cash dividend of \$0.25 per share from the first fiscal quarter of 2006 to the second fiscal quarter of 2008. However, since the third fiscal quarter of 2007, affected by the subprime crisis, the company posted four consecutive quarterly losses and announced a plan to suspend its quarterly dividend on July 15th 2008. I compute daily average dividend implied from options with an expiration date on September 9th 2008 around the date when the intention to omit dividend was publicly stated. As shown in Figure 3(b), before the dividend suspension was announced, there was a gradual decline in option-implied dividends and a deep drop in implied dividends on June 26th 2008, when the stock price of the company plumbed to its lowest level during the past thirty years. After the company announced the dividend suspension, option-implied dividends dropped to around zero.

The two example of the General Motor illustrate that options traders expect decreases in dividends when the company is faced with dividend constraints and weak profitability.

5.3 Return on Dividend Strip

Quarterly return on an individual dividend strip, r^i_{q+1}, is equal to the payoff of the dividend strip in the next quarter, x^i_{q+1}, divided by the price of the dividend strip at the end this quarter, DI^i_q, minus 1:

$$r^i_{q+1} = \frac{x^i_{q+1}}{\mathrm{DI}^i_q} - 1. \tag{5.3}$$

For quarterly dividend payments, if the first unknown quarterly dividend is announced in the next quarter $q+1$, the payoff of the stock i's dividend strip is the realized dividend payment, D^i_{q+1}, and the quarterly return on dividend strip is given by:

$$r^i_{q+1} = \frac{D^i_{q+1}}{\mathrm{DI}^i_q} - 1. \tag{5.4}$$

In case that the first unknown quarterly dividend is not announced in the next quarter, the quarterly return on stock i's dividend strip is the percentage change in the value of the dividend strip from the end of this quarter q to the end of the next quarter $q+1$:

$$r^i_{q+1} = \frac{\mathrm{DI}^i_{q+1}}{\mathrm{DI}^i_q} - 1. \tag{5.5}$$

For stocks that pay monthly dividends, some of the three nearest not-yet-declared monthly dividend payments may be announced in the next quarter while some may remain undeclared in the next quarter. In this case, the payoff of the dividend strip is made up of two parts: the income component, which is any realized dividend(s) in the next quarter, and the price component, which is the value of not-yet-declared dividend(s) at the end of next quarter, and the return on the dividend strip is given by:

$$r^i_{q+1} = \frac{D^i_{q+1} + \mathrm{DI}^i_{q+1}}{\mathrm{DI}^i_q} - 1. \tag{5.6}$$

5.4 Summary Statistics of Prices and Returns of Individual Dividend Strips

[Insert Table 4 here]

Table 4 tabulates summary statistics of annual dividend yield $\mathrm{DY}_{q+1} = D_{q+1}/S_q \times \mathrm{FR}$, annual option-implied dividend yield $\mathrm{IDY}_q = \mathrm{DI}_q/S_q \times \mathrm{FR}$, where FR is the frequency of cash dividends paid in a year, annual dividend premium DP, defined as the difference between realized and options implied annual dividend yield, and the quarterly return on individual dividend strips. Panel A reports results for all stocks with options traded. Stocks in the sample have an average annual dividend yield of 1.18%, higher than the average annual option-implied dividend yield of 1.10%. Annual dividend premium is on average 0.08%, indicating that investors on average ask for a positive risk premium on claims on near-term dividends of individual companies. Dividend premium varies across stocks: the average first quartile of DP is −0.72% and the average third quartile of DP is 0.90%. The average quarterly return on dividends trips of stocks in the sample is 3.12%, with a first quartile and third quartile of −13.07% and 19.69%, respectively, suggesting that returns on short-term assets of individual stocks are high on average and that there are substantial variations in dividend strip returns among stocks.

Since options traded on individual stocks in the U.S. are American-style options, dividends implied from the put-call parity relation are contaminated by early exercise premium (EEP). I substitute OptionMetrics implied-volatility and the most recently announced dividend into the Black and Scholes (1973) option-pricing formula to calculate hypothetical European put and call options prices, and use the prices to calculate EEP-adjusted option-implied dividends. Panel B of Table 4 reports time-series averages of statistics of annual dividend yields, annual EEP-adjusted options-implied dividend yields, annual EEP-adjusted dividend premium and EEP-adjusted return on dividend strips across stocks for which valid EEP can be estimated.[12] After adjusting for EEP, the average IDY is 1.04%, lower than the average IDY without adjusting for EEP, and the average quarterly return on dividend strips is 3.98%, slightly higher than the counterpart without adjusting for EEP. Note that distributions of DY in Panel B are different from those in Panel A because some stocks are removed from the sample due to the inconsistently estimated EEP. To quantify the effect of EEP on option-implied dividends,

[12]When calculating implied volatility, OptionMetrics uses a proprietary algorithm to estimate the frequency, timing, and amount of dividends. Specifically, OptionMetrics uses a stock's cash dividend history to forecast the timing of dividends paid during options lives and calculates a stock's current dividend yield, which is defined as the amount of most recently announced cash dividend divided by the current price of the stock. The current dividend yield is assumed to remain constant during the remaining term of options. I follow the documentation from OptionMetrics to forecast future dividend payments and substitute the present value of dividends into the Black and Scholes (1973) option-pricing formula. However, my estimation of future dividends may not be exactly the same as theirs and thus may result in inconsistency. I drop about 2% of the observations for which the EEP-adjusted options price is less than half of the market price, or the estimated EEP is negative with a magnitude greater than 5% of the market price.

I compute the difference between IDY with and without adjusting for EEP within the sample of stocks for which EEP can be estimated. On average, IDY decreases by 0.02% after EEP is adjusted, which is consistent with the finding in prior studies that put options generally have higher EEP than call options do.[13] Since the difference in IDY due to EEP is small on average, suggesting that whether adjusting for EEP or not may not matter significantly for the estimation of IDY and returns on dividend strips, in the main empirical analysis, I do not adjust for EEP. In a section of robustness check, I repeat the empirical analysis using EEP-adjusted option-implied dividends to ensure that the results are robust after adjusting for EEP.

Panel C of Table 4 reports the results for a subsample of dividend payers, where dividend payers are stocks that have ever paid a positive regular cash dividend in the past five years. On average, dividend payers account for about half of the full sample of stocks with options traded. For the sample of dividend payers, DY, IDY, DP, and quarterly return on dividend strips are all higher than counterparts of the full sample. The ranges of these variables are also greater, suggesting greater cross-sectional variations in the variables among dividend payers.

[13]For example, during the sample period from April 2$^{\text{nd}}$ 1986 to June 20$^{\text{th}}$ 1986 when CBOE concurrently listed European-style and American-style options on the S&P 500 Index, Dueker and Miller (2003) compare differences between prices of the two types of index options and find that average early exercise premiums range from 5.04% to 5.90% for call options and from 7.97% to 10.86% for put options.

Chapter 6

Return on Aggregate Dividend Strip

I first examine the pricing of shot-term dividend strips at the aggregate level. From the prices of dividend strips of individual stocks, I calculate the price of dividend strip for the aggregate market. Let DI_q^A be the price of the aggregate short-term dividend strip at the end of quarter q. It is equal to the sum of each stock's product of number of shares outstanding and option-implied dividend per share at quarter end. Since some stocks have dividends announced while other stocks' dividends remain undeclared in the next quarter, the payoff of the aggregate dividend strip has two components. The first component is the realized dividend of the aggregate portfolio in the next quarter $q+1$, D_{q+1}^A, which is the sum of products of number of shares outstanding and realized cash dividend per share of stocks with the first unknown dividend announced in the next quarter $q+1$. The second component is the value of the aggregate dividend strip at the end of quarter $q+1$, DI_{q+1}^A, which is equal to the sum of products of number of shares outstanding and option-implied dividend per share of stocks whose first unknown dividend is not yet announced in the next quarter $q+1$. Thus, the aggregate dividend strip is a value-weighted portfolio of all individual dividend strips in the sample, and it entitles an investor to all dividends paid from all stocks in the next quarter. Quarterly return on the aggregate dividend strip is $r^A_{q+1} = (D^A_{q+1} + \mathrm{DI}^A_{q+1}) / \mathrm{DI}^A_q - 1$.

Figure 4 shows the time-series plot of prices of the aggregate short-term dividend strips at quarter end and realized quarterly dividends of the aggregate portfolio in the next quarter. During the sample period, there are two NBER recessions. The first recession is the burst of the internet bubble, which occurred between March and November 2001, and the second one is the U.S. subprime crisis, which occurred between December 2007 and June 2009. During the two recessions, dividend prices dwindled because during the economic downturns expected dividend growth rate might decrease, and the discount rate on cash flows was likely to increase.

[Insert Table 5 here]

Table 5 tabulates time-series statistics of quarterly returns on the aggregate near-term dividend strip during the sample period from January 1996 to December 2017. The aggregate dividend strip earns an average return of 4.64% per quarter, with a standard deviation of 15.22%. The average return on the aggregate dividend strip is a value-weighted average of returns on individual dividend strips, which is higher than the equal-weighted average return of individual dividend strip returns (reported in Panel A of Table 4), suggesting that stocks with higher market values of claims on quarterly dividends have higher returns on the short-term assets. During the same sample period, the mean and standard deviation of quarterly return on the S&P 500 index are 2.53% and 8.07%, respectively.

The results that the aggregate short-term dividend strip has a higher average return and higher volatility than the S&P 500 index are consistent with those in van Binsbergen, Brandt and Koijen (2012).[14]

Then, I test whether the high average return on the aggregate short-term asset can be explained by well-known asset pricing models. For the CAPM, I use return on the S&P 500 index as a proxy for return on the aggregate market portfolio, r^m. Data on the S&P 500 index are obtained from CRSP. I also look at whether the three multi-factor asset pricing models, including the Fama and French (1993) three-factor model (FF3), the Carhart (1997) four-factor model (FFM4), and the Fama and French (2015) five-factor model (FF5), can better explain the high return on claim on aggregate short-term dividends by introducing risk factors in addition to the market risk factor. The portfolio-based risk factors are constructed from returns on stocks listed on the three major stock exchanges[15] and are obtained from Kenneth R. French's website. The size factor (SMB), the value factor (HML), the momentum factor (UMD), the profitability factor (RMW) and the investment factor (CMA) are differences between the returns on diversified port-

[14]van Binsbergen, Brandt and Koijen (2012) find that during the sample period from 1996 to 2010, index dividend strip with one-year maturity replicated from S&P 500 index options earns an average monthly return of 1.16% (3.48% a quarter) with a standard deviation of 7.80% (13.51% a quarter), while during their sample period, S&P 500 index earns an average quarterly return of 1.68%, with a standard deviation of 8.10%.

[15]To construct HML, at the end of June of each year, all listed stocks are allocated into six SIZE-BM portfolios using the NYSE median market capitalization breakpoints and NYSE 30$^{\text{th}}$ and 70$^{\text{th}}$ percentile book-to-market (BM) ratio breakpoints. HML is the average excess of the returns on the two high BM portfolios minus the returns on the two low BM portfolios. RMW and CMA are constructed in a similar way, except that the second sorting variable is operating profitability (OP) or annual total asset growth rate (ATG). UMD is also formed similarly, except that the factor is updated monthly and that the second sorting variable is cumulative stock return in the prior 2-12 months. SMB is the average excess of the returns on the nine big stock portfolios with different levels of BM, OP and ATG minus the returns of nine counterparts portfolios with small firm sizes.

folios of stocks with small and large firm size, high and low BM, high and low return in the past one year, robust and weak profitability, and conservative and aggressive investment, respectively. During the sample period from 1996 to 2017, all the portfolio-based factors have positive mean values. Small firms, value stocks, past winners, profitable stocks and high investment stocks outperform large stocks, growth stocks, past losers, unprofitable stocks and low investment stocks by 0.58%, 0.64%, 1.13%, 1.14% and 0.72% per quarter, respectively.

To test the models' ability to explain returns on the aggregate near-term dividend strip, for each model, I run a full sample time-series regression of the aggregate dividend strips' excess return, $\tilde{r}^A_{q+1}$, on contemporaneous quarterly risk factors f_{q+1}, where $f_{q+1} = \tilde{r}^m_{q+1}$ (excess return on the S&P 500 index) for the CAPM, $f_q = [\tilde{r}^m_{q+1}, \text{SMB}_{q+1}, \text{HML}_{q+1}]$ for the FF3, $f_{q+1} = [\tilde{r}^m_{q+1}, \text{SMB}_{q+1}, \text{HML}_{q+1}, \text{UMD}_{q+1}]$ for the FFM4, and $f_{q+1} = [\tilde{r}^m_{q+1}, \text{SMB}_{q+1}, \text{HML}_{q+1}, \text{RMW}_{q+1}, \text{CMA}_{q+1}]$ for the FF5. Panel B of Table 5 reports the intercepts and the slope coefficients on risk factors and associated t-statistics and adjusted-R^2 of the four full-sample time-series regressions. The aggregate short-term asset has a market beta, $\beta^{A,m}$, of 0.29, which is not statistically significant (t-stat = 1.43). The excess return on the aggregate dividend strip relative to the CAPM, $\alpha^{A,m}$ is 3.50%, statistically significant with a t-statistic of 2.11. The results indicate that CAPM fails to explain the high average return on the aggregate short-term asset. For the multi-factor models, the alpha relative to the Fama and French (1993) three-factor model ($\alpha^{A,\text{FF3}} = 3.15\%$) is smaller than it is for the CAPM, mainly due to the significantly positive loading on HML

($\beta^{A,h}$ = 0.57, t-stat = 2.27). The slope on the size factor is insignificantly positive ($\beta^{A,s}$ = 0.22, t-stat = 0.85). The positive coefficient on HML seems to be consistent with the duration-based explanation of the value premium. If value stocks have more cash flows loaded in the short-run than growth stocks, returns on value stocks should covary more with returns on short-term aggregate equity cash flows. However, the alpha relative to three factor model is still high and has a t-statistic close to 2 (t-stat = 1.91), indicating that value premium only partially explain the high average return on the aggregate dividend strip. The results are in line with those documented by prior studies using index derivatives, and the consistent results suggest that short-term dividend strip at the index level and the one aggregated from individual companies have similar risk properties.

Adding the momentum factor provides slight improvement, as evidenced by a smaller and less significant risk-adjusted return on the aggregate dividend ($\alpha^{A,\mathrm{FFM4}}$ = 2.64%, t-stat = 1.77). The aggregate short-term asset also have a positive loading on the profitability factor ($\beta^{A,r}$ = 0.30, t-stat = 1.76) and a positive loading on the investment factor ($\beta^{A,c}$ = 0.57, t-stat = 2.30). The alpha relative to the five-factor model is 2.29%, with a t-statistic of 1.19. The results indicate that three multi-factor models are better than the CAPM at explaining the high expected return on the aggregate dividend strip. Among the multi-factor models, the Fama and French (2015) five-factor model performs the best. A possible reason for the superior performance of the five-factor model in explaining returns on claims on dividend payments is the close relations between profitability, investment, and dividends. Fama and French (2001) find that profitability and investment are important determinants of dividends. They document that firms with high profitability and low investments are more likely to pay dividends, and find that an important reason for the 'disappearing dividend' phenomena from 1978 to 1999 is that publicly listed firms tilted towards firms with low profitability and high investments during that sample period.

Chapter 7

Pricing of Dividend Strips in the Cross Section

7.1 Portfolio Sorting

The previous section examines the properties of the short-term dividend strips at the aggregate level. In this section, I examine the risk and return properties of dividend strips across individual stocks. To mitigate noises in returns on dividend strips replicated from individual equity options, I use a portfolio-based approach by first sorting stocks based on ex-ante short-term dividend risk premiums and then calculating subsequent realized portfolio returns. I use the normalized dividend premium to measure short-term dividend risk premium, which can separate stocks with high returns on dividend strips from those with low returns on dividend strips ex-ante. The annual normalized dividend premium of a stock i in a quarter q, DP_q^i, is given by:

$$\mathrm{DP}_q^i = \frac{\mathrm{PV}_q(D_{q+1}^i) - \mathrm{DI}_q^i}{S_q^i} \times \mathrm{FR}^i, \tag{7.1}$$

where D^i_{q+1} is the realized cash dividend from stock i in quarter $q+1$, $\mathrm{PV}_q(D^i_{q+1})$ is the value of the cash dividend paid in the next quarter discounted at the risk-free rate to the end of quarter q, and DI^i_q is the price of D^i_{q+1} implied from prices of options written on the stock at the end of quarter q. S^i_q denotes the price of stock i at the end of quarter q. FR^i is the frequency of stock i's dividend payments. Normalization of nominal dividend premium by stock price makes dividend premium comparable across stocks with different magnitudes of dividends.[16] Stock i's annual normalized dividend premium DP^i_q of quarter q is computed as following. For each stock i in each day t in a quarter q, I use pairs of options written on the stock that meet the filtering criteria to compute option-implied dividends and then take an average of option-implied dividends across strike prices to get a daily option-implied dividend, $\mathrm{DI}^i_{q,t}$. Daily dividend premium, $\mathrm{DP}^i_{q,t}$, is equal to the difference between the present value of the realized dividend and daily average DI normalized by the daily closing price of the stock. Within a quarter q, daily average normalized dividend premium is averaged across days to calculate normalized dividend premium in that quarter, DP^i_q. Finally, to smooth out noises in option-implied dividends and unexpected components of realized dividends, I take a simple average of quarterly dividend premium in the previous four quarters to compute the historical normalized dividend risk premium:

$$\overline{\mathrm{DP}}^i_q = \sum_{j=1}^{4} \frac{\mathrm{DP}^i_{q-j}}{4}. \tag{7.2}$$

[16] Another approach of normalization is to divide the nominal dividend premium by option-implied dividend DI^i_q. However, DI^i_q can be very close to zero, so I normalize dividend premium by the stock price.

At the end of a quarter q, stocks in the sample are sorted into five portfolios by historical dividend premium.[17] Stocks in portfolio 1 (5) have the lowest (highest) historical dividend premium. Panel A of Table 6 tabulates stock characteristics of five portfolios sorted by $\overline{\text{DP}}$. Several stock characteristics are correlated with dividend premium. Stocks with high historical dividend premium tend to have larger firm size (LogSIZE). Book-to-market ratio (BM) and operating profitability (OP) increase from portfolio 1 to portfolio 5, suggesting that high dividend premium stocks tend to be value stocks and high profitability stocks. Total asset growth rate (ATG) decreases with historical dividend premium, suggesting that stocks with high dividend premium have conservative investments. Average stock return in the previous six months (RET(−1,−6)) is highest (lowest) for the portfolio with the highest (lowest) dividend premium, indicating that past winners have higher dividend premium than past losers. For each portfolio, I calculate its stock retaining ratio (RR), which is the proportion of stocks sorted into a portfolio at the end of quarter $q - 1$ and remain in the same portfolio at the end of quarter q. The two extreme portfolios have an average RR of 92% and 95%. Average RRs of the three middle portfolios are lower than those of portfolio 1 and 5, but they are still around 80%. The high average RRs indicate that stocks with high historical dividend premiums in one quarter tend to have a high dividend premium in the next quarter and that the portfolios have low rebalancing rates.

[Insert Table 6 here]

[17] short-sale constraints of underlying stocks can affect the calculation of option-implied dividend and dividend premium. short-sale constraints should be most pronounced during the subprime crisis from the third quarter of 2008 to the second quarter of 2009. To mitigate the effects of short-sale constraints, for this period, I sort stocks by historical dividend premium calculated at the end of the second quarter of 2008, and portfolios are not re-balanced during the period.

The put-call parity no-arbitrage relation can be violated due to short-sale constraints of underlying stocks. For example, Ofek, Richardson and Whitelaw (2004) find that violations of the put-call parity relation are related to costs and difficulty of short selling. In particular, investors can buy a put option or short a call option when the underlying stock is overpriced. If the options market and the stock market are not fully integrated and options traders are more sophisticated investors, the negative information about the underlying stock will be incorporated into options prices faster than it is incorporated into the stock price, and market stock price will be higher than price of stock synthetically created from pairs of options. Thus, option-implied dividends may be overstated due to the difficulty of short-selling in the stock market, and dividend premium will be understated. If a stock has more severe short-sale constraints, the price of its dividend strip can be more overstated and its dividend premium and return on individual dividend strip can be more understated. Thus, the positive relation between $\overline{\mathrm{DP}}$ and subsequent return on dividend strips may be driven by differences in short-sale constraints of underlying stocks.

To see the potential effects of short-sale constraints on the results, I first look at the relation between dividend risk premium and short-sale constraint, which is measured by the percentage of institutional holding (PIH). Panel A of Table 6 shows that the five portfolios sorted by $\overline{\mathrm{DP}}$ have similar average PIH, suggesting that PIH is not correlated with dividend premium and short-sale constraints may not be a big concern. To further address the potential effect of short-sale constraints on returns of dividend strips, I do a double-sorting analysis. Specifically, at each quarter end, dividend strips are first sorted by the underlying stocks' PIH, and within each PIH group, dividend strips are sorted by $\overline{\text{DP}}$. Thus, $\overline{\text{DP}}$-sorted portfolios have similar levels of short-sale constraints. Panel B of Table 6 reports the characteristics of stocks in the 25 portfolios sorted by PIH and $\overline{\text{DP}}$. The stock characteristics across $\overline{\text{DP}}$-sorted portfolios have similar patterns to those of five portfolios sorted by $\overline{\text{DP}}$ alone. Within each PIH portfolio, logSIZE, BM, OP, and RET(−1,−6) increase from the portfolio with the lowest dividend premium to the portfolio with the highest dividend premium, while ATG tends to decrease as $\overline{\text{DP}}$ increases. Stocks across $\overline{\text{DP}}$ have similar average PIH, indicating a low correlation between short-sale constraints and dividend premium. All 25 portfolios have average retaining ratios (RR) higher than 60%. Within each PIH group, RRs are higher for stocks with the lowest and highest dividend premium than for stocks in the middle portfolios. Consistent with the finding of Nagel (2005) that institutional holdings are positively correlated with market-to-book ratio and lagged stock returns, Panel B of Table 6 shows that BM generally decreases and RET(−1,−6) generally increases from portfolios with low PIH to portfolios with high PIH, suggesting that institutional investors tend to hold growth stocks and past winners. Besides, ATG, LogSIZE, and OP seem to be positively correlated with PIH, indicating that institutional investors prefer to hold stocks with more aggressive investment, larger firm size, and higher profitability. The relations between PIH and stock characteristics are consistent with the average correlations between PIH and other variables reported in Panel B.1 of Table 1.

7.2 Returns on Portfolios of Dividend Strips

For a portfolio p at the end of a quarter q, I calculate the quarterly return on the portfolio of dividend strips, $r^p_{q+1} = (D^p_{q+1} + \mathrm{DI}^p_{q+1})/\mathrm{DI}^p_{q+1} - 1$. The current value of the dividend strip portfolio at the end of quarter q, DI^p_q, is the sum of products of number of shares outstanding and option-implied dividend per share of all stocks in the portfolio. The realized dividend of the portfolio in the next quarter $q+1$, D^p_{q+1}, is equal to the sum of products of number of shares outstanding and realized cash dividend per share of stocks in the portfolios with the first unknown dividend announced and paid in the next quarter $q+1$. The value of the dividend strip portfolio at the end of quarter $q+1$, DI^p_{q+1}, is the sum of products of number of shares outstanding and option-implied dividend per share of stocks in the portfolio with the first unknown dividend not yet announced in quarter $q+1$. Thus, the quarterly return on the dividend strip portfolio p is a value-weighted return on returns on individual dividend strips in the portfolio.[18]

[Insert Table 7]

Panel A of Table 7 reports time-series average quarterly returns on the five dividend strip portfolios of stocks sorted by $\overline{\mathrm{DP}}$. Portfolios are rebalanced on a quarterly basis. Average portfolio returns increase monotonically from low $\overline{\mathrm{DP}}$ portfolio to high $\overline{\mathrm{DP}}$ portfolio. Portfolio 5 with the highest dividend premium earns an average quarterly return of 11.91% (t-stat = 4.60) and portfolio 1 with the lowest dividend premium earns an average

[18] I also calculate equal-weighted and total market capitalization-weighted average portfolio returns. Results are qualitatively similar for different weighting methods.

quarterly return of -2.89% (t-stat = -1.26). The return spread between portfolio 5 and 1 is 14.78% and is highly statistically significant (t-stat = 4.53). The results indicate that there are substantial cross-sectional variations in returns on short-term dividend strips among individual stocks with different dividend risk premiums.

Panel B of Table 7 reports time-series average quarterly returns on 25 portfolios sorted by PIH and $\overline{\text{DP}}$. Within all five portfolios sorted by PIH, there is a strong positive relation between $\overline{\text{DP}}$ and subsequent quarterly return on portfolios of dividend strips: average portfolio return increases monotonically from portfolios in the first quintile of $\overline{\text{DP}}$ to portfolios in the fifth quintile of $\overline{\text{DP}}$. The difference in returns of portfolios with extremely high and extremely low $\overline{\text{DP}}$ tends to be greater among stocks with lower PIH, but return spreads between the two extreme $\overline{\text{DP}}$ portfolios are statistically significant regardless of institutional holdings of underlying stocks. For each $\overline{\text{DP}}$ portfolio, I aggregate dividend strips across the five PIH portfolios and report the average returns of the five aggregate portfolios at the bottom of the table. The five aggregate portfolios have different levels of $\overline{\text{DP}}$ but have similar levels of PIH so that they can be considered as $\overline{\text{DP}}$-sorted portfolios controlling for short-sale constraints. Average returns of the aggregate portfolio 5 and the aggregate portfolio 1 are 12.15% (t-stat = 5.29) and -3.59% (t-stat = -2.33), respectively, and the return spread between the two extreme aggregate portfolios is 15.74% with a t-statistic of 5.82, which is comparable to the return spread not controlling for PIH. In contrast, there is no obvious relation between PIH and subsequent dividend strip returns. If short-sale constraints drive the results, then dividend strips of stocks with lower PIH should earn lower returns due to the overestimation of prices of dividend strips. Within the two portfolios with low $\overline{\text{DP}}$, portfolio returns seem to decrease as PIH decreases. However, within the three portfolios with mid and high $\overline{\text{DP}}$, average returns are higher for portfolios with lower PIH. In short, the cross-sectional differences in dividend strip returns of individual stocks are robust after controlling for PIH and are not simply driven by short-sale constraints of underlying stocks.

7.3 Risk Exposures

In a rational asset-pricing framework, expected returns on financial assets should vary across different types of firms in a systematic way. A financial asset with a higher expected return should be subject to a higher systematic risk, which is related to the covariance between returns on the financial asset and stochastic discount factor. Measurements of systematic risk are different in different asset pricing models. In the standard Capital Asset Pricing Model (CAPM) (Lintner, 1965; Sharpe, 1964), the stochastic discount factor is a linear function of the return on total wealth, which is often proxied by the return on a market portfolio. The CAPM measures an asset's systematic risk by its correlation with the market portfolio, usually referred to as market beta. The more an asset's return covaries with the market portfolio return, the higher the risk premium that investors ask on the asset. Since the introduction of the CAPM, the literature on the pricing of equity has examined the empirical validity of the asset pricing model in the real data. Prior studies question the ability of the CAPM to explain cross-sectional stock returns. Many papers find that some stock characteristics can predict stock returns and differences in returns on stocks sorted by the characteristics cannot be explained by the CAPM. The findings suggest that CAPM is misspecified and that additional factors are needed to describe expected stock returns. Motivated by the implication of the dividend discount model and the empirical findings that the CAPM fails to explain the higher average returns of small stocks and value stocks than those of large stocks and growth stocks (Banz, 1981; Basu, 1983), Fama and French (1993) propose a three-factor model (FF3) which adds two additional factors, SMB (small minus big) and HML (high minus low), to the market factor in CAPM and find that the FF3 can better describe cross-sectional differences in average stock returns than the CAPM. Carhart (1997) adds the momentum factor, UMD (up minus down), to the three-factor model and finds the four-factor model (FFM4) can better explain persistence in mutual funds performances. More recently, Novy-Marx (2013) documents that profitable stocks earn significantly higher FF3-adjusted returns than unprofitable stocks. Titman, Wei and Xie (2004) find that firms which aggressively increase investments subsequently earn lower average returns and that the underperformance cannot be explained by the FF3, suggesting that the FF3 is an incomplete model. Motivated by the evidence, Fama and French (2015) propose a five-factor model (FF5) by introducing two more factors, RMW (robust minus weak) and CMA (conservative minus aggressive), into their three-factor model, and find that the FF5 improves descriptions of average returns across stocks. The asset pricing factors in addition to the excess return on the market portfolio can be interpreted as proxies for state variables and latent risks not captured by the CAPM. Results for the dividend strip aggregated from all individual dividend strips confirm the finding of van Binsbergen, Brandt and Koijen (2012) that the CAPM and the FF3 cannot fully explain average returns on index dividend strips. I examine whether the two models have difficulty in describing returns of dividend strips across individual stocks as well and whether introducing other risk factors can improve the description of average dividend strip returns.

In the absence of arbitrage opportunities, there exists a stochastic discount factor M that can price all future cash flows. The value of the dividend strip portfolio p at the end of quarter q, DI_q^p, is equal to the expected payoff of the portfolio during the next quarter $q+1$, x_{q+1}^p, discounted by the stochastic discount factor, based on the information set available at the end of quarter q:

$$\mathrm{DI}_q^p = E_q(M_{q+1} x_{q+1}^p), \tag{7.3}$$

where $E_q(\cdot)$ denotes expectation conditional on information set at quarter q. The payoff of the portfolio p, x_{q+1}^p, is equal to the sum of realized portfolio dividend in quarter $q+1$, D_{q+1}^p, and the value of the dividend strip portfolio at the end of quarter $q+1$, DI_{q+1}^p. Using the definition of covariance and substituting $E_q(M_{q+1}) = e^{-R_q^f}$, where R_q^f is the continuously compounding quarterly risk free rate, gives the equations:

$$\mathrm{DI}_q^p = E_q(M_{q+1})E_q(x_{q+1}) + \mathrm{Cov}_q(M_{q+1}, x_{q+1}^p), \tag{7.4}$$

$$= E_q(x_{q+1})e^{-R_q^f} + \mathrm{Cov}_q(M_{q+1}, x_{q+1}^p), \tag{7.5}$$

where $\mathrm{Cov}_q(M_{q+1}, x^p_{q+1})$ is the q-conditional covariance between the stochastic discount factor, M_{q+1}, and the future payoff, x^p_{q+1}. The covariance represents a risk adjustment term. A dividend strip whose payoff has a low covariance with the stochastic discount factor performs badly in a bad state of economy when investors' marginal utility is high is less attractive and will sell for a lower price, reflecting a discount for its high systematic risk. In contrast, a dividend strip with a high covariance with the stochastic discount factor serves as a hedge for a bad economic state and investors ask for a lower risk premium on such an asset. Dividing both side of the equation above by the current value of the portfolio p, DI^p_{q+1}, we have:

$$\frac{E_q(x^p_{q+1})e^{-R^f_q} - \mathrm{DI}^p_q}{\mathrm{DI}^p_q} = \mathrm{Cov}_q\left(M_{q+1}, \frac{x^p_{q+1} - \mathrm{DI}^p_q}{\mathrm{DI}^p_q}\right), \tag{7.6}$$

$$E_q(\tilde{r}^p_{q+1}) = -\beta^{p,M}_q \lambda^M_q. \tag{7.7}$$

$\tilde{r}^p_{q+1}$ is the return on the portfolio p of dividend strips in excess of the risk free rate. $\beta^{p,M}_q$ is the slope coefficient from a time-series regression of quarterly returns on the portfolio, r^p_{q+1}, on contemptuous stochastic discount factor, M_{q+1}. $\lambda^M_q = \mathrm{Var}_q(M_{q+1})$ is the price of risk and is the same for all assets, where $\mathrm{Var}_q(\cdot)$ is q-conditional variance. Thus, differences in expected returns of portfolios of dividend strips should be explained by differences in the short-term assets' exposures to risk factors.

Different asset pricing models approximate the pricing kernel M differently. I consider four asset pricing models: the CAPM which ties the stochastic discount factor to the return on the market portfolio, r^m_{q+1}; three multi-factor asset pricing models where the pricing kernel is a linear function of multiple factors. In the Fama and French (1993) three-factor model, the asset pricing factors include the market risk (r^m_{q+1}), the size factor (SMB_{q+1}) and the value factor (HML_{q+1}) . The Carhart (1997) four-factor model includes the three factors of Fama and French (1993) and the momentum factor (UMD_{q+1}) . The more recent five-factor model of Fama and French (2015) adds two new factors, the profitability factor (RMW_{q+1}) and investment factor (CMA_{q+1}), to the Fama and French (1993) three-factor model. Substituting the pricing kernels into the equation above, we have the following relations between expected excess return on a portfolio of dividend strips and and the portfolio's exposure(s) to risk factor(s) under the four asset pricing models:

$$\text{CAPM} \;:\; E_q(\tilde{r}^p_{q+1}) = \beta^{p,m}_q \lambda^m_q, \tag{7.8}$$

$$\text{FF3} \;:\; E_q(\tilde{r}^p_{q+1}) = \beta^{p,m}_q \lambda^m_q + \beta^{p,s}_q \lambda^s_q + \beta^{p,h}_q \lambda^h_q, \tag{7.9}$$

$$\text{FFM4} \;:\; E_q(\tilde{r}^p_{q+1}) = \beta^{p,m}_q \lambda^m_q + \beta^{p,s}_q \lambda^s_q + \beta^{p,h}_q \lambda^h_q + \beta^{p,u}_q \lambda^u_q, \tag{7.10}$$

$$\text{FF5} \;:\; E_q(\tilde{r}^p_{q+1}) = \beta^{p,m}_q \lambda^m_q + \beta^{p,s}_q \lambda^s_q + \beta^{p,h}_q \lambda^h_q + \beta^{p,r}_q \lambda^r_q + \beta^{p,c}_q \lambda^c_q. \tag{7.11}$$

$\beta^{p,f}_q$ is the q-conditional risk exposure of the portfolio p to a risk factor f, and λ^f_q is the q-conditional price of the risk factor f.

For a portfolio p in a quarter q, I estimate its risk exposures by running time-series regressions of its quarterly return r^p_q on the contemporaneous asset pricing factors in a rolling window. Since the return on portfolios of dividend strips is quarterly return, I regress it on quarterly risk factors.[19] There is a trade-off between a short and a long rolling window to estimate risk exposures. On the one hand, a long rolling window which includes more historical data enables us to estimate regression coefficients more precisely and gives more reliable estimations of risk exposures. On the other hand, a short rolling window that puts more weight on recent data can better capture recent information and is more suitable for a conditional asset pricing model in which risk exposures can be time-varying. To balance reliability and relevance of the estimation of conditional risk exposures, I use a rolling window from 12 quarters to 20 quarters as available.[20]

[Insert Table 8]

Panel A of Table 8 tabulates time-series averages of slope coefficients on risk factors and Newey and West (1987) t-statistics adjusted for autocorrelation and heteroscedasticity for five portfolios sorted by $\overline{\text{DP}}$. For the CAPM, portfolios of dividend strips with different levels of dividend premiums have different exposures to the market risk factor. Market beta ($\beta^{p,m}$) increases monotonically as dividend premium increases. Portfolio 5 with the highest $\overline{\text{DP}}$ have an average market beta of 1.68 (t-stat $= 9.52$), while portfolio 1 with the lowest $\overline{\text{DP}}$ has a negative market beta of -0.45 (t-stat $= -4.99$). The five portfolios sorted by $\overline{\text{DP}}$ have different exposures to risk factors other than the market risk factor. For the Fama and French (1993) three-factor model, returns of dividend

[19] Stocks in a portfolio have different ex-dividend dates in a quarter, so the return on a portfolio is earned during the quarter rather than on the last date of the next quarter. The differences in payoff dates results in a timing-mismatching issue that the returns on dividend strip portfolios do not match exactly match the risk factors and leads to a bias in the estimated risk exposures towards zero.

[20] The results are qualitatively similar when lengths of rolling window vary from 8 quarters to 32 quarters.

strip portfolios with high dividend premium tend to have negative exposures to SMB and have positive exposures to HML, and vice versa for portfolios with low dividend premium. Average slope coefficients on the size factor ($\beta^{p,s}$) for portfolio 5 and portfolio 1 are -0.41 (t-stat $= -3.43$) and 0.60 (t-stat $= 4.05$), respectively. Returns on the portfolio in the fifth $\overline{\text{DP}}$ quintile covary positively with returns on value stocks, as suggested by its significantly positive coefficient on the value factor ($\beta^{p,h} = 0.78$, t-stat $= 5.46$). In contrast, the portfolio in the first $\overline{\text{DP}}$ quintile has a significantly negative exposure to the value factor ($\beta^{p,h} = -0.45$, t-stat $= -3.91$), suggesting that returns on portfolio 1 covary positively with growth stocks. The slope coefficient on the momentum factor ($\beta^{p,u}$) in the Carhart (1997) four-factor model is significantly positive for portfolio 5 ($\beta^{p,u}$ $= 0.48$, t-stat $= 3.37$), and decreases monotonically to significantly negative for portfolio 1 ($\beta^{p,u} = -0.27$, t-stat $= -2.48$). For the profitability and investment factors in Fama and French (2015) five-factor model, portfolio 5 has significantly positive slope coefficients on RMW ($\beta^{p,r} = 0.96$, t-stat $= 5.03$) and CMA ($\beta^{p,c} = 0.83$, t-stat $= 4.87$), suggesting that returns on dividend strips with high dividend premium behave more like returns on profitable stocks with conservative investments. RMW beta and CMA beta decrease with $\overline{\text{DP}}$, and become negative for portfolio in the lowest $\overline{\text{DP}}$ quintile, suggesting that returns on portfolio 1 behave more like unprofitable stocks with aggressive investments. Patterns of the coefficients on the four characteristic-based risk factors of the five portfolios line up with the average characteristics of stocks within the portfolios as in Panel A of Table 6, which shows that stocks with high dividend premium tend to have larger firm size, higher book-to-market ratio, higher profitability, more conservative investment and higher historical stock return.

Panel B of Table 8 reports the time-series average risk exposures to different asset pricing factors and their Newey and West (1987) t-statistics for the 25 portfolios sorted by PIH and $\overline{\text{DP}}$. Patterns of slope coefficients of portfolios with high and low dividend premium for the double-sorted portfolios are similar to those for the univariate-sorting. Within each PIH group, dividend strips portfolios with higher dividend premium have more positive exposures to the market risk, value, momentum, profitability and investment factors, while the slope efficient on the size factor is lower for portfolios with higher dividend premium. Slope coefficients of the 25 double-sorted portfolios on risk factors generally line up with average characteristics of stocks within the portfolios, but there are several exceptions. For example, while Panel B of Table 6 reports that within the portfolio with highest $\overline{\text{DP}}$, stocks with higher PIH tend to earn higher average returns in the previous six months, Panel B of Table 8 shows that UMD betas tend to decrease with PIH for the five PIH-sorted portfolios within the highest $\overline{\text{DP}}$ quintile. The reason for the mismatching may be that average portfolio characteristics are from univariate-sorting while regression coefficients are from multivariate regressions that capture the marginal effect of a variable on another variable. The fact that results for the double-sorting analysis are quantitatively similar to those for the univariate-sorting indicates that differences in risk exposures among dividend strip portfolios sorted by $\overline{\text{DP}}$ are robust to controlling for short-sale constraints of underlying stocks.

7.4 Prices of Risk

To estimate the prices of risk factors, for each asset pricing model, I run quarter-by-quarter Fama and MacBeth (1973) cross-sectional regressions of excess returns of dividend strip portfolios on conditional beta coefficients on risk factors, which are estimated from the first-stage time-series regressions:

$$\text{CAPM} \;:\; \tilde{r}^{p}_{q+1} = \lambda^{\text{CAPM}}_{0} + \lambda^{m}\beta^{p,m}_{q} + \varepsilon^{p,\text{CAPM}}_{q+1}, \tag{7.12}$$

$$\text{FF3} \;:\; \tilde{r}^{p}_{q+1} = \lambda^{\text{FF3}}_{0} + \lambda^{m}\beta^{p,m}_{q} + \lambda^{s}\beta^{p,s}_{q} + \lambda^{h}\beta^{p,h}_{q} + \varepsilon^{p,\text{FF3}}_{q+1}, \tag{7.13}$$

$$\text{FFM4} \;:\; \tilde{r}^{p}_{q+1} = \lambda^{\text{FFM4}}_{0} + \lambda^{m}\beta^{p,m}_{q} + \lambda^{s}\beta^{p,s}_{q} + \lambda^{h}\beta^{p,h}_{q} + \lambda^{u}\beta^{p,u}_{q} + \varepsilon^{p,\text{FFM4}}_{q+1}, \tag{7.14}$$

$$\text{FF5} \;:\; \tilde{r}^{p}_{q+1} = \lambda^{\text{FF5}}_{0} + \lambda^{m}\beta^{p,m}_{q} + \lambda^{s}\beta^{p,s}_{q} + \lambda^{h}\beta^{p,h}_{q} + \lambda^{r}\beta^{p,r}_{q} + \lambda^{c}\beta^{p,c}_{q} + \varepsilon^{p,\text{FF5}}_{q+1}. \tag{7.15}$$

If a model is correctly specified, the intercept term from that model should be zero on average. That is, portfolios with zero risk exposures should earn a risk premium of zero. For the CAPM, I run the regressions on returns on both the five portfolios sorted by $\overline{\text{DP}}$ and the 25 portfolios sorted by PIH and $\overline{\text{DP}}$. For the three multi-factor asset pricing models, the regressions are only run on the 25 double-sorted portfolios.

[Insert Table 9]

Table 9 reports the time-series average of intercepts and prices of risk factors, their t-statistics and mean values of adjusted R^2. Panel A reports the results of cross-sectional regressions for the CAPM using the five portfolios sorted by $\overline{\text{DP}}$ as testing portfolios. As shown in the last subsection, average market betas tend to be positive for portfolios with high $\overline{\text{DP}}$ (which earn high average returns) and negative for portfolios with low $\overline{\text{DP}}$ (which earn low average returns), suggesting a positive premium on market risk in the cross section of short-term assets. Consistent with the positive relation between market beta and portfolio return, the average quarterly price of market risk, λ^m, is estimated to be 2.72% with a t-statistic of 2.27. Differences in exposures to market risk explain 48.8% of cross-sectional variations in returns on the five dividend strip portfolios. However, the intercept of the CAPM is significantly positive ($\lambda_0^{\text{CAPM}} = 3.52\%$, t-stat = 2.40), suggesting that variations in market risk exposures alone cannot fully explain differences in expected returns on portfolios of dividend strips.

Panel B reports the results of the cross-sectional regressions to test the four asset pricing models' ability to explain average returns on the 25 portfolios sorted by PIH and $\overline{\text{DP}}$. For the CAPM, the estimated average market risk price is 3.08% (t-stat = 3.18), which is comparable with that estimated from regressions on univariate-sorted portfolios. For the three-factor model, average quarterly prices of the market risk (λ^m) and of the value factor (λ^h) are 3.12% and 1.97%, both statistically significant (t-stat = 2.25 and 2.13, respectively), suggesting that adding size and value factors does not depress the statistical significance of positive market risk premium and that the value factor carries a positive premium in the cross section of individual dividend strips. The insignificant negative price of the size factor ($\lambda^s = -0.84\%$, t-stat = -1.46) indicates that SMB is not a priced factor among portfolios with different ex-ante dividend risk premiums. The intercept of the FF3 is 2.05% per quarter, which is not statistically significant (t-stat =

1.59), and the three-factor model explains 45.4% of variations in returns on the 25 double-sorted portfolios. The intercept with smaller magnitude and the higher average adjusted R^2 from the regression to test the FF3 indicate that introducing HML can improve the description of cross-sectional differences in dividend strip returns. For the four-factor model, the momentum factor is not a priced factor, as suggested by the insignificant price of UMD estimated from the cross-sectional regressions ($\lambda^u = 1.13\%$, t-stat $= 1.08$), while the price of market risk and the price of HML remain significantly positive. The intercept of the FFM4 is 1.90% with a t-statistic of 1.44, slightly lower than that of the three-factor model. The four-factor model on average explains 50.7% of variations in returns on dividend strips, higher than that of the FF3. Introducing slope coefficients on RMW and CMA reduces the average regression intercept to 0.44%, which is statistically insignificant with a t-statistic of 0.30. The price of RMW (λ^r) and the price of CMA (λ^c) are estimated to be 1.61% (t-stat $= 2.70$) and 1.59% (t-stat $= 3.31$) per quarter, both statistically significant. On average, 57.0% of variations in portfolio returns can be explained by the FF5, higher than those of other models. The results indicate that differences in exposures to the profitability and investment factors play important roles in explaining differences in average returns of individual dividend strips. Another thing to note is that introducing beta coefficients on profitability and investment factors does not depress the significance of risk premiums on the market risk and the value factor, which indicate that they are not redundant factors. The four risk factors contain unique information about the pricing of short-term individual dividend strips which are not subsumed by each other.

Figure 5 and 6 give the plots of realized average quarterly excess portfolio returns ($\tilde{r}^p_{q+1}$) against the theoretical values ($E_q[\tilde{r}^p_{q+1}]$) according to each of the four asset pricing models. Figure 5 shows the plots of the five portfolios sorted by historical dividend premium, and Figure 6 shows the plots of the 25 portfolios sorted by institutional holding and dividend premium. The expected excess portfolio return, $E_q[\tilde{r}^p_{q+1}]$, is given by:

$$E_q[\tilde{r}^p_{q+1}] = \sum^{f} \bar{\beta}^{p,f} \lambda^f \tag{7.16}$$

where $\bar{\beta}^{p,f}$ is time-series average of beta coefficient on a risk factor f of portfolio p estimated from the first-stage rolling-window time-series regressions, and λ^f is the price of the risk factor f estimated from the second-stage cross-sectional regressions.

For the five univariate-sorted portfolios, in case of the CAPM, both average portfolio risk exposures and marker risk premium are estimated from regressions on the five portfolios; in case of the three multi-factor models, average risk exposures are estimated from time-series regressions on the five portfolios, while prices of risk factors are estimated from cross-sectional regressions on the 25 double-sorted portfolios. As shown in the left upper of Figure 5, for the CAPM, points of portfolios with high (low) dividend premium lie above (below) the 45-degree line, indicating that the portfolios of dividend strips are underpriced (overpriced) according to the CAPM. For the three-factor model, the points are distributed more closely around the 45-degree line, suggesting that introducing risk factors other than the market risk can better describe returns on portfolios of dividend strips. The better performances are mainly attributed to the significantly positive premium on the value factor and positive (negative) beta coefficient on HML of portfolios with high (low) $\overline{\text{DP}}$. However, realized returns of portfolios with high (low) $\overline{\text{DP}}$ are still higher (lower) than their theoretical values based on the fitted model. Introducing UMD to the FF3 only slightly narrow the gaps between realized portfolio returns and expected portfolio returns according to the FFM4 because the UMD carries an insignificantly positive risk premium. After introducing the profitability factor (RMW) and the investment factor (CMA), expected excess portfolio returns according to the FF5 get closer to the realized values. Expected returns of portfolios with high (low) ex-ante dividend risk get higher (lower) due to their positive (negative) exposures to RMW and CMA, which are positively priced in the cross section of dividend strips. Plots of the 25 double-sorted portfolios show similar patterns. Points of the 25 portfolios are most evenly and closely distributed around the 45-degree line for the five-factor model, while the CAPM, the FF3 and the FFM4 underestimate returns on portfolios with high $\overline{\text{DP}}$ and overestimate returns on portfolios with low $\overline{\text{DP}}$.

To summarize, results from the cross-sectional regressions indicate that the market risk, HML, RMW and CMA are positively priced in the cross section of dividend strips with different ex-ante dividend premiums. Among the four models, the five-factor model is superior in describing average returns of dividend strip portfolios, as suggested by the smallest and the least significant intercept and the highest adjusted R^2 from the cross-section regressions, and further supported by the small discrepancy between realized portfolio returns and expected portfolios returns based on the model.

7.5 Time-Series Regression and the GRS Test

Fama and French (1993) and Fama and French (2015) use the multivariate test proposed by Gibbons, Ross and Shanken (1989) to examine the empirical support for their three-factor model and five-factor model. Following them, I use the Gibbons, Ross and Shanken (1989) test to evaluate how well the four asset pricing models can explain average returns on dividend strips. If a model is correctly specified, the test will fail to reject the null hypothesis that all risk-adjusted portfolio returns are jointly equal to zero. The better the performance of a model is, the higher the p-value of the GRS (1989) test on the model will be. For each sorted portfolio of dividend strips, I run a full-sample time-series regression of quarterly portfolio excess returns on contemporaneous quarterly asset pricing factors under different asset pricing models (i.e., quarterly excess return on the S&P 500 index in case of the CAPM and quarterly market excess return along with quarterly portfolio-based risk factors in case of the three multi-factor models).

[Insert Table 10 here]

Table 10 tabulates alphas and associated t-statistics from time-series regressions to test the four asset pricing models to explain average returns of the five portfolios sorted by $\overline{\text{DP}}$ (Panel A) and of the 25 portfolios sorted by PIH and $\overline{\text{DP}}$ (Panel B). [21] Test statistics and p-values of the Gibbons, Ross and Shanken (1989) test on the four asset pricing models are summarized at the bottom of each panel. For the five portfolios sorted

[21] Slope coefficients on risk factors estimated from the full-sample time series regressions are not reported since their values are similar to average risk exposures estimated from time series regression in a rolling window.

by $\overline{\text{DP}}$, market beta ($\beta^{p,m}$) increases monotonically from portfolio 1 with the lowest $\overline{\text{DP}}$ to portfolio 5 with the highest $\overline{\text{DP}}$. The troublesome portfolios are portfolios 4 and 5 with high dividend premium, whose returns are still significantly positive after adjusting for market risk. The average absolute value of CAPM-alpha is 3.99% per quarter. The GRS (1989) test rejects the CAPM with a p-value of 0.003. The three-factor model slightly improves the description of average returns on $\overline{\text{DP}}$-sorted dividend strips, as evidenced by the lower average absolute value of alpha (3.83% per quarter) and lower GRS test statistic (3.226). The intercept improvement centers on the significantly positive exposures to the value factor ($\beta^{p,h}$) of two portfolios in higher $\overline{\text{DP}}$ quintiles. Returns on portfolios with high dividend premium covary positively with returns of value stocks, and the high risk exposures help explain their high average returns. However, slope coefficients on SMB ($\beta^{p,s}$) go in opposite directions with ex-ante dividend risk premiums. $\beta^{p,s}$ of the portfolio with extremely high $\overline{\text{DP}}$ is negative, suggesting that its returns covary positively with stock returns of large companies, and vice versa for the portfolio with the lowest $\overline{\text{DP}}$. Lower SMB slopes for portfolios with higher dividend premium go in the wrong direction to explain the pattern in average returns of portfolios sorted by $\overline{\text{DP}}$ and deteriorates the performances of the three-factor model. Returns on the two portfolios with high dividend risk premium remain unexplained, and the FF3 is rejected by the GRS (1989) test with a p-value of 0.011. For the FFM4 which introduces the momentum factor, UMD slopes are positively correlated with dividend premium. However, the dispersion of UMD betas among portfolios seems to be smaller than the dispersion of betas on other risk factors. The positive relation between UMD slope $\beta^{p,u}$ and $\overline{\text{DP}}$ shrinks the absolute value of FFM4-alpha to 3.49% per quarter. The improvement of the FFM4 over the FF3 is limited. The GRS test statistics for the four-factor model is 2.565, and the test rejects the null hypothesis that all FFM4-adjusted portfolio returns are jointly equal to zero (p-value = 0.033). For the five-factor model which adds the profitability factor (RMW) and the investment factor (CMA), the average absolute value of regression intercepts is reduced to 2.92% per quarter, and the GRS (1989) test fails to reject the FF5 with a p-value of 0.123. The improvements in the description of average returns on portfolios of dividend strips produced by the five-factor model come from the positive relations between average realized portfolio returns and slopes on RMW and CMA. Portfolios with high dividend premium have positive exposures to RMW and CMA, indicating that returns on dividend strips of stocks with high dividend premium behave more like returns of stocks with high profitability and low investment. Positive exposures to the two factors increase expected portfolio returns and reduce regression intercepts. After adjusting for the two additional factors, the FF5-alpha of portfolio 4 becomes insignificant. Though the risk-adjusted return of portfolio 5 is still significantly positive, its magnitude is smaller than the corresponding values of the other three models.

Results are similar for the 25 double-sorted portfolios. As shown at the bottom of Panel B of Table 10, the CAPM is rejected by the GRS (1989) test with a p-value of 0.003. The average absolute value of CAPM-alpha is 4.30% per quarter. Problems come from portfolios with high dividend premiums. CAPM-alphas are marginally significant for portfolios in the third quintile of $\overline{\mathrm{DP}}$ and are statistically significant with t-statistics greater than 2 for portfolios in the fourth and fifth quintiles of $\overline{\mathrm{DP}}$. One portfolio in the first quintile of dividend premium has significantly negative CAPM-alpha. Introducing risk factors other than the excess return of the market portfolio helps explain cross-sectional differences in average dividend strip returns. Within each PIH group, consistent with the pattern of average portfolio returns, HML, UMD, RMW and CMA slopes tend to be positive (negative) for portfolios with high (low) dividend risk premiums. Positive exposures to the four risk factors shrink regression intercepts. However, the negative relation between SMB slopes and $\overline{\mathrm{DP}}$ exists among portfolios within each PIH group, which worsens the performances of the multi-factor models. Regression intercepts of the FF3 have an average absolute value of 4.23%. The majority of portfolios in the fourth and fifth quintiles of $\overline{\mathrm{DP}}$ have significantly positive FF3-alphas with t-statistics greater than 2. The FF3 still fail to explain the average low return of one portfolio with an extremely low dividend premium. After adding UMD, risk-adjusted returns of portfolios with high $\overline{\mathrm{DP}}$ have smaller magnitudes and lower statistical significance. After adding RMW and CMA, only the five portfolios with extremely high $\overline{\mathrm{DP}}$ have significant FF5-alphas. Negative exposures to RMW and CMA of the portfolio in the 2nd PIH quintile with extremely low dividend premium help explain its very low average return and make its FF5-alpha insignificant. The GRS (1989) test rejects the FF3's and the FFM4's ability to explain returns on the 25 double-sorted dividend strip portfolios with p-values of 0.028 and 0.041, respectively, while the test fails to reject the null hypothesis that alphas of the

25 portfolios relative to the FF5 are jointly equal to zero (p-value $= 0.142$).

In summary, consistent with the results of cross-sectional regressions, the results from time-series regressions and the GRS (1989) test indicate that among the four asset pricing models, the five-factor model performs the best in describing average returns on portfolios of dividend strips with different levels of ex-ante dividend premium.

Chapter 8

Robustness Checks

In this chapter, I conduct a few robustness tests of the main empirical results. In the first analysis, I examine whether option-implied dividends are informative about future dividends beyond historical dividends. The positive results from this analysis would suggest that dividends implied from options prices are reliable estimates of prices of dividend strips and that the main empirical results are not driven simply by errors in option-implied dividends due to, for example, short-sale constraints and.or liquidity issues. In the second analysis, I examine the returns on dividend strips within the sample of dividend payers. The results would shed light on whether the main empirical results are due to the potential difference between dividend payers and non-payers or are general for all stocks. The third analysis examines the effects of early exercise premiums on the results. Finally, I use firm characteristics that can predict subsequent stock returns as alternative sorting variables to sort individual dividend strips and examine whether the five-factor model can best explain average returns of dividend strip portfolios with different sorts. The analysis intends to examine whether the superior performance of the FF5 is specific to portfolios sorted by $\overline{\mathrm{DP}}$ only.

8.1 Predictability of Option-Implied Dividend

Prior studies suggest that options prices predict future dividends.[22] The four examples of changes in dividend policies of Apple Inc. and General Motors Company show that dividends implied from prices of options written on the stocks of the two companies anticipate the changes in dividends before announcements and provide preliminary evidence of predictability of DI for future dividends. This section presents complementary and formal evidence on the predictability of DI. I use a regression approach to show that option-implied dividends contain information about future dividends beyond historical dividends. On a day before the dividend announcement date of stock i's dividend in the next quarter $q+1$ (D^i_{q+1}), I compute option-implied dividends (DI) from prices of pairs of options which meet the filtering criteria as discussed in the Chapter 5 and then take an average of DI across time-to-maturities and strike prices of options to get a daily average DI, which are then averaged across days to compute the average quarterly option-implied dividend, DI^i_q. To ensure that options prices contain relevant information, I calculate DI on days within 20 days before a dividend announcement date. Moreover, to ensure that the predictability of option-implied dividends is not due to incorporation of relevant

[22] For example, using options written on 69 firms on 226 dividend announcement dates from 1984 to 1985, Bae-Yosef and Sarig (1992) find that option-implied dividend surprises are significantly related to stock markets' reactions to dividend announcements. Fodor, Stowe and Stowe (2017) examine option-implied dividends of 67 firms that cut dividends during the financial crisis from 2008 to 2009 and find that option-implied dividends can predict dividend omissions better than some equity market and account variables. Kragt (2017) finds that option-implied dividend growth rate can predict realized dividend growth rate in the cross-section.

information released on earnings announcements before dividend announcements,[23] for a given stock, I use options prices on days at least five days before the stock's earnings announcement date in the same quarter. For a stock i with at least one change in dividend and with at least 12 quarters of observations,[24] I run the following time-series regression for the whole sample period with options data available:

$$\frac{D_{q+1}^i - D_q^i}{S_q^i} = \gamma^i \frac{\mathrm{DI}_q^i - D_q^i}{S_q^i} + \sum_j \eta_j^i l_{j,q+1}^i + \varepsilon_{q+1}^i, \tag{8.1}$$

where $(D_{q+1}^i - D_q^i)/S_q^i$ is price-normalized change in quarterly dividend and $(\mathrm{DI}_q^i - D_q^i)/S_q^i$ is price-normalized option-implied change in quarterly dividend. To control for seasonality in quarterly dividend payments, I include four dummy variables, $l_{j,q+1}^i$ (j= 1, 2, 3 or 4), which take the value of 1 if quarter $q+1$ is the j^{th} fiscal quarter in a year and take the value of 0 if otherwise. If option-implied dividends contain information about future realized dividends, the regression coefficient γ should be significantly positive.

[Insert Table 11 here]

Table 11 reports the distribution of the regression coefficient γ^i, its Newey and West (1987) t-statistics adjusted for autocorrelation and heteroscedasticity, and adjusted R^2 across individual stocks. The average values of the regression coefficient γ^i and its t-statistics of the time-series regression are 0.457 and 4.949. The time-series regressions have

[23] Some papers find that earnings announcements and dividend announcements contain similar information. For example, Kane, Lee and Marcus (1984) examine abnormal stock returns around earnings and dividends announcements. They that the abnormal return corresponding to earnings announcements depend on the value of contemporaneous dividend announcements, vice versa, suggesting a corroborative relation between the two announcements.

[24] 3,734 stocks meet these requirements.

an average adjusted R^2 of 0.503, indicating that on average a considerable proportion of time-series variations in changes in dividends can be explained by options-implied changes in dividends. 74.40% of the individual stocks have significantly positive coefficients of γ^i. The regression results indicate that dividends implied from options are informative about future realized dividends and that option-traders' expectations about future dividends are on average correct.

8.2 Dividend Payer Sample

Dividend policies vary across individual companies. Firms that have paid dividends in the past, i.e., dividend payers, are likely to continue to pay dividends in the future, and vice versa for dividend non-payers, which have not dividends in the past. As a result, returns on dividend strips from dividend payers may be consistently high while those from dividend non-payers may be consistently low. In this case, the main empirical results can be simply due to the difference between dividend payers and non-payers. To examine whether this drives the main results, I repeat the analysis using a subsample of dividend payers, which are defined as companies that have ever paid a positive regular cash dividend in the previous five years. The results are reported in Table 12.

[Insert Table 12]

As shown in Panel A of Table 12, average returns on dividend strips of dividend payers seem to be higher than average returns on dividend strips of the full sample of stocks with options. Within dividend payers, average portfolio returns of dividend strips also exhibit substantial variations across stocks sorted by $\overline{\text{DP}}$. Portfolio 1 with the lowest $\overline{\text{DP}}$ earns an average quarterly return of -2.90% (t-stat $= -1.13$), and average portfolio return increases monotonically to 14.03% (t-stat $= 5.04$) per quarter for portfolio 5 with the highest $\overline{\text{DP}}$. The return spread between the two extreme portfolios is 16.93% (t-stat $= 4.58$), which is larger and more significant than the corresponding value for the full sample. short-sale constraints of underlying stocks do not drive differences in returns of dividend strips of dividend payers sorted by $\overline{\text{DP}}$. For the 25 portfolios sorted by PIH and $\overline{\text{DP}}$, the difference between the average return of the portfolio in the fifth quintile of $\overline{\text{DP}}$ and the average return of the portfolio in the first quintile of $\overline{\text{DP}}$ are statistically significant within each of the five PIH groups.

Portfolios of dividend strips of dividend payers with different average returns have different exposures to the market risk. As shown in Panel B of Table 12, same as the results for the full sample of stocks, average market beta ($\bar{\beta}^{p,m}$) increases from -0.45 (t-stat $= -4.43$) for portfolio 1 with the lowest dividend premium to 1.83 (t-stat $= 9.49$) for portfolio 5 with the highest dividend premium. The risk premium of the market factor λ^m is estimated to be 3.50% (t-stat $= 3.77$) per quarter, which is comparable with the one estimated from dividend strips of the full sample of stocks, and the CAPM explains over 50% of variations in returns on the five portfolios sorted by $\overline{\text{DP}}$. However, the CAPM intercept from the cross-sectional regression is still significantly positive. The average absolute value of the CAPM-alpha (reported in Panel D) from the time-series regressions of quarterly excess returns of the quintile portfolios on quarterly excess return on the market portfolio is 4.73%, and the GRS (1989) test rejects the CAPM with a p-value that is zero to three decimal places (reported in Panel E). Results are similar for the 25 double-sorted portfolios. The results from the cross-sectional and time-series regressions indicate that the CAPM does not well explain average returns on dividend strips for the sample of dividend payers.

Multi-factor models that introduce portfolio-based risk factors other than the market risk perform better than the CAPM, and the five-factor model performs the best. As shown in Panel B, portfolios of dividend payers' dividend strips have very different tilts toward portfolio-based risk factors. Returns on portfolios with high $\overline{\text{DP}}$ are positively correlated with HML, UMD, RMW and CMA and are negatively correlated with SMB, suggesting that portfolios with high dividend premiums tilt toward stocks which have high book-to-market ratio, perform well in the past year, have high profitability, invest conservatively and have large market capitalization. Using the 25 double-sorted dividend strip portfolios as testing portfolios in quarter-by-quarter cross-sectional regressions to test the FF5, average prices of HML (λ^h), RMW (λ^r) and CMA (λ^c) are estimated to be 1.79% (t-stat = 2.75), 1.91% (t-stat = 3.27) and 1.81% (t-stat = 4.27) , which are comparable with the risk premiums estimated from the full sample of stocks with options traded. SMB and UMD do not carry significant risk premiums in the cross section of dividend payers' dividend strips. Average intercepts from the cross-sectional regression to test the FF3 and the the FFM4 are 3.31% and 3.11%, lower than it is for the CAPM (4.76%), but are still statistically significant with t-statistics of 2.67 and 2.51, respectively. Adding RMW and CMA betas reduces the regression intercept to 1.44% (t-stat = 1.76), suggesting that the FF5 is better than the other three models in describing average dividend strip returns within the subsample of dividend payers. Results from the time-series regressions (as reported in panel D and E) confirm the superior performance of the FF5. For the five portfolios sorted by $\overline{\mathrm{DP}}$, average absolute value of risk-adjusted dividend strip returns of dividend payers relative to the FF3, the FFM4, and the FF5 are 4.55%, 4.19% and 3.39%, lower than the counterpart of the CAPM for the dividend payer sample while slightly higher than the corresponding values for the full sample of stocks. The GRS (1989) test rejects the FF3 and the FFM4 with p-values of 0.009 and 0.017, while the test fails to reject the FF5 at conventional significance level (p-value = 0.078). The FF3 is better than the CAPM due to the positive association between average realized portfolio returns and HML betas. Positive (negative) exposures to the value factor help explain the high (low) average return of portfolios with high (low) dividend premiums. However, similar to the results for the full sample, adding SMB deteriorates the performance of multi-factor models, since lower SMB betas of portfolios with higher $\overline{\mathrm{DP}}$ contradict their higher average returns. Adding the momentum factor (UMD) produces improvements as UMD betas increase monotonically from the first $\overline{\mathrm{DP}}$ quintile portfolio to the fifth $\overline{\mathrm{DP}}$ quintile portfolio. The improvements in the description of average dividend strip returns produced by the FF5 trace to patterns of the RMW and CMA slopes that absorb the patterns in average portfolio returns. Specifically, the positive (negative) exposures to RMW and CMA increase (decrease) the predicted returns of portfolios with high (low)

$\overline{\text{DP}}$ and push regression intercepts toward zero. All results of time-series regressions to test the three multi-factor models hold for the 25 portfolios sorted by dividend premium and institutional holding, suggesting that the results are not affected by short-sale constraints of underlying stocks.

In short, the main empirical findings of the full sample of stocks with options traded are qualitatively similar for the subsample of dividend payers, which indicate that the results are not driven by potential differences between dividend payers and non-payers and are general among all stocks.

8.3 Early Exercise Premium

8.3.1 The Black and Scholes (1973) Model Approach

Options traded on exchange and written on individual stocks in the U.S. market are American-style options that can be exercised at any time on or before the option expiration date. Prices of American-style put options and call options written on dividend-paying stocks should contain early exercise premium (EEP). Therefore, dividends implied by American options prices from the put-call parity relation are contaminated by the difference between the EEP of put and call options. To examine the effect of EEP on the main results, I repeat the sorting portfolio analysis using option-implied dividends which are adjusted for EEP and report the results in Table 13.

[Insert Table 13]

Both the sorting variable $\overline{\text{DP}}$ and portfolio returns r^p are adjusted by EEP since it affects the measurements of prices of dividend strips. Panel A of Table 13 reports average EEP-adjusted returns of portfolios of dividend strips sorted by EEP-adjusted historical dividend premium. Again, to alleviate the effects of short-sale constraints, I do a double-sorting analysis by sorting dividend strips by institutional holding (PIH) and $\overline{\text{DP}}$. After adjusting for EEP, average portfolios seem to be higher than the counterparts not adjusted for EEP, suggesting that EEP of put options are on average higher than EEP of call options and that the difference in EEP of put and call options on average lead to an overestimation of prices and an underestimation of returns on dividends strips. Cross-sectional variations on returns on dividend strips are robust to adjusting for EEP. For the five univariate-sorted portfolios, average realized returns increase monotonically from -2.39% for portfolio 1 with the lowest $\overline{\text{DP}}$ to 12.16% for portfolio 5 with the highest $\overline{\text{DP}}$. The fifth quintile portfolio outperforms the first quintile portfolio by 14.55% per quarter, and the large return spread is statistically significant, with a t-statistic of 3.53. For the 25 double-sorted portfolios, return spreads between the two portfolios with extremely high and low dividend premiums seem to be larger among stocks with lower PIH, but spreads in return are significantly positive within each PIH group. As shown in the bottom of Panel A, the return spread between the portfolio with the highest $\overline{\text{DP}}$ and the portfolio with the lowest $\overline{\text{DP}}$ aggregated from all PIH groups is significantly positive (16.82%, t-stat $= 4.25$). Thus, cross-sectional variations in realized returns of portfolios sorted by the ex-ante measure of dividend risk are robust to adjusting for EEP and are not driven by short-sale constraints of underlying assets.

Variations in dividend strip returns after adjusting for EEP can be well explained by their exposures to risk factors of the five-factor model. As reported in Panel C of Table 13, for the 25 double-sorted portfolios, average intercept estimated from the quarter-by-quarter cross-sectional regressions of the FF5 has the smallest magnitude and least statistical significance (λ_0 = 0.28%, t-stat = 0.21) compared to the corresponding values of the CAPM (λ_0 = 3.59%, t-stat = 3.11), the FF3 (λ_0 = 2.10%, t-stat = 1.62) and the FFM4 (λ_0 =1.79%, t-stat = 1.57), and the five-factor model explains the highest proportion of variations in dividend strip returns (average adjusted R^2 = 58.5%). Results of the time-series regressions and the GRS (1989) test confirm the results from the cross-sectional regressions. Panel D reports the pricing errors of different asset pricing models of the five univariate-sorted portfolios and the 25 double-sorted portfolios. For univariate-sorting, though the higher market betas of portfolios with higher dividend premiums (reported in Panel B) go in the correct direction to explain the average portfolio returns, differences in market betas cannot fully explain differences in portfolio returns. CAPM-alphas of the $\overline{\text{DP}}$-sorted quintile portfolios of dividend strips has an average absolute value of 4.20%. The portfolio in the middle quintile has marginally significant CAPM alpha, and the fourth and fifth quintile portfolios have significantly positive CAPM-alphas more than two standard errors above zero. As shown in Panel B, positive exposures to HML of the three portfolios with high dividend premium help explain their high average returns. However, the negative exposures to the size factor of portfolios 4 and 5 plague the three-factor model. FF3-alphas of the fourth and fifth portfolio remain significantly positive. Introducing UMD reduces the absolute value of regression intercepts to 3.65%. UMD slopes of the two portfolios with high dividend premiums are significantly positive, but still not high enough to explain their high average returns. The GRS (1989) test rejects the CAPM, the FF3, and the FFM4 with p-values of 0.003, 0.008, and 0.027, respectively. After RMW and CMA are added, the average absolute value of FF5-alphas decreases to 3.17%, and the p-value of the GRS (1989) test is 0.115. The improvements in the explanation of average dividend strip returns of the five-factor model come from the fact that returns on high dividend premium portfolios covary positively with returns on stocks with high profitability and conservative investments, while the returns of low dividend premium portfolios behave more like returns on stocks with low profitability and aggressive investments. Positive (negative) exposures to the two risk factors increase (decrease) expected portfolio returns of high (low) $\overline{\text{DP}}$ portfolios and push risk-adjusted return toward zero. Results are similar for the 25 portfolios sorted by PIH and $\overline{\text{DP}}$. The CAPM is strongly rejected by the GRS (1989) test with a p-value of 0.001, as CAPM-alphas of portfolios in the fourth and fifth quintiles of $\overline{\text{DP}}$ are highly significantly positive and the CAPM-alphas have a high average absolute value of 4.75%. The FF3 and the FFM4 improve the description of average portfolio returns, as suggested by a lower average absolute value of regression intercepts (4.61% and 4.21%, respectively). However, the improvements are limited, as the high average returns of portfolios in the fourth and fifth quintiles remain unexplained, and the GRS (1989) test rejects the two models with p-values less than 0.05. After RMW and CMA are introduced, only one portfolio in the fourth quintile of $\overline{\text{DP}}$ has a positive FF5-alpha with a t-statistics greater than 2, and while portfolios in the fifth quintile of $\overline{\text{DP}}$ still remain significantly positive, their magnitudes get smaller than counterparts without RMW and CMA. The average absolute value of regression intercepts for the FF5 is reduced to 3.66%, and the five-factor model's ability to describe portfolio returns is not rejected by the GRS (1989) at the conventional significance level (p-value $= 0.102$).

In summary, after prices of dividend strips are adjusted by EEP of American options, dividend strip returns of portfolios sorted by ex-ante dividend risk measure still present substantial cross-sectional variations, and the variations can be explained by portfolios' different exposures to risk factors of the five-factor model, which confirms the superior ability of the FF5 to describe average returns of dividend strips.

8.3.2 The Least-Square Simulation Methodology under the Heston (1993) Stochastic Volatility Model

In the analysis above, I use the difference between quoted price of American-style options and the hypothetical European-style options price estimated by substituting OptionMetrics implied-volatility and the most recently announced dividend into the Black and Scholes (1973) (BS) option-pricing formula to measure EEP. There are two concerns with this approach. First, this approach assumes that the BS model holds. However, the BS model assumes that stock returns are log-normally distributed with constant volatility, which is inconsistent with what is observed in the financial market. Many papers test the empirical validity of the model and find that prices obtained from the model differ from quoted options prices (Derman and Kani, 1994; Rubinstein, 1985). Thus, the hypothetical European options prices and estimated EEP under the BS model may be biased by differences in mispricing relative to the BS model of put and call options. Second, since OptionMetrics uses the most recently announced dividend for dividend-paying stocks when calculating option-implied volatility, I also use historical dividend as a proxy for expected dividend when calculating the BS European options prices. However, I find that on average dividends paid by individual firms change a lot from quarter to quarter, suggesting that it may be problematic to assume that future dividends will remain at the historical levels. Prior studies often criticize the historical dividend as a measure of expected dividend since it may not incorporate investors' most recent expectations for the future dividend. Therefore, EEP calculated under the constant dividend assumption may be contaminated by differences between investors' true expectations for future dividends and historical dividends.

To address the two concerns with the approach to estimate EEP under the BS model using historical dividend as a proxy for expected dividend, I use an alternative simulation-based approach under a stochastic volatility option-pricing model and use option-implied dividend as a measure of expected dividends to calculate hypothetical European-style options prices and to estimate EEP, and I examine whether differences in EEP estimated under the old and new approach will affect calculation of prices of individual dividend strips and cross-sectional variations in returns on the short-term assets.

The Heston (1993) Stochastic Volatility Model

In light of biases that are associated with the BS, the option-pricing literature has made substantial progress to develop more realistic option-pricing models which relax the restrictive assumptions of the model. Bakshi, Cao and Chen (1997) examine performances of various option-pricing models that allow for stochastic volatility, interest rates, and/or jumps in stock price. They find that incorporating stochastic volatility can reduce both in-sample and out-of-sample pricing errors and improve hedging performances as well. I consider the Heston (1993) stochastic volatility (HSV) option-pricing model , which is commonly used in the literature, as an alternative to the BS model. Specifically, under the risk-neutral measure, dynamics of the price of an underlying stock i, S_t^i, are governed by the following stochastic differential equation:

$$dS_t^i \;=\; r_t^f S_t^i dt + \sqrt{V_t^i} S_t^i dW_t^{S,i}, \tag{8.2}$$

where r_t^f is the risk-free rate and $dW_t^{S,i}$ is a standard Wiener process of the price of stock i. If the stock i pays a dividend, D_t^i, the price of stock i will drop by the amount of dividend before and after the ex-dividend date:

$$S_{t^+}^i - S_{t^-}^i \;=\; D_t^i,\; t^- < t < t^+. \tag{8.3}$$

The variance of the stock i, V_t^i, follows a mean-reverting process in the following form:

$$dV_t^i \;=\; \kappa^i(\theta^i - V_t^i)dt + \xi^i \sqrt{V_t^i} dW_t^{V,i}, \tag{8.4}$$

where κ^i is the rate of mean-reversion, θ^i is the long-run variance of stock i, ξ^i is the volatility of stock i's variance, and $dW_t^{V,i}$ is a standard Wiener process of variance of stock i. To take into account the leverage effect, Wiener stochastic processes $dW_t^{S,i}$ and $dW_t^{V,i}$ are assumed to be correlated with a correlation $\rho^{i,S,V}$:

$$dW_t^{S,i} \cdot dW_t^{V,i} = \rho^{i,S,V} dt. \tag{8.5}$$

The Least Square Monte Carlo Simulation Algorithm

The Heston (1993) model does not have an analytical solution for American-style options. I use the least-square methodology of Longstaff and Schwartz (2001) (LSM) to calculate American-style options prices under the stochastic volatility model using Monte Carlo Simulation.

Suppose that an American-style option written on a stock i can be exercised for N discrete times during the option's life $(0 < t_1 \leqslant t_2 \leqslant \cdots \leqslant t_N = T)$.[25] Under the LSM, at any time t_n before the option maturity date T on a given path w of the price of the underlying stock i, holders of an in-the-money American-style option written on the stock choose the optimal exercise time by comparing the payoff from immediate exercise ($\max(S^i_{t_n} - K, 0)$ for call options and $\max(K - S^i_{t_n}, 0)$ for put options) and conditional expected payoff from continuation, which is the expected value under the risk-neutral

[25] Exchange-traded individual equity options in the U.S. market are continuously exercisable. The LSM can approximate the value of the options by taking N to be sufficiently large. When calibrating the stochastic volatility model and calculating simulated options prices, I assume that options can be exercised once a day. Using more frequent exercising gives similar results.

measure Q of remaining discounted cash flows from holding the option:

$$F^i(w;t_n) \quad = \quad E_Q\Big[\sum_{j=n+1}^{N} \exp\Big(-\int_{t_j}^{t_n} r(w,t)dt\Big)\mathrm{CF}^i(w,t_j;t_n,T) \mid \mathcal{F}_{tn}\Big], \qquad (8.6)$$

where $\mathrm{CF}^i(w,t_j;t_n,T)$ denotes the path of cash flows of an option written on the stock i if the option is not exercised at or prior to time t_n and will be exercised on or after time t_n based on the optimal stopping rule.

Under the LSM, $F^i(w;t_n)$ is represented by a weighted linear combination of Laguerre polynomials basis functions, $L_p(X)$. Assuming that X is the value of the underlying stock, the expected value from holding the option, $F^i(w;t_n)$, is given by:

$$F^i(w;t_n) \quad = \quad a^i + \sum_{j=0}^{\infty} b^i_j L_p(X), \qquad (8.7)$$

$$L_p(X) \quad = \quad \exp(-X/2)\frac{e^X}{n!}\frac{d^n}{dX^n}(X^n e^{-X}). \qquad (8.8)$$

The intercept term a^i and coefficients on polynomials b^i_j are estimated using least squares by regressing discounted values of cash flows from an option, $\mathrm{CF}^i(w,t_j;t_k,T)$, on the basis functions of stock prices[26] for paths where the option is in-the-money. The fitted value from the regression is the estimated expected value to continue holding the option at time t_n , $\hat{F}^i(w;t_n)$.

The goal of the LSM algorithm is to find the optimal stopping rule which can maximize the value of an American-style option. To implement the algorithm, I work backward from time t_{N-1}, the last exercisable time before the option maturity date T. I run the

[26]Following Longstaff and Schwartz (2001), I use the first three Laguerre polynomials. Using three basis functions is sufficient to obtain convergence.

cross-sectional regressions to estimate expected value from continuation at time t_{N-1}, $\hat{F}^i(w; t_{N-1})$, for each in-the-money path at that time. On a particular in-the-money path at time t_{N-1}, optionholders should exercise an option if the payoff from immediate exercise is equal to or greater than $\hat{F}^i(w; t_{N-1})$. Thus, the paths of cash flows $\mathrm{CF}^i(w, t_j; t_{N-1}, T)$ can be estimated. Then I repeat the procedure one-period backward each time until the exercising decision at each time on each path is determined. On each path where at least for one time an American option should be exercised, the first exercisable time is the optimal stopping time, and the payoff from exercising at that time is the expected cash flows from the option on the path. Finally, the price of the American option is computed by taking an average of present values of expected cash flows from the option over all stock price paths.

Calibration of the Heston (1993) Model

For each stock i at the end of quarter q, I calibrate the Heston (1993) model to the mid prices of the pair of call and put options written on the stock used to construct the synthetic dividend strip, $C_q^i(T, K)$ and $P_q^i(T, K)$. Specifically, I calculate LSM-simulated prices of the American-style call and put based on 100,000 paths of the stock price.[27] On each path, investors expect the stock price to drop by the amount of dividend paid during option life, D_{q+1}^i. I use the dividends implied from options averaged across strike prices, time-to-maturities and days on and before the quarter q end, DI_q^i, as a proxy for the expected dividend. As shown in the first robustness test, option-implied dividend

[27] 50,000 plus 50,000 antithetic paths.

can predict future realized dividend beyond the historical dividend, and prior studies find that option-implied dividends incorporate investors' expectations for dividends better than historical dividends.

For a stock i with N_Q^i quarterly observations of options prices, four parameters of the stochastic volatility model, the rate of mean reversion of variance (κ^i), the long-term variance (θ^i), the volatility of variance (ξ^i) and the correlation between stock price and variance ($\rho^{i,S,V}$), are fixed parameters that do not vary over time. The instantaneous variances for each quarter, $V_q^i (1 \leqslant q \leqslant N_Q^i)$, are allowed to be time-varying. The stock i's parameters of the Heston (1993) model, $\Theta^i = \{V_1^i, V_2^i, ..., V_{N_Q^i}^i, \kappa^i, \theta^i, \xi^i, \rho^{i,S,V}\}$, are estimated by solving the following constrained optimization problem:

$$\begin{aligned} \min_{\Theta^i} \quad & \sum_{q=1}^{N_Q^i} w_q^{i,C(T,K)} \left[C_q^{\Theta^i}(T,K) - C_q^i(T,K)\right]^2 \\ & \quad + w_q^{i,P(T,K)} \left[P_q^{\Theta^i}(T,K) - P_q^i(T,K)\right]^2, \end{aligned} \tag{8.9}$$

$$s.t.\ \mathrm{lb} \leqslant \Theta^i \leqslant \mathrm{ub}, \tag{8.10}$$

$$\xi^{i2} \leqslant 2\kappa^i\theta^i. \tag{8.11}$$

The correlation between stock price and variance is bounded between -1 and 1, and the other parameters have a lower bound of 0. $C_q^{\Theta^i}(T,K)$ and $P_q^{\Theta^i}(T,K)$ are model-implied prices of call and put options written on the stock i with strike price K and maturity date T at the end of quarter q.[28] $w_q^{i,C(T,K)}$ and $w_q^{i,P(T,K)}$ are the weightings of squared pricing

[28] The model's parameters are calibrated to quoted prices of the most at-the-money call and put options which are used to replicate synthetic dividend strips. Calibrating parameters to all options which meet the filtering criteria gives similar results, except that pricing errors are on average higher.

errors of call and put options. Squared pricing errors are weighted by the number of options contracts traded. Thus, for each stock i, the estimated set of parameters, $\hat{\Theta}^i$, are the ones that can minimize the trading volume weighted average squared pricing errors of options written on the stock across all quarters.

[Insert Table 14 here]

Panel A of Table 14 reports summary statistics of estimated parameters of the Heston (1993) model for individual stocks with options traded. Individual stocks have a high average rate of mean-reversion of variance (κ) of 8.05, suggesting that variances of individual stocks revert to long-term means fast. For the instantaneous variance (V), I first calculate its time-series mean ($\overline{V}$) and standard deviation ($\sigma(V)$) for each stock, and report the distributions of $\overline{V}$ and $\sigma(V)$ across stocks. For the other parameters, cross-sectional distributions are reported. The correlation between individual stock price and variance ($\rho^{S,V}$) has a mean value of -0.11, which indicates that typically declining stock prices are accomplished by rising stock variances.

Panel B of Table 14 tabulates summary statistics of relative pricing errors of the Heston (1993) option-pricing model of call and put options used to replicate synthetic individual dividend strips, $e^C = (C^{\hat{\Theta}} - C)/C$ and $e^P = (P^{\hat{\Theta}} - P)/P$, which are the differences between model-implied options prices and quoted mid options prices normalized by the mid market prices, and the absolute values of relative pricing errors, $|e^C|$ and $|e^P|$. On average, the Heston (1993) model overprices call options by 0.17% and overprices put options by 0.14%, respectively. The mean values of magnitudes of relative mispricing are

0.60% and 0.52% for call and put options. The small discrepancy between model-implied and observed market options prices indicate that the Heston (1993) model performs well in describing prices of options written on individual stocks.

EEP of American Options under the Heston (1993) Model

Based on the estimated parameters of the stochastic volatility model, for each stock i at the end of each quarter q, I use the simulation approach to calculate model-implied American-style call and put options prices and hypothetical European-style call and put options prices, and take a difference to estimate EEP.

Panel C of Table 14 reports summary statistics of EEP of call and put options as a percentage of mid market prices of options under the simulation-based Heston (1993) stochastic volatility (HSV) option pricing model ($\mathrm{EEP}^{\mathrm{HSV}}(C)$ and $\mathrm{EEP}^{\mathrm{HSV}}(P)$) using the average dividend implied from options prices as a proxy for expected dividends, and the difference between EEP of calls and puts as a percentage of average mid options prices. ($\mathrm{EEP}^{\mathrm{HSV}}(P-C)$) . For easy comparison, the table also shows corresponding values under the closed-form Black and Scholes (1973) (BS) option-pricing model using the historical dividend to measure expected dividends. On average, under the BS, EEP of call options accounts for less than 1% (0.65%) of mid call prices, and EEP of put options accounts for a slightly higher yet still low average proportion of mid put prices (0.83%). The average positive difference in EEP of put and call options as a percentage of average mid prices of puts and calls (0.18%) is consistent with the finding in the previous section that average returns on individual dividend strips get higher after adjusting for EEP. After considering stochastic volatility and using option-implied dividends to measure expected dividends, average values of EEP relative to mid options prices of both call and put options get higher (0.72% and 0.89%, respectively). The positive change in EEP of calls (mean value = 0.07% of mid call prices) is on average greater than the increase in EEP of puts (mean value = 0.05% of mid put prices), resulting in a lower average difference between EEP of put and call options under the new approach to estimate EEP. A possible reason for this is that options-implied dividends incorporate investors' expectations for dividend growth, and higher expected dividends may make it more optimal to exercise call options written on dividend-paying stocks before maturity dates. Overall, the results indicate that under both approaches to estimate EEP, the differences in EEP of call and put options amount to low proportions of American-style options prices and may not significantly affect the main empirical results. The difference in difference between EEP of put and call ($\text{EEP}^{\text{HSV}-\text{BS}}(P-C)$) has a mean value of -0.01%, which indicates that on average, the two approaches give similar approximations for EEP. However, the differences in differences of EEP of calls and puts are -0.57% and 0.67% of average mid options prices for underlying stocks in the first quartile and in the third quartile respectively, suggesting that the differences in differences of calls' and puts' EEP estimated under the two approaches vary across individual firms.

To trace the source of differences in EEP estimated under the old and the new approach, for the pooled sample of all stocks with options traded in all quarters, I regress differences in EEP of calls as percentage of mid call prices ($\text{EEP}^{\text{HSV}-\text{BS}}(C)$), differences in EEP of puts as percentage of mid put prices ($\text{EEP}^{\text{HSV}-\text{BS}}(P)$), and differences in differences of EEP of puts and calls ($\text{EEP}^{\text{HSV}-\text{BS}}(P-C)$) as percentage of average mid call and put prices estimated under the HSV model and the BS model on calibrated parameters of the Heston (1993) model, the risk-free rate (r^f), options time-to-maturity days (τ), moneyness ratio (K/S) and average option-implied dividend yield (DI/S). Panel D of Table 14 reports beta coefficients and associated t-statistics of the full-sample pooled regressions. Parameters of the stochastic volatility option-pricing models seem to explain the differences in EEP estimated under the old and the new approach. Regression coefficients of κ and ξ on $\text{EEP}^{\text{HSV}-\text{BS}}(P)$ are significantly negative, suggesting that relative to the HSV model, the BS model overestimates EEP of puts more for stocks whose variances mean revert to long-term values faster and vary more over time. The rate of mean reversion and volatility of variance also negatively affect $\text{EEP}^{\text{HSV}-\text{BS}}(C)$, though the effects are insignificant and much weaker than those for put options. Beta coefficients of the long-run stock variance (θ) on difference in EEP of both calls and puts under the two approaches are significantly positive, and regression coefficients of the instantaneous variance on $\text{EEP}^{\text{HSV}-\text{BS}}(C)$ and $\text{EEP}^{\text{HSV}-\text{BS}}(P)$ are significantly and marginally significantly positive, indicating that the old approach underestimates EEP of both calls and puts more for more volatile stocks in the short and long run. The correlation between stock price and stock variance ($\rho^{S,V}$) loads significantly negative on $\text{EEP}^{\text{HSV}-\text{BS}}(C)$ and $\text{EEP}^{\text{HSV}-\text{BS}}(P)$, which indicates that the new approach increases the estimate of EEP of both call and put options more for stocks with greater leverage effects. The level of risk-free rate also affects the difference in EEP estimated under the two approaches. The significantly negative coefficients of the risk-free rate (r^f) on $\mathrm{EEP}^{\mathrm{HSV-BS}}(C)$ and $\mathrm{EEP}^{\mathrm{HSV-BS}}(P)$ indicate that the HSV model gives higher estimate of EEP for both call and put options than the BS model when risk-free rate is lower. Both options time-to-maturity (τ) and moneyness (K/S) affect the estimates of EEPs, and the effects are opposite for call and put options: the regression coefficient of τ on $\mathrm{EEP}^{\mathrm{HSV-BS}}(C)$ is significantly positive while on $\mathrm{EEP}^{\mathrm{HSV-BS}}(P)$ is significantly negative, and K/S has significantly negative loading on $\mathrm{EEP}^{\mathrm{HSV-BS}}(C)$ while significantly positive loading on $\mathrm{EEP}^{\mathrm{HSV-BS}}(P)$, suggesting that the higher estimate of EEP under the HSV model is greater for more in-the-money call options with longer time-to-maturity and for more in-the-money put options with shorter time-to-maturity. The estimate of EEP of call options under the two approaches is affected by expected dividends. The significantly positive coefficient of DI/S on $\mathrm{EEP}^{\mathrm{HSV-BS}}(C)$ indicates that EEPs of calls are more underestimated under the old approach for call options written on underlying assets with higher expected dividends. Expected dividends also positively affect $\mathrm{EEP}^{\mathrm{HSV-BS}}(P)$, but the regression coefficient is insignificant. The difference in potential bias in prices of individual dividend strips caused by differences in EEP of put and call options under the new and old approaches ($\mathrm{EEP}^{\mathrm{HSV-BS}}(P-C)$) is greater for stocks with lower volatility of variance, lower long-term stock variance, lower instantaneous variance, options with shorter time-to-maturity and options with higher moneyness ratio.

To check whether and how the cross-sectional variations in differences in estimation of EEP under the two approaches may affect the cross-sectional variations in the pricing of individual short-term synthetic dividend strips, I examine the correlations between $\text{EEP}^{\text{HSV}-\text{BS}}(P-C)$ and prices of individual dividend strips. Specifically, at the end of each quarter, stocks with options whose EEPs can be estimated under both approaches are sorted into quintile portfolios by stock price normalized dividend implied from the pair of call and put options used to replicate individual dividend strips, and I calculate the mean values of $\text{EEP}^{\text{HSV}-\text{BS}}(P-C)$ of stocks in each portfolio. Panel D of Table 14 reports time-series averages of the differences in differences of EEP of paired put and call options of the quintile portfolios. For all the sorted portfolios with different levels of normalized prices of individual dividend strips, average difference in EEP of puts and calls gets lower under the new approach to estimate EEP, and the quintile portfolios have similar levels of average values of $\text{EEP}^{\text{HSV}-\text{BS}}(P-C)$, suggesting that the estimated potential biases in prices of individual dividend strips due to differences in EEP of call and put options estimated under the two approaches do not differ systematically with prices of individual dividend strips inferred from American-style options prices.

To further check whether different approaches to estimate EEP will affect the cross-sectional variations in returns on short-term assets among individual stocks with different levels of dividend risk premium, I also examine whether $\text{EEP}^{\text{HSV}-\text{BS}}(P-C)$ is correlated with the two variables, $\overline{\text{DP}}$, an ex-ante measure of dividend risk premium, and PIH, a proxy for short-sale constraints of underlying assets, by which individual dividend strips are sorted into portfolios. The last two rows of Panel E of Table 14 report mean values of

$\mathrm{EEP}^{\mathrm{HSV-BS}}(P-C)$ of stocks sorted by $\overline{\mathrm{DP}}$ and PIH. The table shows no obvious patterns of the differences in differences of calls' and puts' EEP estimated under the HSV model and the BS model among stocks with different dividend risk premiums or short-sale constraints: regardless of the level of $\overline{\mathrm{DP}}$ or PIH, EEP estimated under the new approach is slightly lower than it is under the old approach, and the average magnitude of the difference is similar across $\overline{\mathrm{DP}}$-sorted and PIH-sorted portfolios. The results indicate that using the new approach which considers stochastic volatility and uses option-implied dividends to measure expected dividends to adjust for EEP will slightly increase the current values and slightly reduce the returns on individual dividend strips by similar amounts, and the cross-sectional variations in EEP-adjusted returns on dividend strips sorted by $\overline{\mathrm{DP}}$ and/or PIH should be similar under the two approaches to estimate EEP.

As a summary, the potential biases in prices of individual dividend strips due to differences in EEP of call and put options estimated under the Black and Scholes (1973) model using historical dividends to measure expected dividends and under the Heston (1993) stochastic volatility model using option-implied dividends to measure expected dividends on average have very similar magnitudes, and the variations in differences in biases due to EEP estimated under the two approaches are not correlated with prices of individual dividend strips, dividend risk premium or short-sale constraints of underlying assets. The findings indicate that the two problems of the approach used in the previous section to adjust for EEP—that options can be mispriced by the BS model and that historical dividends are not good proxy for expected dividends—are not big concerns, and adjusting for EEP under this simpler approach will give results of sorting portfolio analysis similar to those if a more realistic option-pricing model with stochastic volatility and a better proxy for expected dividends are used.

8.4 Portfolios Sorted by Stock Characteristics

In the main empirical analysis, dividend strips are sorted into portfolios by the ex-ante measure of dividend risk premium. In this section, I sort dividend strips into portfolios by four well-known variables, book-to-market ratio (BM), operating profitability (OP), total asset growth rate (ATG) and cumulative stock return in the past six months (RET(−1,−6)), which are documented by prior studies to predict subsequent cross-sectional stock returns (Fama and French, 1992, 2015; Titman, Wei and Xie, 2004; Jegadeesh and Titman, 1993). A stock can be considered as a portfolio of dividend strips maturing at different horizons. The total stock return is a value-weighted average of returns on short-term and long-term dividend strips and contains information about short-run risk and long-run risk of a firm. If the firm characteristics are related to risks of firms, and short-run risk embedded in claims on near-term cash flows and long-run risk embedded in claims on long-term cash flows of a stock share common information, it stands to reason that the firm characteristics are also associated with subsequent returns on short-term dividend strips. I first test this conjecture by investigating whether there are variations in returns on dividend strips whose underlying stocks have different firm characteristics and then examine whether the predictability of stock characteristics on subsequent returns on short-term assets can be explained by asset pricing models. This analysis is a robustness check on whether the superior performances of the five-factor model is limited to the portfolios sorted by $\overline{\text{DP}}$.

8.4.1 Portfolio Sorting and Realized Portfolio Returns

At the end of each quarter, dividend strips are sorted into quintile portfolios by one of the four stock return predictors. As shown in Table 2, distributions of the four variables are different between the sample of all listed stocks and the sample of listed stocks with options traded. To ensure that stocks in the sorted portfolios have similar average values of firm characteristics as the full sample, I use quintile breakpoints of the four variables of all listed stocks to sort dividend strips. To control for short-sale constraints of underlying stocks, for each firm characteristic, I do a double-sorting analysis by first sorting stocks based on PIH and then sorting stocks based on the firm characteristic within each PIH group. For each sorted portfolio in each quarter, I compute its realized quarterly value-weighted returns and report the time-series average portfolio returns and associated t-statistics in Table 15.

[Insert Table 15 here]

Panel A reports time-series average returns of portfolios of dividend strips sorted by each of the four firm characteristics of underlying stocks. The four stock return predictors can strongly predict subsequent dividend strip returns in the same directions with their predictions on subsequent stock returns. For univariate-sorting, average returns of portfolios of dividend strips increase monotonically as book-to-market ratio (BM), operating profitability (OP) and cumulative returns in the past six months (RET(−1,−6)) increase, and average portfolio returns are lower for stocks with more aggressive investments (higher ATG). Dividend strips of extreme value stocks significantly outperform dividend strips of extreme growth stocks by 9.81% per quarter (t-stat = 4.56). Return spread between portfolio 5 with the highest profitability and portfolio 1 with the lowest profitability is 12.13%, which is statistically significant, with a t-statistic of 3.17. Stocks that invest most aggressively earn an average dividend strip return of −2.21%, significantly lower than the average dividend strip return of 9.52% of stocks with the most conservative investments. Near-term dividend strips of stocks that perform best in the past six months earn significantly higher average returns than those of stocks with lowest returns in the past six months (average return spread = 10.14%, t-stat = 3.38).

Cross-sectional variations in dividend strip returns of portfolios sorted by the four firm characteristics are robust after short-sale constraints are controlled. Spreads between returns of portfolios with extreme values of firm characteristics tend to be larger among stocks with lower PIH. However, within each PIH group, average portfolio returns increase with BM, OP, and RET(−1,−6) and decrease with ATG in a monotonic way. For each quintile portfolio sorted by a firm characteristic, I construct a portfolio by aggregating dividend strips across the five PIH portfolios and report the time-series average returns of the aggregated portfolios in the row labeled 'ALL'. The aggregate portfolios have similar levels of PIH so that differences in returns among the portfolios will not be driven by differences in short-sale constraints. The return spreads between the fifth and first quintile portfolios with the highest and lowest BM, OP, ATG and RET(−1,−6) are 9.99% (t-stat = 6.12), 11.66% (t-stat = 5.52), −10.83% (t-stat = −7.09) and 10.10% (t-stat = 5.22), which are statistically significant and comparable with the counterparts for univariate-sorting. Though not the main interest of this study, the results show that there is not a clear relation between PIH and subsequent dividend strip returns. Among stocks with low BM, low profitability, aggressive investments, and low past returns, average dividend strip portfolio returns tend to be lower for stocks with lower PIH. However, average portfolio returns are positively associated with PIH for value stocks, profitable stocks, stocks with conservative investments, and past winners. In short, the predictability of the firm characteristics on future dividend strip returns is not driven by short-sale constraints of underlying stocks.

8.4.2 Asset Pricing Tests

Then I examine whether differences in average portfolio returns of stocks sorted by firm characteristics can be explained by variations in exposures to risk factors of the four asset pricing models. Table 16 reports average slope coefficients on of portfolio returns with respect to different risk factors estimated from time-series regressions in a rolling window. Panel A reports results for quintile portfolios sorted by firm characteristics alone, and Panel B reports results for 25 portfolios sorted by PIH and firm characteristics. I use both the Fama and MacBeth (1973) cross-sectional regressions and full sample period time-series regressions to examine the performances of the asset pricing models in describing average returns on portfolios with different sorts and report the results of regression analysis in Table 17 and Table 18.

Portfolios Sorted by BM

Variations in dividend strip returns of growth stocks and value stocks can be explained by the three multi-factor models, while the CAPM is an incomplete description of BM-sorted dividend strip returns. As shown in Panel A of Table 18, for the five portfolios sorted by BM, portfolio 4 and 5 with high BM have significantly positive time-series CAPM-alphas that are more than two standard errors above zero. The GRS (1989) test (Panel C of Table 18) rejects the CAPM to explain average returns on the five BM-sorted dividend strip portfolios with a p-value of 0.001. The lousy performance of the CAPM model traces to the fact that the association between market betas and BM-sorted portfolio returns are not monotonic and not strong. Notably, as shown in Panel A of Table 16, the first quintile portfolio with the lowest BM and the lowest realized return has a positive market beta as high as that of the middle portfolio with neutral BM. Though the market beta increases from portfolio 2 to portfolio 5, the positive exposures to the market risk of portfolio 4 and 5 are not high enough to explain their high average returns. Adding risk factors other than the market risk factor improves the description of average portfolio returns, as portfolios sorted by BM have very different tilts toward portfolio-based risk factors. SMB betas and HML betas of the five portfolios increase monotonically as BM increases. Returns on dividend strips of value stocks have positive exposures to SMB and HML, which increase expected portfolio returns and shrink regression intercepts. In contrast, returns on dividend strips of growth stocks behave more like stock returns of growth stocks with large firm size, and the negative exposures to SMB and HML help explain their low average returns. Absolute values of FF3-alphas of all portfolios are lower than the counterparts of the CAPM, and only the portfolio with extremely high BM remains significantly positive. The GRS (1989) test fails to reject the three-factor model at the conventional significance level (p-value = 0.065). Adding UMD produces slight improvements in explaining average returns. Portfolios in the first and second quintiles of BM have negative UMD betas while the three portfolios with higher BM have positive UMD slopes. However, the relation between the UMD beta and BM is not monotonic. The portfolio of dividend strips of extreme value stocks does not have the highest exposure to the momentum factor. The four-factor model is not rejected by the GRS (1989) test with a slightly higher p-value of 0.077. Introducing RMW and CMA significantly improves the description of average BM-sorted dividend strip returns. The strongly positive regression intercept of the highest BM portfolio in the three other models becomes insignificant in the five-factor model. The GRS (1989) test fails to reject the FF5 with a p-value of 0.239. Panel B shows that the improvement produced by the FF5 traces to the patterns of RMW and CMA slope coefficients among portfolios sorted by BM. The positive exposures to RMW and CMA of portfolios with high BM and negative exposures to RMW and CMA of portfolios with low BM push regressions intercepts toward zero. Results are similar for the 25 portfolios sorted by PIH and BM. Regression intercepts of the FF5 have the smallest average absolute value, and the GRS (1989) test fails to reject the FF5 with the highest p-value of 0.175. Within each PIH group, slopes of SMB, HML, RMW, and CMA increase in a monotonic way from portfolios of extreme growth stocks to portfolios of extreme value stocks. The issue of non-monotonic relations between market beta and UMD beta and average portfolio returns concentrates among stocks with low PIH. Contrary to the patterns of realized returns, extreme growth stocks with low PIH do not have low exposures to market risk, and extreme value stocks with low PIH do not have high exposures to the momentum factor, which plague the performances of the CAPM and the four-factor model.

Results from cross-sectional regressions also show that the five-factor model performs the best in explaining average returns of dividend strips sorted by BM. As shown in Table 17, risk premiums of all risk factors except for the UMD are estimated to be significantly positive. Average regression intercept is most statistically positive for the CAPM (λ_0 = 3.04%, t-stat = 2.08) and is smallest and least significant for the FF5 (λ_0 = 1.01%, t-stat = 0.80). The five-factor model explains 63.1% of variations in average returns of the 25 portfolios sorted by PIH and BM, which is the highest among the four models.

Portfolios Sorted by OP

Dividend strips of stocks with high and low profitability have different exposures to risk factors. Patterns of portfolios' beta coefficients on the market factor, RMW, and CMA are consistent with patterns of realized portfolio returns. As shown in Panel A of Table 13, for the five portfolios sorted by OP, slope coefficients on the market factor, RMW, and CMA increase monotonically from the portfolio with the most unprofitable underlying stocks to the portfolio with the most profitable underlying stocks. For the 25 PIH and OP double-sorted portfolios, the monotonic patterns between the three risk exposures and realized portfolio returns hold within each PHI group. Relations between betas coefficients on HML and UMD and profitability of underlying stocks are humped. For the univariate-sorting, HML and UMD betas increase from portfolio 1 to portfolio 4 but then decrease from portfolio 4 to portfolio 5. The humped pattern of UMD beta is more pronounced among stocks with low PIH, suggesting that returns on portfolios in the highest OP quintile with low PIH behave more like returns of past losers. Low exposures to the value factor are common for portfolios with the highest profitability within each PIH group, and the problem is the most serious for the portfolio with the highest OP and highest PIH, which has a negative HML beta. Returns on dividend strips of stocks with high (low) OP behave more like returns on large (small) market capitalization stocks, as suggested by the monotonically decreasing SMB betas from portfolio 5 to portfolio 1. The pattern of SMB betas of portfolios sorted by OP is inconsistent with the pattern of average portfolio returns. For the 25 double-sorted portfolios, the negative relation between SMB beta and OP is universal within each PIH group.

The patterns of risk exposures give hints on the performances of the four asset pricing models in describing returns on dividend strips portfolios sorted by OP. As shown in Panel A of Table 18, though market betas are positively associated with average returns on OP-sorted portfolios, dispersion in market risk exposures is not enough to explain the substantial differences in average dividend strip returns. CAPM-alphas from the time-series regressions of portfolio 4 and 5 are strongly positive with t-statistics greater than 2. For the 25 double-sorted portfolios, high average returns of portfolios in the fourth and fifth OP quintiles within all PIH groups are left unexplained by the CAPM. The significant regression intercepts result in a strong rejection of the CAPM by the GRS (1989) test in describing average returns of the univariate-sorted portfolios (with a p-value of 0.009) and the double-sorted portfolios (with a p-value of 0.014). Introducing SMB and HML hardly produces improvements. FF3-alphas of three of the five portfolios sorted by OP have absolute values higher than the counterparts of the CAPM. For the 25 portfolios sorted by PIH and OP, highly significant regression intercepts of portfolios in the fourth and fifth OP quintiles do not disappear in the three-factor model. The failure of the FF3 is linked to the negative (positive) exposures to the size factor of portfolios with high (low) OP, which push expected returns away from realized returns. Besides, returns of dividend strip portfolios with the highest OP do not have strong enough associations with the value factor, especially for portfolios with high PIH. Adding the momentum factor improves the description of average returns slightly as positive (negative) loadings on UMD helps explain the high average returns of dividend strips of profitable (unprofitable) stocks. The two exceptions are the two portfolios with extremely high OP and with low PIH, whose regression intercepts are higher after UMD is added because their returns covary more with past losers than with past winners. Both the FF3 and the FFM4 are rejected by the GRS (1989) test with p-values smaller than 0.05. The five-factor model which adds RMW and CMA moves regression intercepts of all portfolios toward zero and makes the intercepts less significant. The GRS (1989) test fails to reject the FF5 in describing average returns on the five OP-sorted portfolios and on the 25 portfolios sorted by PIH and OP at the 10% significance level. Major contributions are made by RMW slopes, which are strongly positive for higher three quintile portfolios and are strongly negative for lower two quintile portfolios sorted by OP. The pattern holds within each PIH group for the 25 double-sorted portfolios. CMA betas have a similar while less pronounced pattern.

Results of cross-sectional regressions using the 25 portfolios sorted by PIH and OP as testing portfolios on the four asset pricing models are reported in Table 17. The market risk, RMW, and CMA are priced factors with significantly positive risk premiums in the cross section of dividend strips sorted by PIH and OP. Prices of HML and UMD are estimated to be positive while not statistically significant, while the price of SMB is insignificantly negative. Consistent with results from the GRS (1989) test, the five-factor model can well explain differences in returns of dividend strips sorted by OP, as evidenced by the small and insignificant regression intercept (λ_0 = 1.02%, t-stat = 1.00) and the high average adjusted R^2 (58.5%) from cross-sectional regressions to test the FF5.

Portfolios Sorted by ATG

Results from cross-sectional regressions (reported in Table 17) and time-series regressions (reported in Table 18) agree that the FF5 provides the best description of average returns of ATG-sorted and PIH-ATG sorted dividend strip portfolios. Notably, the average intercept from cross-sectional regressions using the PIH-ATG double-sorted portfolio as testing portfolios for the CAPM is significantly positive ($\lambda_0 = 3.74\%$, t-stat = 2.15), indicating difficulty of the CAPM in describing average portfolio returns. Average regression intercepts slightly decreases to 3.56% (t-stat = 1.94) for the FF3 which adds SMB and HML and to 3.13% (t-stat = 1.78) for the FFM4 which further adds UMD, indicating that exposures of portfolio returns to the three factors do not play central roles in explaining average returns of dividend strips whose underlying stocks have different levels of investments. Introducing RMW and CMA substantially reduces the average regression intercept to 1.02%, which is insignificant with a t-statistic of 1.17, and the five-factor model explains 60.1% of variations in returns of the 25 PIH-ATG sorted portfolios, which is higher than the proportions explained by the other three models. For time-series analysis, regression intercepts of the CAPM are significantly positive for portfolios in the first and second ATG quintiles. The FF3 and the FFM4 models move regression intercepts toward zero. However, the models still produce positive intercepts, which are about two standard errors above zero for the lower two ATG quintile portfolios. The five-factor model can explain the strongly positive intercepts of the second ATG quintile portfolios under the other models, and though high average returns of portfolios with extremely low ATG still remain unexplained, absolute values of their regression intercepts get smaller than corresponding values without RMW and CMA. The GRS (1989) test statistic to test the FF5's ability to explain average portfolio returns is 1.787 (p-value = 0.125) for ATG-sorted portfolios and is 1.411 (p-value = 0.142) for PIH-ATG double-sorted portfolios, which are lower than the test statistics on the CAPM, the FF3, and the FFM4.

Patterns of average exposures of portfolio returns to risk factors (as reported in Table 17) help interpret the performances of asset pricing models. Market betas generally decrease from portfolios with low asset growth rates to portfolios with high asset growth rates, though the relation is not strictly monotonic from portfolio 4 to portfolio 5. The double-sorting analysis reveals that the problem comes from portfolios with the highest ATG and low PIH, which have market betas higher than portfolios in the fourth ATG quintiles with low PIH. The pattern of market betas of the portfolios shrinks returns spreads between portfolios with high and low ATG. However, dispersion in market betas is not enough to fully explain differences in average portfolio returns. Exposures to portfolio-based risk factors vary across the dividend strip portfolios and produce improvements over the CAPM. Portfolios with lower ATG have more positive SMB betas, which holds for both univariate-sorted portfolios and quintile portfolios of ATG within each PIH group. The pattern of SMB slopes is consistent with the pattern of realized portfolio returns and improves the description of average returns for the FF3 model. The pattern of HML slopes is not monotonic. In particular, the portfolio with the most conservative investments has low exposure to the value factor. The double-sorting analysis shows that this issue is common for all portfolios in the lowest ATG quintile and is more severe for stocks with higher PIH. Except for portfolios with extremely low ATG, HML betas are generally higher for portfolios with lower ATG, which helps explain average returns of the portfolios and contributes to the better performance of the FF3 than the CAPM. The

FFM4 that adds UMD performs better than the FF3, which is due to the monotonically positive relation between UMD betas and realized portfolio returns, for both univariate-sorted portfolios and double-sorted portfolios. However, the dispersion in UMD slopes is not large compared to exposures to other risk factors, so the improvement of the FFM4 is limited. The five-factor model which adds RMW and CMA provides more significant improvements than the four-factor model does. The primary lifting of the FF5 comes from the pattern of CMA betas. For both univariate-sorting and double-sorting, CMA betas decrease monotonically from dividend strips of stocks with the most conservative investments to dividend strips of stocks with the most aggressive investments. RMW betas show a similar while relatively less pronounced pattern. Portfolios in the first ATG quintile have strongly positive exposures to RMW, while portfolios in the fifth ATG quintile have strongly negative exposures to RMW. Positive (negative) RMW and CMA betas help explain high (low) average returns of dividend strip with profitable (unprofitable) underlying stocks.

Portfolios Sorted by RET(−1,−6)

The significant outperformance of dividend strips of past winners over those of past losers cannot be explained by the CAPM. As shown in Table 16, for the five portfolios sorted by lagged stock returns, average market betas increase monotonically from portfolio 1 to portfolio 5. For portfolios sorted by PIH and RET(−1,−6), the positive relation between market beta and lagged stock return holds within each PIH group. However, compared to that of portfolios sorted by other variables, the dispersion in market betas among dividend strip portfolios sorted by RET(−1,−6) is less wide. For both univariate-sorting and double-sorting, though market betas of the portfolios in the fourth and fifth quintiles of RET(−1,−6) are higher than market betas of the three lower RET(−1,−6) quintiles, their market betas are not high enough to explain the high realized portfolio returns and time-series regression intercepts of the two portfolios are significantly positive with t-statistics greater than two. The GRS (1989) test strongly rejects the CAPM in explaining average returns of univariate-sorted portfolios and double-sorted portfolios with p-values less than 0.01. Consistent with results from time-series analysis, average regression intercept from cross-sectional regressions of quarterly excess returns of the 25 double-sorted portfolios on quarterly excess return of the market portfolio is 2.85%, statistically significant with a t-statistic of 2.01, and the CAPM on average explains 26.7% variations in portfolio returns, indicating that the CAPM does not well describe average returns on dividend strips sorted by RET(−1,−6).

The three-factor model is better at explaining dividend strip returns sorted by lagged returns than the CAPM. Introducing SMB and HML shrinks time-series intercepts of the portfolios. The FF3 is still rejected by the GRS (1989) test at conventional significance level, but the p-values are higher than those of the CAPM (p-value $=$ 0.021 for univariate-sorting and p-value $=$ 0.017 for double-sorting). Average intercept of cross-sectional regressions is smaller and less significant ($\lambda_0 = 2.11\%$, t-stat $= 1.97$) and average adjusted R^2 gets higher (average $\bar{R}^2 = 39.9\%$) after betas on SMB and HML are included as explanatory variables. Improvement of the FF3 mainly traces to the pattern of SMB slopes of the portfolios. Dividend strips of past winners (losers) have positive (negative) exposures to SMB, which increase (decrease) expected portfolio returns. HML slopes also contributes to the better performance of the FF3, as portfolios in the three higher quintiles of RET(−1,−6) have positive exposures to HML and portfolios in the two lower quintiles of RET(−1,−6) have negative exposures to HML. The pattern of HML is not strictly monotonic, as the portfolio with the highest lagged stock return has a HML beta lower than that of the portfolio with the second highest lagged stock return. The double-sorting analysis shows that the non-monotonic issues concentrates on portfolios with low PIH. The portfolios have very different exposures to the momentum factor. For both univariate-sorting and double-sorting, UMD betas increase monotonically from significantly negative for the first RET(−1,−6) quintiles to significantly positive for the fifth RET(-1.-6) quintiles. Though the FFM4 still underestimates expected returns of portfolios with extremely high RET(−1,−6), compared to the FF3, intercepts from time-series regressions of the portfolios are pushed toward zero and the p-values of the GRS (1989) test (p-value = 0.090 for univariate-sorting and p-value = 0.112 for double-sorting) are higher than those of the three-factor model. The FF5 factor model which adds RMW and CMA also provides big improvements in the description of average returns on portfolios sorted by RET(−1,−6). Dividend strips whose underlying stocks earn high cumulative returns in the previous six months have positive RMW and CMA betas, suggesting that returns on such dividend strips behave more like returns on profitable stocks with conservative investments. Positive exposures to RMW and CMA help explain the high realized returns of past winners' dividend strips and move time-series regression intercepts toward zero. Regression intercepts of the FF5 are smaller and less significant than intercepts of the CAPM and FF3, and are comparable in terms of magnitudes and significance with those of the four-factor model which includes the momentum factor. The FF5 model is rejected by the GRS (1989) test with p-values (0.112 for univariate-sorting and 0.126 for double-sorting) slightly higher than those of the FFM4. Results from cross-sectional regressions also indicate that both the FFM4 and the FF5 are better descriptions of average portfolio returns of dividend stripes sorted by PIH and RET(-1,-6) than the FF3 and the CAPM. Average regression intercepts of the FF5 is 1.09% (t-stat = 1.47), smaller and less significant than that of the FFM4 (λ_0 = 1.43%, t-stat = 1.78), and the average proportion of variations in average portfolio returns explained by the FF5 is 55.5%, higher than that of the FFM4 (average $\bar{R}^2$ = 49.4%).

Summary of Asset Pricing Tests

In summary, similar to their ability to predict future stock returns, the four firm characteristics can also predict subsequent dividend strip returns, indicating that firm risks in the short run and in the long run may share common information. Variations in average returns of dividend strips sorted by underlying stocks' characteristics can be well explained by the five-factor model while the other three models seem to be incomplete specifications. Dividend strips of stocks with firm characteristics that are associated with high realized dividend strip returns (i.e., high $\overline{\text{DP}}$, high BM, high OP, low ATG and high RET(-1,-6)) typically have positive exposures to RMW and CMA, and dividend strips with low realized returns (i.e., low $\overline{\text{DP}}$, low BM, low OP, high ATG and low RET(−1,−6)) generally have negative loadings on RMW and CMA. RMW and CMA carry significantly positive risk premiums regardless of the testing portfolios. Market betas of dividend strip portfolios have a similar pattern. However, the positive relation between market beta and realized dividend strip return is not strong enough to fully explain differences in average dividend strip returns. Patterns of SMB betas produce mixed results. Relations between SMB betas and sorting variables are in the correct direction to explain average returns of dividend strips sorted by BM, ATG and RET(−1,−6) while are in the wrong direction for portfolios sorted by $\overline{\text{DP}}$ and OP. HML betas help improve descriptions of dividend strip returns in many cases but show strong humped relations with realized returns in some cases. For the momentum factor, UMD betas are generally positively associated with realized portfolio returns for all sorting variables. However, except to the portfolios sorted by RET(−1,−6), the relation between UMD betas and realized portfolio returns are relatively flat and price of UMD is estimated to be insignificantly positive in the cross section of dividend strips. The results suggest the superior performance of the FF5 is not specific to dividend strip portfolios sorted by historical dividend premium and that average dividend strip returns associated with different firm characteristics share common exposures to risks other than the market factors which are better captured by RMW and CMA than by HML, SMB and UMD. Low RMW and CMA, i.e., when firms with robust profitability and conservative investments underperform firms with weak profitability and aggresive investments, represent a bad economic state. Dividend strips that have negative association with RMW and CMA provide hedge against the bad state and investors ask for low risk premium on such assets. Dividend strips that have positive association with RMW and CMA perform badly in the bad state and are less attractive assets for which investors ask high risk premiums.

Chapter 9

Conclusions

Cash dividend remains an essential way for companies to distribute cash flows to equity holders, and is an important component of stock price. Studying the pricing of dividend strips which entitle investors to dividends paid during a finite period and contain information about equity discount rates at different maturities can help us better understand the formation of stock price. I use options written on individual equity in the U.S. market to replicate claims on near-term dividend payments from individual firms and recover their values from the put-call parity relation. I examine the asset pricing properties of dividend strips at the aggregate level and in the cross section of individual firms. The return on individual dividend strip is on average high, which is related to the fact that in contrast to the conventional wisdom of sticky dividends, actual quarterly dividends on average deviate a lot from expected dividends measured either by historical dividends or by analyst consensus dividend forecasts, suggesting considerable uncertainty in quarterly dividend payments from individual stocks. Returns of claims on short-term dividends vary substantially across stocks sorted by the ex-ante measure of dividend risk premium.

Asset pricing tests indicate that both the average return on the aggregate dividend strip made up of all individual dividend strips and the cross-sectional variations dividend strip returns can be well explained by the Fama and French (2015) five-factor model, but are not driven by measurement errors, differences in dividend policies, short-sale constraints of underlying stocks or early exercise premiums in prices of American-style options. The five-factor model also performs the best in explaining variations in returns on dividend strips of stocks with different firm characteristics, suggesting that dividend strip returns associated with different sorts share common exposures to risk factors well captured by the profitability (RMW) and investment (CMA) factors.

Results from this thesis indicate that and adding RMW and CMA may help explain the puzzling finding of the high average return of claims on short-term equity cash flows documented by prior studies using index derivatives. The high average value and substantial cross-sectional variations of returns on single cash flows of individual companies indicate that it is interesting to examine the term structure of equity at the corporate level. This thesis provides a model-free approach that can reliably calculate prices and returns of claims on single cash flows at the firm level from options prices. Future research can use this model-free approach to estimate a term structure of equity for individual firms when the market of derivatives on individual stocks becomes more liquid, and contracts with longer time-to-maturities are available.

Bibliography

Ang, A., & Liu, J., 2004. How to discount cashflows with time-varying expected returns. *Journal of Finance* 59(6), 2745–2783.

Andres, C., Betzer, A., van den Bongard, I., Haesner, C., & Theissen, E., 2013. The information content of dividend surprises: Evidence from Germany. *Journal of Business Finance & Accounting* 40(5–6), 620–645.

Bae-Yosef, S. A. & Sarig, O. H, 1992. Dividend surprises inferred from option and stock prices. *Journal of Finance* 47(4), 1623–1640.

Bakshi, G., Cao, C., & Chen, Z.. 1997. Empirical performance of alternative option pricing models. *Journal of Finance* 52(5), 2003–2049.

Banz, R. W., 1981. The relationship between return and market value of common stocks. *Journal of Financial Economics* 9(1), 3–18.

Barth, M. E., Kasznik, R., & McNichols, M. F., 2001. Analyst coverage and intangible assets. *Journal of Accounting Research* 39(1), 1–34.

Basu, S., 1983. The relationship between earnings yield, market value and reurns for NYSE common stocks. *Journal of Financial Economics* 1(12), 129–156.

Black, F., & Scholes, M., 1973. The pricing of options and corporate liabilities. *Journal of Political Economy* 81(3), 637–654.

Bilinski, P., & Bradshaw, M. T., 2015. Analyst dividend forecasts and their usefulness to investors: International evidence. *Working Paper.*

van Binsbergen, J., Brandt, M., & Koijen, R., 2012. On the timing and pricing of dividends. *American Economic Review* 102(4), 1596–1618.

van Binsbergen, J., Hueskes, W., Koijen, R., & Vrugt, E., 2013. Equity yields. *Journal of Financial Economics* 110(3), 503–519.

van Binsbergen, J. H., & Koijen, R. S., 2017. The term structure of returns: Facts and theory. *Journal of Financial Economics* 124(1), 1–21.

Brav, A., Graham, J. R., Harvey, C. R., & Michaely, R., 2005. Payout policy in the 21st century. *Journal of Financial Economics* 77(3), 483–527.

Brennan, M. J., 1998. Stripping the S&P 500 index. *Financial Analysts Journal* 54(1), 12–22.

Carhart, M. M., 1997. On persistence in mutual fund performance. *Journal of Finance* 52(1), 57–82.

Callen, J. L., & Lyle, M. R., 2019. The term structure of implied costs of equity capital. *Working Paper.*

Cejnek, G., & Randl, O., 2016. Risk and return of short-duration equity investments. *Journal of Empirical Finance* 36, 181–198.

Clara, N., 2018. The term-structure of systematic risk. Working Paper.

Cox, J. C., Ross, S. A., & Rubinstein, M., 1979. Option pricing: A simplified approach. *Journal of Financial Economics* 7(3), 229–263.

Derman, E., & Kani, I., 1994. Riding on a smile. *Risk*, 7(2), 32–39.

Dueker, M., & Miller Jr, T. W., 2003. Directly measuring early exercise premiums using American and European S&P 500 index options. *Journal of Futures Markets: Futures, Options, and Other Derivative Products* 23(3), 287–313.

Fama, E. F., & French, K. R., 1992. The cross-section of expected stock returns. *Journal of Finance* 47(2), 427–465.

Fama, E. F., & French, K. R., 1993. Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics* 33(1), 3–56.

Fama, E. F., & French, K. R., 2001. Disappearing dividends: changing firm characteristics or lower propensity to pay?. *Journal of Financial Economics* 60(1), 3–43.

Fama, E. F., & French, K. R., 2007. The anatomy of value and growth stock returns. *Financial Analysts Journal* 63(6), 44–54.

Fama, E. F., & French, K. R., 2015. A five-factor asset pricing model. *Journal of Financial Economics* 116(1), 1–22.

Fama, E. F., & MacBeth, J. D., 1973. Risk, return, and equilibrium: Empirical tests. *Journal of Political Economy* 81(3), 607–636.

Fodor, A., Stowe, D. L., & Stowe, J. D., 2017. Option Implied Dividends Predict Dividend Cuts: Evidence from the Financial Crisis. *Journal of Business Finance & Accounting* 44(5–6), 755–779.

Gibbons, M. R., Ross, S. A., & Shanken, J., 1989. A test of the efficiency of a given portfolio. *Econometrica* 57(5), 1121–1152.

Gordon, M. J., 1962. *The Investment, Financing, and Valuation of the Corporation.* Homewood, IL: RD Irwin.

Gormsen, N. J., & Lazarus, E., 2019. Duration-Driven Returns. *Working Paper.*

Grullon, G., & Michaely, R., 2002. Dividends, share repurchases, and the substitution hypothesis. *Journal of Finance* 57(4), 1649–1684.

Guo, W., & Su, T., 2006. Option put-call parity relations when the underlying security pays dividends. *International Journal of Business and Economics* 5(3), 225.

Guttman, I., Kadan, O., & Kandel, E., 2010. Dividend stickiness and strategic pooling. *Review of Financial Studies* 23(12), 4455–4495.

Heston, S. L., 1993. A closed-form solution for options with stochastic volatility with applications to bond and currency options. *Review of Financial Studies* 6(2), 327–343.

Jegadeesh, N., & Titman, S., 1993. Returns to buying winners and selling losers: Implications for stock market efficiency. *Journal of Finance* 48(1), 65–91.

Julio, B., & Ikenberry, D. L., 2004. Reappearing dividends. *Journal of Applied Corporate Finance* 16(4), 89–100.

Kane, A., Lee, Y. K., & Marcus, A., 1984. Earnings and dividend announcements: is there a corroboration effect?. *Journal of Finance* 39(4), 1091–1099.

Kim, J., Lee, K. H., & Lie, E., 2017. Dividend Stickiness, Debt Covenants, and Earnings Management. *Contemporary Accounting Research* 34(4), 2022–2050.

Kragt, J., 2017. Option implied dividends. *Working Paper*.

Lie, E., 2005. Financial flexibility, performance, and the corporate payout choice. *Journal of Business* 78(6), 2179–2201.

Lintner, J., 1965. The valuation of risky assets and the selection of risky investments in stock portfolios and capital budgets. *Review of Economics and Statistics* 47(1), 13–37.

Longstaff, F. A., & Schwartz, E. S., 2001. Valuing American options by simulation: a simple least-squares approach. *Review of Financial Studies* 14(1), 113–147.

Lu, J., & Karaban, S., 2009. Trading index dividends. *Working Paper*.

Lyle, M. R., & Wang, C. C., 2015. The cross section of expected holding period returns and their dynamics: A present value approach. *Journal of Financial Economics* 116(3), 505–525.

Manley, R., & Mueller-Glissmann, C., 2008. The Market for Dividends and Related Investment Strategies (corrected). *Financial Analysts Journal* 64(3), 17-29.

Michaely, R., & Moin, A., 2019. Disappearing and reappearing dividends. *Working Paper*.

Nagel, S., 2005. short-sales, institutional investors and the cross-section of stock returns. *Journal of Financial Economics* 78(2), 277–309.

Newey, W. K. & K. D. West, 1987. A Simple positive definite, heteroskedasticity and autocorrelation consistent covariance matrix. *Econometrica* 55, 703–705.

Novy-Marx, R., 2013. The other side of value: The gross profitability premium. *Journal of Financial Economics* 108(1), 1–28.

Ofek, E., Richardson, M., & Whitelaw, R. F., 2004. Limited arbitrage and short-sales restrictions: Evidence from the options markets. *Journal of Financial Economics* 74(2), 305–342.

Rubinstein, M., 1985. Nonparametric tests of alternative option pricing models using all reported trades and quotes on the 30 most active CBOE option classes from August 23, 1976 through August 31, 1978. *Journal of Finance* 40(2), 455–480.

Sharpe, W. F., 1964. Capital asset prices: A theory of market equilibrium under conditions of risk. *Journal of Finance* 19(3), 425–442.

Stoll, H. R., 1969. The relationship between put and call option prices. *Journal of Finance* 24(5), 801–824.

Titman, S., Wei, K. J., & Xie, F., 2004. Capital investments and stock returns. *Journal of Financial and Quantitative Analysis* 39(4), 677–700.

Yoon, P. S., & Starks, L. T., 1995. Signaling, investment opportunities, and dividend announcements. *Review of Financial Studies* 8(4), 995–1018.

Table 1
Summary Statistics: Stock Characteristics

Panel A.1 and A.2 present equity characteristics for listed stocks with options and for all stocks listed on NYSE, AMEX and NASDAQ. LogSIZE is the natural logarithm of total market capitalization. BM is the book-to-market ratio. ATG is the annual total asset growth rate. OP is the operating profitability. RET(−1,−6) is the compounding stock return in the prior six months and is reported in percentage. PIH is the percentage of institutional holdings. Mean, standard deviation (std), first quartile (p25), median (p50) and third quartile (p75) are reported. Panel B.1 and B.2 report cross-sectional Pearson correlations between each pair of variables for the stocks with options and for all listed stocks. I first calculate cross-sectional statistics in each quarter and report time-series averages of the statistics. The sample period is from January 1996 to December 2017.

A. Stock Characteristics

A.1 Sample of Stocks with Options Traded

	mean	std	p25	p50	p75
LogSIZE	20.97	1.62	19.83	20.84	21.98
BM	0.57	0.70	0.26	0.51	1.10
ATG	0.24	0.88	−0.01	0.09	0.24
OP	0.31	3.73	0.00	0.25	0.39
RET(−1,−6)	7.66	40.07	−13.18	3.51	21.48
PIH	0.66	0.25	0.51	0.72	0.86

A.2 Sample of Stocks Listed on NYSE, AMEX and NASDAQ

	mean	std	p25	p50	p75
LogSIZE	19.55	2.06	18.08	19.48	20.93
BM	0.69	0.73	0.29	0.58	1.01
ATG	0.19	1.51	−0.03	0.06	0.20
OP	0.17	2.82	0.01	0.18	0.34
RET(−1,−6)	6.79	43.09	−14.51	2.58	20.55
PIH	0.46	0.32	0.16	0.47	0.74

Table 1
Summary Statistics: Stock Characteristics, Cont.

B. Correlation Matrix

B.1 Sample of Stocks with Options Traded

	BM	ATG	OP	RET(−1,−6)	PIH
LogSIZE	−0.076	0.054	0.033	0.033	0.435
BM		−0.007	−0.001	−0.003	−0.011
ATG			−0.001	−0.029	0.008
OP				0.006	0.016
RET(−1,−6)					0.051

B.2 Sample of Stocks Listed on NYSE, AMEX and NASDAQ

	BM	ATG	OP	RET(−1,−6)	PIH
LogSIZE	−0.083	0.044	0.087	0.011	0.127
BM		−0.035	−0.021	−0.042	−0.029
ATG			−0.017	−0.045	0.002
OP				0.014	0.076
RET(−1,−6)					0.067

Table 2
Uncertainty of Individual Dividends

Panel A and B report cross-sectional distributions of the mean and root mean square error of quarterly dividend growth rate and analyst dividend surprise, respectively. In Panel A, g^d is time-series average of quarterly dividend growth rate, which is equal to the percentage change of dividend of a stock in a quarter from the dividend of that stock in the same fiscal quarter of the previous fiscal year. RMSE(g^d) is the root mean squared error of quarterly dividend growth rate, which is the square root of mean squared quarterly dividend growth rate. A.1 reports results for all stocks listed on NYSE, AMEX and NASDAQ with at least one positive regular cash dividend during the sample period. A.2 reports results for listed dividend payers with options traded. A.3 presents results for listed stocks with analyst dividend forecasts available. A.4 presents results for listed stocks with analyst following and with options traded. In Panel B, e^d is analyst dividend forecast error, defined as the ratio of actual dividend per share to the last consensus analyst forecast on dividend per share preceding dividend announcements minus 1. RMSE(e^d) is the root mean squared analyst dividend forecast error. Mean, standard deviation (std), the first quartile (p25), median (p50) and third quartile (p75) are reported in percentage. For Panel A.1 and Panel A.2, the sample period is from January 1996 to December 2017. For Panel A.3, Panel A.4 and Panel B, the sample period is from January 2002 to December 2017.

A. Naive Model					
A.1 All Dividend Payers					
	mean	std	p25	p50	p75
g^d	1.17	25.34	−4.53	1.60	8.38
RMSE(g^d)	31.85	50.55	16.33	29.62	52.10
A.2 Dividend Payers with Options					
	mean	std	p25	p50	p75
g^d	2.02	18.37	−1.99	2.40	8.29
RMSE(g^d)	28.64	35.93	15.98	26.19	42.63
A.3 Dividend Payers with Analyst Forecasts					
	mean	std	p25	p50	p75
g^d	2.26	17.83	−2.87	2.85	7.99
RMSE(g^d)	29.82	37.14	16.18	26.98	43.11
A.4 Dividend Payers with Analyst Forecasts and with Options					
	mean	std	p25	p50	p75
g^d	3.14	16.94	−1.45	3.35	8.32
RMSE(g^d)	27.06	37.47	15.60	25.88	42.08

Table 2
Uncertainty of Individual Dividends, Cont.

B. Analyst Dividend Forecast

B.1 Dividend Payers with Analyst Forecasts

	mean	std	p25	p50	p75
e^d	0.87	18.88	−3.56	0.29	3.02
RMSE(e^d)	26.31	38.62	9.44	24.44	45.43

B.2 Dividend Payers with Analyst Forecasts and with Options

	mean	std	p25	p50	p75
e^d	0.71	17.93	−2.89	0.23	3.29
RMSE(e^d)	24.96	35.07	9.26	23.66	40.99

Table 3
Summary Statistics: Options Characteristics

This table presents characteristics of option contracts written on individual stocks that are used to calculate values of dividend strips. K/S is the ratio of strike price to the price of the underlying stock, τ is number of days until the option maturity date, IV is option-implied volatility, OI is open interest, and VOL is daily trading volumes of options in contracts. Mean, standard deviation (std), first quartile (p25), median (p50) and third quartile (p75) are reported. I first calculate cross-sectional statistics in each quarter and report time-series averages of the statistics. The sample period is from January 1996 to December 2017.

	mean	std	p25	p50	p75
K/S	1.00	0.04	0.96	1.00	1.04
τ	90	33	59	89	115
IV	0.49	0.25	0.32	0.43	0.60
VOL	45	302	0	1	12
OI	911	3,758	41	154	574

Table 4
Summary Statistics: Dividend Premium, Dividend Yield and Option-Implied Dividend Yield

DY is annualized dividend (D) in the next quarter divided by current stock price, IDY is annualized option-implied dividend (DI) divided by current stock price, DP is difference between present value of annualized D and annualized DI divided by current stock price, and r is quarterly return on dividend strips. I first calculate cross-sectional statistics in each quarter and report the time-series averages of the statistics. Panel A presents summary statistics for the full sample of stocks with options traded. Panel B reports summary statistics of variables with DI adjusted for early exercise premium. DIF is the difference between IDY not adjusted for and adjusted for early exercise premium. Panel C presents summary statistics for the sample of dividend payers, defined as stocks that have ever paid a positive regular cash dividend in the previous five years. DP, DY, IDY and DIF are in annual percentage terms, and r is in quarterly percentage terms. Mean, standard deviation (std), the first quartile (p25), median (p50) and third quartile (p75) are reported. The sample period is from January 1996 to December 2017.

A. Full Sample	mean	std	p25	p50	p75
DY	1.18	2.27	0.00	0.06	1.72
IDY	1.10	1.95	0.04	0.20	1.68
DP	0.08	2.20	−0.72	0.05	0.90
r	3.12	32.62	−13.07	1.66	19.69
B. Adjust for Early Exercise Premium	mean	std	p25	p50	p75
DY	1.11	2.21	0.00	0.05	1.67
IDY	1.04	1.96	0.01	0.18	1.62
DP	0.07	2.12	−0.67	0.10	0.86
r	3.98	32.46	−12.34	3.08	21.77
DIF	0.02	0.95	−0.05	0.03	0.09
C. Dividend Payers	mean	std	p25	p50	p75
DY	2.57	2.74	0.91	1.95	3.40
IDY	2.27	2.14	0.81	1.75	3.12
DP	0.30	2.52	−0.85	0.06	1.05
r	5.61	36.53	−15.50	3.31	26.75

Table 5
Return on Aggregate Dividend Strip

Panel A reports times-series statistics of quarterly return on the aggregate dividend strip, quarterly return on the market portfolio and quarterly portfolio-based risk factors. Return on the aggregate dividend strip $r^A_{q+1} = (D^A_{q+1} + \mathrm{DI}^A_{q+1})/\mathrm{DI}^A_q - 1$, where D^A_{q+1} is the realized aggregate dividend in quarter $q+1$, and DI^A_q and DI^A_{q+1} are the values of the claim on aggregate dividend at the end of quarter q and quarter $q+1$. r^m is the return on the S&P 500 index. $\tilde{r}^A$ and $\tilde{r}^m$ are the return on the aggregate dividend strip and on the market index in excess of the risk-free rate. SMB is the size factor. HML is the value factor. UMD is the momentum factor. RMW is the profitability factor. CMA is the investment factor. Mean, median (med), standard deviation (std), skewness (skew) and kurtosis (kurt) are reported. Numbers are reported in quarterly percentage terms. Panel B reports intercepts and slope coefficients from regressions of excess return on the aggregate dividend strip on risk factors of different asset pricing models. $\alpha^{A,\mathrm{CAPM}}$, $\alpha^{A,\mathrm{FF3}}$, $\alpha^{A,\mathrm{FFM4}}$ and $\alpha^{A,\mathrm{FF5}}$ are intercepts of the capital asset pricing model (CAPM), the Fama and French (1993) three-factor model (FF3), the Carhart (1997) four-factor model (FFM4) and the Fama and French (2015) five-factor model (FF5). Alphas are reported in percentage. $\beta^{A,m}$, $\beta^{A,s}$, $\beta^{A,h}$, $\beta^{A,u}$, $\beta^{A,r}$, and $\beta^{A,c}$ are the slope coefficients of the excess return on the aggregate dividend strip on the excess return on the market portfolio, SMB, HML, UMD, RMW and CMA, respectively. $\bar{R}^2$ is adjusted R^2. t-statistics are reported in parentheses. The sample period is from January 1996 to December 2017.

A. Summary Statistics of Returns on Assets and Risk Factors

	mean	med	std	skew	kurt
r^m	2.53	3.12	8.07	−0.54	3.54
$\tilde{r}^m$	1.98	2.62	8.09	−0.52	3.43
SMB	0.58	0.44	4.72	0.07	2.84
HML	0.64	0.31	6.40	0.84	5.88
UMD	0.72	−0.14	4.39	1.34	6.52
RMW	1.13	0.67	5.52	0.94	8.11
CMA	1.14	1.36	8.84	−0.85	7.98
r^A	4.62	4.25	15.22	−0.06	3.52
$\tilde{r}^A$	4.08	3.89	15.53	−0.07	3.31

Table 5
Return on Aggregate Dividend Strip, Cont.

B. Asset Pricing Tests on Aggregate Dividend Strip

	$\alpha^{A,\text{CAPM}}$	$\beta^{A,m}$					$\bar{R}^2$
CAPM	3.50	0.29					0.0476
	(2.11)	(1.43)					
	$\alpha^{A,\text{FF3}}$	$\beta^{A,m}$	$\beta^{A,s}$	$\beta^{A,h}$			$\bar{R}^2$
FF3	3.15	0.27	0.22	0.57			0.102
	(1.90)	(1.32)	(0.85)	(2.27)			
	$\alpha^{A,\text{FFM4}}$	$\beta^{A,m}$	$\beta^{A,s}$	$\beta^{A,h}$	$\beta^{A,u}$		$\bar{R}^2$
FFM4	2.64	0.26	0.16	0.55	0.10		0.125
	(1.77)	(1.00)	(0.38)	(2.22)	(0.54)		
	$\alpha^{A,\text{FF5}}$	$\beta^{A,m}$	$\beta^{A,s}$	$\beta^{A,h}$	$\beta^{A,r}$	$\beta^{A,c}$	$\bar{R}^2$
FF5	2.29	0.27	0.16	0.61	0.30	0.57	0.174
	(1.19)	(1.38)	(0.57)	(2.04)	(1.76)	(2.30)	

Table 6
Sorting Portfolio Analysis: Stock Characteristics

This table presents average values of characteristics of quintile portfolios sorted by $\overline{\text{DP}}$, the average normalized dividend premium in the last four quarters, and 25 portfolios sorted by PIH, the percentage of institutional holding, PIH, and $\overline{\text{DP}}$. For the univariate-sorting, at the end of each quarter q, stocks are sorted into portfolios based on $\overline{\text{DP}}$. Portfolio 1 (5) has the lowest (highest) $\overline{\text{DP}}$. For double-sorting, at the end of each quarter q, stocks are first sorted into five portfolios based on PIH, and within each portfolio, stocks are then sorted by $\overline{\text{DP}}$. In the column labeled $\overline{\text{DP}}$, Portfolio 1 (5) has the lowest (highest) $\overline{\text{DP}}$. In the row labeled PIH, Portfolio 1 (5) has the lowest (highest) PIH. LogSIZE is the natural logarithm of total market capitalization. BM is the book-to-market ratio. ATG is the annual total asset growth rate. OP is the operating profitability. RET(-1,-6) is the compounding stock return in the prior 6 months and is reported in percentage. PIH is defined as shares held by institutions divided by total number of shares outstanding. RR is portfolio retaining rate, defined as the proportion of stocks in a portfolio in the previous quarter that remains in the same portfolio in this quarter. In each quarter for each portfolio, I calculate mean values of characteristics of stocks in the sample and report time-series averages of mean values of the variables for each portfolio. The sample period is from January 1996 to December 2017.

A. Stock Characteristics, Quintile Portfolios Sorted by $\overline{\text{DP}}$

	$\overline{\text{DP}}$				
	1	2	3	4	5
BM	0.41	0.49	0.55	0.64	0.72
LogSIZE	19.53	19.97	20.76	21.35	21.79
ATG	0.34	0.29	0.25	0.22	0.16
OP	0.15	0.27	0.34	0.40	0.45
RET(-1,-6)	1.26	1.70	2.21	2.46	2.78
PIH	0.69	0.68	0.66	0.67	0.67
RR	0.92	0.85	0.78	0.81	0.95

Table 6
Sorting Portfolio Analysis: Stock Characteristics, Cont.

B. Stock Characteristics, 25 Portfolios Sorted by PIH and $\overline{\text{DP}}$

PIH: Percentage of Institutional Holding

		$\overline{\text{DP}}$				
		1	2	3	4	5
	1	0.37	0.30	0.29	0.28	0.27
	2	0.58	0.59	0.58	0.59	0.56
PIH	3	0.73	0.73	0.72	0.72	0.73
	4	0.84	0.84	0.83	0.84	0.84
	5	0.94	0.94	0.93	0.93	0.94

BM: Book-to-market Ratio

		$\overline{\text{DP}}$				
		1	2	3	4	5
	1	0.45	0.51	0.58	0.68	0.74
	2	0.43	0.49	0.57	0.66	0.72
PIH	3	0.41	0.51	0.56	0.63	0.72
	4	0.40	0.50	0.52	0.62	0.70
	5	0.38	0.48	0.51	0.60	0.68

LogSIZE: Firm Size

		$\overline{\text{DP}}$				
		1	2	3	4	5
	1	19.04	19.29	20.26	20.51	21.00
	2	19.78	19.91	20.53	21.15	21.95
PIH	3	19.85	20.32	21.00	21.14	21.12
	4	19.70	20.01	20.81	21.49	22.05
	5	19.42	20.30	20.44	21.19	22.11

ATG: Total Assets Growth Rate

		$\overline{\text{DP}}$				
		1	2	3	4	5
	1	0.30	0.25	0.23	0.21	0.14
	2	0.32	0.24	0.25	0.22	0.16
PIH	3	0.33	0.27	0.25	0.21	0.18
	4	0.35	0.28	0.24	0.23	0.19
	5	0.35	0.32	0.25	0.22	0.19

Table 6
Sorting Portfolio Analysis: Stock Characteristics, Cont.

B. Stock Characteristics, 25 Portfolios Sorted by PIH and $\overline{\text{DP}}$

OP: Operating Profitability

		$\overline{\text{DP}}$				
		1	2	3	4	5
	1	−0.06	0.15	0.32	0.33	0.39
	2	0.17	0.23	0.34	0.37	0.44
PIH	3	0.17	0.29	0.36	0.38	0.46
	4	0.18	0.29	0.36	0.40	0.46
	5	0.21	0.31	0.35	0.42	0.45

RET(−1,−6): Past 6-months Stock Return

		$\overline{\text{DP}}$				
		1	2	3	4	5
	1	0.56	1.11	1.64	2.33	2.60
	2	1.39	1.71	1.92	2.14	2.55
PIH	3	1.41	1.82	2.28	2.49	2.65
	4	1.42	1.92	2.35	2.61	3.21
	5	1.34	1.87	2.48	3.03	3.24

RR: Retaining Ratio

		$\overline{\text{DP}}$				
		1	2	3	4	5
	1	0.93	0.77	0.71	0.75	0.88
	2	0.87	0.74	0.68	0.77	0.87
PIH	3	0.86	0.74	0.68	0.70	0.79
	4	0.79	0.66	0.60	0.62	0.72
	5	0.88	0.73	0.66	0.67	0.81

Table 7
Portfolio Realized Returns

Panel A reports time-series average returns on portfolios, r^p, in quarterly percentage terms, of the five portfolios of dividend strips sorted by $\overline{\text{DP}}$. At the end of each quarter q, stocks are sorted into portfolios based on $\overline{\text{DP}}$, the average historical normalized dividend premium in the last four quarters. Portfolio 1 (5) has the lowest (highest) $\overline{\text{DP}}$. Panel B reports time-series average returns on the portfolios of dividend strips, r^p, in quarterly percentage terms, of the 25 portfolios sorted by PIH and $\overline{\text{DP}}$. At the end of each quarter q, stocks are first sorted into five portfolios based on the percentage of institutional holding, PIH, and within each portfolio, stocks are then sorted into five sub-portfolios based on the average dividend premium in the last four quarters, $\overline{\text{DP}}$. In the row labeled $\overline{\text{DP}}$, Portfolio 1 (5) has the lowest (highest) $\overline{\text{DP}}$. In the column labeled PIH, Portfolio 1 (5) has the lowest (highest) PIH. In each column, the five PIH portfolios are aggregated into one portfolio, and returns on the aggregate portfolios are reported in the last row labeled by ALL. Column labeled 5−1 represents spread in returns between Portfolio 5 and 1. The sample period is from January 1996 to December 2017.

A. Portfolio Realized Returns r^p, univariate-sorting

$\overline{\text{DP}}$					
1	2	3	4	5	5−1
−2.87	−1.55	3.71	7.38	11.91	14.78
(−1.26)	(−0.69)	(2.12)	(3.27)	(4.60)	(4.53)

B. Portfolio Realized Returns r^p, double-sorting

		$\overline{\text{DP}}$					
		1	2	3	4	5	5−1
	1	−3.32	−2.83	4.75	8.34	14.63	17.95
		(−1.29)	(−1.15)	(2.46)	(3.25)	(4.89)	(4.09)
	2	−5.87	−1.22	4.83	8.48	11.93	17.80
		(−2.21)	(−0.50)	(2.50)	(3.44)	(4.46)	(4.90)
PIH	3	−3.07	−1.37	4.78	6.51	11.33	14.40
		(−1.21)	(−0.50)	(2.26)	(2.56)	(4.11)	(4.54)
	4	−3.09	−0.54	4.11	4.36	10.75	13.84
		(−1.31)	(−0.21)	(2.09)	(1.79)	(4.01)	(4.11)
	5	−2.62	−0.42	3.44	6.77	12.11	14.73
		(−1.02)	(−0.17)	(1.79)	(2.92)	(4.41)	(4.00)
ALL		−3.59	−1.28	4.38	6.89	12.15	15.74
		(−2.33)	(−0.59)	(2.61)	(3.37)	(5.29)	(5.82)

Table 8
Portfolio Risk Exposures

This table reports the time-series means of conditional risk exposures and associated t-statistics of the five portfolios sorted by $\overline{\text{DP}}$ (Panel A) and of the 25 portfolios sorted by PIH and $\overline{\text{DP}}$ (Panel B). $\bar{\beta}^{p,m}$, $\bar{\beta}^{p,s}$, $\bar{\beta}^{p,h}$, $\bar{\beta}^{p,u}$, $\bar{\beta}^{p,r}$ and $\bar{\beta}^{p,c}$ are time-series averages of risk exposures of dividend strip portfolio p's return, r^p, with respect to the market risk factor, the size factor (SMB), the value factor (HML), the momentum factor (UMD), the profitability factor (RMW) and the investment factor (CMA), and are estimated from time-series regressions in a rolling window of data. t-statistics of betas are adjusted for autocorrelation and heteroscedasticity. The sample period is from January 1996 to December 2017.

A. Risk Exposures, univariate-sorting

	$\overline{\text{DP}}$						$\overline{\text{DP}}$				
	1	2	3	4	5		1	2	3	4	5
CAPM: Capital Asset Pricing Model											
$\bar{\beta}^{p,m}$	−0.45	−0.21	0.29	0.74	1.68	$t(\bar{\beta}^{p,m})$	−4.99	−1.97	3.25	7.71	9.52
FF3: Fama and French Three-Factor Model											
$\bar{\beta}^{p,m}$	−0.41	−0.23	0.28	0.74	1.63	$t(\bar{\beta}^{p,m})$	−4.85	−1.98	3.08	5.86	9.46
$\bar{\beta}^{p,s}$	0.60	0.46	0.24	−0.18	−0.41	$t(\bar{\beta}^{p,s})$	4.05	2.17	1.97	−1.45	−3.43
$\bar{\beta}^{p,h}$	−0.45	−0.25	0.35	0.65	0.78	$t(\bar{\beta}^{p,h})$	−3.91	−2.55	2.62	5.27	5.46
FFM4: Carhart Four-Factor Model											
$\bar{\beta}^{p,m}$	−0.41	−0.22	0.32	0.81	1.69	$t(\bar{\beta}^{p,m})$	−5.28	−2.02	2.58	6.08	9.12
$\bar{\beta}^{p,s}$	0.61	0.37	0.32	−0.27	−0.41	$t(\bar{\beta}^{p,s})$	4.60	1.68	2.04	−2.23	−2.74
$\bar{\beta}^{p,h}$	−0.44	−0.19	0.35	0.63	0.75	$t(\bar{\beta}^{p,h})$	−3.19	−2.26	3.07	4.65	5.55
$\bar{\beta}^{p,u}$	−0.27	−0.20	0.22	0.38	0.48	$t(\bar{\beta}^{p,u})$	−2.48	−1.99	1.94	3.33	3.37
FF5: Fama and French Five-Factor Model											
$\bar{\beta}^{p,m}$	−0.45	−0.19	0.30	0.81	1.64	$t(\bar{\beta}^{p,m})$	−4.00	−2.32	2.95	5.75	8.81
$\bar{\beta}^{p,s}$	0.57	0.48	0.27	−0.22	−0.42	$t(\bar{\beta}^{p,s})$	4.03	2.06	1.97	−1.37	−3.54
$\bar{\beta}^{p,h}$	−0.46	−0.25	0.32	0.65	0.79	$t(\bar{\beta}^{p,h})$	−3.26	−2.19	2.45	4.96	5.81
$\bar{\beta}^{p,r}$	−0.34	−0.27	0.46	0.65	0.96	$t(\bar{\beta}^{p,r})$	−3.15	−2.33	2.42	2.90	5.03
$\bar{\beta}^{p,c}$	−0.30	−0.09	0.39	0.67	0.83	$t(\bar{\beta}^{p,c})$	−2.57	−0.72	3.44	3.90	4.87

Table 8 Portfolio Risk Exposures, Cont.

B. Risk Exposures, double-sorting

		$\overline{\text{DP}}$					$\overline{\text{DP}}$				
		1	2	3	4	5	1	2	3	4	5
CAPM: Capital Asset Pricing Model											
				$\bar{\beta}^{p,m}$					$t(\bar{\beta}^{p,m})$		
	1	−0.40	−0.23	0.43	0.76	1.53	−4.49	−2.50	3.89	6.76	9.52
	2	−0.48	−0.26	0.43	0.82	1.67	−5.68	−1.96	3.96	6.15	9.52
PIH	3	−0.16	−0.25	0.37	0.82	1.54	−1.52	−2.29	3.37	6.69	9.54
	4	−0.40	−0.11	0.28	0.68	1.36	−5.09	−1.29	3.14	6.02	8.08
	5	−0.26	−0.13	0.31	0.64	1.37	−3.95	−1.14	3.23	6.00	8.25
FF3: Fama and French Three-Factor Model											
				$\bar{\beta}^{p,m}$					$t(\bar{\beta}^{p,m})$		
	1	−0.39	−0.26	0.46	0.73	1.52	−4.29	−2.43	3.02	6.02	8.68
	2	−0.47	−0.27	0.42	0.76	1.53	−4.46	−2.20	4.12	5.05	8.02
PIH	3	−0.19	−0.27	0.27	0.78	1.49	−1.76	−2.10	3.32	4.59	9.12
	4	−0.46	−0.10	0.25	0.66	1.38	−3.25	−0.99	2.98	6.66	7.73
	5	−0.26	−0.16	0.22	0.66	1.38	−2.53	−0.98	3.01	5.89	8.29
				$\bar{\beta}^{p,s}$					$t(\bar{\beta}^{p,s})$		
	1	1.00	0.72	0.40	−0.09	−0.59	6.21	4.96	2.15	−0.59	−2.76
	2	0.74	0.69	0.29	−0.14	−0.60	4.25	3.79	1.50	−0.95	−3.88
PIH	3	0.57	0.42	0.26	−0.17	−0.73	4.49	2.80	2.08	−1.24	−5.16
	4	0.44	0.38	0.28	−0.19	−0.34	2.53	2.24	1.29	−1.30	−2.51
	5	0.36	0.43	0.25	−0.29	−0.76	2.45	3.59	1.51	−2.05	−5.24
				$\bar{\beta}^{p,h}$					$t(\bar{\beta}^{p,h})$		
	1	−0.67	−0.29	0.46	0.67	0.85	−4.18	−3.36	3.46	4.10	6.50
	2	−0.46	−0.27	0.41	0.75	0.81	−4.48	−2.93	3.42	4.21	4.96
PIH	3	−0.52	−0.24	0.33	0.56	0.70	−4.18	−1.69	3.05	5.12	3.57
	4	−0.18	−0.08	0.22	0.58	0.62	−1.91	−1.30	3.10	3.46	4.09
	5	−0.19	−0.09	0.16	0.52	0.65	−1.00	−1.15	1.14	3.49	4.89

Table 8 Portfolio Risk Exposures, Cont.

		$\overline{\text{DP}}$					$\overline{\text{DP}}$				
		1	2	3	4	5	1	2	3	4	5
FFM4: Carhart Four-Factor Model											
				$\bar{\beta}^{p,m}$					$t(\bar{\beta}^{p,m})$		
	1	−0.40	−0.22	0.41	0.70	1.46	−3.55	−2.89	2.85	5.33	8.78
	2	−0.45	−0.26	0.40	0.83	1.66	−4.29	−2.12	3.42	6.61	8.81
PIH	3	−0.15	−0.19	0.29	0.77	1.56	−1.21	−1.56	2.97	5.03	8.02
	4	−0.38	−0.16	0.38	0.73	1.39	−3.19	−1.36	2.76	6.08	7.19
	5	−0.19	−0.09	0.30	0.67	1.42	−1.68	−0.94	2.80	5.82	7.94
				$\bar{\beta}^{p,s}$					$t(\bar{\beta}^{p,s})$		
	1	0.96	0.74	0.46	−0.09	−0.57	5.09	4.08	2.43	−0.42	−2.22
	2	0.83	0.65	0.34	−0.17	−0.61	4.25	5.24	2.11	−1.12	−3.58
PIH	3	0.57	0.43	0.28	−0.15	−0.61	3.94	2.14	1.15	−1.07	−3.92
	4	0.41	0.33	0.25	−0.18	−0.33	2.15	1.86	1.62	−1.16	−2.39
	5	0.35	0.44	0.19	−0.22	−0.76	2.74	2.51	1.21	−1.38	−5.12
				$\bar{\beta}^{p,h}$					$t(\bar{\beta}^{p,h})$		
	1	−0.65	−0.23	0.49	0.65	0.84	−4.32	−2.46	3.23	3.96	5.26
	2	−0.51	−0.30	0.42	0.62	0.87	−4.78	−3.12	3.01	5.04	5.64
PIH	3	−0.43	−0.12	0.25	0.57	0.77	−4.46	−0.75	2.11	4.34	4.33
	4	−0.16	−0.13	0.24	0.55	0.71	−1.44	−1.54	3.14	4.14	4.32
	5	−0.09	−0.05	0.17	0.57	0.69	−0.70	−0.55	1.22	3.43	4.45
				$\bar{\beta}^{p,u}$					$t(\bar{\beta}^{p,u})$		
	1	−0.75	−0.56	0.25	0.45	0.58	−3.94	−2.43	2.36	2.71	4.02
	2	−0.50	−0.31	0.28	0.36	0.48	−3.77	−1.24	3.27	2.52	4.39
PIH	3	−0.26	−0.20	0.25	0.36	0.47	−1.45	−1.26	3.73	3.28	3.27
	4	−0.14	−0.09	0.15	0.33	0.50	−0.51	−0.70	1.16	2.50	3.21
	5	−0.05	−0.01	0.13	0.35	0.42	−0.30	−0.09	1.41	3.18	2.90

Table 8 Portfolio Risk Exposures, Cont.

		$\overline{\text{DP}}$					$\overline{\text{DP}}$				
		1	2	3	4	5	1	2	3	4	5
FF5: Fama and French Five-Factor Model											
				$\bar{\beta}^{p,m}$					$t(\bar{\beta}^{p,m})$		
	1	−0.43	−0.24	0.42	0.71	1.49	−3.88	−2.90	3.09	5.60	8.59
	2	−0.43	−0.27	0.43	0.82	1.65	−4.25	−2.47	3.80	6.36	9.00
PIH	3	−0.12	−0.25	0.31	0.79	1.55	−1.70	−2.11	3.61	5.58	8.72
	4	−0.41	−0.11	0.33	0.67	1.38	−2.92	−0.99	3.43	6.62	7.61
	5	−0.21	−0.07	0.28	0.68	1.40	−2.00	−0.71	2.89	5.55	8.29
				$\bar{\beta}^{p,s}$					$t(\bar{\beta}^{p,s})$		
	1	0.98	0.76	0.45	−0.07	−0.55	5.33	4.80	2.85	−0.40	−1.77
	2	0.82	0.73	0.32	−0.15	−0.63	3.87	4.46	1.99	−0.83	−3.79
PIH	3	0.57	0.42	0.26	−0.09	−0.61	3.83	2.49	1.22	−0.65	−4.90
	4	0.44	0.35	0.24	−0.14	−0.35	3.83	2.46	1.53	−0.81	−1.87
	5	0.31	0.43	0.19	−0.22	−0.73	2.46	2.29	1.46	−1.26	−4.97
				$\bar{\beta}^{p,h}$					$t(\bar{\beta}^{p,h})$		
	1	−0.65	−0.24	0.46	0.63	0.87	−4.15	−2.26	3.42	4.06	5.90
	2	−0.51	−0.28	0.47	0.65	0.84	−5.40	−3.93	3.04	4.79	5.13
PIH	3	−0.44	−0.11	0.26	0.57	0.75	−5.08	−1.37	2.31	4.08	4.71
	4	−0.13	−0.10	0.24	0.54	0.70	−1.73	−1.90	3.00	3.93	4.35
	5	−0.10	−0.04	0.19	0.60	0.68	−1.05	−0.69	0.84	3.95	4.80
				$\bar{\beta}^{p,r}$					$t(\bar{\beta}^{p,r})$		
	1	−0.53	−0.39	0.48	0.70	0.93	−2.44	−3.25	2.35	3.33	4.23
	2	−0.62	−0.31	0.52	0.66	1.08	−4.76	−3.15	2.31	2.93	5.27
PIH	3	−0.29	−0.25	0.46	0.69	1.08	−2.67	−1.81	3.34	3.01	5.16
	4	−0.20	−0.21	0.49	0.63	0.89	−1.17	−2.45	3.22	3.73	4.87
	5	−0.24	0.02	0.39	0.58	1.16	−1.80	0.18	2.83	3.60	5.34
				$\bar{\beta}^{p,c}$					$t(\bar{\beta}^{p,c})$		
	1	−0.34	−0.21	0.49	0.66	1.07	−1.70	−1.49	2.31	3.06	5.83
	2	−0.49	−0.25	0.46	0.68	0.90	−4.31	−1.70	1.75	2.95	5.25
PIH	3	−0.29	−0.20	0.43	0.70	0.87	−3.97	−2.06	1.59	2.90	5.20
	4	−0.19	−0.07	0.36	0.56	0.97	−1.30	−1.22	1.52	2.58	4.41
	5	−0.20	−0.14	0.25	0.63	0.90	−1.82	−2.05	1.09	2.72	4.07

Table 9
Cross-sectional Regressions and Price of Risk

This table reports the cross-sectional regression results of quarterly excess returns of portfolios of dividend strips, $\tilde{r}^p$, on conditional beta coefficients on risk factors under the four asset pricing models, the Capital Asset Pricing Model (CAPM), the Fama and French (1993) three-factor model (FF3), the Carhart (1997) four-factor model and the Fama and French (2015) five-factor model. λ_0 is regression intercept. λ^m, λ^s, λ^h, λ^u, λ^r and λ^c are prices of the market risk factor, the size factor (SMB), the value factor (HML), the momentum factor (UMD), the profitability factor (RMW) and the investment factor (CMA). The table reports time-series average of estimated prices of risks, t-statistic adjusted for autocorrelation and heteroscedasticity in parentheses, and mean value of adjusted R^2, $\bar{R}^2$ of regressions. In Panel A, testing portfolios are the quintile portfolios sorted by $\overline{\text{DP}}$. In Panel B, testing portfolios are the 25 portfolios sorted by PIH and $\overline{\text{DP}}$. The sample period is from January 1996 to December 2017.

A. Quintile Portfolios Sorted by $\overline{\text{DP}}$

	λ_0	λ^m	λ^s	λ^h	λ^u	λ^r	λ^c	$\bar{R}^2$
Est.	3.52	2.72						0.488
t-stat	(2.40)	(2.27)						

B. 25 Portfolios Sorted by PIH and $\overline{\text{DP}}$

	λ_0	λ^m	λ^s	λ^h	λ^u	λ^r	λ^c	$\bar{R}^2$
Est.	3.45	3.08						0.405
t-stat	(2.25)	(3.18)						
Est.	2.05	3.12	−0.84	1.97				0.454
t-stat	(1.59)	(2.25)	(−1.46)	(2.13)				
Est.	1.90	3.17	−0.85	1.86	1.13			0.507
t-stat	(1.44)	(2.69)	(−1.37)	(2.06)	(1.08)			
Est.	0.44	3.09	−1.12	1.59		1.61	1.59	0.570
t-stat	(0.30)	(2.64)	(−1.78)	(2.08)		(2.70)	(3.31)	

Table 10
Time-series Regression and GRS Test

The table reports pricing errors for the CAPM (α^{CAPM}), the FF3 (α^{FF3}), the FFM4 (α^{FFM4}) and the FF5 (α^{FF5}) estimated from the time-series regression of portfolio quarterly excess returns $\tilde{r}^p_{q+1}$ on quarterly risk factors f_{q+1}:

$$\tilde{r}^p_{q+1} = \alpha^p + \beta^p f_{q+1} + \varepsilon^p_{q+1},$$

where $f_{q+1} = \tilde{r}^m_{q+1}$ (excess return on the S&P 500 index) for the CAPM, $f_{q+1} = [\tilde{r}^m_{q+1}, \text{SMB}_{q+1}, \text{HML}_{q+1}]$ for the FF3, $f_{q+1} = [\tilde{r}^m_{q+1}, \text{SMB}_{q+1}, \text{HML}_{q+1}, \text{UMD}_{q+1}]$ for the FFM4, and $f_{q+1} = [\tilde{r}^m_{q+1}, \text{SMB}_{q+1}, \text{HML}_{q+1}, \text{RMW}_{q+1}, \text{CMA}_{q+1}]$ for the FF5. Panel A is for the quintile portfolios sorted by $\overline{\text{DP}}$, average normalized dividend premium in the last four quarters, and Portfolio 1 (5) has the lowest (highest) $\overline{\text{DP}}$. Panel B is for the 25 portfolios sorted by PIH, the percentage of institutional holdings, and by $\overline{\text{DP}}$. In each row labeled $\overline{\text{DP}}$, Portfolio 1 (5) has the lowest (highest) $\overline{\text{DP}}$, and in each column labeled PIH, Portfolio 1 (5) has the lowest (highest) PIH. Bottoms of Panel A and B report Gibbons, Ross and Shanken (1989) test statistics and p-values. The sample period is from January 1996 to December 2017.

A. univariate-sorting, Pricing Errors

	$\overline{\text{DP}}$						$\overline{\text{DP}}$				
	1	2	3	4	5		1	2	3	4	5
α^{CAPM}	−2.51	−1.63	2.58	5.20	8.02	$t(\alpha^{\text{CAPM}})$	−1.09	−0.71	1.43	2.37	3.72
α^{FF3}	−2.56	−1.70	2.23	4.87	7.76	$t(\alpha^{\text{FF3}})$	−1.15	−0.74	1.25	2.13	3.32
α^{FFM4}	−2.31	−1.54	1.90	4.52	7.20	$t(\alpha^{\text{FFM4}})$	−1.04	−0.67	1.05	1.98	3.04
α^{FF5}	−2.04	−1.39	1.34	3.71	6.14	$t(\alpha^{\text{FF5}})$	−0.95	−0.61	0.74	1.62	2.64

univariate-sorting, GRS (1989) Test

	CAPM	FF3	FFM4	FF5
GRS	3.914	3.226	2.565	1.798
p-value	0.003	0.011	0.033	0.123

Table 10 Time-series Regression and GRS Test, Cont.

B. double-sorting, Pricing Errors

		$\overline{\text{DP}}$					$\overline{\text{DP}}$				
		1	2	3	4	5	1	2	3	4	5
		α^{CAPM}					$t(\alpha^{\text{CAPM}})$				
	1	−3.05	−2.92	3.39	6.24	11.06	−1.19	−1.16	1.74	2.46	4.08
	2	−5.47	−1.21	3.42	6.29	8.13	−2.05	−0.48	1.74	2.61	3.56
PIH	3	−3.31	−1.35	3.63	4.34	7.67	−1.28	−0.48	1.67	1.73	3.16
	4	−2.80	−0.89	3.04	2.50	7.45	−1.18	−0.34	1.51	1.03	3.08
	5	−2.67	−0.71	2.28	4.94	8.86	−1.02	−0.27	1.17	2.16	3.53
		α^{FF3}					$t(\alpha^{\text{FF3}})$				
	1	−3.23	−3.15	2.81	6.04	10.89	−1.30	−1.28	1.42	2.37	3.80
	2	−5.59	−1.41	3.04	5.94	8.06	−2.09	−0.58	1.57	2.41	3.11
PIH	3	−3.31	−1.52	3.30	4.10	7.74	−1.38	−0.55	1.52	1.59	3.14
	4	−2.95	−1.00	2.76	2.29	7.25	−1.24	−0.39	1.40	0.93	2.81
	5	−2.78	−0.84	2.15	4.75	8.86	−1.08	−0.33	1.09	2.08	3.27
		α^{FFM4}					$t(\alpha^{\text{FFM4}})$				
	1	−2.31	−2.45	2.56	5.49	10.35	−0.96	−0.99	1.29	2.14	3.63
	2	−5.07	−1.06	2.62	5.52	7.55	−1.94	−0.44	1.34	2.23	2.97
PIH	3	−3.01	−1.22	2.95	3.63	7.17	−1.26	−0.44	1.35	1.40	2.89
	4	−2.73	−1.02	2.62	1.90	6.84	−1.15	−0.40	1.32	0.78	2.66
	5	−2.74	−0.88	1.96	4.45	8.36	−1.07	−0.34	1.00	1.89	3.11
		α^{FF5}					$t(\alpha^{\text{FF5}})$				
	1	−2.35	−2.57	1.97	4.73	9.20	−0.98	−1.06	0.98	1.82	3.33
	2	−4.50	−0.94	2.03	4.74	6.20	−1.70	−0.39	1.03	1.92	2.61
PIH	3	−2.85	−1.19	2.46	2.89	5.83	−1.24	−0.44	1.13	1.14	2.37
	4	−2.66	−0.75	1.95	1.19	5.54	−1.16	−0.30	0.97	0.49	2.21
	5	−2.57	−0.90	1.44	3.63	7.02	−1.02	−0.35	0.71	1.65	2.65

double-sorting, GRS (1989) Test

	CAPM	FF3	FFM4	FF5
GRS	2.400	1.847	1.752	1.410
p-value	0.003	0.028	0.041	0.142

Table 11
Robustness Test: Predictability of Option-Implied Dividend

This table reports the estimated coefficients of the time-series regression:

$$\frac{D^i_{q+1} - D^i_q}{S^i_q} = \gamma^i \frac{\mathrm{DI}^i_q - D^i_q}{S^i_q} + \sum_j \eta^i_j l^i_{j,q+1} + \varepsilon^i_{q+1},$$

where D^i_{q+1} is realized dividend of stock i in the next quarter $q+1$ and DI^i_q is the option-implied quarterly dividend estimated before the next dividend announcement date averaged across strike prices, time to maturities and option-pricing dates. S^i_q is stock price at the end of quarter q. $l^i_{j,q+1}$ (j= 1, 2, 3 or 4) are dummy variables which take the value of 1 if quarter $q+1$ is the j^{th} fiscal quarter in a year and take the value of 0 if otherwise. $t(\gamma^i)$ is t-statistics of γ^i and is adjusted for autocorrelation and heteroscedasticity according to Newey and West (1987). $\bar{R}^{2,i}$ is adjusted R^2. Mean, standard deviation (std), first quartile (p25), median (p50) and third quartile (p75) of γ^i, $t(\gamma^i)$ and $\bar{R}^{2,i}$ are reported. The sample period is from January 1996 to December 2017.

	mean	std	p25	p50	075
γ^i	0.457	0.441	0.175	0.423	0.832
$t(\gamma^i)$	4.949	6.099	1.848	3.802	9.650
$\bar{R}^{2,i}$	0.503	0.341	0.174	0.472	0.704

Table 12
Robustness Test: Dividend Payer Sample

This table tabulates results of portfolio analysis for the sample of dividend payers, defined as firms which have ever paid a positive regular cash dividend in the previous five years. Panel A reports time-series mean quarterly portfolio returns, r^p, in percentage, and associated t-statistics in parentheses. For the univariate-sorting analysis, at the end of each quarter q, stocks are sorted into portfolios based on $\overline{\text{DP}}$, the average dividend premium in the last four quarters. Portfolio 1 (5) has the lowest (highest) $\overline{\text{DP}}$. 5−1 is the spread in average returns between Portfolio 5 and 1. For double-sorting analysis, at the end of each quarter q, stocks are first sorted into five portfolios based on PIH, the percentage of institutional holdings, and within each portfolio, stocks are then sorted into five sub-portfolios by $\overline{\text{DP}}$. In the row labeled $\overline{\text{DP}}$, Portfolio 1 (5) has the lowest (highest) $\overline{\text{DP}}$. In each column, the five PIH portfolios are aggregated into one portfolio, and returns on the aggregate portfolios are reported in the last row labeled by ALL. The sample period is from January 1996 to December 2017.

A. Portfolio Realized Returns r^p, univariate-sorting

	$\overline{\text{DP}}$					
	1	2	3	4	5	5−1
	−2.90	−1.05	4.92	8.87	14.03	16.93
	(−1.13)	(−0.47)	(2.55)	(3.60)	(5.04)	(4.58)

Portfolio Realized Returns r^p, double-sorting

		$\overline{\text{DP}}$					
		1	2	3	4	5	5−1
	1	−2.25	−1.00	6.71	9.46	17.74	19.98
		(−0.69)	(−0.37)	(2.17)	(3.15)	(5.25)	(4.05)
	2	−3.21	−0.55	6.30	9.28	14.72	17.93
		(−0.92)	(−0.17)	(2.07)	(3.20)	(4.43)	(3.89)
PIH	3	−2.68	0.13	5.23	8.45	14.49	17.17
		(−0.80)	(0.05)	(1.57)	(2.70)	(4.33)	(4.17)
	4	−1.72	0.00	5.29	8.14	15.30	17.02
		(−0.54)	(0.00)	(1.59)	(2.68)	(4.99)	(4.52)
	5	−0.79	−0.05	5.08	8.04	15.36	16.15
		(−0.28)	(−0.02)	(1.64)	(2.30)	(4.94)	(4.09)
ALL		−2.13	−0.29	5.72	8.67	15.52	17.65
		(−0.99)	(−0.12)	(2.07)	(3.25)	(5.90)	(5.79)

Table 12
Robustness Test: Dividend Payer Sample, Cont.
Panel B reports the time-series means of conditional risk exposures and associated t-statistics of the five portfolios sorted by $\overline{\text{DP}}$ (Panel A) and of the 25 portfolios sorted by PIH and $\overline{\text{DP}}$ (Panel B) of dividend payers. $\bar{\beta}^{p,m}$, $\bar{\beta}^{p,s}$, $\bar{\beta}^{p,h}$, $\bar{\beta}^{p,u}$, $\bar{\beta}^{p,r}$ and $\bar{\beta}^{p,c}$ are time-series averages of risk exposures of portfolio p's return, r^p, with respect to the market risk factor, the size factor (SMB), the value factor (HML), the momentum factor (UMD), the profitability factor (RMW) and the investment factor (CMA), and are estimated from time-series regressions in a rolling window of data. t-statistics of betas are adjusted for autocorrelation and heteroscedasticity.

A. Risk Exposures, univariate-sorting

	$\overline{\text{DP}}$						$\overline{\text{DP}}$				
	1	2	3	4	5		1	2	3	4	5
CAPM: Capital Asset Pricing Model											
$\bar{\beta}^{p,m}$	−0.45	−0.17	0.40	0.93	1.83	$t(\bar{\beta}^{p,m})$	−4.43	−2.21	3.30	6.86	9.49
FF3: Fama and French Three-Factor Model											
$\bar{\beta}^{p,m}$	−0.47	−0.21	0.43	1.02	1.86	$t(\bar{\beta}^{p,m})$	−4.16	−2.25	4.35	6.35	8.42
$\bar{\beta}^{p,s}$	0.57	0.37	0.29	−0.33	−0.69	$t(\bar{\beta}^{p,s})$	4.90	3.10	1.67	−2.03	−4.25
$\bar{\beta}^{p,h}$	−0.47	−0.26	0.41	0.52	0.80	$t(\bar{\beta}^{p,h})$	−5.06	−2.42	3.73	4.06	5.69
FFM4: Carhart Four-Factor Model											
$\bar{\beta}^{p,m}$	−0.46	−0.20	0.47	0.99	1.86	$t(\bar{\beta}^{p,m})$	−4.23	−1.89	3.82	6.47	9.30
$\bar{\beta}^{p,s}$	0.57	0.40	0.24	−0.27	−0.72	$t(\bar{\beta}^{p,s})$	4.35	3.05	1.82	−2.01	−5.09
$\bar{\beta}^{p,h}$	−0.47	−0.17	0.36	0.50	0.75	$t(\bar{\beta}^{p,h})$	−4.95	−1.76	3.70	4.44	5.72
$\bar{\beta}^{p,u}$	−0.26	−0.19	0.33	0.39	0.51	$t(\bar{\beta}^{p,u})$	−2.01	−1.23	2.30	3.20	3.51
FF5: Fama and French Five-Factor Model											
$\bar{\beta}^{p,m}$	−0.47	−0.17	0.46	0.97	1.90	$t(\bar{\beta}^{p,m})$	−3.95	−1.76	3.63	6.07	9.59
$\bar{\beta}^{p,s}$	0.57	0.43	0.23	−0.28	−0.69	$t(\bar{\beta}^{p,s})$	4.68	3.34	1.69	−2.35	−4.73
$\bar{\beta}^{p,h}$	−0.46	−0.21	0.40	0.51	0.78	$t(\bar{\beta}^{p,h})$	−4.15	−2.54	3.89	4.78	5.65
$\bar{\beta}^{p,r}$	−0.35	−0.15	0.45	0.72	0.98	$t(\bar{\beta}^{p,r})$	−2.76	−0.80	3.57	4.12	5.45
$\bar{\beta}^{p,c}$	−0.33	−0.17	0.46	0.66	0.90	$t(\bar{\beta}^{p,c})$	−2.16	−1.13	3.08	3.88	4.63

Table 12 Robustness Test: Dividend Payer Sample, Cont.

B. Risk Exposures, double-sorting

		$\overline{\text{DP}}$					$\overline{\text{DP}}$				
		1	2	3	4	5	1	2	3	4	5
CAPM: Capital Asset Pricing Model											
				$\bar{\beta}^{p,m}$					$t(\bar{\beta}^{p,m})$		
	1	−0.43	−0.35	0.47	0.97	1.83	−4.07	−3.44	3.14	7.07	9.99
	2	−0.63	−0.35	0.47	0.85	1.85	−6.70	−3.55	4.10	7.25	10.08
PIH	3	−0.50	−0.31	0.43	0.88	1.83	−7.85	−3.03	4.11	8.52	9.59
	4	−0.33	−0.18	0.41	0.93	1.97	−2.90	−0.69	3.76	8.91	9.69
	5	−0.15	−0.05	0.45	0.92	1.97	−1.43	−0.48	4.03	8.38	9.62
FF3: Fama and French Three-Factor Model											
				$\bar{\beta}^{p,m}$					$t(\bar{\beta}^{p,m})$		
	1	−0.53	−0.35	0.45	1.01	1.88	−5.32	−2.68	3.16	7.45	9.52
	2	−0.64	−0.38	0.43	0.86	1.79	−5.05	−3.74	3.29	6.91	9.32
PIH	3	−0.49	−0.22	0.50	0.89	1.85	−4.22	−2.62	4.88	6.97	9.42
	4	−0.30	−0.24	0.30	0.88	1.85	−2.56	−2.71	3.75	7.19	9.26
	5	−0.14	−0.07	0.44	0.93	1.91	−1.99	−1.18	5.22	7.19	10.17
				$\bar{\beta}^{p,s}$					$t(\bar{\beta}^{p,s})$		
	1	0.98	0.77	0.40	−0.17	−0.39	5.48	3.78	2.67	−1.00	−2.81
	2	0.73	0.64	0.44	−0.21	−0.59	4.94	3.77	2.37	−1.41	−3.17
PIH	3	0.76	0.43	0.29	−0.25	−0.63	3.67	2.52	2.33	−1.30	−3.37
	4	0.44	0.33	0.21	−0.03	−0.53	3.49	1.82	2.01	−0.18	−4.03
	5	0.29	0.44	0.16	−0.27	−0.76	1.43	2.71	1.11	−1.99	−4.36
				$\bar{\beta}^{p,h}$					$t(\bar{\beta}^{p,h})$		
	1	−0.73	−0.34	0.44	0.66	1.06	−5.04	−1.53	2.05	4.40	5.83
	2	−0.59	−0.24	0.46	0.65	0.79	−4.03	−1.64	2.26	5.27	4.23
PIH	3	−0.44	−0.22	0.32	0.68	0.81	−4.07	−1.10	2.60	4.25	4.94
	4	−0.42	−0.17	0.29	0.66	0.80	−2.50	−1.15	2.60	4.12	4.71
	5	−0.15	−0.13	0.28	0.65	0.76	−1.16	−0.68	1.65	4.41	4.53

Table 12 Robustness Test: Dividend Payer Sample, Cont.

		$\overline{\mathrm{DP}}$					$\overline{\mathrm{DP}}$				
		1	2	3	4	5	1	2	3	4	5
FFM4: Carhart Four-Factor Model											
				$\bar{\beta}^{p,m}$					$t(\bar{\beta}^{p,m})$		
	1	−0.53	−0.39	0.47	1.08	1.86	−4.92	−2.89	4.23	7.65	9.85
	2	−0.64	−0.31	0.45	0.92	1.84	−4.67	−2.99	4.40	7.14	9.26
PIH	3	−0.56	−0.36	0.48	0.90	1.85	−3.61	−3.70	4.20	7.02	9.38
	4	−0.33	−0.22	0.37	0.91	1.94	−2.52	−2.98	4.05	7.97	9.07
	5	−0.17	−0.10	0.44	0.95	1.88	−1.70	−1.32	4.87	7.11	9.82
				$\bar{\beta}^{p,s}$					$t(\bar{\beta}^{p,s})$		
	1	1.08	0.81	0.39	−0.14	−0.47	5.60	3.18	2.74	−0.81	−3.73
	2	0.73	0.66	0.32	−0.23	−0.55	4.27	3.45	2.63	−1.65	−2.99
PIH	3	0.62	0.39	0.29	−0.12	−0.66	3.94	2.46	3.13	−0.68	−3.86
	4	0.46	0.34	0.32	0.06	−0.54	2.61	1.47	2.45	0.49	−3.87
	5	0.38	0.44	0.07	−0.27	−0.79	1.82	2.69	0.66	−2.07	−4.86
				$\bar{\beta}^{p,h}$					$t(\bar{\beta}^{p,h})$		
	1	−0.63	−0.34	0.51	0.73	0.92	−4.46	−1.35	3.08	5.57	6.51
	2	−0.65	−0.21	0.47	0.73	0.90	−4.74	−1.76	3.45	5.51	5.17
PIH	3	−0.46	−0.21	0.32	0.64	0.81	−3.18	−1.68	3.09	3.99	3.75
	4	−0.35	−0.04	0.35	0.68	0.78	−2.82	−0.22	2.82	3.17	3.74
	5	−0.14	−0.17	0.20	0.61	0.68	−1.00	−1.54	0.90	4.79	3.94
				$\bar{\beta}^{p,u}$					$t(\bar{\beta}^{p,u})$		
	1	−0.47	−0.21	0.31	0.33	0.62	−2.12	−1.43	2.45	2.52	4.94
	2	−0.47	−0.20	0.28	0.35	0.63	−2.97	−0.68	2.26	2.76	4.39
PIH	3	−0.39	−0.28	0.25	0.41	0.66	−1.97	−1.45	2.22	2.27	4.81
	4	−0.17	−0.31	0.24	0.44	0.73	−0.69	−2.70	1.40	2.23	4.44
	5	0.04	−0.02	0.35	0.37	0.76	0.16	−0.07	1.52	2.70	5.07

Table 12 Robustness Test: Dividend Payer Sample, Cont.

		$\overline{\text{DP}}$					$\overline{\text{DP}}$				
		1	2	3	4	5	1	2	3	4	5
FF5: Fama and French Five-Factor Model											
				$\bar{\beta}^{p,m}$					$t(\bar{\beta}^{p,m})$		
	1	−0.47	−0.35	0.50	1.04	1.89	−5.12	−2.21	3.70	7.73	9.26
	2	−0.65	−0.30	0.48	0.90	1.91	−5.01	−2.10	4.06	7.40	9.38
PIH	3	−0.43	−0.30	0.44	0.89	1.86	−3.36	−3.31	3.78	7.50	9.47
	4	−0.29	−0.16	0.36	0.90	1.94	−3.08	−1.77	3.02	7.67	9.20
	5	−0.16	−0.04	0.44	0.92	1.90	−2.49	−0.54	3.96	7.17	8.23
				$\bar{\beta}^{p,s}$					$t(\bar{\beta}^{p,s})$		
	1	0.94	0.81	0.40	−0.07	−0.44	4.98	4.00	2.73	−0.39	−2.85
	2	0.76	0.69	0.38	−0.16	−0.57	4.27	3.46	2.88	−0.97	−2.47
PIH	3	0.63	0.45	0.22	−0.21	−0.67	3.71	2.53	2.16	−1.05	−3.52
	4	0.45	0.33	0.26	0.06	−0.48	2.81	1.80	2.40	0.37	−3.40
	5	0.30	0.42	0.19	−0.26	−0.74	1.39	3.11	1.45	−1.55	−4.30
				$\bar{\beta}^{p,h}$					$t(\bar{\beta}^{p,h})$		
	1	−0.69	−0.28	0.52	0.68	0.92	−4.11	−1.45	2.98	4.98	5.71
	2	−0.58	−0.25	0.46	0.67	0.81	−3.85	−1.89	2.80	5.08	4.38
PIH	3	−0.42	−0.21	0.38	0.61	0.80	−2.70	−1.50	3.16	4.06	4.25
	4	−0.34	−0.06	0.36	0.61	0.76	−2.24	−0.39	3.50	4.32	4.62
	5	−0.13	−0.01	0.25	0.60	0.68	−0.62	−0.06	0.70	4.00	4.57
				$\bar{\beta}^{p,r}$					$t(\bar{\beta}^{p,r})$		
	1	−0.55	−0.34	0.53	0.75	0.99	−1.67	−1.22	2.88	4.64	6.01
	2	−0.61	−0.30	0.44	0.65	1.05	−2.57	−1.17	2.42	4.92	6.17
PIH	3	−0.28	−0.13	0.54	0.66	1.00	−1.23	−0.87	2.47	3.84	5.49
	4	−0.14	−0.11	0.48	0.64	0.91	−0.73	−0.65	3.45	3.19	5.96
	5	−0.14	−0.04	0.38	0.59	0.93	−0.50	−0.10	2.58	3.23	5.06
				$\bar{\beta}^{p,c}$					$t(\bar{\beta}^{p,c})$		
	1	−0.42	−0.26	0.59	0.77	1.13	−1.96	−1.38	2.71	3.78	5.74
	2	−0.48	−0.19	0.56	0.65	0.88	−2.48	−1.52	2.62	3.36	4.31
PIH	3	−0.27	−0.21	0.44	0.62	0.90	−1.71	−1.20	2.12	2.96	4.30
	4	−0.20	−0.18	0.32	0.64	0.90	−0.92	−1.13	2.13	3.37	4.33
	5	−0.25	−0.12	0.35	0.55	0.89	−1.10	−0.50	1.92	3.30	4.03

Table 12
Robustness Test: Dividend Payer Sample, Cont.
This table reports the cross-sectional regression results of quarterly excess returns on portfolios of dividend strips of dividend payers, $\tilde{r}^p$, on conditional beta coefficients on risk factors under different asset pricing models, the Capital Asset Pricing Model (CAPM), the Fama and French (1993) three-factor model (FF3), the Carhart (1997) four-factor model and the Fama and French (2015) five-factor model. λ_0 is regression intercept. λ^m, λ^s, λ^h, λ^u, λ^r and λ^c are prices of the market risk factor, the size factor (SMB), the value factor (HML), the momentum factor (UMD), the profitability factor (RMW) and the investment factor (CMA). The table reports time-series average of estimated coefficients, t-statistic adjusted for autocorrelation and heteroscedasticity in parentheses, and mean value of adjusted R^2, $\bar{R}^2$ of regressions.

C. Cross Sectional Regression: Price of Risk

Quintile Portfolios Sorted by $\overline{\text{DP}}$

	λ_0	λ^m	λ^s	λ^h	λ^u	λ^r	λ^c	$\bar{R}^2$
Est.	2.97	3.50						0.512
t-stat	(2.16)	(3.77)						

25 Portfolios Sorted by PIH and $\overline{\text{DP}}$

	λ_0	λ^m	λ^s	λ^h	λ^u	λ^r	λ^c	$\bar{R}^2$
Est.	4.76	3.57						0.286
t-stat	(2.76)	(3.79)						
Est.	3.31	3.69	−0.21	1.83				0.377
t-stat	(2.67)	(3.60)	(−0.36)	(2.28)				
Est.	3.11	3.57	−0.79	1.78	1.04			0.430
t-stat	(2.51)	(4.01)	(−1.24)	(2.31)	(1.22)			
Est.	1.44	3.49	−0.59	1.79		1.94	1.81	0.512
t-stat	(1.76)	(4.36)	(−0.91)	(2.75)		(3.27)	(4.27)	

Table 12
Robustness Test: Dividend Payer Sample, Cont.
Panel D report pricing errors for the CAPM (α^{CAPM}), the FF3 (α^{FF3}), the FFM4 (α^{FFM4}) and the FF5 (α^{FF5}) of the time-series regression of portfolio quarterly excess returns $\tilde{r}^p_{q+1}$ for the sample of dividend payers on quarterly risk factors f_{q+1}:

$$\tilde{r}^p_{q+1} = \alpha^p + \beta^p f_{q+1} + \varepsilon^p_{q+1},$$

where $f_{q+1} = \tilde{r}^m_{q+1}$ (excess return on the S&P 500 index) for the CAPM, $f_{q+1} = [\tilde{r}^m_{q+1}, \text{SMB}_{q+1}, \text{HML}_{q+1}]$ for the FF3, $f_{q+1} = [\tilde{r}^m_{q+1}, \text{SMB}_{q+1}, \text{HML}_{q+1}, \text{UMD}_{q+1}]$ for the FFM4, and $f_{q+1} = [\tilde{r}^m_{q+1}, \text{SMB}_{q+1}, \text{HML}_{q+1}, \text{RMW}_{q+1}, \text{CMA}_{q+1}]$ for the FF5. Panel E reports Gibbons, Ross and Shanken (1989) test statistics and p-values.

D. Pricing Errors of Times Series Regressions

univariate-sorting

	$\overline{\text{DP}}$						$\overline{\text{DP}}$				
	1	2	3	4	5		1	2	3	4	5
α^{CAPM}	−2.54	−1.27	3.58	6.44	9.84	$t(\alpha^{\text{CAPM}})$	−0.97	−0.55	1.82	2.70	4.30
α^{FF3}	−2.53	−1.30	3.05	6.20	9.66	$t(\alpha^{\text{FF3}})$	−1.03	−0.57	1.52	2.58	3.75
α^{FFM4}	−2.25	−1.13	2.71	5.75	9.12	$t(\alpha^{\text{FFM4}})$	−0.93	−0.50	1.34	2.35	3.52
α^{FF5}	−2.01	−1.17	1.97	4.33	7.48	$t(\alpha^{\text{FF5}})$	−0.82	−0.51	0.95	1.74	2.79

double-sorting

		$\overline{\text{DP}}$					$\overline{\text{DP}}$				
		1	2	3	4	5	1	2	3	4	5
		α^{CAPM}					$t(\alpha^{\text{CAPM}})$				
	1	−1.92	−1.08	5.21	6.97	13.56	−0.83	−0.46	2.65	2.94	5.72
	2	−2.73	−1.17	4.77	6.96	10.43	−1.03	−0.46	2.32	3.21	4.69
PIH	3	−2.08	−1.02	3.86	6.12	10.30	−0.81	−0.40	1.94	2.54	4.36
	4	−1.61	−1.16	3.93	5.78	10.84	−0.62	−0.43	2.02	2.43	4.83
	5	−1.01	−0.90	3.61	5.69	11.03	−0.36	−0.37	1.81	2.62	4.84
		α^{FF3}					$t(\alpha^{\text{FF3}})$				
	1	−2.04	−1.27	4.50	6.24	12.62	−0.90	−0.56	2.23	2.66	4.48
	2	−2.79	−1.32	4.12	6.30	10.03	−1.06	−0.54	1.89	2.89	3.72
PIH	3	−2.38	−1.33	3.20	5.78	9.94	−0.96	−0.52	1.57	2.28	4.04
	4	−1.70	−1.19	3.54	5.22	10.48	−0.67	−0.45	1.80	2.18	3.96
	5	−1.08	−1.06	3.39	5.23	10.89	−0.39	−0.45	1.69	2.34	3.89

Table 12
Robustness Test: Dividend Payer Sample, Cont.

		$\overline{\text{DP}}$					$\overline{\text{DP}}$				
		1	2	3	4	5	1	2	3	4	5
		α^{FFM4}					$t(\alpha^{\text{FFM4}})$				
	1	−1.56	−0.91	3.77	5.43	11.80	−0.70	−0.40	1.85	2.30	4.27
	2	−2.20	−1.18	3.70	5.62	8.96	−0.84	−0.48	1.71	2.57	3.36
PIH	3	−1.66	−0.64	2.85	5.02	9.06	−0.67	−0.25	1.39	1.97	3.67
	4	−1.38	−0.87	3.01	4.50	9.52	−0.54	−0.33	1.53	1.87	3.58
	5	−1.24	−0.92	2.83	4.64	9.94	−0.45	−0.39	1.40	2.06	3.57
		α^{FF5}					$t(\alpha^{\text{FF5}})$				
	1	−1.09	−0.72	3.23	4.58	10.61	−0.50	−0.31	1.56	1.89	3.89
	2	−1.75	−0.96	2.99	4.49	7.80	−0.67	−0.40	1.37	1.93	2.87
PIH	3	−1.74	−0.78	2.44	4.36	7.86	−0.70	−0.31	1.17	1.67	3.10
	4	−1.36	−0.97	2.66	3.95	8.61	−0.54	−0.37	1.31	1.59	3.30
	5	−0.68	−1.01	2.68	4.35	9.32	−0.25	−0.43	1.31	1.89	3.36

E. GRS (1989) Test

	univariate-sorting		double-sorting	
	GRS	p-value	GRS	p-value
CAPM	3.924	0.003	3.387	0.000
FF3	3.310	0.009	2.173	0.008
FFM4	2.952	0.017	2.060	0.012
FF5	2.076	0.078	1.589	0.076

Table 13
Robustness Test: Early Exercise Premium

This table tabulates results of portfolio analysis, where the option-implied dividend is adjusted for early exercise premium (EEP). Panel A reports time-series mean EEP-adjusted quarterly portfolio return, r^p, in percentage, and t-statistics in parentheses. For the univariate-sorting analysis, at the end of each quarter q, stocks are sorted into portfolios based on $\overline{\text{DP}}$, the average normalized dividend premium adjusted for EEP in the last four quarters. Portfolio 1 (5) has the lowest (highest) EEP-adjusted $\overline{\text{DP}}$. 5−1 is the spread in returns between Portfolio 5 and 1. For double-sorting analysis, at the end of each quarter q, stocks are first sorted into five portfolios based on PIH, the percentage of institutional holdings, and within each portfolio, stocks are then sorted by EEP-adjusted $\overline{\text{DP}}$. In the row labeled $\overline{\text{DP}}$, Portfolio 1 (5) has the lowest (highest) EEP-adjusted $\overline{\text{DP}}$. In the column labeled PIH, Portfolio 1 (5) has the lowest (highest) PIH. In each column, the five PIH portfolios are aggregated into one portfolio, and reported in the last row labeled by ALL. The sample period is from January 1996 to December 2017.

A. Portfolio Realized Returns r^p, univariate-sorting

$\overline{\text{DP}}$ 1	2	3	4	5	5−1
−2.39	−0.69	4.49	8.21	12.16	14.55
(−0.95)	(−0.32)	(2.40)	(3.42)	(4.53)	(3.53)

Portfolio Realized Returns r^p, double-sorting

		$\overline{\text{DP}}$ 1	2	3	4	5	5−1
	1	−3.79	−1.41	4.51	9.53	15.36	19.15
		(−1.46)	(−0.62)	(2.36)	(3.92)	(5.73)	(4.64)
	2	−4.07	−1.60	4.87	8.68	16.35	20.42
		(−1.61)	(−0.71)	(2.49)	(3.53)	(5.96)	(5.29)
PIH	3	−2.48	−0.41	4.21	8.03	14.86	17.34
		(−0.93)	(−0.16)	(2.18)	(3.73)	(5.78)	(4.84)
	4	−1.02	−0.75	3.92	7.36	12.18	13.20
		(−0.41)	(−0.30)	(2.15)	(3.06)	(4.38)	(3.58)
	5	−1.22	−0.98	3.93	8.17	12.77	13.99
		(−0.45)	(−0.39)	(2.01)	(3.43)	(4.59)	(3.50)
ALL		−2.52	−1.03	4.29	8.35	14.30	16.82
		(−1.95)	(−0.55)	(3.15)	(4.91)	(6.60)	(4.25)

Table 13
Robustness Test: Early Exercise Premium, Cont.
Panel B reports the time-series means of conditional risk exposures and associated t-statistics of the five portfolios sorted by EEP-adjusted $\overline{\mathrm{DP}}$ (Panel A) and of the 25 portfolios sorted by PIH and EEP-adjusted $\overline{\mathrm{DP}}$ (Panel B). $\bar{\beta}^{p,m}$, $\bar{\beta}^{p,s}$, $\bar{\beta}^{p,h}$, $\bar{\beta}^{p,u}$, $\bar{\beta}^{p,r}$ and $\bar{\beta}^{p,c}$ are time-series averages of risk exposures of portfolio p's EEP-adjusted return with respect to the market risk factor, the size factor (SMB), the value factor (HML), the momentum factor (UMD), the profitability factor (RMW) and the investment factor (CMA), and are estimated from time-series regressions in a rolling window of data. t-statistics of betas are adjusted for autocorrelation and heteroscedasticity.

A. Risk Exposures, univariate-sorting

	$\overline{\mathrm{DP}}$						$\overline{\mathrm{DP}}$				
	1	2	3	4	5		1	2	3	4	5
CAPM: Capital Asset Pricing Model											
$\bar{\beta}^{p,m}$	−0.32	−0.06	0.31	0.89	1.64	$t(\bar{\beta}^{p,m})$	−3.78	−0.97	3.06	6.40	8.82
FF3: Fama and French Three-Factor Model											
$\bar{\beta}^{p,m}$	−0.32	−0.11	0.33	0.86	1.63	$t(\bar{\beta}^{p,m})$	−3.08	−1.73	2.67	5.92	9.74
$\bar{\beta}^{p,s}$	0.61	0.41	0.24	−0.25	−0.66	$t(\bar{\beta}^{p,s})$	3.85	2.93	1.42	−2.07	−5.09
$\bar{\beta}^{p,h}$	−0.47	−0.18	0.38	0.52	0.84	$t(\bar{\beta}^{p,h})$	−4.22	−1.97	2.78	3.64	5.40
FFM4: Carhart Four-Factor Model											
$\bar{\beta}^{p,m}$	−0.33	−0.09	0.36	0.89	1.59	$t(\bar{\beta}^{p,m})$	−3.58	−1.44	3.02	7.04	9.35
$\bar{\beta}^{p,s}$	0.56	0.42	0.26	−0.30	−0.68	$t(\bar{\beta}^{p,s})$	4.31	3.13	1.87	−2.05	−5.37
$\bar{\beta}^{p,h}$	−0.47	−0.26	0.39	0.63	0.79	$t(\bar{\beta}^{p,h})$	−4.11	−2.61	3.60	4.16	5.36
$\bar{\beta}^{p,u}$	−0.30	−0.18	0.30	0.40	0.58	$t(\bar{\beta}^{p,u})$	−3.34	−1.41	2.06	2.62	4.28
FF5: Fama and French Five-Factor Model											
$\bar{\beta}^{p,m}$	−0.30	−0.10	0.32	0.88	1.61	$t(\bar{\beta}^{p,m})$	−3.36	−2.23	2.75	5.28	8.92
$\bar{\beta}^{p,s}$	0.56	0.40	0.24	−0.28	−0.65	$t(\bar{\beta}^{p,s})$	3.97	2.18	2.00	−2.46	−4.63
$\bar{\beta}^{p,h}$	−0.47	−0.18	0.41	0.56	0.83	$t(\bar{\beta}^{p,h})$	−3.19	−2.35	2.85	3.14	5.23
$\bar{\beta}^{p,r}$	−0.25	−0.15	0.44	0.73	0.93	$t(\bar{\beta}^{p,r})$	−1.85	−1.51	3.60	4.77	5.16
$\bar{\beta}^{p,c}$	−0.33	−0.16	0.44	0.69	0.89	$t(\bar{\beta}^{p,c})$	−1.84	−1.33	3.08	3.18	3.80

Table 13 Robustness Test: Early Exercise Premium, Cont.

B. Risk Exposures, double-sorting

		$\overline{\text{DP}}$					$\overline{\text{DP}}$				
		1	2	3	4	5	1	2	3	4	5
CAPM: Capital Asset Pricing Model											
				$\bar{\beta}^{p,m}$					$t(\bar{\beta}^{p,m})$		
	1	−0.41	−0.27	0.27	0.84	1.65	−4.17	−2.33	2.44	5.98	9.74
	2	−0.59	−0.45	0.29	0.91	1.54	−6.20	−3.68	2.54	6.40	8.63
PIH	3	−0.16	−0.14	0.29	0.74	1.32	−2.03	−0.86	2.55	6.06	8.14
	4	−0.24	−0.19	0.26	0.84	1.45	−2.01	−1.09	2.28	5.78	7.49
	5	−0.14	−0.08	0.18	0.84	1.46	−1.76	−1.31	1.81	6.54	8.16
FF3: Fama and French Three-Factor Model											
				$\bar{\beta}^{p,m}$					$t(\bar{\beta}^{p,m})$		
	1	−0.43	−0.27	0.27	0.85	1.65	−3.80	−3.21	2.81	5.66	9.16
	2	−0.60	−0.45	0.37	0.90	1.61	−5.04	−3.01	3.49	6.29	9.02
PIH	3	−0.16	−0.17	0.34	0.82	1.44	−1.94	−1.23	2.40	6.89	8.44
	4	−0.24	−0.09	0.30	0.81	1.42	−2.34	−1.01	2.32	5.89	8.40
	5	−0.25	−0.04	0.25	0.77	1.44	−2.01	−0.47	3.44	6.05	8.04
				$\bar{\beta}^{p,s}$					$t(\bar{\beta}^{p,s})$		
	1	0.89	0.74	0.35	−0.11	−0.61	5.58	4.01	2.68	−0.57	−3.66
	2	0.79	0.66	0.35	−0.14	−0.70	5.00	3.93	2.44	−1.31	−3.49
PIH	3	0.55	0.45	0.32	−0.17	−0.83	4.28	2.86	2.39	−1.10	−5.23
	4	0.47	0.37	0.22	−0.26	−0.46	3.50	2.56	2.03	−2.19	−3.65
	5	0.34	0.37	0.10	−0.24	−0.76	2.55	2.98	0.96	−1.46	−4.83
				$\bar{\beta}^{p,h}$					$t(\bar{\beta}^{p,h})$		
	1	-0.64	-0.26	0.52	0.68	0.95	-4.40	-2.23	3.73	4.20	5.43
	2	-0.55	-0.24	0.46	0.68	0.95	-3.72	-2.32	2.82	3.38	4.78
PIH	3	-0.32	-0.07	0.40	0.61	0.80	-3.05	-0.63	2.39	3.69	4.28
	4	-0.12	-0.04	0.37	0.57	0.79	-1.05	-0.27	2.82	3.44	4.56
	5	-0.10	-0.12	0.33	0.67	0.77	-0.64	-1.15	3.14	3.83	4.45

Table 13 Robustness Test: Early Exercise Premium, Cont.

		$\overline{\text{DP}}$					$\overline{\text{DP}}$				
		1	2	3	4	5	1	2	3	4	5
FFM4: Carhart Four-Factor Model											
				$\bar{\beta}^{p,m}$					$t(\bar{\beta}^{p,m})$		
	1	−0.48	−0.28	0.35	0.78	1.61	−4.08	−3.22	3.25	5.80	9.63
	2	−0.67	−0.41	0.37	0.92	1.58	−5.85	−3.62	3.39	6.43	9.48
PIH	3	−0.15	−0.09	0.25	0.81	1.38	−1.41	−0.68	2.82	6.41	8.71
	4	−0.28	−0.16	0.27	0.81	1.44	−3.02	−1.89	3.10	7.08	7.94
	5	−0.21	−0.09	0.21	0.84	1.42	−1.25	−0.90	2.70	7.75	8.59
				$\bar{\beta}^{p,s}$					$t(\bar{\beta}^{p,s})$		
	1	0.86	0.71	0.38	−0.10	−0.58	4.47	4.21	3.04	−0.51	−3.32
	2	0.83	0.65	0.39	−0.20	−0.65	5.23	3.99	2.74	−1.93	−3.28
PIH	3	0.59	0.47	0.33	−0.03	−0.76	3.95	2.74	2.52	−0.16	−4.58
	4	0.47	0.33	0.26	−0.34	−0.50	2.97	1.98	2.32	−3.01	−3.96
	5	0.39	0.42	0.08	−0.32	−0.77	2.44	2.96	0.68	−1.74	−4.11
				$\bar{\beta}^{p,h}$					$t(\bar{\beta}^{p,h})$		
	1	−0.62	−0.26	0.45	0.65	0.94	−3.32	−2.10	2.66	4.42	5.35
	2	−0.56	−0.26	0.52	0.71	0.93	−3.13	−2.04	3.77	4.03	5.32
PIH	3	−0.37	−0.12	0.35	0.51	0.84	−3.13	−1.05	3.06	3.75	4.45
	4	−0.19	−0.02	0.38	0.57	0.77	−1.40	−0.09	2.49	2.87	5.41
	5	−0.03	−0.10	0.31	0.65	0.75	−0.17	−0.87	2.92	2.50	3.39
				$\bar{\beta}^{p,u}$					$t(\bar{\beta}^{p,u})$		
	1	−0.75	−0.50	0.27	0.46	0.59	−2.53	−2.47	2.01	3.11	4.15
	2	−0.54	−0.25	0.29	0.44	0.60	−2.04	−1.90	2.24	2.03	3.89
PIH	3	−0.35	−0.32	0.25	0.34	0.44	−2.50	−2.53	2.91	2.96	2.81
	4	−0.16	−0.12	0.17	0.34	0.44	−1.17	−0.41	2.78	2.78	3.63
	5	−0.13	−0.09	0.09	0.36	0.58	−0.65	−0.86	0.56	2.78	4.73

Table 13 Robustness Test: Early Exercise Premium, Cont.

		$\overline{\text{DP}}$					$\overline{\text{DP}}$				
		1	2	3	4	5	1	2	3	4	5
FF5: Fama and French Five-Factor Model											
				$\bar{\beta}^{p,m}$					$t(\bar{\beta}^{p,m})$		
	1	−0.42	−0.24	0.31	0.88	1.67	−3.33	−2.83	2.37	5.72	9.19
	2	−0.62	−0.40	0.37	0.92	1.63	−4.98	−3.48	3.62	5.93	9.47
PIH	3	−0.12	−0.12	0.26	0.74	1.43	−0.88	−0.85	2.50	5.14	8.41
	4	−0.24	−0.16	0.28	0.86	1.48	−2.13	−1.49	2.04	5.96	8.29
	5	−0.19	−0.13	0.19	0.83	1.44	−1.40	−1.35	2.20	5.57	8.44
				$\bar{\beta}^{p,s}$					$t(\bar{\beta}^{p,s})$		
	1	0.87	0.72	0.38	−0.04	−0.57	5.06	4.26	2.61	−0.17	−2.79
	2	0.77	0.65	0.34	−0.16	−0.67	4.82	4.29	2.05	−1.02	−3.34
PIH	3	0.57	0.46	0.27	−0.08	−0.78	3.71	2.88	2.02	−0.56	−4.72
	4	0.48	0.36	0.22	−0.36	−0.48	3.59	2.06	1.99	−2.56	−3.30
	5	0.34	0.38	0.09	−0.25	−0.81	2.03	2.49	0.35	−1.49	−4.03
				$\bar{\beta}^{p,h}$					$t(\bar{\beta}^{p,h})$		
	1	−0.56	−0.27	0.48	0.68	0.95	−3.13	−2.35	3.10	3.91	5.50
	2	−0.56	−0.26	0.50	0.67	0.92	−3.03	−2.17	3.42	3.81	4.82
PIH	3	−0.34	−0.10	0.39	0.57	0.83	−2.01	−0.69	3.39	4.13	3.97
	4	−0.18	−0.08	0.38	0.57	0.81	−1.10	−0.36	2.54	3.03	4.26
	5	−0.06	−0.07	0.34	0.58	0.79	−0.40	−0.56	2.70	2.43	3.27
				$\bar{\beta}^{p,r}$					$t(\bar{\beta}^{p,r})$		
	1	−0.54	−0.19	0.45	0.77	1.03	−2.11	−0.97	2.83	3.38	5.55
	2	−0.66	−0.24	0.44	0.75	1.09	−3.47	−1.46	2.73	3.35	4.72
PIH	3	−0.28	−0.11	0.49	0.72	0.95	−1.20	−0.52	3.04	3.37	4.19
	4	−0.23	−0.04	0.43	0.63	0.90	−0.95	−0.15	2.40	3.20	4.01
	5	−0.11	−0.03	0.39	0.60	0.96	−0.38	−0.15	2.65	3.26	4.51
				$\bar{\beta}^{p,c}$					$t(\bar{\beta}^{p,c})$		
	1	−0.40	−0.20	0.47	0.75	1.14	−1.79	−1.42	2.66	3.19	5.22
	2	−0.52	−0.19	0.54	0.71	1.10	−2.80	−1.29	3.02	2.73	5.16
PIH	3	−0.31	−0.17	0.36	0.70	1.09	−1.22	−1.51	2.53	3.03	4.38
	4	−0.21	0.05	0.47	0.62	0.93	−1.18	0.15	3.11	3.30	3.91
	5	−0.14	0.06	0.36	0.63	0.96	−0.95	0.44	2.97	2.70	4.02

Table 13
Robustness Test: Early Exercise Premium, Cont.

This table reports the cross-sectional regression results of EEP-adjusted quarterly excess returns of portfolios of dividend strips, $\tilde{r}^p$, on conditional beta coefficients on risk factors under different asset pricing models, the Capital Asset Pricing Model (CAPM), the Fama and French (1993) three-factor model (FF3), the Carhart (1997) four-factor model and the Fama and French (2015) five-factor model. λ_0 is regression intercept. λ^m, λ^s, λ^h, λ^u, λ^r and λ^c are prices of the market risk factor, the size factor (SMB), the value factor (HML), the momentum factor (UMD), the profitability factor (RMW) and the investment factor (CMA). The table reports time-series average of estimated risk premiums, t-statistic adjusted for autocorrelation and heteroscedasticity in parentheses, and mean value of adjusted R^2, $\bar{R}^2$ of regressions.

C. Cross Sectional Regression: Price of Risk

Quintile Portfolios Sorted by $\overline{\text{DP}}$

	λ_0	λ^m	λ^s	λ^h	λ^u	λ^r	λ^c	$\bar{R}^2$
Est.	3.36	3.69						0.479
t-stat	(2.00)	(2.04)						

25 Portfolios Sorted by PIH and $\overline{\text{DP}}$

	λ_0	λ^m	λ^s	λ^h	λ^u	λ^r	λ^c	$\bar{R}^2$
Est.	3.59	3.71						0.337
t-stat	(3.11)	(4.00)						
Est.	2.10	3.22	−0.65	1.99				0.427
t-stat	(1.62)	(2.71)	(−0.92)	(2.69)				
Est.	1.79	3.47	−0.51	1.78	1.61			0.492
t-stat	(1.57)	(2.90)	(−0.76)	(2.52)	(1.42)			
Est.	0.28	3.56	−0.85	1.89		1.74	1.73	0.585
t-stat	(0.21)	(2.96)	(−1.20)	(2.37)		(2.19)	(3.45)	

Table 13
Robustness Test: Early Exercise Premium, Cont.

Panel D reports pricing errors for the CAPM (α^{CAPM}), the FF3 (α^{FF3}), the FFM4 (α^{FFM4}) and the FF5 (α^{FF5}) of the time-series regression of portfolio quarterly excess returns $\tilde{r}^p_{q+1}$ which are adjusted for EEP on quarterly risk factors f_{q+1}:

$$\tilde{r}^p_{q+1} = \alpha^p + \beta^p f_{q+1} + \varepsilon^p_{q+1},$$

where $f_{q+1} = \tilde{r}^m_{q+1}$ (excess return on the S&P 500 index) for the CAPM, $f_{q+1} = [\tilde{r}^m_{q+1}, \text{SMB}_{q+1}, \text{HML}_{q+1}]$ for the FF3, $f_{q+1} = [\tilde{r}^m_{q+1}, \text{SMB}_{q+1}, \text{HML}_{q+1}, \text{UMD}_{q+1}]$ for the FFM4, and $f_{q+1} = [\tilde{r}^m_{q+1}, \text{SMB}_{q+1}, \text{HML}_{q+1}, \text{RMW}_{q+1}, \text{CMA}_{q+1}]$ for the FF5. Panel E reports Gibbons, Ross and Shanken (1989) test statistics and p-values.

D. Pricing Errors of Times Series Regressions

univariate-sorting

	$\overline{\text{DP}}$						$\overline{\text{DP}}$				
	1	2	3	4	5		1	2	3	4	5
α^{CAPM}	−2.30	−1.03	3.37	5.90	8.38	$t(\alpha^{\text{CAPM}})$	−0.90	−0.47	1.77	2.55	3.84
α^{FF3}	−2.31	−1.14	2.89	5.76	8.20	$t(\alpha^{\text{FF3}})$	−0.92	−0.54	1.48	2.33	3.24
α^{FFM4}	−1.91	−0.98	2.52	5.24	7.62	$t(\alpha^{\text{FFM4}})$	−0.76	−0.47	1.29	2.11	3.05
α^{FF5}	−1.80	−0.94	2.13	4.43	6.55	$t(\alpha^{\text{FF5}})$	−0.71	−0.45	1.11	1.83	2.52

double-sorting

		$\overline{\text{DP}}$					$\overline{\text{DP}}$				
		1	2	3	4	5	1	2	3	4	5
		α^{CAPM}					$t(\alpha^{\text{CAPM}})$				
	1	−3.50	−1.41	3.43	7.26	11.50	−1.36	−0.61	1.77	3.10	5.10
	2	−3.37	−1.25	3.72	6.33	12.75	−1.34	−0.55	1.88	2.69	5.32
PIH	3	−2.80	−0.68	3.10	6.08	11.68	−1.03	−0.26	1.58	2.90	5.04
	4	−1.13	−0.93	2.82	5.11	8.74	−0.45	−0.36	1.53	2.22	3.51
	5	−1.42	−1.41	3.00	6.00	9.42	−0.51	−0.55	1.51	2.61	3.73
		α^{FF3}					$t(\alpha^{\text{FF3}})$				
	1	−3.53	−1.59	2.89	6.83	11.26	−1.38	−0.71	1.45	2.98	4.49
	2	−3.40	−1.42	3.07	6.02	12.44	−1.42	−0.63	1.49	2.66	4.99
PIH	3	−2.79	−0.85	2.67	5.55	11.52	−1.04	−0.33	1.32	2.41	5.12
	4	−1.25	−1.25	2.48	5.02	8.48	−0.50	−0.49	1.38	2.25	3.82
	5	−1.53	−1.61	2.70	5.83	9.34	−0.55	−0.63	1.35	2.49	3.68

Table 13
Robustness Test: Early Exercise Premium, Cont.

		$\overline{\text{DP}}$					$\overline{\text{DP}}$				
		1	2	3	4	5	1	2	3	4	5
		α^{FFM4}					$t(\alpha^{\text{FFM4}})$				
	1	−2.66	−1.13	2.48	6.59	10.66	−1.01	−0.50	1.24	2.79	4.16
	2	−2.73	−1.20	2.66	5.41	11.73	−1.09	−0.55	1.28	2.34	4.51
PIH	3	−2.40	−0.57	2.45	5.14	10.95	−0.91	−0.22	1.20	2.23	4.69
	4	−0.95	−0.93	2.25	4.71	7.97	−0.38	−0.36	1.24	2.10	3.43
	5	−1.43	−1.46	2.73	5.33	8.70	−0.52	−0.57	1.37	2.25	3.37
		α^{FF5}					$t(\alpha^{\text{FF5}})$				
	1	−2.70	−1.29	2.02	5.50	9.23	−1.06	−0.58	0.95	2.25	3.66
	2	−2.26	−1.06	2.29	4.62	10.41	−0.93	−0.48	1.08	1.97	3.93
PIH	3	−2.33	−0.66	1.93	4.36	9.64	−0.88	−0.25	0.94	1.88	4.16
	4	−0.82	−1.06	1.59	3.87	6.79	−0.33	−0.42	0.85	1.63	2.75
	5	−1.32	−1.50	2.08	4.62	7.59	−0.48	−0.58	1.02	1.88	2.80

E. GRS (1989) Test

	univariate-sorting		double-sorting	
	GRS	p-value	GRS	p-value
CAPM	3.938	0.003	2.579	0.001
FF3	3.426	0.008	2.468	0.002
FFM4	2.685	0.027	1.798	0.034
FF5	1.838	0.115	1.506	0.102

Table 14
Robustness Test: Alternative Approach to Estimate EEP

This table tabulates results of the Longstaff and Schwartz (2001) least-square Monte Carlo simulation approach under the stochastic volatility model of Heston (1993) (HSV) using average option-implied dividend as a measure of expected dividend to estimate EEP of American options. This new approach is an alternative to the simple approach to estimate EEP under the Black and Scholes (1973) (BS) closed-form option-pricing formula using historical dividends as inputs. Panel A reports summary statistics of parameters of the Heston (1993) model across individual stocks. The parameters are estimated by calibrating the HSV model to quoted prices of paired call and put options used to replicate synthetic individual dividend strips. κ is the rate of mean reversion. θ is the long-run variance of stock. ξ is the volatility of variance. $\rho^{S,V}$ is the correlation between stock price and variance. V is the instantaneous variance. $\overline{V}$ and $\sigma(V)$ are time-series mean and standard deviations of instantaneous variance. Panel B reports summary statistics (in percentage) of pricing errors of the Heston (1993) model relative to mid quoted options prices of calls and puts (e^C and e^P) and their absolute values ($|e^C|$ and $|e^P|$). Panel C reports summary statistics (in percentage) of EEP of calls and puts under the BS model as a percentage of mid call and put options prices, $\text{EEP}^{\text{BS}}(C)$ and $\text{EEP}^{\text{BS}}(P)$, and under the HSV model, $\text{EEP}^{\text{HSV}}(C)$ and $\text{EEP}^{\text{HSV}}(P)$, and differences in EEP of puts and calls under the two models as a percentage of average mid prices of calls and puts, $\text{EEP}^{\text{BS}}(P-C)$ and $\text{EEP}^{\text{HSV}}(P-C)$. $\text{EEP}^{\text{HSV}-\text{BS}}(C)$, $\text{EEP}^{\text{HSV}-\text{BS}}(P)$ and $\text{EEP}^{\text{HSV}-\text{BS}}(P-C)$ are differences in EEP of calls under the two models as a percentage of mid call prices, differences in EEP of puts under the two models as percentage of mid put prices, and differences in differences of puts and calls under the two models as a percentage of average mid prices of puts and calls. Mean, standard deviation (std) , first quartile (p25), median (p50) and third quartile (p75) are reported. Panel D tabulates beta coefficients and associated t-statistics of full-sample pooled regressions of parameters of the Heston (1993) model, the risk-free rate (r^f), options time-to-maturity (τ), moneyness ratio (K/S) and average option-implied dividend normalzied by stock prcie (DI/S) on (percentage) $\text{EEP}^{\text{HSV}-\text{BS}}(C)$, $\text{EEP}^{\text{HSV}-\text{BS}}(P)$ and $\text{EEP}^{\text{HSV}-\text{BS}}(P-C)$. Panel E reports time-series mean values of $\text{EEP}^{\text{HSV}-\text{BS}}(P-C)$ of quintile portfolios of underlying stocks sorted by stock price normalized option-implied dividend (DI/S), historical average normalized dividend risk premium ($\overline{\text{DP}}$) and percentage of institutional holding (PIH). Portfolio 5 (1) has the highest (lowest) value of a sorting variable. The sample period is from January 1996 to December 2017.

A. Summary Statistics of Parameters of the Heston (1993) Model

	mean	std	p25	p50	p75
κ	8.05	6.00	3.20	6.55	14.03
θ	0.23	0.20	0.11	0.19	0.29
ξ	0.40	0.25	0.19	0.40	0.56
$\rho^{S,V}$	-0.11	0.48	-0.34	-0.06	0.23
$\overline{V}$	0.35	0.25	0.16	0.26	0.41
$\sigma(V)$	0.45	0.31	0.11	0.23	0.55

Table 14
Robustness Test: Alternative Approach to Estimate EEP, Cont.

B. Pricing Errors of the Heston (1993) Model

	mean	std	p25	p50	p75
e^C	0.17	0.72	−0.27	0.11	0.54
$\lvert e^C \rvert$	0.60	0.49	0.29	0.47	0.77
e^P	0.14	0.65	−0.25	0.06	0.45
$\lvert e^P \rvert$	0.52	0.46	0.24	0.44	0.67

C. Summary Statistics of EEP estimated under the Black and Scholes (1973) Model and the Heston (1993) Model

	mean	std	p25	p50	p75
$\mathrm{EEP}^{\mathrm{BS}}(C)$	0.65	1.63	0.10	0.31	0.68
$\mathrm{EEP}^{\mathrm{BS}}(P)$	0.83	1.75	0.26	0.46	0.92
$\mathrm{EEP}^{\mathrm{BS}}(P-C)$	0.18	1.69	−0.14	0.39	0.86
$\mathrm{EEP}^{\mathrm{HSV}}(C)$	0.72	1.58	0.01	0.40	0.95
$\mathrm{EEP}^{\mathrm{HSV}}(P)$	0.89	0.69	0.41	0.79	1.28
$\mathrm{EEP}^{\mathrm{HSV}}(P-C)$	0.17	1.81	−0.30	0.35	1.02
$\mathrm{EEP}^{\mathrm{HSV-BS}}(C)$	0.07	1.37	−0.31	0.20	0.63
$\mathrm{EEP}^{\mathrm{HSV-BS}}(P)$	0.05	1.73	−0.22	0.26	0.67
$\mathrm{EEP}^{\mathrm{HSV-BS}}(P-C)$	−0.01	1.51	−0.57	0.03	0.67

Table 14
Robustness Test: Alternative Approach to Estimate EEP, Cont.

D. Differences in EEPs under the Black and Scholes (1973) Model and the Heston (1993) Model: Pooled Regression

	$\text{EEP}^{\text{HSV}-\text{BS}}(C)$		$\text{EEP}^{\text{HSV}-\text{BS}}(P)$		$\text{EEP}^{\text{HSV}-\text{BS}}(P-C)$	
	β	t-stat	β	t-stat	β	t-stat
κ	−0.0009	(−1.53)	−0.0018	(−2.54)	−0.0003	(−0.54)
ξ	−0.0041	(−0.30)	−0.0621	(−3.59)	−0.0362	(−2.37)
θ	0.1948	(13.51)	0.1680	(8.40)	−0.1055	(−5.87)
V	0.0841	(7.58)	0.0220	(1.58)	−0.0906	(−7.41)
$\rho^{S,V}$	−0.0164	(−2.46)	−0.0154	(−1.85)	0.0075	(1.02)
r^f	−1.7079	(−12.67)	−1.4461	(−8.58)	0.1791	(1.20)
τ	0.0006	(8.70)	−0.0006	(−8.07)	−0.0011	(−15.78)
K/S	−0.0231	(−3.44)	0.0268	(2.63)	0.0587	(7.87)
DI/S	1.5787	(2.20)	1.0840	(1.09)	−0.0318	(−0.04)

E. Sorting Portfolio Analysis: Differences in Differences of EEP of Puts and Calls under the Black and Scholes (1973) Model and the Heston (1993) Model

	$\text{EEP}^{\text{HSV}-\text{BS}}(P-C)$				
	1	2	3	4	5
DI/S	−0.0076	−0.0075	−0.0072	−0.0070	−0.0077
$\overline{\text{DP}}$	−0.0077	−0.0067	−0.0087	−0.0059	−0.0081
PIH	−0.0079	−0.0080	−0.0077	−0.0062	−0.0075

Table 15
Portfolios Sorted by Firm Characteristics: Realized Returns

Panel A reports time-series average returns on portfolios of dividend strips, r^p, in quarterly percentage terms, of the five portfolios of dividend strips sorted by underlying stocks' book-to-market ratio (BM), operating profitability (OP), total asset growth rate (ATG) or cumulative stock returns in the previous six months (RET(−1,−6)). At the end of each quarter q, stocks are sorted into portfolios by quintile breakpoints of a firm characteristic among all listed stocks. Portfolio 1 (5) has the lowest (highest) value of a firm characteristic. Panel B reports time-series average returns on the portfolios of dividend strips, r^p, in quarterly percentage terms, of the 25 portfolios sorted by PIH and firm characteristics. At the end of each quarter q, stocks are first sorted into five portfolios based on the percentage of institutional holding, PIH, and within each portfolio, stocks are then sorted into five sub-portfolios by quintile breakpoints of a firm characteristics. In the rows labels with a firm characteristic, Portfolio 1 (5) has the lowest (highest) value of the firm characteristic. In the column labeled PIH, Portfolio 1 (5) has the lowest (highest) PIH. In each column, the five PIH portfolios are aggregated into one portfolio, and returns on the aggregate portfolios are reported in the last row labeled by ALL. Column labeled 5-1 represents spread in returns between Portfolio 5 and 1. The sample period is from January 1996 to December 2017.

A. Portfolio Realized Returns r^p, univariate-sorting

		BM			
1	2	3	4	5	5−1
−1.64	−0.78	3.94	6.57	8.17	9.81
(−0.71)	(−0.38)	(2.16)	(2.90)	(3.45)	(4.56)
		OP			
1	2	3	4	5	5−1
−2.32	−1.12	4.12	7.18	9.81	12.13
(−1.02)	(−0.47)	(2.06)	(3.00)	(3.78)	(3.17)
		ATG			
1	2	3	4	5	5−1
9.52	6.82	4.32	−1.22	−2.21	−11.73
(3.72)	(2.92)	(2.22)	(−0.53)	(−0.93)	(−4.27)
		RET(−1,−6)			
1	2	3	4	5	5−1
−1.73	−1.02	4.31	6.18	8.41	10.14
(−0.80)	(−0.50)	(2.22)	(3.01)	(3.73)	(3.38)

Table 15
Portfolios Sorted by Firm Characteristics: Realized Returns, Cont.

B. Portfolio Realized Returns r^p, double-sorting

		BM					
		1	2	3	4	5	5−1
	1	−2.14	−1.34	4.15	6.73	8.65	10.79
		(−0.93)	(−0.61)	(2.00)	(2.94)	(3.46)	(3.48)
	2	−2.46	−1.06	4.10	6.62	8.25	10.71
		(−1.00)	(−0.45)	(2.01)	(2.88)	(3.33)	(4.18)
PIH	3	−1.65	−0.75	3.95	6.58	8.27	9.92
		(−0.67)	(−0.33)	(1.94)	(2.77)	(3.22)	(4.50)
	4	−1.35	−0.35	3.92	6.29	7.95	9.30
		(−0.55)	(−0.15)	(1.92)	(2.93)	(3.23)	(4.15)
	5	−1.23	0.56	3.87	6.30	8.02	9.25
		(−0.53)	(0.26)	(1.92)	(2.62)	(3.02)	(3.05)
ALL		−1.77	−0.59	4.00	6.50	8.23	9.99
		(−1.00)	(−0.31)	(2.38)	(3.22)	(3.90)	(6.12)

		OP					
		1	2	3	4	5	5−1
	1	−3.36	−1.43	4.32	8.21	9.92	13.28
		(−1.49)	(−0.66)	(2.13)	(3.59)	(3.97)	(3.87)
	2	−2.27	−1.54	4.27	8.02	10.21	12.48
		(−0.98)	(−0.63)	(2.08)	(3.72)	(3.95)	(3.34)
PIH	3	−1.59	−1.17	4.15	7.26	9.83	11.42
		(−0.70)	(−0.53)	(2.05)	(2.99)	(3.76)	(4.61)
	4	−1.21	−0.92	3.96	7.17	9.26	10.47
		(−0.53)	(−0.43)	(1.95)	(3.20)	(3.81)	(4.66)
	5	−1.32	−1.25	3.87	6.87	9.34	10.66
		(−0.58)	(−0.55)	(1.95)	(2.99)	(3.60)	(3.52)
ALL		−1.95	−1.26	4.11	7.51	9.71	11.66
		(−1.45)	(−0.73)	(2.23)	(3.86)	(4.50)	(5.52)

Table 15
Portfolios Sorted by Firm Characteristics: Realized Returns, Cont.

B. Portfolio Realized Returns r^p, double-sorting

		ATG					
		1	2	3	4	5	5−1
	1	9.95	7.03	4.85	−1.33	−3.21	−13.16
		(3.86)	(2.97)	(2.35)	(−0.59)	(−1.36)	(−4.10)
	2	9.72	6.92	4.72	−1.26	−3.54	−13.26
		(3.77)	(2.89)	(2.30)	(−0.51)	(−1.37)	(−6.74)
PIH	3	9.53	6.80	4.29	1.12	2.23	−7.30
		(3.67)	(2.86)	(2.08)	(0.47)	(0.86)	(−2.55)
	4	9.24	6.72	4.12	−0.96	−1.32	−10.56
		(3.72)	(2.77)	(1.95)	(−0.43)	(−0.57)	(−4.40)
	5	8.95	6.32	3.92	−0.82	−0.92	−9.87
		(3.69)	(2.78)	(1.92)	(−0.38)	(−0.41)	(−3.29)
ALL		9.48	6.76	4.38	−0.65	−1.35	−10.83
		(4.72)	(3.33)	(2.51)	(−0.34)	(−0.83)	(−7.09)

		RET(−1,−6)					
		1	2	3	4	5	5−1
	1	−2.21	−1.32	4.61	6.20	8.51	10.72
		(−1.03)	(−0.61)	(2.39)	(2.86)	(3.71)	(3.38)
	2	−2.03	−1.22	4.51	6.22	8.94	10.97
		(−0.93)	(−0.56)	(2.31)	(2.85)	(3.83)	(3.21)
PIH	3	−1.72	−1.02	4.32	6.17	8.41	10.13
		(−0.76)	(−0.50)	(2.24)	(2.85)	(3.74)	(3.93)
	4	−1.24	−0.94	4.21	5.93	8.21	9.45
		(−0.60)	(−0.48)	(2.19)	(2.91)	(3.65)	(4.60)
	5	−1.19	−0.93	4.23	6.21	8.05	9.24
		(−0.58)	(−0.43)	(2.19)	(3.02)	(3.76)	(3.55)
ALL		−1.68	−1.09	4.38	6.15	8.42	10.10
		(−1.32)	(−0.67)	(2.84)	(3.37)	(4.45)	(5.22)

Table 16
Portfolios Sorted by Firm Characteristics: Risk Exposures

The table reports the time-series mean of conditional risk exposures. $\bar{\beta}^{p,m}$, $\bar{\beta}^{p,s}$, $\bar{\beta}^{p,h}$, $\bar{\beta}^{p,u}$, $\bar{\beta}^{p,r}$ and $\bar{\beta}^{p,c}$ are exposures of quarterly excess returns on portfolios of dividend strips with respect to the quarterly excess returns of the market portfolio, SMB, HML, UMD, RMW and CMA, respectively, and are estimated from the time-series regressions in a rolling window of data. t-statistics of betas are adjusted for autocorrelation and heteroscedasticity. Panel A is for five portfolios sorted by underlying stocks' book-to-market ratio (BM), operating profitability (OP), total asset growth rate (ATG) or cumulative stock returns in the previous six months (RET(−1,−6)). Panel B is for 25 portfolios sorted by percentage of institutional holding (PIH) and each of the four firm characteristics.

A. Risk Exposures, univariate-sorting

	BM					OP					ATG					RET(−1,−6)				
	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5
CAPM: Capital Asset Pricing Model																				
$\bar{\beta}^{p,m}$	0.29	-0.06	0.30	0.45	0.61	-0.27	-0.11	0.31	0.40	0.74	0.74	0.49	0.26	-0.15	-0.06	-0.20	-0.09	0.34	0.50	0.51
$t(\bar{\beta}^{p,m})$	3.92	-0.56	4.66	5.48	6.11	-3.66	-1.27	3.76	4.27	8.37	7.21	5.48	3.62	-2.82	-1.37	-3.67	-2.15	4.68	7.33	7.74
FF3: Fama and French Three-Factor Model																				
$\bar{\beta}^{p,m}$	0.28	-0.09	0.33	0.51	0.63	-0.25	-0.12	0.32	0.44	0.78	0.73	0.47	0.32	-0.24	-0.05	-0.27	-0.14	0.33	0.50	0.44
$t(\bar{\beta}^{p,m})$	3.56	-1.15	4.76	5.45	7.04	-3.26	-1.62	4.00	5.85	7.04	8.29	5.00	4.03	-2.98	-0.87	-3.55	-1.84	3.55	5.81	5.03
$\bar{\beta}^{p,s}$	-0.62	-0.22	0.32	0.53	0.61	0.78	0.57	0.30	-0.26	-0.52	0.67	0.54	0.31	-0.38	-0.73	-0.46	-0.28	0.25	0.56	0.65
$t(\bar{\beta}^{p,s})$	-5.07	-2.85	3.12	3.88	5.61	5.87	4.62	3.69	-2.90	-4.70	5.47	4.45	3.16	-3.74	-5.11	-4.48	-2.49	2.84	5.03	6.07
$\bar{\beta}^{p,h}$	-0.61	-0.24	0.47	0.86	1.47	-0.37	-0.23	0.46	0.64	0.04	-0.16	0.64	0.43	-0.28	-0.45	-0.38	-0.22	0.44	0.58	0.39
$t(\bar{\beta}^{p,h})$	-3.76	-2.09	4.21	6.52	9.29	-4.62	-3.05	3.83	6.08	0.46	-1.74	6.77	4.27	-2.40	-4.42	-3.29	-2.44	3.61	5.34	2.99

Table 16
Portfolios Sorted by Firm Characteristics: Risk Exposures, Cont.

A. Risk Exposures, univariate-sorting

	BM					OP					ATG					RET(-1,-6)				
	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5
FFM4: Carhart Four-Factor Model																				
$\bar{\beta}^{p,m}$	0.28	-0.08	0.31	0.52	0.64	-0.26	-0.15	0.35	0.44	0.75	0.77	0.48	0.35	-0.20	-0.08	-0.26	-0.12	0.39	0.51	0.47
$t(\bar{\beta}^{p,m})$	3.93	-1.09	4.45	5.48	6.47	-3.17	-1.52	3.68	5.48	7.14	7.63	5.18	3.92	-2.69	-1.16	-3.41	-1.21	4.07	5.44	4.04
$\bar{\beta}^{p,s}$	-0.51	-0.23	0.32	0.49	0.57	0.69	0.55	0.31	-0.31	-0.59	0.67	0.56	0.26	-0.31	-0.64	-0.42	-0.24	0.32	0.54	0.65
$t(\bar{\beta}^{p,s})$	-4.27	-2.92	3.64	3.56	5.38	5.95	5.16	3.38	-3.11	-4.59	5.92	4.73	2.54	-3.43	-4.90	-4.32	-2.37	3.43	4.83	6.20
$\bar{\beta}^{p,h}$	-0.49	-0.27	0.47	0.88	1.32	-0.33	-0.25	0.44	0.64	0.07	-0.11	0.66	0.42	-0.27	-0.54	-0.40	-0.34	0.46	0.63	0.38
$t(\bar{\beta}^{p,h})$	-3.40	-2.32	2.81	6.14	8.22	-4.08	-3.23	3.60	7.00	0.70	-1.56	7.13	4.33	-2.36	-5.24	-4.73	-3.52	3.28	5.83	2.27
$\bar{\beta}^{p,u}$	-0.28	-0.18	0.20	0.33	0.20	-0.31	-0.28	0.25	0.35	0.28	0.44	0.30	0.25	-0.19	-0.35	-0.77	-0.46	0.33	0.77	1.12
$t(\bar{\beta}^{p,u})$	-2.50	-3.45	1.80	2.57	1.36	-2.72	-2.00	2.40	3.44	0.79	4.92	3.64	3.02	-1.95	-3.88	-6.56	-3.26	2.78	5.53	9.17
FF5: Fama and French Five-Factor Model																				
$\bar{\beta}^{p,m}$	0.30	-0.09	0.29	0.46	0.64	-0.29	-0.17	0.34	0.45	0.77	0.68	0.47	0.30	-0.22	-0.08	-0.22	-0.13	0.30	0.50	0.47
$t(\bar{\beta}^{p,m})$	3.76	-1.03	4.30	5.66	6.64	-3.03	-2.25	3.79	5.03	7.17	7.67	5.14	3.52	-3.42	-1.21	-3.41	-2.11	3.96	5.52	4.25
$\bar{\beta}^{p,s}$	-0.57	-0.28	0.31	0.46	0.57	0.74	0.55	0.32	-0.25	-0.54	0.67	0.53	0.28	-0.35	-0.70	-0.48	-0.25	0.30	0.56	0.64
$t(\bar{\beta}^{p,s})$	-5.26	-3.19	2.58	3.92	4.79	6.01	3.97	2.86	-2.25	-4.46	3.79	3.70	2.48	-2.99	-4.47	-4.35	-2.59	2.88	4.97	5.99
$\bar{\beta}^{p,h}$	-0.53	-0.20	0.45	0.85	1.38	-0.36	-0.22	0.47	0.66	0.01	-0.12	0.63	0.40	-0.28	-0.46	-0.41	-0.28	0.49	0.56	0.41
$t(\bar{\beta}^{p,h})$	-3.19	-1.56	2.94	6.43	9.00	-3.73	-2.18	3.89	4.90	0.12	-0.55	7.94	3.56	-1.82	-3.90	-3.67	-2.92	3.31	5.05	2.86
$\bar{\beta}^{p,r}$	-0.39	-0.21	0.37	0.47	0.56	-0.70	-0.35	0.43	0.83	1.52	0.68	0.62	0.43	-0.28	-0.41	-0.28	-0.17	0.48	0.64	0.69
$t(\bar{\beta}^{p,r})$	-2.11	-1.61	2.06	3.10	3.93	-4.21	-2.72	4.10	6.09	8.56	6.43	5.98	3.71	-2.26	-4.22	-2.45	-1.19	3.21	4.88	6.26
$\bar{\beta}^{p,c}$	-0.37	-0.14	0.46	0.57	0.66	-0.41	-0.30	0.36	0.60	0.64	1.34	0.91	0.47	-0.31	-0.43	-0.35	-0.21	0.41	0.59	0.67
$t(\bar{\beta}^{p,c})$	-2.64	-1.25	2.87	3.14	4.22	-3.06	-2.13	3.26	5.39	6.56	9.22	7.16	4.42	-2.36	-5.05	-2.45	-2.26	3.27	5.28	5.73

Table 16 Portfolios Sorted by Firm Characteristics: Risk Exposures, Cont.

B. Risk Exposures, double-sorting

		BM					BM					OP					OP				
		1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5
CAPM: Capital Asset Pricing Model																					
				$\bar{\beta}^{p,m}$					$t(\bar{\beta}^{p,m})$					$\bar{\beta}^{p,s}$					$t(\bar{\beta}^{p,s})$		
	1	0.35	-0.20	0.28	0.43	0.39	3.99	-2.18	3.05	4.07	3.13	-0.32	-0.24	0.26	0.47	0.69	-4.56	-3.35	2.61	4.78	6.98
	2	0.25	-0.16	0.35	0.48	0.49	4.82	-1.54	4.35	5.54	4.61	-0.36	-0.21	0.33	0.46	0.70	-4.64	-3.27	3.46	4.70	7.09
PIH	3	0.07	-0.11	0.38	0.46	0.75	0.78	-1.09	3.86	4.73	6.19	-0.23	-0.12	0.33	0.56	0.78	-2.42	-1.76	3.79	5.61	8.87
	4	-0.14	-0.05	0.33	0.44	0.69	-1.71	-0.56	3.64	5.68	6.32	-0.18	-0.03	0.29	0.49	0.76	-2.93	-0.46	2.79	4.71	8.36
	5	-0.18	0.13	0.32	0.47	0.70	-1.47	1.15	2.94	4.86	6.36	-0.18	-0.11	0.28	0.53	0.78	-1.23	-1.55	3.01	5.11	8.79
FF3: Fama and French Three-Factor Model																					
				$\bar{\beta}^{p,m}$					$t(\bar{\beta}^{p,m})$					$\bar{\beta}^{p,m}$					$t(\bar{\beta}^{p,m})$		
	1	0.35	-0.14	0.29	0.37	0.39	3.26	-2.21	3.20	3.84	2.80	-0.25	-0.23	0.31	0.37	0.73	-3.97	-2.63	3.38	3.51	8.05
	2	0.25	-0.10	0.32	0.46	0.48	3.52	-1.82	3.50	4.53	4.88	-0.36	-0.14	0.32	0.40	0.70	-4.23	-1.77	3.75	4.88	7.75
PIH	3	0.03	-0.10	0.33	0.44	0.73	0.49	-2.19	3.69	4.60	5.81	-0.31	-0.13	0.34	0.57	0.82	-4.38	-2.35	3.24	5.85	9.08
	4	-0.20	-0.05	0.32	0.43	0.67	-3.08	-0.54	3.31	4.05	5.42	-0.12	-0.06	0.29	0.44	0.78	-1.92	-1.03	3.39	5.44	8.80
	5	-0.20	0.08	0.32	0.46	0.69	-1.81	1.17	3.40	4.31	5.41	-0.18	-0.12	0.28	0.53	0.80	-2.03	-1.90	3.23	5.30	8.30
				$\bar{\beta}^{p,s}$					$t(\bar{\beta}^{p,s})$					$\bar{\beta}^{p,s}$					$t(\bar{\beta}^{p,s})$		
	1	-0.39	-0.16	0.31	0.55	0.82	-5.74	-1.51	2.87	5.79	7.70	0.88	0.63	0.43	-0.07	-0.27	7.02	5.11	3.01	-0.58	-2.62
	2	-0.47	-0.16	0.34	0.53	0.69	-3.48	-1.54	2.30	4.54	6.48	0.80	0.59	0.38	-0.24	-0.33	6.30	4.55	3.50	-3.25	-3.42
PIH	3	-0.54	-0.17	0.29	0.51	0.65	-3.45	-1.30	2.79	3.78	6.10	0.68	0.57	0.33	-0.28	-0.48	6.35	4.64	3.60	-2.59	-4.72
	4	-0.60	-0.34	0.35	0.42	0.55	-5.22	-2.95	3.74	4.48	5.64	0.73	0.44	0.25	-0.36	-0.56	6.46	4.75	2.85	-3.31	-4.05
	5	-0.64	-0.49	0.25	0.17	0.26	-4.01	-2.82	2.11	1.61	2.40	0.58	0.45	0.27	-0.47	-0.84	4.33	3.98	2.66	-3.66	-6.12
				$\bar{\beta}^{p,h}$					$t(\bar{\beta}^{p,h})$					$\bar{\beta}^{p,h}$					$t(\bar{\beta}^{p,h})$		
	1	-0.64	-0.26	0.52	1.04	1.62	-4.38	-2.36	3.87	5.64	11.61	-0.44	-0.27	0.61	0.84	0.33	-4.28	-2.73	4.33	7.80	3.61
	2	-0.52	-0.23	0.44	0.96	1.33	-3.44	-1.71	3.87	6.44	8.88	-0.39	-0.20	0.56	0.70	0.14	-3.97	-1.93	4.50	6.54	1.69
PIH	3	-0.30	-0.18	0.44	0.88	1.40	-2.84	-1.37	3.93	4.70	7.28	-0.31	-0.24	0.54	0.70	0.25	-3.13	-2.60	4.52	7.00	2.25
	4	-0.36	-0.11	0.44	0.69	1.03	-3.08	-0.60	4.23	5.50	7.41	-0.30	-0.28	0.43	0.59	0.14	-3.60	-3.11	4.22	5.64	1.45
	5	-0.32	-0.03	0.35	0.79	1.03	-2.40	-0.30	2.98	4.80	6.43	-0.24	-0.18	0.39	0.45	-0.39	-2.88	-2.01	3.30	4.54	-3.64

Table 16 Portfolios Sorted by Firm Characteristics: Risk Exposures, Cont.

B. Risk Exposures, double-sorting

		BM					BM					OP					OP				
		1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5
FFM4: Carhart Four-Factor Model																					
				$\bar{\beta}^{p,m}$					$t(\bar{\beta}^{p,m})$					$\bar{\beta}^{p,m}$					$t(\bar{\beta}^{p,m})$		
	1	0.35	-0.14	0.30	0.39	0.39	4.21	-2.17	3.03	2.90	2.69	-0.40	-0.23	0.30	0.46	0.73	-5.78	-2.32	4.32	5.21	7.75
	2	0.28	-0.04	0.32	0.45	0.49	3.40	-0.35	3.98	5.60	4.32	-0.34	-0.16	0.37	0.47	0.71	-4.24	-2.24	3.91	5.17	7.31
PIH	3	0.03	-0.11	0.32	0.47	0.76	0.32	-1.03	3.61	5.50	6.07	-0.34	-0.14	0.41	0.56	0.79	-3.45	-1.94	3.43	5.72	8.02
	4	-0.21	-0.03	0.31	0.54	0.68	-2.13	-0.33	3.37	5.30	6.05	-0.13	-0.09	0.32	0.47	0.77	-2.03	-1.02	2.80	4.81	7.84
	5	-0.25	0.09	0.29	0.47	0.69	-2.39	0.94	3.47	4.72	5.74	-0.21	-0.19	0.33	0.58	0.79	-1.28	-2.53	2.60	5.39	7.42
				$\bar{\beta}^{p,s}$					$t(\bar{\beta}^{p,s})$					$\bar{\beta}^{p,s}$					$t(\bar{\beta}^{p,s})$		
	1	-0.37	-0.22	0.30	0.65	0.75	-5.37	-2.02	2.84	5.71	7.70	0.84	0.69	0.43	-0.23	-0.28	7.79	6.64	3.04	-1.95	-2.87
	2	-0.44	-0.13	0.29	0.53	0.67	-3.30	-1.26	2.05	5.50	6.07	0.78	0.62	0.35	-0.25	-0.35	7.11	6.16	2.75	-2.84	-3.86
PIH	3	-0.55	-0.23	0.25	0.48	0.61	-3.35	-1.58	2.43	3.93	5.74	0.66	0.59	0.34	-0.21	-0.48	6.66	5.72	3.21	-1.93	-4.30
	4	-0.57	-0.30	0.33	0.47	0.56	-4.62	-2.65	3.64	4.40	5.49	0.65	0.54	0.25	-0.30	-0.51	6.84	5.43	2.43	-2.35	-4.13
	5	-0.64	-0.53	0.24	0.18	0.27	-3.77	-2.77	2.65	1.90	2.23	0.64	0.49	0.21	-0.38	-0.87	6.42	5.82	2.20	-2.42	-6.30
				$\bar{\beta}^{p,h}$					$t(\bar{\beta}^{p,h})$					$\bar{\beta}^{p,h}$					$t(\bar{\beta}^{p,h})$		
	1	-0.37	-0.22	0.30	0.65	0.75	-5.37	-2.02	2.84	5.71	7.70	0.84	0.69	0.43	-0.23	-0.28	7.79	6.64	3.04	-1.95	-2.87
	2	-0.44	-0.13	0.29	0.53	0.67	-3.30	-1.26	2.05	5.50	6.07	0.78	0.62	0.35	-0.25	-0.35	7.11	6.16	2.75	-2.84	-3.86
PIH	3	-0.55	-0.23	0.25	0.48	0.61	-3.35	-1.58	2.43	3.93	5.74	0.66	0.59	0.34	-0.21	-0.48	6.66	5.72	3.21	-1.93	-4.30
	4	-0.57	-0.30	0.33	0.47	0.56	-4.62	-2.65	3.64	4.40	5.49	0.65	0.54	0.25	-0.30	-0.51	6.84	5.43	2.43	-2.35	-4.13
	5	-0.64	-0.53	0.24	0.18	0.27	-3.77	-2.77	2.65	1.90	2.23	0.64	0.49	0.21	-0.38	-0.87	6.42	5.82	2.20	-2.42	-6.30
				$\bar{\beta}^{p,u}$					$t(\bar{\beta}^{p,u})$					$\bar{\beta}^{p,u}$					$t(\bar{\beta}^{p,u})$		
	1	-0.36	-0.32	0.21	0.31	-0.16	-3.43	-2.66	1.63	2.12	-0.92	-0.48	-0.32	0.31	0.15	-0.15	-4.41	-2.39	2.26	0.72	-0.52
	2	-0.24	-0.30	0.19	0.29	-0.34	-2.27	-3.43	1.85	3.14	-2.86	-0.36	-0.31	0.31	0.04	-0.09	-3.89	-2.11	3.37	0.24	-0.59
PIH	3	-0.23	-0.13	0.19	0.31	0.48	-1.87	-1.25	2.12	2.10	5.29	-0.34	-0.26	0.29	0.44	0.54	-2.92	-2.14	1.88	5.92	3.53
	4	-0.26	-0.04	0.11	0.31	0.47	-2.38	-0.34	1.82	2.40	6.31	-0.32	-0.26	0.29	0.50	0.55	-2.02	-2.22	2.61	5.00	6.41
	5	-0.24	-0.04	0.17	0.22	0.50	-1.60	-0.38	3.67	1.72	6.45	-0.18	-0.17	0.24	0.47	0.57	-1.29	-1.24	2.65	4.42	6.37

Table 16 Portfolios Sorted by Firm Characteristics: Risk Exposures, Cont.

B. Risk Exposures, double-sorting

		BM					BM					OP					OP				
		1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5
FF5: Fama and French Five-Factor Model																					
				$\bar{\beta}^{p,m}$					$t(\bar{\beta}^{p,m})$					$\bar{\beta}^{p,m}$					$t(\bar{\beta}^{p,m})$		
	1	0.32	-0.15	0.30	0.40	0.39	3.66	-2.01	3.47	3.91	2.57	-0.29	-0.27	0.28	0.46	0.73	-3.52	-2.38	3.22	5.00	6.77
	2	0.25	-0.09	0.31	0.47	0.48	3.01	-0.79	3.93	5.78	4.59	-0.31	-0.19	0.35	0.44	0.70	-2.91	-1.76	3.38	5.32	6.04
PIH	3	0.01	-0.09	0.33	0.45	0.73	0.08	-1.21	3.78	4.94	6.38	-0.29	-0.14	0.38	0.56	0.82	-2.72	-1.83	3.80	5.73	8.27
	4	-0.18	-0.04	0.32	0.44	0.68	-2.05	-0.42	3.14	4.78	5.94	-0.13	-0.09	0.24	0.49	0.78	-1.82	-0.85	3.68	4.68	7.90
	5	-0.21	0.12	0.31	0.45	0.70	-2.12	1.21	3.15	4.93	6.22	-0.23	-0.13	0.28	0.56	0.82	-1.57	-1.57	2.30	5.50	8.15
				$\bar{\beta}^{p,s}$					$t(\bar{\beta}^{p,s})$					$\bar{\beta}^{p,s}$					$t(\bar{\beta}^{p,s})$		
	1	-0.43	-0.17	0.28	0.57	0.74	-5.55	-1.52	2.13	6.27	7.53	0.86	0.69	0.41	-0.09	-0.32	5.50	3.76	2.29	-0.71	-3.30
	2	-0.46	-0.21	0.28	0.52	0.67	-3.71	-2.26	1.58	5.38	6.82	0.76	0.59	0.36	-0.24	-0.39	5.57	3.66	2.58	-2.71	-3.29
PIH	3	-0.55	-0.17	0.25	0.49	0.59	-3.70	-1.00	2.03	4.01	6.24	0.67	0.58	0.30	-0.24	-0.45	4.86	3.47	2.78	-2.03	-3.49
	4	-0.56	-0.34	0.35	0.49	0.55	-4.52	-2.16	3.28	4.07	5.27	0.70	0.49	0.26	-0.26	-0.55	5.28	3.08	2.21	-2.26	-4.31
	5	-0.63	-0.51	0.20	0.17	0.25	-4.76	-3.01	1.65	1.10	1.71	0.58	0.41	0.26	-0.36	-0.91	4.49	3.06	1.95	-2.14	-6.21
				$\bar{\beta}^{p,h}$					$t(\bar{\beta}^{p,h})$					$\bar{\beta}^{p,h}$					$t(\bar{\beta}^{p,h})$		
	1	-0.56	-0.21	0.48	1.00	1.60	-4.44	-1.68	3.66	5.72	10.09	-0.47	-0.37	0.58	0.79	0.33	-3.91	-2.15	2.98	5.49	3.08
	2	-0.48	-0.22	0.46	0.95	1.37	-3.43	-1.23	3.99	5.64	9.32	-0.35	-0.27	0.55	0.66	0.13	-2.96	-2.18	3.22	4.57	0.94
PIH	3	-0.29	-0.19	0.43	0.82	1.27	-1.89	-1.24	3.84	4.97	7.92	-0.33	-0.24	0.51	0.69	0.20	-3.40	-2.16	3.45	5.88	0.79
	4	-0.37	-0.12	0.45	0.70	0.95	-2.67	-0.54	3.68	4.46	6.85	-0.29	-0.21	0.44	0.55	0.17	-2.35	-1.99	3.91	5.26	1.02
	5	-0.36	-0.05	0.35	0.73	1.00	-1.63	-0.33	2.26	4.46	5.89	-0.20	-0.15	0.37	0.44	-0.30	-0.92	-0.78	2.96	3.74	-2.82
				$\bar{\beta}^{p,r}$					$t(\bar{\beta}^{p,r})$					$\bar{\beta}^{p,r}$					$t(\bar{\beta}^{p,r})$		
	1	-0.48	-0.20	0.37	0.49	0.59	-3.01	-1.22	2.24	2.53	3.62	-0.85	-0.62	0.43	0.88	1.82	-6.20	-3.60	2.45	6.87	9.86
	2	-0.47	-0.17	0.36	0.45	0.61	-3.23	-1.22	2.16	3.21	3.58	-0.63	-0.46	0.44	0.79	1.43	-4.04	-2.32	2.95	6.30	9.86
PIH	3	-0.40	-0.16	0.37	0.44	0.55	-2.22	-0.78	2.14	2.73	3.06	-0.58	-0.34	0.45	0.76	1.38	-4.32	-1.97	3.24	6.53	8.74
	4	-0.31	-0.22	0.35	0.42	0.54	-1.34	-1.17	1.98	3.03	3.06	-0.45	-0.28	0.45	0.82	1.48	-3.39	-2.40	3.45	7.71	8.73
	5	-0.11	-0.15	0.28	0.44	0.51	-0.61	-0.93	1.90	2.15	2.09	-0.32	-0.32	0.47	0.78	1.61	-2.35	-1.82	3.23	5.95	9.68
				$\bar{\beta}^{p,c}$					$t(\bar{\beta}^{p,c})$					$\bar{\beta}^{p,c}$					$t(\bar{\beta}^{p,c})$		
	1	-0.31	-0.24	0.56	0.67	0.81	-2.48	-1.41	3.98	4.71	5.66	-0.39	-0.12	0.36	0.66	0.71	-3.20	-1.24	1.94	4.50	7.27
	2	-0.35	-0.27	0.52	0.51	0.61	-3.22	-2.03	4.06	4.03	4.25	-0.52	-0.17	0.43	0.51	0.67	-4.15	-1.05	3.14	4.57	6.49
PIH	3	-0.26	-0.20	0.44	0.50	0.60	-1.30	-0.90	3.28	4.38	4.18	-0.38	-0.25	0.42	0.56	0.57	-3.18	-1.71	2.66	4.85	6.04
	4	-0.27	-0.15	0.43	0.53	0.60	-2.07	-0.96	2.25	4.06	4.47	-0.38	-0.24	0.35	0.59	0.67	-2.66	-2.02	2.54	5.92	6.09
	5	-0.23	-0.06	0.38	0.46	0.63	-1.40	-0.35	1.91	3.36	5.25	-0.27	-0.23	0.34	0.47	0.58	-2.15	-2.27	2.67	4.34	5.92

Table 16 Portfolios Sorted by Firm Characteristics: Risk Exposures, Cont.

B. Risk Exposures, double-sorting

		ATG					ATG					RET(−1,−6)					RET(−1,−6)				
		1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5
CAPM: Capital Asset Pricing Model																					
				$\bar{\beta}^{p,m}$					$t(\bar{\beta}^{p,m})$					$\bar{\beta}^{p,s}$					$t(\bar{\beta}^{p,s})$		
	1	0.65	0.47	0.23	-0.24	0.08	7.61	5.61	3.40	-2.22	0.43	-0.25	-0.21	0.36	0.48	0.43	-3.71	-2.85	4.38	5.17	6.21
	2	0.69	0.42	0.35	-0.25	0.22	7.72	5.25	4.01	-2.63	2.02	-0.33	-0.17	0.35	0.48	0.47	-4.56	-2.55	4.79	5.74	6.93
PIH	3	0.86	0.50	0.28	-0.18	-0.27	8.42	5.64	2.63	-2.56	-4.12	-0.18	-0.12	0.30	0.54	0.64	-3.67	-1.53	3.69	5.77	7.53
	4	0.76	0.48	0.28	-0.12	-0.24	8.31	5.34	3.70	-1.90	-3.74	-0.16	-0.07	0.24	0.54	0.58	-2.59	-0.83	2.64	6.12	7.11
	5	0.79	0.42	0.30	-0.11	-0.29	7.91	5.37	4.67	-2.40	-3.23	-0.08	-0.05	0.21	0.44	0.55	-1.67	-0.86	2.85	5.62	6.98
FF3: Fama and French Three-Factor Model																					
				$\bar{\beta}^{p,m}$					$t(\bar{\beta}^{p,m})$					$\bar{\beta}^{p,m}$					$t(\bar{\beta}^{p,m})$		
	1	0.58	0.45	0.19	-0.29	0.10	5.30	5.04	2.25	-2.97	0.89	-0.33	-0.20	0.36	0.48	0.45	-4.54	-2.43	4.27	4.32	3.97
	2	0.67	0.44	0.38	-0.24	0.26	6.77	4.52	3.71	-2.68	2.78	-0.35	-0.22	0.35	0.43	0.47	-5.31	-2.58	4.24	4.61	4.76
PIH	3	0.95	0.54	0.28	-0.18	-0.34	9.38	5.26	3.20	-2.15	-4.91	-0.20	-0.14	0.32	0.53	0.65	-2.34	-1.47	4.32	5.21	5.87
	4	0.87	0.49	0.28	-0.17	-0.28	8.97	4.04	3.58	-2.23	-3.35	-0.15	-0.07	0.26	0.53	0.62	-2.45	-1.21	3.28	4.52	5.67
	5	0.77	0.45	0.30	-0.19	-0.30	8.25	4.63	3.65	-2.24	-3.37	-0.13	-0.03	0.29	0.51	0.48	-1.23	-0.27	3.99	4.88	4.21
				$\bar{\beta}^{p,s}$					$t(\bar{\beta}^{p,s})$					$\bar{\beta}^{p,s}$					$t(\bar{\beta}^{p,s})$		
	1	0.82	0.57	0.42	-0.27	-0.62	9.26	4.18	3.93	-1.56	-4.43	-0.56	-0.33	0.43	0.69	0.79	-4.86	-3.71	3.31	4.89	5.73
	2	0.68	0.50	0.42	-0.27	-0.66	6.61	4.02	3.77	-2.43	-3.44	-0.45	-0.31	0.35	0.72	0.73	-4.22	-3.24	3.95	6.22	5.80
PIH	3	0.67	0.53	0.29	-0.40	-0.63	6.38	4.46	2.32	-4.13	-4.61	-0.32	-0.24	0.38	0.52	0.65	-2.73	-2.79	3.77	5.66	5.71
	4	0.58	0.46	0.21	-0.32	-0.67	4.77	4.14	1.72	-3.25	-7.24	-0.27	-0.18	0.34	0.42	0.59	-2.95	-1.81	3.97	4.58	5.85
	5	0.60	0.45	0.27	-0.41	-0.80	5.09	4.40	2.76	-2.88	-7.08	-0.33	-0.21	0.19	0.37	0.49	-2.77	-1.98	1.92	3.72	5.65
				$\bar{\beta}^{p,h}$					$t(\bar{\beta}^{p,h})$					$\bar{\beta}^{p,h}$					$t(\bar{\beta}^{p,h})$		
	1	0.22	0.69	0.45	-0.35	-0.61	1.68	6.31	4.37	-4.47	-5.31	-0.47	-0.34	0.54	0.66	0.16	-4.07	-3.65	4.13	7.23	2.11
	2	0.04	0.66	0.47	-0.25	-0.45	0.30	5.32	4.59	-2.29	-3.86	-0.60	-0.33	0.56	0.59	0.18	-5.94	-3.09	3.89	6.44	2.55
PIH	3	-0.09	0.62	0.39	-0.22	-0.43	-0.81	4.43	3.77	-2.45	-3.51	-0.37	-0.34	0.51	0.69	0.60	-3.07	-3.21	3.72	6.32	5.45
	4	-0.24	0.61	0.46	-0.14	-0.29	-2.54	4.71	4.21	-1.63	-2.83	-0.38	-0.30	0.50	0.59	0.70	-3.73	-2.54	3.61	5.21	6.58
	5	-0.33	0.55	0.37	-0.13	-0.18	-3.64	4.95	3.70	-1.57	-1.93	-0.22	-0.10	0.38	0.46	0.61	-2.71	-1.20	3.32	5.74	5.22

Table 16 Portfolios Sorted by Firm Characteristics: Risk Exposures, Cont.

B. Risk Exposures, double-sorting

		ATG					ATG					RET(−1,−6)					RET(−1,−6)				
		1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5
FFM4: Carhart Four-Factor Model																					
				$\bar{\beta}^{p,m}$					$t(\bar{\beta}^{p,m})$					$\bar{\beta}^{p,m}$					$t(\bar{\beta}^{p,m})$		
	1	0.62	0.45	0.25	-0.28	0.06	5.11	4.73	2.75	-2.47	0.54	-0.31	-0.22	0.36	0.48	0.53	-4.10	-2.61	3.56	4.33	6.42
	2	0.70	0.46	0.35	-0.29	0.24	5.99	4.04	3.82	-2.98	2.47	-0.32	-0.19	0.33	0.46	0.69	-5.20	-2.51	4.54	4.54	6.79
PIH	3	0.86	0.49	0.32	-0.20	-0.32	7.24	4.22	3.29	-2.26	-4.26	-0.24	-0.14	0.33	0.57	0.64	-3.41	-1.37	4.03	5.22	5.71
	4	0.79	0.51	0.31	-0.19	-0.29	7.21	4.03	3.83	-2.22	-3.23	-0.16	-0.09	0.26	0.54	0.59	-2.99	-1.31	3.65	4.86	4.20
	5	0.75	0.49	0.36	-0.20	-0.27	6.87	4.78	4.04	-2.01	-3.24	-0.16	-0.07	0.28	0.46	0.57	-1.36	-0.71	2.92	4.04	4.55
				$\bar{\beta}^{p,s}$					$t(\bar{\beta}^{p,s})$					$\bar{\beta}^{p,s}$					$t(\bar{\beta}^{p,s})$		
	1	0.86	0.59	0.38	-0.26	-0.64	8.86	4.25	3.92	-1.73	-4.70	-0.56	-0.31	0.45	0.63	0.77	-4.16	-3.23	3.42	5.30	6.00
	2	0.70	0.52	0.37	-0.21	-0.63	7.16	3.82	3.00	-2.00	-3.71	-0.46	-0.31	0.37	0.64	0.53	-5.02	-3.02	3.48	5.86	6.23
PIH	3	0.71	0.52	0.34	-0.36	-0.62	7.14	4.92	2.31	-4.40	-5.49	-0.34	-0.21	0.36	0.52	0.63	-3.52	-2.34	2.81	5.25	6.93
	4	0.62	0.43	0.15	-0.40	-0.67	5.94	3.72	1.64	-4.99	-7.32	-0.30	-0.15	0.24	0.47	0.56	-3.26	-1.35	3.05	3.99	6.13
	5	0.55	0.49	0.19	-0.42	-0.74	5.77	4.99	2.02	-3.56	-7.29	-0.35	-0.21	0.24	0.35	0.48	-3.38	-1.70	2.49	3.64	5.24
				$\bar{\beta}^{p,h}$					$t(\bar{\beta}^{p,h})$					$\bar{\beta}^{p,h}$					$t(\bar{\beta}^{p,h})$		
	1	0.31	0.72	0.47	-0.38	-0.66	2.40	5.94	3.91	-4.29	-6.12	-0.47	-0.35	0.53	0.63	0.17	-5.42	-3.59	4.47	7.07	1.72
	2	0.04	0.66	0.47	-0.23	-0.43	0.25	4.52	4.21	-2.09	-4.54	-0.66	-0.36	0.55	0.64	0.19	-6.07	-3.84	4.52	7.01	2.77
PIH	3	-0.06	0.63	0.42	-0.27	-0.39	-0.60	4.15	3.81	-3.05	-4.07	-0.38	-0.37	0.49	0.63	0.62	-4.10	-3.63	4.76	7.51	7.31
	4	-0.24	0.63	0.36	-0.15	-0.33	-2.03	6.47	3.76	-1.45	-3.39	-0.34	-0.34	0.46	0.52	0.65	-3.52	-2.49	4.37	5.72	7.34
	5	-0.31	0.55	0.38	-0.17	-0.20	-3.27	5.08	3.41	-2.19	-2.39	-0.28	-0.04	0.37	0.40	0.58	-2.88	-0.36	4.14	5.23	6.40
				$\bar{\beta}^{p,u}$					$t(\bar{\beta}^{p,u})$					$\bar{\beta}^{p,u}$					$t(\bar{\beta}^{p,u})$		
	1	0.44	0.34	0.25	-0.27	-0.44	4.07	2.22	1.38	-1.95	-3.54	-1.08	-0.66	0.37	0.85	1.30	-8.29	-6.44	3.55	7.05	8.20
	2	0.52	0.35	0.24	-0.24	-0.39	4.52	3.36	2.16	-1.52	-2.62	-0.84	-0.52	0.37	0.79	1.16	-7.73	-4.90	3.46	7.23	7.80
PIH	3	0.45	0.36	0.21	-0.19	-0.28	3.74	2.25	1.36	-1.76	-2.65	-0.76	-0.31	0.28	0.75	1.04	-6.74	-2.34	2.35	7.15	8.14
	4	0.44	0.30	0.20	-0.16	-0.31	3.34	2.23	1.05	-1.86	-2.68	-0.60	-0.40	0.28	0.71	0.98	-4.82	-3.53	3.22	6.11	7.81
	5	0.44	0.32	0.23	-0.11	-0.17	3.83	2.67	2.24	-1.18	-1.44	-0.46	-0.20	0.20	0.66	1.02	-4.06	-1.18	3.25	6.53	8.05

Table 16 Portfolios Sorted by Firm Characteristics: Risk Exposures, Cont.

B. Risk Exposures, double-sorting

		ATG					ATG					RET(−1,−6)					RET(−1,−6)				
		1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5
FF5: Fama and French Five-Factor Model																					
		$\bar{\beta}^{p,m}$					$t(\bar{\beta}^{p,m})$					$\bar{\beta}^{p,m}$					$t(\bar{\beta}^{p,m})$				
	1	0.59	0.45	0.22	-0.29	0.10	5.74	4.70	3.40	-2.21	0.73	-0.27	-0.23	0.37	0.46	0.46	-4.40	-3.12	4.33	5.13	5.15
	2	0.69	0.44	0.38	-0.25	0.23	7.28	4.80	4.54	-2.58	2.16	-0.33	-0.20	0.34	0.46	0.47	-4.98	-2.47	3.91	4.89	5.11
PIH	3	0.86	0.51	0.28	-0.18	-0.30	8.73	4.80	3.83	-1.68	-3.24	-0.18	-0.14	0.34	0.54	0.64	-2.11	-2.07	3.77	5.94	8.31
	4	0.77	0.48	0.27	-0.18	-0.26	8.23	4.66	3.56	-2.45	-3.18	-0.15	-0.12	0.26	0.54	0.58	-2.57	-1.17	3.68	5.14	6.73
	5	0.79	0.43	0.31	-0.17	-0.28	8.96	4.39	4.09	-1.76	-2.71	-0.10	-0.09	0.24	0.47	0.56	-0.97	-0.93	3.13	5.12	6.76
		$\bar{\beta}^{p,s}$					$t(\bar{\beta}^{p,s})$					$\bar{\beta}^{p,s}$					$t(\bar{\beta}^{p,s})$				
	1	0.84	0.56	0.42	-0.25	-0.60	5.42	4.00	3.82	-1.42	-3.72	-0.53	-0.32	0.43	0.67	0.79	-4.49	-2.29	2.76	5.10	6.04
	2	0.70	0.53	0.38	-0.26	-0.63	4.31	3.14	2.52	-1.64	-4.04	-0.49	-0.33	0.41	0.68	0.75	-4.34	-3.15	2.90	5.57	5.17
PIH	3	0.65	0.51	0.29	-0.34	-0.66	4.62	3.75	2.02	-2.55	-4.95	-0.36	-0.24	0.39	0.56	0.66	-2.91	-1.78	2.86	4.96	5.00
	4	0.56	0.46	0.19	-0.35	-0.68	3.96	3.89	1.23	-2.77	-5.06	-0.30	-0.15	0.23	0.44	0.57	-2.26	-1.81	2.05	3.67	4.48
	5	0.55	0.42	0.14	-0.44	-0.81	3.59	3.05	1.16	-2.87	-4.97	-0.35	-0.19	0.17	0.39	0.41	-3.41	-1.28	1.30	3.63	4.34
		$\bar{\beta}^{p,h}$					$t(\bar{\beta}^{p,h})$					$\bar{\beta}^{p,h}$					$t(\bar{\beta}^{p,h})$				
	1	0.23	0.70	0.47	-0.34	-0.64	1.22	4.03	2.32	-3.35	-4.34	-0.46	-0.33	0.54	0.65	0.12	-4.86	-3.08	3.62	4.91	1.00
	2	0.02	0.67	0.45	-0.25	-0.41	0.12	4.25	2.72	-1.87	-4.10	-0.66	-0.37	0.52	0.59	0.17	-6.07	-2.79	3.51	4.76	1.27
PIH	3	-0.04	0.60	0.43	-0.23	-0.45	-0.32	4.12	2.20	-1.44	-4.51	-0.34	-0.35	0.50	0.62	0.62	-3.82	-2.44	3.27	4.43	3.79
	4	-0.23	0.62	0.37	-0.16	-0.34	-1.11	3.89	2.93	-1.10	-2.59	-0.29	-0.28	0.46	0.56	0.68	-2.40	-2.45	3.74	4.29	5.52
	5	-0.32	0.57	0.36	-0.13	-0.18	-1.66	2.76	3.50	-1.15	-2.10	-0.23	-0.11	0.36	0.43	0.56	-2.09	-0.72	2.94	3.61	4.41
		$\bar{\beta}^{p,r}$					$t(\bar{\beta}^{p,r})$					$\bar{\beta}^{p,r}$					$t(\bar{\beta}^{p,r})$				
	1	0.76	0.65	0.45	-0.42	-0.55	6.49	3.93	3.55	-2.35	-4.67	-0.45	-0.30	0.51	0.64	0.69	-3.48	-2.36	3.55	4.63	5.75
	2	0.69	0.70	0.45	-0.34	-0.47	5.56	3.91	2.70	-1.90	-4.00	-0.44	-0.18	0.51	0.62	0.68	-3.76	-1.48	3.25	4.67	4.88
PIH	3	0.68	0.63	0.42	-0.31	-0.41	5.19	4.70	2.57	-2.23	-2.83	-0.32	-0.18	0.47	0.65	0.62	-2.38	-1.45	4.89	5.41	4.35
	4	0.65	0.52	0.38	-0.19	-0.32	4.46	3.40	2.70	-1.34	-2.14	-0.12	-0.09	0.51	0.62	0.67	-0.47	-0.65	4.22	4.64	5.49
	5	0.68	0.55	0.38	-0.16	-0.20	5.50	3.73	2.84	-1.52	-1.86	-0.10	-0.07	0.43	0.60	0.56	-0.64	-0.24	3.39	4.43	4.47
		$\bar{\beta}^{p,c}$					$t(\bar{\beta}^{p,c})$					$\bar{\beta}^{p,c}$					$t(\bar{\beta}^{p,c})$				
	1	1.82	1.16	0.66	-0.43	-0.64	9.93	6.12	3.25	-4.09	-6.51	-0.53	-0.32	0.43	0.65	0.62	-4.12	-2.87	3.65	4.45	4.38
	2	1.64	0.91	0.63	-0.36	-0.59	9.05	5.80	3.08	-2.68	-5.14	-0.48	-0.29	0.41	0.62	0.71	-3.91	-2.40	3.73	4.77	6.08
PIH	3	1.29	0.85	0.50	-0.27	-0.31	7.58	6.00	2.35	-2.45	-3.47	-0.34	-0.20	0.43	0.60	0.66	-2.50	-1.51	3.01	4.51	6.27
	4	1.01	0.76	0.47	-0.18	-0.28	6.90	3.34	3.31	-2.05	-2.29	-0.10	-0.21	0.38	0.52	0.61	-0.95	-1.26	2.40	4.76	4.38
	5	0.97	0.73	0.44	-0.11	-0.22	4.20	2.87	2.42	-1.10	-1.80	-0.11	-0.03	0.40	0.53	0.60	-1.37	-0.17	3.13	4.98	6.44

Table 17
Portfolios Sorted by Firm Characteristics:
Cross-sectional Regressions and Price of Risk

This table reports the cross-sectional regression results of portfolio quarterly excess returns, $\tilde{r}^p$, on conditional beta coefficients on risk factors under different asset pricing models, the Capital Asset Pricing Model (CAPM), the Fama and French (1993) three-factor model (FF3), the Carhart (1997) four-factor model (FFM4) and the Fama and French (2015) five-factor model (FF5). λ_0 is regression intercept. λ^m, λ^s, λ^h, λ^u, λ^r and λ^c are prices of the market risk factor, the size factor (SMB), the value factor (HML), the momentum factor (UMD), the profitability factor (RMW) and the investment factor (CMA). Testing portfolios are 25 portfolios sorted by PIH and firms characteristics, including book-to-market ratio (BM), operating profitability (OP), total asset growth rate (ATG) and cumulative stock return in the previous six months (RET(−1,−6)). The table reports time-series average of estimated coefficients, t-statistic adjusted for autocorrelation and heteroscedasticity in parentheses, and mean value of adjusted R^2 ($\bar{R}^2$) of regressions. The sample period is from January 1996 to December 2017.

25 Portfolios Sorted by PIH and BM

	λ_0	λ^m	λ^s	λ^h	λ^u	λ^r	λ^c	$\bar{R}^2$
Est.	3.04	2.26						0.284
t-stat	(2.08)	(2.38)						
Est.	1.99	3.02	1.58	2.26				0.413
t-stat	(1.94)	(2.23)	(2.45)	(2.80)				
Est.	1.88	2.60	1.51	2.11	1.24			0.494
t-stat	(1.86)	(2.18)	(2.34)	(2.43)	(1.32)			
Est.	1.01	2.01	1.31	2.03		1.68	1.59	0.631
t-stat	(0.80)	(1.75)	(2.08)	(2.98)		(2.89)	(3.34)	

25 Portfolios Sorted by PIH and OP

	λ_0	λ^m	λ^s	λ^h	λ^u	λ^r	λ^c	$\bar{R}^2$
Est.	3.13	2.95						0.311
t-stat	(2.36)	(2.95)						
Est.	3.37	3.28	−0.38	1.58				0.390
t-stat	(3.13)	(1.91)	(−0.43)	(1.37)				
Est.	3.17	3.21	−0.43	1.59	1.68			0.452
t-stat	(3.02)	(2.33)	(−0.54)	(1.64)	(1.58)			
Est.	1.02	3.32	−0.28	1.25		2.27	1.42	0.585
t-stat	(1.00)	(2.47)	(−0.36)	(1.58)		(3.43)	(2.66)	

Table 17 Portfolios Sorted by Firm Characteristics: Cross-sectional Regressions and Price of Risk, Cont.

25 Portfolios Sorted by PIH and ATG

	λ_0	λ^m	λ^s	λ^h	λ^u	λ^r	λ^c	$\bar{R}^2$
Est.	3.74	2.84						0.339
t-stat	(2.15)	(3.22)						
Est.	3.56	3.15	2.00	1.27				0.384
t-stat	(1.94)	(2.38)	(2.57)	(2.10)				
Est.	3.13	3.17	1.46	1.06	2.97			0.437
t-stat	(1.78)	(3.30)	(2.00)	(1.83)	(2.38)			
Est.	1.02	2.82	1.40	1.16		1.58	2.39	0.601
t-stat	(1.17)	(2.51)	(2.22)	(1.83)		(2.24)	(5.06)	

25 Portfolios Sorted by PIH and RET(−1,−6)

	λ_0	λ^m	λ^s	λ^h	λ^u	λ^r	λ^c	$\bar{R}^2$
Est.	2.85	3.47						0.267
t-stat	(2.01)	(3.34)						
Est.	2.11	3.46	2.70	0.60				0.399
t-stat	(1.97)	(2.12)	(3.28)	(0.66)				
Est.	1.43	3.49	2.46	0.70	2.39			0.494
t-stat	(1.78)	(2.84)	(3.14)	(0.83)	(2.33)			
Est.	1.09	3.54	2.65	1.17		1.42	1.77	0.555
t-stat	(1.47)	(2.45)	(3.51)	(1.47)		(2.53)	(3.96)	

Table 18
Portfolios Sorted by Firm Characteristics: Times-Series Regressions and GRS Test

Panel A and B report pricing errors for the CAPM (α^{CAPM}), the FF3 (α^{FF3}), the FFM4 (α^{FFM4}) and the FF5 (α^{FF5}) of the time-series regression of quarterly excess returns $\tilde{r}^{p}_{q+1}$ of portfolios of dividend strips on quarterly risk factors f_{q+1}, where $f_{q+1} = \tilde{r}^{m}_{q+1}$ (excess return on the S&P 500 index) for the CAPM, $f_{q+1} = [\tilde{r}^{m}_{q+1}, \text{SMB}_{q+1}, \text{HML}_{q+1}]$ for the FF3, $f_{q+1} = [\tilde{r}^{m}_{q+1}, \text{SMB}_{q+1}, \text{HML}_{q+1}, \text{UMD}_{q+1}]$ for the FFM4, and $f_{q+1} = [\tilde{r}^{m}_{q+1}, \text{SMB}_{q+1}, \text{HML}_{q+1}, \text{RMW}_{q+1}, \text{CMA}_{q+1}]$ for the FF5. Panel A is for quintile portfolios sorted by book-to-market ratio (BM), operating profitability (OP), total asset growth rate (ATG) or cumulative stock return in the previous six months (RET(−1,−6)). Panel B is for portfolios first sorted by percentage of institutional holding (PIH) and then by one of the four firm characteristics. Panel C summarizes GRS (1989) test statistics and p-values.

A. Pricing Errors of Times Series Regressions: univariate-sorting

	BM 1	2	3	4	5		BM 1	2	3	4	5
α^{CAPM}	−2.73	−1.20	2.84	5.12	6.43	$t(\alpha^{\text{CAPM}})$	−1.16	−0.56	1.52	2.23	2.73
α^{FF3}	−1.99	−0.89	2.27	4.20	5.08	$t(\alpha^{\text{FF3}})$	−0.93	−0.44	1.27	1.87	2.31
α^{FFM4}	−1.77	−0.64	2.10	3.81	4.97	$t(\alpha^{\text{FFM4}})$	−0.84	−0.32	1.18	1.69	2.27
α^{FF5}	−1.40	−0.57	1.62	3.35	4.11	$t(\alpha^{\text{FF5}})$	−0.68	−0.29	0.92	1.46	1.89

	OP 1	2	3	4	5		OP 1	2	3	4	5
α^{CAPM}	−2.31	−1.42	2.97	5.83	7.80	$t(\alpha^{\text{CAPM}})$	−1.01	−0.58	1.45	2.39	3.02
α^{FF3}	−2.59	−1.55	2.43	5.48	8.00	$t(\alpha^{\text{FF3}})$	−1.19	−0.66	1.19	2.25	3.01
α^{FFM4}	−2.17	−1.23	2.16	5.16	7.74	$t(\alpha^{\text{FFM4}})$	−1.01	−0.52	1.06	2.13	2.91
α^{FF5}	−1.50	−0.89	1.62	4.19	5.84	$t(\alpha^{\text{FF5}})$	−0.72	−0.38	0.77	1.72	2.35

	ATG 1	2	3	4	5		ATG 1	2	3	4	5
α^{CAPM}	7.56	5.31	3.27	−1.50	−2.61	$t(\alpha^{\text{CAPM}})$	2.99	2.24	1.63	−0.63	−1.07
α^{FF3}	7.25	4.66	2.69	−0.92	−1.92	$t(\alpha^{\text{FF3}})$	2.79	2.06	1.40	−0.40	−0.85
α^{FFM4}	6.68	4.33	2.46	−0.75	−1.53	$t(\alpha^{\text{FFM4}})$	2.57	1.90	1.26	−0.33	−0.67
α^{FF5}	5.44	3.27	1.93	−0.43	−1.19	$t(\alpha^{\text{FF5}})$	2.21	1.50	1.01	−0.20	−0.51

	RET(−1,−6) 1	2	3	4	5		RET(−1,−6) 1	2	3	4	5
α^{CAPM}	−1.87	−1.36	3.12	4.70	6.94	$t(\alpha^{\text{CAPM}})$	−0.85	−0.65	1.58	2.28	3.06
α^{FF3}	−1.25	−0.93	2.66	3.94	6.35	$t(\alpha^{\text{FF3}})$	−0.62	−0.46	1.40	1.90	2.80
α^{FFM4}	−0.47	−0.46	2.25	3.04	5.00	$t(\alpha^{\text{FFM4}})$	−0.22	−0.22	1.22	1.50	2.22
α^{FF5}	−0.79	−0.62	1.82	2.82	5.04	$t(\alpha^{\text{FF5}})$	−0.40	−0.31	0.93	1.33	2.23

Table 18 Portfolios Sorted by Firm Characteristics: Times-Series Regressions and GRS Test, Cont.

B. Pricing Errors of Times Series Regressions: double-sorting

		BM					BM				
		1	2	3	4	5	1	2	3	4	5
		α^{CAPM}					$t(\alpha^{\mathrm{CAPM}})$				
	1	−3.36	−1.62	3.03	5.42	7.33	−1.45	−0.72	1.44	2.34	2.90
	2	−3.48	−1.39	2.93	5.17	6.77	−1.38	−0.57	1.41	2.22	2.71
PIH	3	−2.25	−1.08	2.77	5.18	6.29	−0.88	−0.47	1.33	2.14	2.46
	4	−1.49	−0.83	2.76	4.90	6.09	−0.60	−0.35	1.32	2.26	2.49
	5	−1.35	−0.14	2.71	4.85	6.11	−0.57	−0.06	1.31	2.00	2.31
		α^{FF3}					$t(\alpha^{\mathrm{FF3}})$				
	1	−2.73	−1.36	2.48	4.33	5.82	−1.24	−0.62	1.20	2.01	2.51
	2	−2.94	−1.11	2.39	4.20	5.51	−1.26	−0.47	1.14	1.87	2.36
PIH	3	−1.71	−0.87	2.27	4.28	4.98	−0.71	−0.39	1.09	1.84	2.03
	4	−0.98	−0.48	2.24	4.18	5.07	−0.41	−0.21	1.11	1.92	2.09
	5	−0.82	0.12	2.33	4.23	5.30	−0.35	0.06	1.17	1.81	2.02
		α^{FFM4}					$t(\alpha^{\mathrm{FFM4}})$				
	1	−2.40	−0.98	2.24	4.05	6.08	−1.09	−0.45	1.08	1.89	2.61
	2	−2.69	−0.80	2.29	3.94	5.98	−1.16	−0.34	1.10	1.76	2.54
PIH	3	−1.45	−0.68	2.11	3.94	4.46	−0.60	−0.30	1.01	1.71	1.83
	4	−0.60	−0.42	2.15	3.61	4.49	−0.25	−0.18	1.07	1.65	1.86
	5	−0.44	0.23	2.10	4.00	4.78	−0.19	0.11	1.06	1.71	1.81
		α^{FF5}					$t(\alpha^{\mathrm{FF5}})$				
	1	−1.99	−1.05	1.75	3.50	4.70	−0.91	−0.49	0.84	1.63	2.00
	2	−2.22	−0.79	1.71	3.39	4.48	−0.99	−0.34	0.82	1.54	1.95
PIH	3	−1.13	−0.61	1.61	3.49	4.08	−0.49	−0.27	0.76	1.50	1.70
	4	−0.43	−0.26	1.56	3.33	4.12	−0.18	−0.11	0.77	1.54	1.72
	5	−0.51	0.31	1.76	3.45	4.25	−0.22	0.15	0.88	1.50	1.62

Table 18 Portfolios Sorted by Firm Characteristics: Times-Series Regressions and GRS Test, Cont.

B. Pricing Errors of Times Series Regressions: double-sorting

		OP					OP				
		1	2	3	4	5	1	2	3	4	5
		α^{CAPM}					$t(\alpha^{\text{CAPM}})$				
	1	−3.39	−1.50	3.21	6.86	7.93	−1.49	−0.69	1.54	2.97	3.21
	2	−2.09	−1.76	3.08	6.69	8.29	−0.89	−0.70	1.47	3.06	3.22
PIH	3	−1.52	−1.44	2.93	5.61	7.66	−0.66	−0.63	1.42	2.28	2.98
	4	−1.54	−1.35	2.84	5.74	7.19	−0.66	−0.62	1.36	2.54	3.01
	5	−1.49	−1.55	2.80	5.27	7.23	−0.65	−0.67	1.38	2.28	2.83
		α^{FF3}					$t(\alpha^{\text{FF3}})$				
	1	−3.55	−1.77	2.60	6.27	7.93	−1.60	−0.84	1.28	2.67	3.07
	2	−2.31	−1.87	2.50	6.28	8.47	−0.99	−0.75	1.18	2.86	3.12
PIH	3	−1.72	−1.63	2.42	5.31	7.81	−0.76	−0.73	1.19	2.17	2.82
	4	−1.71	−1.45	2.37	5.48	7.44	−0.77	−0.69	1.15	2.47	2.88
	5	−1.66	−1.72	2.37	5.18	7.97	−0.73	−0.75	1.20	2.19	2.76
		α^{FFM4}					$t(\alpha^{\text{FFM4}})$				
	1	−2.75	−1.32	2.21	6.20	8.06	−1.26	−0.62	1.08	2.67	3.09
	2	−1.71	−1.72	2.26	6.25	8.45	−0.72	−0.68	1.07	2.85	3.11
PIH	3	−1.25	−1.38	2.00	4.80	7.18	−0.55	−0.61	0.98	1.94	2.60
	4	−1.33	−1.24	1.99	4.94	6.78	−0.59	−0.57	0.96	2.19	2.60
	5	−1.55	−1.44	2.06	4.62	7.34	−0.67	−0.63	1.03	1.94	2.53
		α^{FF5}					$t(\alpha^{\text{FF5}})$				
	1	−2.34	−0.89	1.83	4.80	5.45	−1.03	−0.42	0.89	2.05	2.28
	2	−1.25	−1.35	1.73	5.02	6.27	−0.54	−0.55	0.80	2.28	2.43
PIH	3	−0.72	−1.08	1.63	4.03	5.81	−0.34	−0.49	0.79	1.61	2.22
	4	−0.99	−1.07	1.58	4.22	5.36	−0.45	−0.51	0.75	1.94	2.25
	5	−1.11	−1.27	1.65	3.97	5.75	−0.50	−0.57	0.84	1.69	2.47

Table 18 Portfolios Sorted by Firm Characteristics: Times-Series Regressions and GRS Test, Cont.

B. Pricing Errors of Times Series Regressions: double-sorting

		ATG					ATG				
		1	2	3	4	5	1	2	3	4	5
		α^{CAPM}					$t(\alpha^{\text{CAPM}})$				
	1	8.18	5.59	3.89	−1.38	−3.76	3.20	2.34	1.84	−0.60	−1.56
	2	7.80	5.52	3.42	−1.27	−4.46	3.04	2.27	1.64	−0.50	−1.68
PIH	3	7.30	5.26	3.17	0.92	2.25	2.88	2.19	1.51	0.38	0.85
	4	7.17	5.25	3.06	−1.26	−1.34	2.93	2.14	1.42	−0.56	−0.57
	5	6.86	4.93	2.76	−1.16	−0.91	2.89	2.14	1.33	−0.53	−0.40
		α^{FF3}					$t(\alpha^{\text{FF3}})$				
	1	7.63	4.84	3.39	−0.93	−3.20	3.07	1.98	1.63	−0.41	−1.42
	2	7.46	4.80	2.89	−1.02	−3.89	2.87	2.02	1.40	−0.42	−1.57
PIH	3	6.92	4.50	2.74	1.31	2.93	2.41	1.97	1.32	0.56	1.16
	4	6.97	4.55	2.60	−0.89	−0.72	2.52	1.93	1.25	−0.41	−0.31
	5	6.76	4.34	2.42	−0.71	−0.31	2.49	1.91	1.18	-−0.33	−0.14
		α^{FFM4}					$t(\alpha^{\text{FFM4}})$				
	1	5.42	3.20	2.33	−0.14	−2.11	2.32	1.37	1.16	−0.06	−0.96
	2	5.43	3.27	1.95	−0.30	−2.94	2.14	1.41	0.96	−0.13	−1.23
PIH	3	5.27	3.23	1.88	1.76	3.63	2.03	1.50	0.95	0.77	1.49
	4	5.48	3.40	1.92	−0.50	−0.16	2.23	1.55	0.92	−0.23	−0.07
	5	5.28	3.16	1.67	−0.44	0.07	2.13	1.48	0.83	−0.21	0.03
		α^{FF5}					$t(\alpha^{\text{FF5}})$				
	1	7.04	4.38	3.08	−0.60	−2.63	2.86	1.81	1.49	−0.27	−1.16
	2	6.76	4.30	2.68	−0.69	−3.48	2.62	1.81	1.30	−0.28	−1.43
PIH	3	6.49	4.20	2.48	1.56	3.30	2.29	1.84	1.19	0.66	1.30
	4	6.46	4.22	2.37	−0.67	−0.34	2.33	1.78	1.13	−0.30	−0.15
	5	6.27	3.93	2.08	−0.54	−0.19	2.30	1.72	1.00	−0.25	−0.09

Table 18 Portfolios Sorted by Firm Characteristics: Times-Series Regressions and GRS Test, Cont.

B. Pricing Errors of Times Series Regressions: double-sorting

		RET(−1,−6)					RET(−1,−6)				
		1	2	3	4	5	1	2	3	4	5
		α^{CAPM}					$t(\alpha^{\text{CAPM}})$				
	1	−2.27	−1.44	3.38	4.76	7.14	−1.05	−0.66	1.71	2.18	3.07
	2	−1.90	−1.42	3.28	4.79	7.50	−0.87	−0.64	1.65	2.16	3.18
PIH	3	−1.93	−1.30	3.22	4.54	6.61	−0.84	−0.62	1.63	2.09	2.95
	4	−1.50	−1.38	3.23	4.33	6.54	−0.71	−0.69	1.64	2.13	2.90
	5	−1.58	−1.41	3.36	4.87	6.40	−0.75	−0.64	1.69	2.33	2.99
		α^{FF3}					$t(\alpha^{\text{FF3}})$				
	1	−1.51	−1.08	2.76	3.92	6.55	−0.72	−0.54	1.42	1.75	2.94
	2	−1.22	−0.97	2.71	4.00	6.91	−0.63	−0.48	1.39	1.75	2.96
PIH	3	−1.42	−0.95	2.56	3.83	5.83	−0.64	−0.48	1.31	1.74	2.56
	4	−1.05	−1.18	2.69	3.67	5.71	−0.53	−0.62	1.37	1.79	2.46
	5	−1.21	−1.25	2.77	4.17	5.89	−0.58	−0.57	1.44	1.99	2.75
		α^{FFM4}					$t(\alpha^{\text{FFM4}})$				
	1	−0.40	−0.29	2.36	2.94	4.88	−0.21	−0.14	1.20	1.40	2.14
	2	−0.20	−0.36	2.28	3.05	5.63	−0.09	−0.17	1.15	1.35	2.37
PIH	3	−0.54	−0.56	2.28	2.89	4.66	−0.25	−0.28	1.17	1.29	2.13
	4	−0.42	−0.64	2.36	2.83	4.60	−0.20	−0.34	1.20	1.42	2.02
	5	−0.59	−0.85	2.64	3.42	4.57	−0.28	−0.39	1.35	1.61	2.13
		α^{FF5}					$t(\alpha^{\text{FF5}})$				
	1	−0.68	−0.46	1.89	2.74	5.78	−0.32	−0.24	0.95	1.19	2.57
	2	−0.36	−0.54	1.84	2.84	5.99	−0.19	−0.27	0.93	1.20	2.56
PIH	3	−0.88	−0.56	1.70	2.64	4.88	−0.40	−0.28	0.85	1.15	2.14
	4	−0.94	−0.80	1.86	2.63	4.96	−0.47	−0.42	0.92	1.24	2.15
	5	−0.99	−1.13	2.11	3.18	5.00	−0.48	−0.52	1.09	1.53	2.37

Table 18 Portfolios Sorted by Firm Characteristics: Times-Series Regressions and GRS Test, Cont.

C. GRS (1989) Test

	univariate-sorting, BM		double-sorting, BM	
	GRS	p-value	GRS	p-value
CAPM	4.544	0.001	2.507	0.002
FF3	2.179	0.065	1.653	0.058
FFM4	2.079	0.077	1.582	0.077
FF5	1.386	0.239	1.348	0.175
	univariate-sorting, OP		double-sorting, OP	
	GRS	p-value	GRS	p-value
CAPM	3.326	0.009	2.018	0.014
FF3	3.370	0.008	1.880	0.024
FFM4	2.862	0.020	1.784	0.036
FF5	1.844	0.114	1.497	0.105
	univariate-sorting, ATG		double-sorting, ATG	
	GRS	p-value	GRS	p-value
CAPM	3.930	0.003	2.589	0.001
FF3	2.947	0.017	1.908	0.022
FFM4	2.480	0.039	1.740	0.043
FF5	1.787	0.125	1.411	0.142
	univariate-sorting, RET(−1,−6)		double-sorting, RET(−1,−6)	
	GRS	p-value	GRS	p-value
CAPM	3.372	0.008	2.578	0.001
FF3	2.835	0.021	1.976	0.017
FFM4	1.985	0.090	1.464	0.117
FF5	1.856	0.112	1.445	0.126

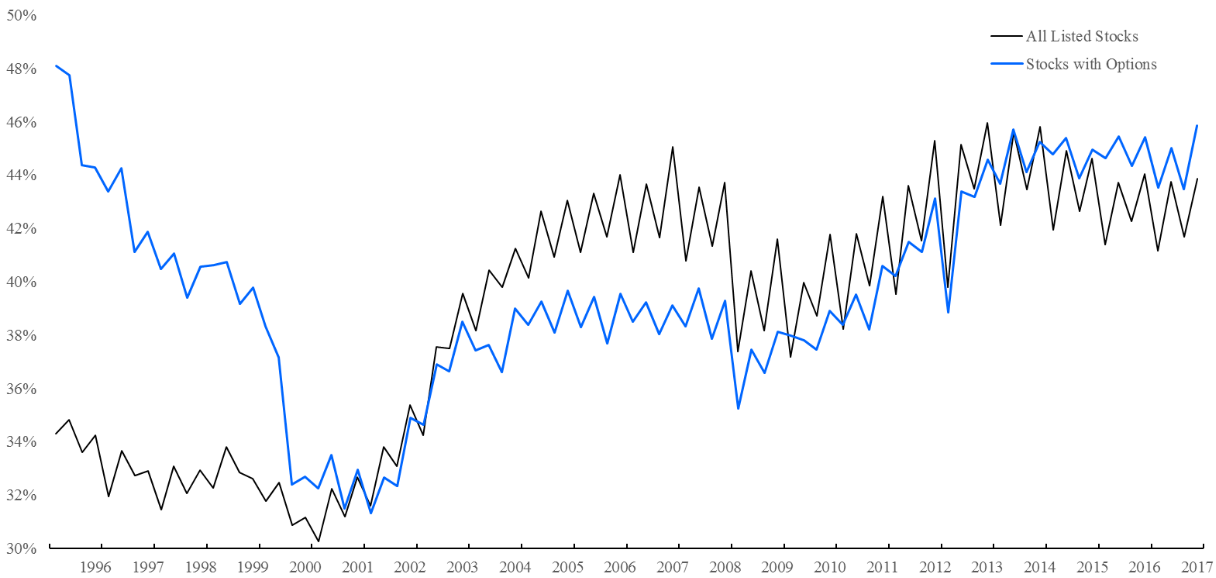
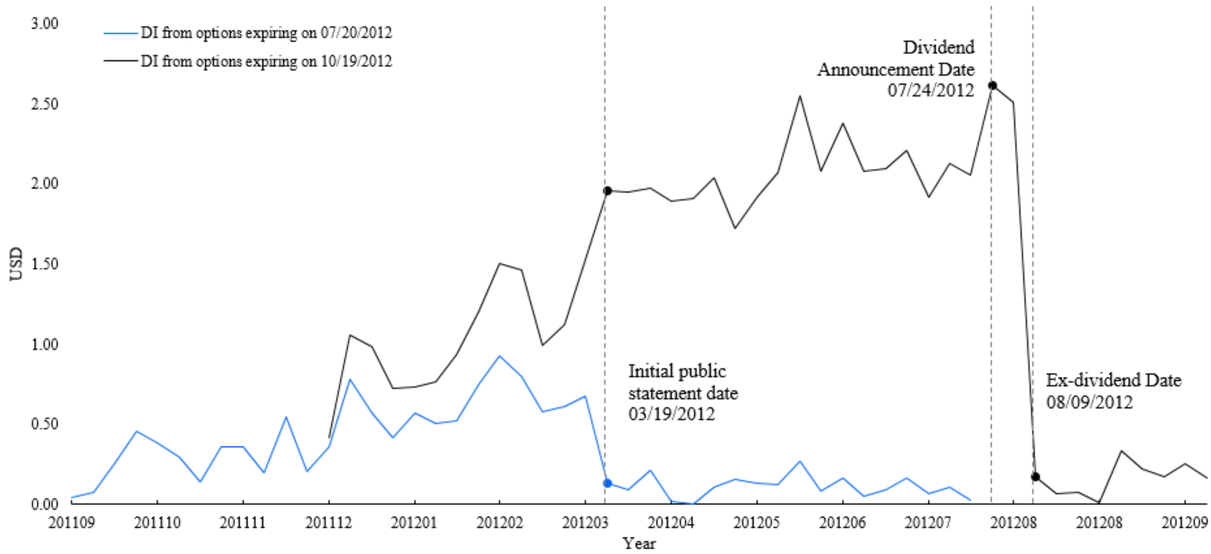
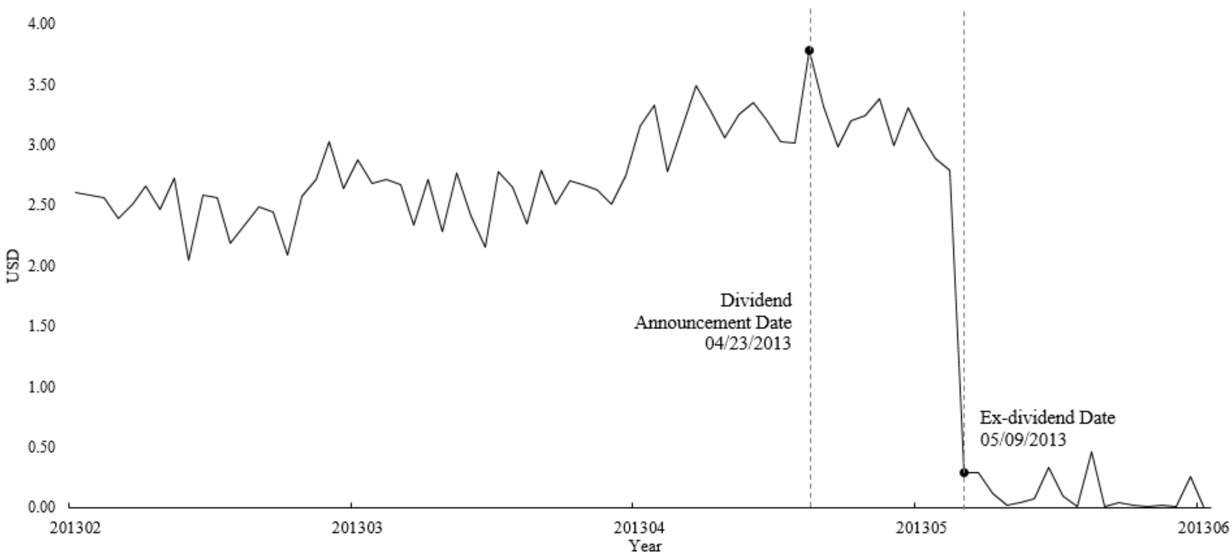


Figure 1
Fraction of Dividend Payers

The figure shows the times series of the percentage of stocks that pay cash dividends in a quarter. The black line is for all stocks listed on NYSE, AMEX and NASDAQ. The blue line is for stocks listed on the three stock exchanges with exchange-traded options. The sample period is from the first quarter of 1996 to the fourth quarter of 2017.



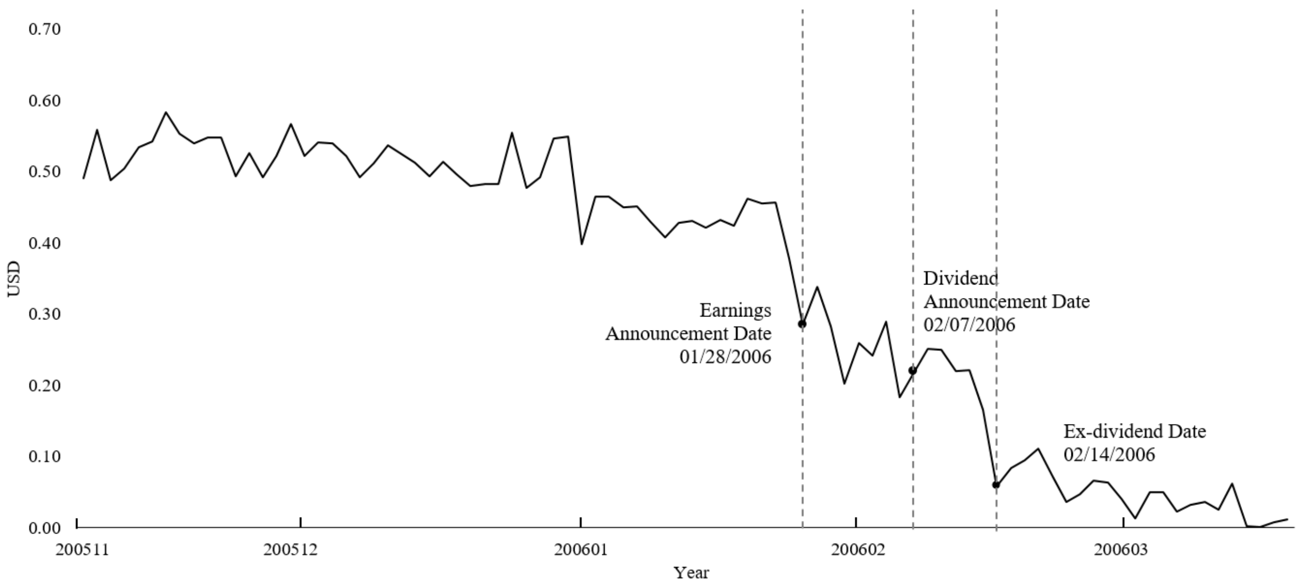
(a) DI of Apple Inc. around Dividend Initiation in 2012



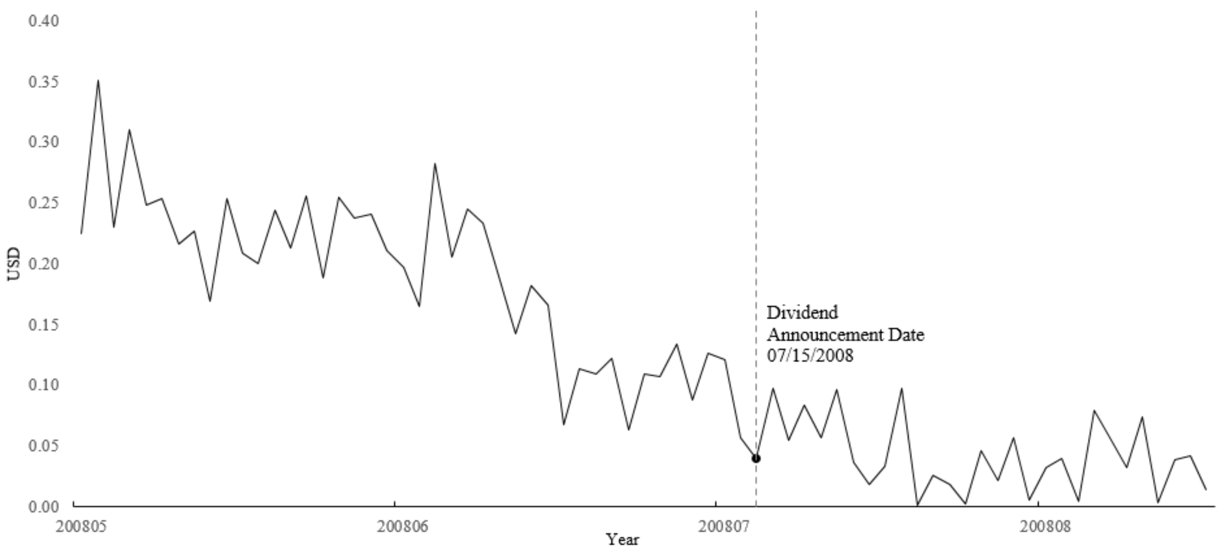
(b) DI of Apple Inc. around Dividend Increase in 2013

Figure 2
Predictability of Option-Implied Dividends: Apple Inc.

The figures show average dividend implied from prices of options written on stocks of Apple Inc. around the dividend initiation in 2012 and the dividend increase in 2013. Figure 2(a) plots weekly average dividend implied from options which expire on July 20th 2012 (the blue line) and on October 19th 2012 (the black line) of weeks before and after the company publicly stated its intention to initiate quarterly dividends on March 19th 2012. Figure 2(b) plots daily average dividend implied from options which expire on July 19th 2013 on days before and after the company announced to increase its quarterly dividend from \$2.65 to \$3.05 per share on April 23th 2013.



(a) DI of General Motors Company around Dividend Cut in 2006



(b) DI of General Motors Company around Dividend Omission in 2008

Figure 3
Predictability of Option-Implied Dividends: General Motors Company

The figures show average dividend implied from prices of options written on stocks of General Motors Company around the dividend cut in 2006 and the dividend omission in 2008. Figure 3(a) plots daily average dividend implied from options which expire on March 17$^{\text{th}}$ 2006 on days before and after the company announced on February 7$^{\text{th}}$ that it would reduce quarterly dividends by half from \$0.5 to \$0.25 per share. Figure 3(b) plots daily average dividend implied from options which expire on September 9$^{\text{th}}$ 2008 on days before and after the company announced on July 15$^{\text{th}}$ that it would suspend cash dividends.

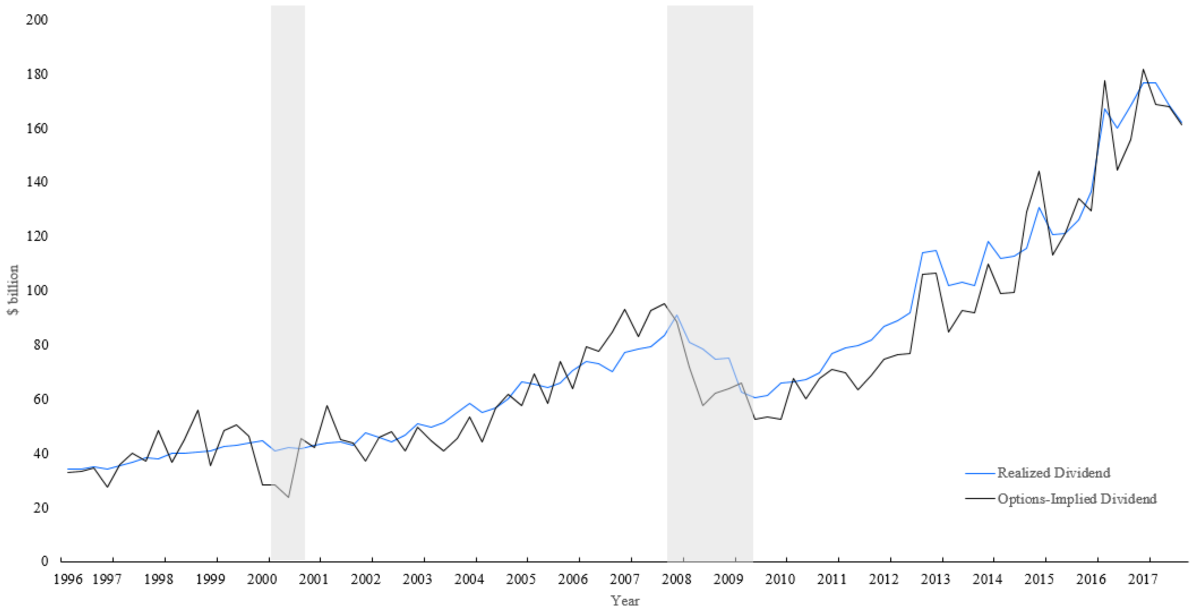


Figure 4
Prices and Realizations of Aggregate Dividend Strip

The figure shows the prices of the aggregate dividend strip at the end of each quarter (the black line) and realized aggregate dividends in the next quarter (the blue line). The two shaded areas cover two NBER recession periods. The first recession period is from the first quarter of 2000 to the third quarter of 2000. The second recession period is from the fourth quarter of 2007 to the second quarter of 2009. The sample period is from 1996 to 2017.

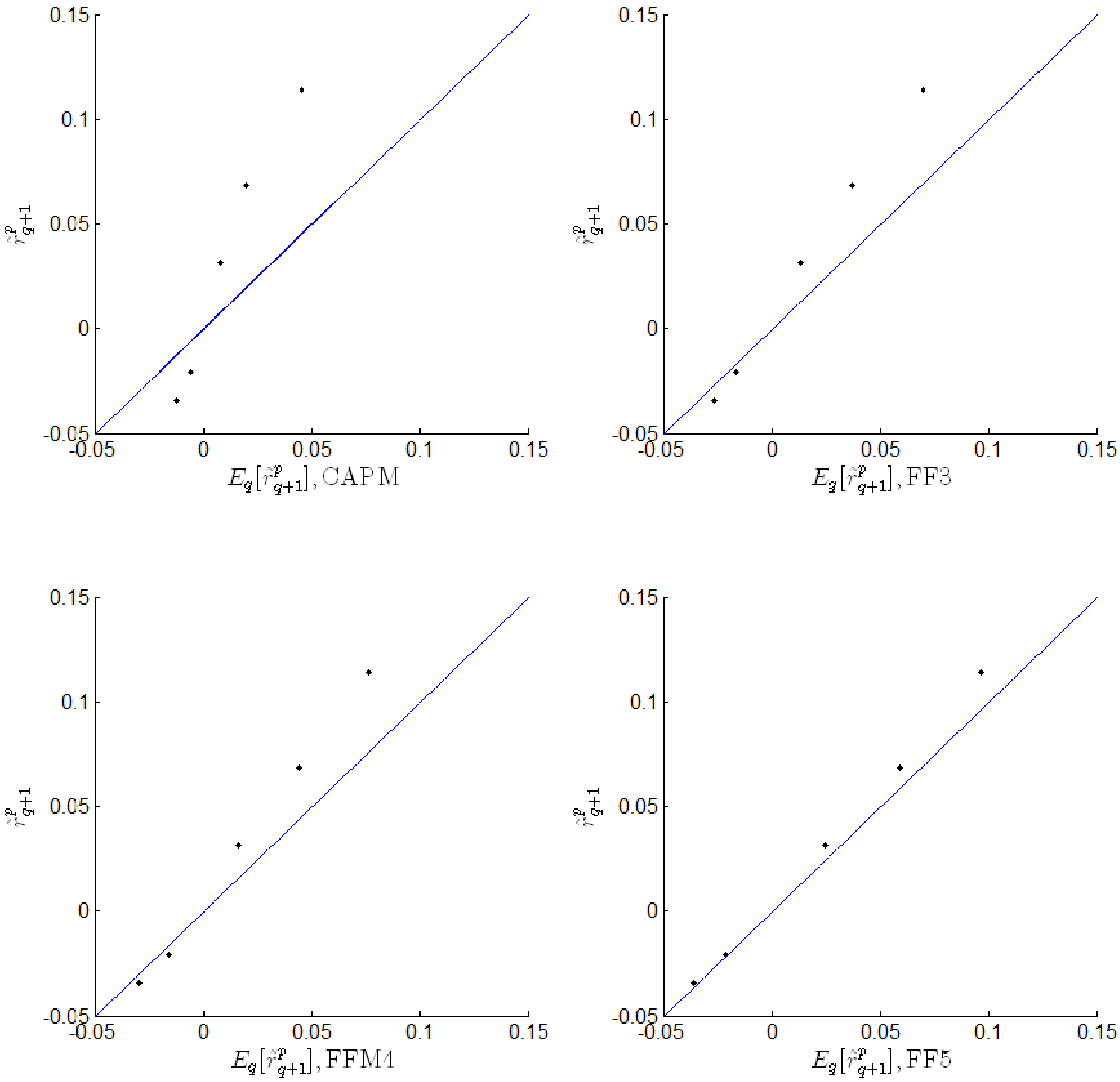


Figure 5
Cross-sectional Fit: Average Realized Excess Return and Expected Excess Return of Quintile Portfolios Sorted by $\overline{\text{DP}}$

The figure shows the scatter plot of average excess return of portfolios of dividend strips in quarter $q+1$, $\tilde{r}^p_{q+1}$, against expected quarterly excess returns according to the CAPM, the FF3, the FFM4 and the FF5. Dividend strips are sorted into quintile portfolios by $\overline{\text{DP}}$ at the end of a quarter q. The line represents the 45 degree line. The sample period is from January 1996 to December 2017.

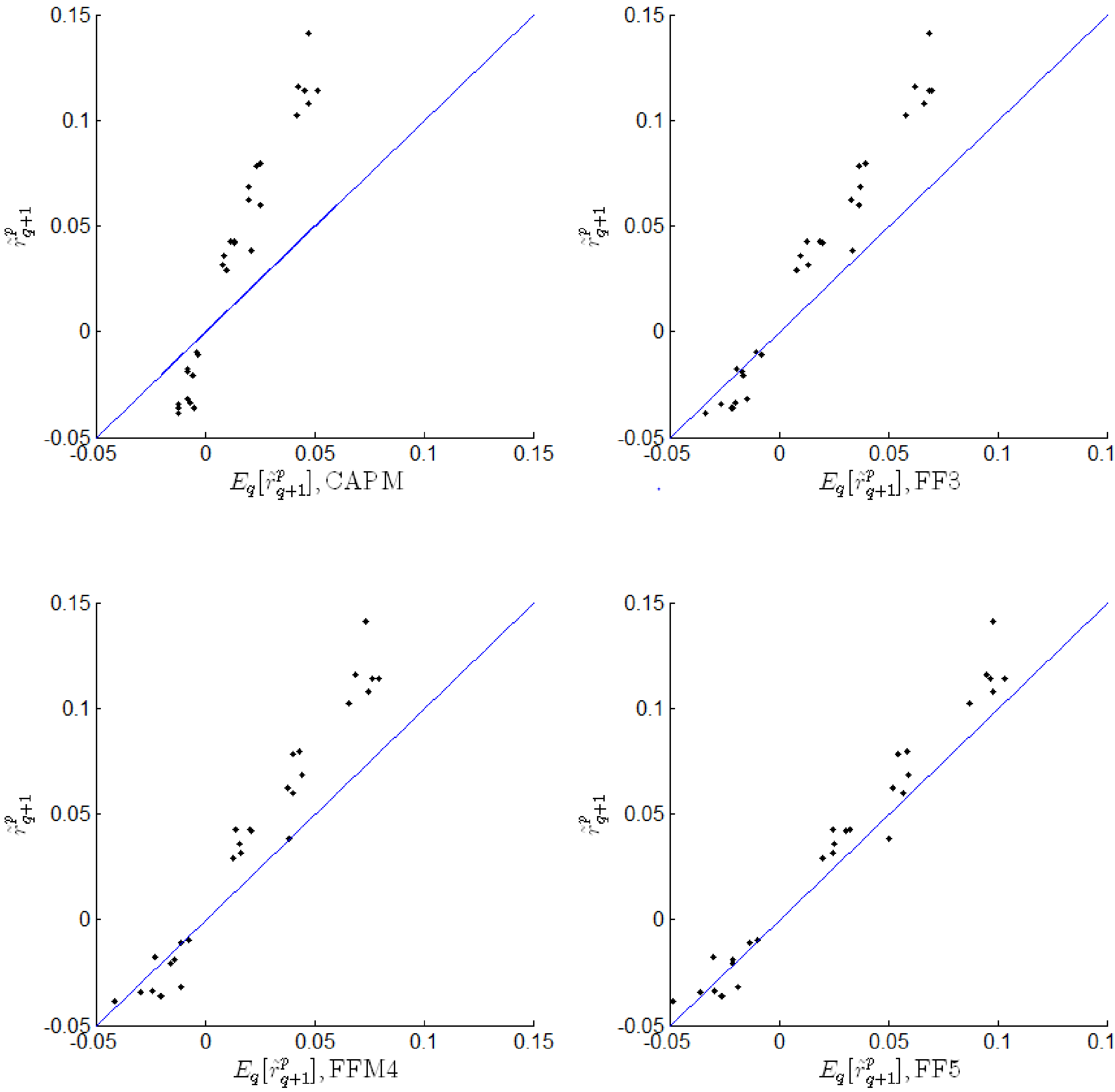


Figure 6
Cross-sectional Fit: Average Realized Excess Return and Expected Excess Return of 25 Portfolios Sorted by PIH and $\overline{\text{DP}}$

The figure shows the scatter plot of average excess return of portfolios of dividend strips in quarter $q+1$, $\tilde{r}^{p}_{q+1}$, against expected quarterly excess returns according to the CAPM, the FF3, the FFM4 and the FF5. Dividend strips are first sorted into quintile portfolios by PIH and then within each PIH group are sorted into quintile portfolios by $\overline{\text{DP}}$ at the end of a quarter q. The line represents the 45 degree line. The sample period is from January 1996 to December 2017.