ESSAYS ON THE VALUE EFFECT IN THE TIME SERIES AND CROSS SECTION OF STOCK RETURNS

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___________________(Signed)

_______XU Jin______(Name of student)

To my parents

Essays on the Value Effect in the Time Series and Cross Section of Stock Returns

Abstract

This thesis consists of three essays. The commonality of the essays lies their investigation of the value effect, in either the time series or cross section of stock returns. Specifically, the first essay examines the predictive power of the aggregate book-to-market ratio for aggregate stock returns in the U.S. stock market, after aggregate profitability and asset investment have been controlled for. The second essay studies the crash risks of the size (SMB), value (HML), and momentum (UMD) factors in the G7 countries, and whether such risks can be internationally diversified. The third essay looks at how the Fama-French three-factor model performs in the Chinese stock market, after the special features of the market have been accounted for.

In the first essay, we find that both aggregate profitability and asset investment have significant predictive power for aggregate stock returns. While previous studies that use the book-to-market ratio (B/M) to predict aggregate stock returns emphasize the need to control for expected profitability, we show that it is important to control for expected investment as well. Just knowing expected future profits is not enough—it is also important to control for how much additional investment is needed to generate those profits. On the other side, at both the aggregate-market and 48-industry levels, profitability and investment are positively correlated with each other yet predict future returns in opposite directions; B/M and profitability are negatively correlated with each other yet predict future returns in the same direction. This correlation structure also calls on a simultaneous control for all three variables when predicting aggregate stock returns in order to extract the most forecast power out of them. Using aggregate B/M, profitability, and asset investment as predictors produces statistically and economically significant improvement in out-of-sample R^2s and certainty equivalent return (CER) gains in equity premium forecasts. A decomposition of total assets into its components shows that cash and short-term asset growth predicts one-year-ahead (but not two-year-

ahead) stock returns, while the growth rate of longer-term assets predicts two-year-ahead stock returns only. Since total asset growth consists of both the short- and long-term components of investment, its predictive power for future stock returns is robust across different time horizons.

In the second essay, we find that the crash risks of momentum tend to be higher than those of size and value. International diversification lowers the crash risks of size and value, but not momentum. By examining the conditional correlations and return coexceedances of style portfolios across countries, we conclude that this difference in the effect of diversification is due to the left (right) tails of momentum (size and value) portfolios being more correlated than their right (left) tails across countries.

The third essay explores to what extent the Fama-French three factors explain the variation in Chinese stock returns. We document empirical evidence on this issue and identify some pitfalls that arise in the application of the three-factor model to Chinese stock returns. We find that several special features in China affect the three factors considerably and also influence the explanatory power of the three-factor model.

Publications Arising from the Thesis

Chapter 2 of this thesis was published in the *Financial Analyst Journal* in 2015; Chapter 3 was published in the *China Accounting and Finance Review* in 2014. The detailed references are as follows:

Chue, Timothy K., Yong Wang, and Jin Xu, 2015, The crash risks of style investing: Can they be internationally diversified? *Financial Analyst Journal* 71, 34-46.

Xu, Jin, and Shaojun Zhang, 2014, The Fama-French three factors in Chinese stock market, *China Accounting and Finance Review* 16, 210-227.

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Chapter 1
Profitability, Asset Investment, and Aggregate Stock Returns

1.1 Introduction

Many recent studies find that profitability and investment have conditional predictive power for future stock returns in the cross section. Fama and French (henceforth FF, 2006, p.493) work within the scheme of the valuation model of Miller and Modigliani (1961, henceforth MM) and argue that "cleanly identifying book-to-market, profitability, or investment effects in expected returns requires controls for the other two variables, which are often missing in earlier tests. Our goal is to provide an overall perspective on how the three combine to explain the cross section of average stock returns". FF (2015, p.4) point out that the need to jointly control for the book-to-market (B/M), profitability, and investment is due to the correlation structure among the three variables—"The valuation equation does not predict that B/M, OP (operating profitability), and Inv (investment) effects show up in average returns without the appropriate controls. Moreover, Fama and French (1995) show that the three variables are correlated. High B/M value stocks tend to have low profitability and investment, and low B/M growth stocks – especially large low B/M stocks – tend to be profitable and invest aggressively". Hou, Xue, and Zhang (henceforth HXZ, 2014, p.12) also emphasize the need to jointly control for profitability and investment—"The negative investment-return relation is conditional on a given level of ROE. The correlation could be positive unconditionally if large investment delivers exceptionally high ROE. Similarly, the positive ROE-return relation is conditional on a given level of investment. The correlation could be negative unconditionally if high ROE comes with exceptionally large investment. A joint sort on investment and ROE controls for these conditional relations".

This study extends FF and HXZ's insights to the time series—the predictive power of aggregate B/M, profitability, and investment for aggregate stock returns is also conditional in nature. At aggregate level, B/M and profitability are negatively correlated yet predict stock returns in the same direction; investment and profitability are positively correlated yet predict stock returns in the opposite directions. Because of the correlation structure of these variables, one needs to simultaneously control for all three variables to get the most predictive power out of them. Previous studies have examined the time-series predictive power of individual

B/M/profitability/investment, or that of B/M and profitability jointly[1], but not that of all three together. We fill this blank and show that the improvement in predictive power by doing so is highly substantial.

FF use the valuation model of MM to motivate the link between B/M, profitability, investment, and stock returns. Using the notations of FF (2015), MM's model can be written as:

$$\frac{M_t}{B_t} = \frac{\sum_{\tau=1}^{\infty} E_t(Y_{t+\tau} - dB_{t+\tau})/(1+r_t)^{\tau}}{B_t}\,, \tag{1.1}$$

where M_t is a firm's market value of equity at the end of period *t*, B_t is the book value of equity at the end of period *t*, $Y_{t+\tau}$ is the earnings to be received at the end of period t+τ, $dB_{t+\tau}$ is the change in book equity in period t+τ, defined as $(B_{t+\tau} - B_{t+\tau-1})$, and r is expected stock return. FF (2006, 2015, 2016) and Aharoni, Grundy, and Zeng (2013) examine if this relationship that links B/M, profitability, investment, and stock returns together holds for firm-specific deviations from market averages. For instance, with a firm's market-adjusted B/M being held constant, they evaluate if the firm's expected stock returns would be higher than the market average when its market-adjusted profitability is high or its market-adjusted investment is low.

HXZ (2014, 2015) motivate the importance of profitability and investment with a *q*-theory-based model:

$$E_0[r_{i1}] = \frac{E_0[\Pi_{i1}]}{1+a(I_{i0}/A_{i0})}\,, \tag{1.2}$$

where $E_0[r_{i1}]$ is the expected date 1 stock return of firm *i* as of date 0; $E_0[\Pi_{i1}]$ is the expected date 1 profitability of firm *i* as at date 0, and can be viewed as the marginal benefit of investment; A_{i0} and I_{i0} are the assets and investment of firm *i* at date 0, respectively; a is a constant parameter; and $1 + a(I_{i0}/A_{i0})$ is the marginal cost of investment. Equation (1.2) implies that the investment return (the ratio between the date 1 marginal benefit and date 0 marginal cost of investment) should equal the discount rate—a relationship that is also examined by Cochrane (1991), Liu, Whited, and Zhang (2009), Li and Zhang (2010), and Lin and Zhang (2013). The empirical analysis of HXZ (2014, 2015) examines the cross-sectional

[1] See, for example, Vuolteenaho (2002) and the discussion therein.

relationship between profitability, asset investment, and expected stock returns—effectively focusing on variations of these variables relative to their market averages.

Do these mechanisms that tie B/M, profitability, investment, and stock returns together only hold for firm-specific deviations from market averages, or do they also hold for time-series variations in the market averages themselves?[2] Does the valuation model in FF hold not only for firm-specific, but also for market-wide, components of its variables? Do firms in HXZ's model consider not only firm-specific, but also market-wide, components of their costs and benefits when making investment decisions? To answer these questions, we evaluate if the relationships between profitability, investment, and stock returns, as implied by FF and HXZ, are also present at the aggregate level.[3] This exercise serves as an out-of-sample test of FF and HXZ—although FF and HXZ only examine variations in the firm-specific components of their variables, the mechanisms that they use to justify their models, as given by equations (1.1) and (1.2), also apply to the market-wide components that are common across firms. It is important to note that a firm-level variable's predictive power in the cross section needs not translate into predictive power for its aggregate counterpart in the time series. For example, although Sloan (1996) finds that firm-level accruals negatively predicts stock returns in the cross section, Hirshleifer, Hou, and Teoh (2009) show that aggregate accruals is a positive time-series predictor of aggregate stock returns. Hirshleifer, Hou, and Teoh (2009, p. 392) interpret their results as providing "out-of-sample evidence about the extent to which the behavioral theory used to explain the firm-level findings explains a broader range of stylized facts." Kothari, Lewellen, and Warner (2006) find that the firm-level post-earnings announcement drift effect (PEAD), as documented by Bernard and Thomas (1990), becomes much weaker at the aggregate level. They also motivate their study as "a simple out-of-sample test of recent behavioral theories … [that] cite PEAD as a prime example of the type of irrational price behavior predicted by their models." (Kothari, Lewellen, and Warner 2006, p. 538)

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[2] In the evaluation of equations (1.1) and (1.2) at the aggregate level, the expected future aggregate variables computed as of period *t* exclude firms that only get listed after period *t*.

[3] Although equation (1.1) refers to equity investment, $dB_{t+\tau}/B_t$, we follow FF (2006, 2015, 2016) and HXZ (2015) to measure investment as asset growth, $dA_{t+\tau}/A_t$, which FF judge to give a better picture of investment. In fact, we get qualitatively similar results by using $dB_{t+\tau}/B_t$. $dB_{t+\tau}/B_t$ is highly correlated with $dA_{t+\tau}/A_t$, with a correlation of 0.86 (p<.0001). The predictive power of $dB_{t+\tau}/B_t$ for future stock returns is somewhat weaker but remains significantly negative, and its correlation structure with B/M and profitability remains unchanged—significantly negative correlation with B/M and significantly positive correlation with profitability. As a result, the conditional predictive power of B/M and profitability—whether conditional on $dA_{t+\tau}/A_t$ or $dB_{t+\tau}/B_t$—is unaffected.

To examine the conditional predictive power of B/M, profitability, and asset investment for future stock returns, we simply aggregate period *t* firm-level B/M, profits, and asset growth rates to obtain period *t* market-level B/M, profitability, and investment, and then use these aggregate variables to predict aggregate stock returns in *t*+1 and/or *t*+2. In this way, period *t* aggregate profitability and investment serve as proxies for *expected* future profitability and investment that appear in equation (1.1).[4] We find that high B/M, high aggregate profits, and low aggregate investment indeed predict high future aggregate stock returns. The predictive power of these variables is the strongest when controlling for the other two variables. Quantitatively, we find that the out-of-sample (OOS) R^2s for predicting one-quarter-, one-year-, and two-year-ahead aggregate stock returns is 7%, 20%, and 29%, respectively. Using Clark and McCracken's (2001) ENC-NEW statistic, we show that these OOS forecasts are associated with statistically significant improvements in forecast accuracy relative to the historical mean.

To see whether the conditional predictive power of B/M, profitability, and investment for aggregate stock returns is market-wide or industry-specific, we carry out the analysis on the industry level. We run industry-level panel regressions with industry fixed effects, where industries are defined as Fama-French 48 industries (excluding the financial industries). We either equal-weight or value-weight each industry in each period. The specification with B/M, profitability, and asset growth controlled for still gains the strongest explanatory power—the adjusted in-sample (IS) R^2s are 3%, 8%, and 13% respectively when predicting one-quarter-, one-year-, and two-year-ahead industry-level stock returns if we value-weight each industry. The results are comparable if we equal-weight each industry.

To show that jointly using aggregate B/M, profitability, and investment as predictors does make an economically significant impact on equity premium forecasts, we begin with what an investor observed in mid-2016. At that time, purely from a valuation standpoint, the stock market already appeared "expensive"—B/M was more than one standard deviation (s.d.) below its historical mean. As a result, the one-year-ahead equity premium forecast—based on B/M alone—was 2.5%. Yet, at the same time, since aggregate profitability was 1.2 s.d. above its mean and investment .38 s.d. below its mean, the forecasted equity premium became 11.3% when all three variables were used as predictors instead.[5] To evaluate the implication of our

[4] FF (2006) suggest using *observed* period *t* profitability and investment as proxies for *expected* future profitability and investment at the firm level.

[5] With the benefit of hindsight, we now know that the actual equity premium from June 2016 to June 2017 is 14.7%.

results for portfolio choice more systematically, we calculate the certainty equivalent return (CER) gain from using aggregate B/M, profitability, and investment as predictors—relative to the case where only the B/M is used. We find that, depending on the value of the risk aversion parameter, the CER gain ranges from 2.23% to 3.61% when one-year-ahead equity premium forecasts are used, and ranges from 2.97% to 6.88% when two-year-average equity premium forecasts are used for portfolio allocation.

In sum, we show that the nature of the predictive power of aggregate B/M, profitability, and investment for future aggregate stock returns is also conditional. As a result, one has to simultaneously control for all three variables when predicting aggregate stock returns. On the other side, we show that the mechanisms that FF and HXZ find to account for a substantial fraction of cross-sectional variations in stock returns can also explain the time series. These results provide out-of-sample empirical support for FF and HXZ—as even though FF and HXZ only examine variations in the firm-specific components of their variables, the mechanisms that they use to justify their models also hold for variations in the market-wide components.

Our second contribution lies in the identification of predictors of aggregate stock returns that are more robust than those used in previous studies. Related to earnings, Kothari, Lewellen, and Warner (2006) find that scaled aggregate earnings growth has no predictive power for aggregate stock returns. Bali, Demirtas, and Tehranian (2008) overturn previous results reported by Lamont (1998) and show that both the aggregate earnings/price and the aggregate dividend/earnings ratios have no predictive power for aggregate stock returns. By contrast, we find that aggregate profitability displays significant predictive power for aggregate stock returns—especially when used in conjunction with the B/M and asset investment—consistent with the implications of FF.

With respect to investment, Cochrane (1991) constructs an aggregate investment measure from macroeconomic data that negatively predicts subsequent stock returns, but the predictive power is subsumed by the dividend yield. Lamont (2000) reports a stronger predictive relationship between investment and stock returns, but the investment measure is based on survey data on managers' *expected* (rather than actual) investment. Arif and Lee (2014) construct an aggregate investment measure that focuses on certain components of total asset growth. Their investment measure displays strong predictive power for two-year-ahead (but not one-year-ahead) aggregate stock returns. By contrast, total asset growth, the investment measure used by FF and HXZ and examined here, exhibits predictive power for aggregate stock returns that is robust across both the one- and two-year horizons.

To gain a deeper understanding of the source of the predictive power of aggregate asset growth for future aggregate stock returns, we follow Cooper, Gulen, and Schill (2008) and decompose total assets into its major components—from both an investment perspective (left-hand side of the balance sheet) and a financing perspective (right-hand side of the balance sheet). From the investment perspective, total assets are decomposed into cash and short-term assets,[6] other current assets, property, plant, and equipment (PPE), and other assets. From the financing perspective, total assets are decomposed into operating liabilities, retained earnings, equity financing, and debt financing. We find that the predictive power of total asset growth for future stock returns is more robust across different investment horizons than its individual components. The growth in cash and short-term assets can only predict one-year-ahead (but not two-year-ahead) stock returns while the growth in longer-term assets can only predict two-year-ahead (but not one-year-ahead) stock returns. By incorporating the predictive power of all its individual components, total asset growth can forecast future stock returns at *both* investment horizons. This is why, by focusing on only certain components of asset investment, Arif and Lee's (2014) investment measure is not as robust a predictor of the equity premium as total asset growth across different time horizons.

To further investigate where the predictive power of B/M, profitability, and investment comes from, we examine if high B/M, high profits, and low asset investment—predictors of higher future aggregate returns—forecast higher aggregate return volatility. We find that they do not. In fact, lower asset growth forecasts lower (not higher) future market volatility, and higher B/M forecasts lower (not higher) future market volatility. Profitability exhibits weak predictive power for future market volatility in the right direction, but the marginal predictive power is gone after controlling for B/M and asset growth. These results show that the higher equity premium associated with higher B/M/profitability and lower asset investment is not simply a compensation for higher market volatility risk.

We also investigate if the predictive power of B/M, profitability, and asset investment comes from their correlations with other known predictors of the equity premium. In particular,

[6] This component corresponds to Compustat item *CHE*. As discussed in detail by Duchin, Gilbert, Harford, and Hrdlicka (2017), this item represents the sum of the balance sheet accounts "cash and cash equivalents" and "short-term investments", which include, respectively, financial assets with maturity of up to 90 days at issuance and financial assets that the firm intends to liquidate within a year.

we control for the T-bill rate, term spread, default spread, CAY (the consumption-wealth ratio constructed by Lettau and Ludvigson 2001), equity issuance (Baker and Wurgler 2000), aggregate operating accruals (Hirshleifer, Hou, and Teoh 2009), and the investor sentiment measures proposed by Baker and Wurgler (2006, 2007) and Huang, Jiang, Tu, and Zhou (2015). We find that, even in the presence of these control variables, the predictive power of the three variables remains relatively unchanged.

As we discuss in Footnote 2 above, to use equations (1.1) and (1.2) for an aggregate-level analysis, we should only include those firms that are already in existence in period t when calculating the aggregate market return to be forecasted in period t+1 or t+2. To examine how sensitive our results are to this restriction, we replace our market return measures by the CRSP value-weighted returns—which include new firms that get listed between period t and period t+1 or t+2. Not surprisingly, we find that the results become weaker, but all our main conclusions remain unchanged.

Our analysis emphasizes the evaluation of out-of-sample return predictability—which is more relevant for investors in real time and is less subject to the Stambaugh (1999) small-sample bias (see Busetti and Marcucci 2013). Relative to typical predictive regressions that only use valuation ratios as predictors, our concern for this small-sample bias is further reduced by profitability and investment being less persistent than the valuation ratios,[7] and the correlations between aggregate stock returns and contemporaneous asset investment and profitability both being insignificantly different from zero.

The rest of the paper proceeds as follows. Section 1.2 provides a brief review of studies that are related to ours. Section 1.3 documents data and sample construction. Section 1.4.1 reports our equity premium forecasts and their statistical significance. Section 1.4.2 evaluates economic significance. Section 1.4.3 decomposes asset growth into its individual components and evaluates their predictive power over different forecast horizons. Section 1.4.4 examines if the predictive power of B/M, profitability, and investment is related to aggregate stock market volatility. Section 1.5 carries out a series of robustness checks. Section 1.6 concludes.

[7] The first-order autocorrelations of asset investment and profitability are equal to 0.6 and 0.8, respectively, whereas those for the valuation ratios are in the neighborhood of 0.9.

1.2 Literature Review

Our study builds on the literature that uses various investment and profitability measures to explain the *cross section* of expected stock returns. FF (2006, 2015, 2016), Aharoni, Grundy, and Zeng (2013), and HXZ (2015) control for both the profitability and investment factors, while Novy-Marx (2013) and Ball, Gerakos, Linnainmaa, and Nikolaev (2015, 2016) focus on the explanatory power of profitability. Titman, Wei, and Xie (2004) find that firms with higher capital investment tend to have lower subsequent stock returns. Using a variance decomposition approach, Mao and Wei (2016) further demonstrate that investors' cash flow expectations for high-investment firms tend to be overoptimistic. Cooper, Gulen, and Schill (2008) find that total asset growth negatively predicts future abnormal stock returns. Lipson, Mortal, and Schill (2011) further show that total asset growth subsumes the predictive power of other investment measures, and that the asset growth effect is concentrated in firms that are relatively costly to arbitrage. Li and Zhang (2010) also document that limits-to-arbitrage proxies help explain the asset growth effect.

The investment effect can also be understood from a rational perspective. Based on the *q*-theory of investment, Lin and Zhang (2013) and HXZ (2015) propose a two-period model, as displayed in equation (1.2) above, in which firms invest until the marginal cost of date 0 investment equals its expected date 1 marginal benefit. This *q*-theory-based model has received empirical support from HXZ (2015), who find that a four-factor model that combines the market, size, profitability, and investment factors can account for many anomalies in the cross section of stock returns. Xing (2008) finds that the value effect disappears once an investment growth factor has been controlled for, where the investment growth factor is defined as the difference in returns between low-investment and high-investment stocks. Bakke and Whited (2010) show that private investor information affects corporate investment but stock market mispricing does not. Warusawitharana and Whited (2016) find that stock misevaluation affects firms' financing rather than their investment decisions. Using an international sample, Watanabe, Xu, Yao, and Yu (2013) further show that the negative cross-sectional relationship between asset growth and subsequent stock returns is stronger in markets with more efficient stock prices, suggesting that the relationship is more likely due to an optimal investment effect rather than mispricing. Kogan and Papanikolanou (2013) show that the investment anomaly is related to investment-specific technology (IST) shocks. Specifically, they find that firms' investment rates are associated with future IST risk exposures, even after other risks have been controlled for. They find that heterogeneity in IST shocks account for a large fraction of the average return variations that are associated with investment rates.

A long literature examines the predictive power of various valuation ratios for future stock returns. FF (1988) study the predictive relationship between the dividend-price ratio and subsequent aggregate stock returns, and find that this predictive power tends to strengthen at longer forecast horizons. Campbell and Shiller (1988a, 1988b) use a vector-autoregressive (VAR) framework to examine how this predictive relationship is linked to the variation in the dividend-price ratio over time. Vuolteenaho (2002) extends this framework and relates variations in the book-to-market ratio to movements in future stock returns and profitability.

Recent empirical evidence on the predictive power of valuation ratios is more mixed. Ang and Bekaert (2007) find that the dividend yield can only predict aggregate stock returns at short (but not long) horizons. Henkel, Martin, and Nardari (2011) further show that the dividend yield exhibits short-horizon forecast power for stock returns only during business cycle contractions (but not expansions). Welch and Goyal (2008) find that the out-of-sample forecast performance of valuation ratios is much poorer than their in-sample counterparts. On the other hand, Campbell and Thompson (2008) show that, after imposing sign restrictions on coefficient estimates and return forecasts, valuation ratios beat the historical mean in their out-of-sample forecast accuracy.[8] Cochrane (2008) finds that the evidence for the absence of dividend growth predictability is more compelling than the presence of stock return predictability. Given that either future stock returns or future dividend growth rates must be predictable to justify the variation in the dividend-price ratio, the author interprets the lack of dividend growth predictability as supportive evidence for return predictability.

To account for the weak empirical relationship between the dividend-price ratio and subsequent stock returns, Menzly, Santos, and Veronesi (2004) propose a general equilibrium model that exhibits time-varying expected dividend growth rates. These time-varying expectations induce a negative relationship between the dividend yield and expected returns, offsetting the positive relationship that would be present if expected dividend growth rates were constant. Lettau and Van Nieuwerburgh (2008) examine the effects of possible shifts in the steady-state means of the valuation ratios. Jank (2015) further examines how such shifts

[8] All our out-of-sample equity premium forecasts are computed by imposing these restrictions.

occurred when a large number of low-dividend-paying firms entered the stock market since the 1970s, resulting in a decline of the aggregate dividend-price ratio.

Other recent studies exploit disaggregate information in making aggregate-level forecasts. To predict the aggregate stock return, Ferreira and Santa-Clara (2011) forecast its three components—the dividend-price ratio, earnings growth, and the price-earnings ratio growth. Kelly and Pruitt (2013) extract a single factor from the cross section of firm-level book-to-market ratios. Both methods achieve considerable improvements in out-of-sample forecast accuracy.

1.3 Data and Sample Construction

We obtain U.S. financial statement data from the CRSP/Compustat merged annual and quarterly data files, and stock returns data from the CRSP monthly stock file. We include all common shares (share codes 10 and 11) listed on the NYSE/AMEX/Nasdaq (exchange codes 1, 2, and 3) with December fiscal year-ends, but exclude all financial firms (SIC codes 6000-6999). We also exclude firm-years (or firm-quarters) with book assets less than $25 million or book equity less than $12.5 million. Our annual (quarterly) accounting data covers the period 1962-2014 (1975Q1-2016Q4), and the corresponding stock returns data spans July 1963-Jun 2016 (Aug 1975-Jul 2017).

Our main predictors include the log book-to-market ratio, profitability, and asset growth. The book-to-market ratio B_{it}/M_{it} of firm *i* in year *t* equals firm *i*'s book equity in year *t* divided by its market equity at the end of year *t*. Book equity equals total assets (Compustat item AT), minus total liabilities (Compustat item LT), plus balance sheet deferred taxes and investment tax credit (Compustat item TXDITC), if available, minus the book value of preferred stock. We use liquidating value (Compustat item PSTKL), if available, or redemption value (Compustat item PSTKRV), if available, or carrying value (Compustat item PSTK), if available, for the book value of preferred stock. Firm i's profitability in year *t*, GP_{it}/B_{it-1}, is defined as the firm's gross profits in year *t* divided by its book equity in year *t-1*, where gross profits is defined as revenues (Compustat item REVT) minus cost of goods sold (Compustat item COGS). Novy-Marx (2013, p.2) argues that "Gross profits is the cleanest accounting measure of true economic profitability". We follow him to use gross profits as a measure of earnings.[9] Asset growth in year t, dA_{it}/A_{it-1}, is given by $(A_{it} - A_{it-1})/A_{it-1}$, where A_{it} is firm i's total assets (Compustat item AT) in year t. We use quarterly accounting data to compute B/M, profitability, and asset growth in the quarterly analysis. The detailed constructions of the quarterly variables are described in Appendix 1.A. These firm-level accounting variables are winsorized at the 0.5 and 99.5 percentiles every year/quarter.

Aharoni, Grundy, and Zeng (2013) point out that the valuation model (1) holds at the firm rather than per-share level. We follow their suggestion and measure all variables at the firm level, without scaling them by the number of shares outstanding. We then aggregate each firm-level variable together by using firms' end-of-period market capitalizations as the weights.

Since we only include firms with December year-ends in our sample, in the annual analysis, we use accounting variables in year t to forecast aggregate stock returns (in excess of the risk-free rate) from July of year t+1 to June of year t+2—thus allowing a six-month gap for accounting information to become publicly available after a fiscal year ends. Firm-level annual stock returns are obtained by compounding monthly stock returns (adjusted for delisting returns) from July in t+1 to June in t+2. If a firm's delisting return is missing and the delisting is performance related, we assume a -30% delisting return. Otherwise, we set the missing returns to zero.[10] In the quarterly analysis, we impose a four-month gap between the quarterly accounting variables and the quarterly aggregate stock returns. For instance, the accounting variables in the first fiscal quarter of year t (which is also the first calendar quarter of year t) would be used to forecast the aggregate stock returns covering August, September, and October of year t.

After subtracting the compounded one-month Treasury bill rates over the same 12 months to obtain excess returns, we compute aggregate excess stock returns in year t+1 (R^e_{t+1}) by aggregating firm-level excess returns using the market capitalizations at the end of year t as weights. The two-year average return $R^e_{(t+1,t+2)}$ is defined as the geometric average of annual excess stock returns R^e_{t+1} and R^e_{t+2}. We compute quarterly aggregate stock returns in a similar way—firm-level excess returns are aggregated by using the quarterly updated market capitalizations as weights—we use the market capitalization at the end of March of year t to weight the quarterly firm-level stock returns beginning from August of year t, and use the

[9] In Section 1.5.2, we use cash-based operating profitability as an alternative earnings measure, which is proposed by Ball et al. (2016). Our results are robust to this change.
[10] This treatment of missing delisting returns follows the suggestion of Shumway (1997).

market capitalization at the end of June of year *t* to weight the quarterly stock returns beginning from November of year *t*, and so on. Our firm-level annual accounting data contain 70,970 firm-years over the period 1962-2014. The corresponding return prediction period spans July 1963-June 2016. Our quarterly accounting data contain 241,071 firm-quarters over the period 1975Q1-2016Q4. The corresponding return prediction period spans August 1975-July 2017.

1.4 Empirical Results

This section reports our main empirical results. Section 1.4.1 uses OOS R^2s to compare the forecast accuracy of our predictors relative to the historical mean and tests the statistical significance of the difference. Section 1.4.2 compares our forecasts with those that only use B/M as predictor, and quantifies the economic significance of the difference by calculating the certainty equivalent return (CER) gains. We then explore the source of the predictive power of asset growth by decomposing it into various components, and use these results to understand why the predictive power of the investment measure constructed by Arif and Lee (2014) is less robust than total asset growth across different time horizons. Last, we examine if higher B/M, higher aggregate profitability and lower asset growth—predictors of higher equity premium—also predict higher aggregate stock market volatility.

1.4.1 Statistical Significance of the Equity Premium Forecasts

MM's valuation model, which motivates our analysis, implies that equation (1.1) holds for all firms in period *t*. But since this relationship applies to all firms in period *t*, firms that only get listed *after* period *t* should not be included in our calculation of expected future aggregate variables. For this reason, we construct market returns (in periods t+1 and t+2) to be forecasted by including only those firms that are already in our sample in period *t* when the equity premium forecast is made—instead of using the returns on a stock market index, which allows new firms to enter after period *t*.[11] In addition to B/M, profitability, and asset investment, which we already discuss in Section 1.3 above, we also control for other predictors for the

[11] In Section 1.5.2 below, we show that our main results become only slightly weaker at annual frequency when the CRSP value-weighted index is used instead to measure aggregate market returns.

equity premium. These variables are discussed in detail in Appendix 1.A. Table 1.1 reports their summary statistics and the correlation matrix of the main variables.

To compute OOS R^2s, in the annual analysis, we use a training window that runs from 1962 to June 1992, which includes accounting data up to 1990 and stock returns data up to June 1992. The first OOS equity premium forecast is for the period July 1992-June1993, using values of the explanatory variables in 1991 and coefficient estimates of the predictive regression obtained from the training period. Coefficient estimates of the predictive regression are updated at the end of June every year, incorporating data that just become available in real time. For example, the OOS forecast made in June 1993 for the period July 1993-June1994 is based on the predictive regression estimated using accounting data from 1962 to 1991 and stock returns data through June 1993. In the quarterly analysis, the training window goes over the period 1975-July 1991, which includes accounting data over 1975Q1-1990Q4 and stock returns data up to July 1991. The OOS forecast period is over August 1991-July 2017.

As in Kelly and Pruitt (2013), we compute the OOS R^2 as:

$$R^2_{OOS} = 1 - \frac{\sum_t (y_t - \hat{y}_t)^2}{\sum_t (y_t - \bar{y}_t)^2}\,, \tag{1.3}$$

where y_t is the actual stock return in period *t*, $\hat{y}_t$ is the fitted value from a predictive regression estimated through period *t-1*, and $\bar{y}_t$ is the historical average return estimated through period *t-1*.

To compare the OOS forecast accuracy of a predictive model with that of the historical mean return, we apply Clark and McCracken (2001)'s statistic ENC-NEW. The null hypothesis is that there is no improvement in forecast accuracy by using the predictive model under consideration, relative to using just the historical mean. The ENC-NEW statistic is given by:

$$\mathrm{ENC-NEW} = P\,\frac{P^{-1}\sum_t\left(\hat{u}^2_{1,t+1} - \hat{u}_{1,t+1}\hat{u}_{2,t+1}\right)}{P^{-1}\sum_t \hat{u}^2_{2,t+1}}\,, \tag{1.4}$$

where P is the number of return forecasts, $\hat{u}_{1,t+1}$ is the forecast error from using the historical mean, and $\hat{u}_{2,t+1}$ is the forecast error from using the predictive model.

All our OOS equity premium forecasts are computed by imposing the sign restrictions suggested by Campbell and Thompson (2008). Specifically, whenever the estimated slope of a predictor in a given period has a "wrong" sign (opposite to the one in the full-sample regression), it would be set to zero, and the regression would be rerun with the other predictor(s) until the rest predictor(s) all get the correct sign. If none of the predictors can get the correct sign, the regression would be rerun with a constant. We also restrict an equity premium forecast to be non-negative—if an equity premium forecast is negative, it would be set to zero. The OOS R^2 and ENC-NEW statistics are thus computed based on the OOS equity premium forecasts with the sign restrictions.

1.4.1.1 Forecasting Aggregate Stock Returns

We first use actual variables observed in period t as predictors to forecast one-year-ahead excess stock returns (R_{t+1}^{e}) and the geometric average of excess stock returns over t+1 and t+2 ($R_{(t+1,t+2)}^{e}$). We then use these variables to predict quarterly aggregate stock returns. Table 1.2, Panel A reports our baseline one-year-ahead return prediction results, using B/M, profitability, and asset growth as predictors. All right-hand-side (RHS) variables are standardized by their own time-series mean and standard deviation. A coefficient estimate can thus be interpreted as the change in annual stock return that is associated with a one-standard-deviation move in the corresponding predictor. The t-statistics in parentheses are computed using Newey-West (1987) standard errors with three lags.

Neither B/M nor profitability is significant when they enter the regressions separately. But when these two variables enter together, B/M exhibits significantly positive relationships with future stock returns—a one-standard-deviation increase in B/M would drive up future stock returns by 5.0%, with a t-statistic of 2.1; profitability remains insignificant, but its t-statistic increases from 0.4 to 1.4. This result is consistent with the insight of previous studies that highlight the need to control for expected future profitability when B/M is used to predict future stock returns—as a low B/M can be driven not only by low expected future returns, but also by high expected future profits. More mechanically, since B/M and expected profitability are negatively correlated with each other (the correlation coefficient is -0.52 and significant at the 1% level, as shown in Table 1.1, Panel B) and both of them positively forecast future stock returns, their predictive power cancels out when they enter the regression separately.

Asset growth by itself is a strong predictor for future stock returns—a one-standard-deviation increase in asset growth would lower one-year-ahead stock returns by 4.6%, and is statistically significant at the 1% level. The variation in asset growth accounts for 6% of the variation in future stock returns, when measured in terms of adjusted R^2. The OOS R^2 of asset growth (with the sign restrictions) is 12%, and the forecast accuracy improvement relative to the historical mean is statistically significantly at the 5% level, as indicated by the ENC-NEW statistic.

The specification in Column 6 simultaneously controls for B/M, profitability, and asset growth, directly following the guidance from the MM model. The overall explanatory power substantially increases both in sample and out of sample, compared to the specification that only controls for B/M and profitability and that controls for B/M and asset growth—the adjusted IS R^2 and OOS R^2 are 13% and 20% respectively.[12] Controlling for asset growth in addition to B/M and profitability increases the adjusted IS R^2 by 9% and OOS R^2 by 19%. Adding profitability to the specification with B/M and asset growth also brings about an 8% increase in adjusted IS R^2 and a 19% increase in OOS R^2. The forecast accuracy improvement is statistically significant at the 5% level, as indicated by the ENC-NEW statistic of 4.00. All three variables are significant in this specification—profitability and asset growth even exhibit the strongest forecast power (in terms of coefficient magnitude and *t*-statistic) compared to themselves in the other specifications. A one-standard-deviation increase in profitability would raise the aggregate stock return by 6.2%, significant at the 1% level; a one-standard-deviation increase in asset growth would depress the aggregate stock return by 6.2%, with a 1% significance level. The strengthened forecast power of profitability and asset growth can also be explained by the correlation structure between them—profitability and asset growth are positively correlated (the correlation coefficient is 0.50 and significant at the 1% level) but predict aggregate stock returns in the opposite directions. As such, their predictive power of aggregate stock returns could be canceled out without controlling for each other in the predictive regressions.

We further use period t variables to forecast the average returns over periods $t+1$ and $t+2$, and report these results in Table 1.2, Panel B. When the forecast horizon extends to two years, B/M displays weaker forecast power for two-year average returns than for one-year-ahead returns, whereas the opposite is observed for profitability and asset growth—in the specification which simultaneously controls for all three variables, profitability and asset growth attain even higher *t*-statistics than those in the one-year-ahead return forecast. As

[12] Using different approaches, Ferreira and Santa-Clara (2011) and Kelly and Pruitt (2013) report OOS R^2 of 13.4% and 13%, respectively.

before, this specification obtains the best OOS performance, with an OOS R^2 of 29%. The corresponding forecast accuracy improvement is significant at the 1% level.

At last, we use these variables to predict quarterly aggregate stock returns and report the results in Table 1.2, Panel C. B/M, profitability, and asset growth are computed by using quarterly accounting data. To reduce the effect of seasonality in quarterly earnings, we use the sum of the latest four quarters' gross profits rather than the current quarter's gross profits as the numerator of profitability. Accordingly, we use four-quarter lagged book equity rather than one-quarter lagged book equity as the denominator of profitability. In that sense, we still measure firms' profitability over a year, only with the difference that the profitability is now updated each quarter rather than each year. Considering firms' asset growth does not change much quarter to quarter, we compute quarterly asset growth by using the change in total assets between the current quarter and the fourth lagged quarter—similar to the computation of profitability, we measure asset growth over a year and update its value each quarter. The quarterly prediction results keep consistent with those in the annual analysis—the specification controlling for all three variables generates the highest IS adjusted R^2 (6%) and OOS R^2 (7%), with the forecast accuracy improvement significant at the 1% level; profitability performs the best when controlling for B/M and asset growth, echoing its correlations with the other two variables.

1.4.1.2 Cumulative Squared Forecast Errors

To investigate how the OOS forecast performance of different predictive models evolves over time, we examine their cumulative squared forecast errors (CSFE). In each year of the OOS forecast period, we compute the squared forecast error of the historical mean and then subtract from it a predictive model's squared forecast errors. All OOS forecasts are computed by imposing the sign restrictions of Campbell and Thompson (2008). We then add up these differences cumulatively at each point in time over the entire OOS forecast period. We plot these differences in CSFE in Figures 1.1 and 1.2, which display the plots in the annual and quarterly analyses respectively. If a predictive model outperforms the historical mean over a certain time period, the model would display a positively-sloped CSFE difference curve over this period.

Figure 1.1, Panel A displays the CSFE difference for the B/M. Its slope throughout the forecast period is predominantly negative—suggesting that B/M consistently underperforms the historical mean as a predictor. The specification of B/M plus profitability and the one of B/M plus asset growth perform slightly better—especially since the financial crisis of 2008. Panels D and E display the models that use standalone asset growth and all three variables as predictors respectively. These CSFE difference curves display an overall positive slope—suggesting that their superior OOS performance is not driven by an isolated episode. During 1993-2001, the CSFE difference curve of standalone asset growth is nearly horizontal, meaning that asset growth does not underperform or overperform the historical mean return as a predictor in this period. Differently, the model that uses all three predictors outperforms the historical mean return in the periods 1993-1994 and 1997-2001, and underperforms in the period 1994-1997. In the two years leading up to the global financial crisis, the three-predictor model displays a notable negative slope. After that, the model displays a steeper positive slope than standalone asset growth lasting until 2014.

In the quarterly CSFE difference plots displayed by Figure 1.2, the model using standalone B/M still has an overall negative slope. A highly fluctuating pattern in the entire period is observed for the model that uses B/M plus profitability. The model with all three predictors outperforms that with only asset growth, especially after October 2007, suggested by a more pronounced positive slope.

1.4.1.3 Forecasting Industry-Level Stock Returns

To see whether the predictive power of B/M, profitability, and asset growth pervades in the whole market or only exists in certain industries, we run industry-level predictive regressions. Specifically, we aggregate firm-level B/M, profitability, and asset growth to the industry level and use them to predictive industry-level stock returns. We categorize all firms in our sample into Fama-French 48 industries. Since we have excluded the financial firms from our sample, there are no observations for industries 44-47. We then run panel regressions using the industry-level variables with industry fixed effects. By doing so, we actually look at the average time-series effects of the industry-level predictors on industry-level stock returns. We either equal-weight or value-weight an industry in every period. To make the estimate coefficients comparable to those in the pure time-series regressions, we scale the RHS variables by their own aggregate standard deviation, which is the same scaler as in the aggregate regressions. We report the results by value-weighting industries in Table 1.3 (the equal-weighting results are similar). The *t*-statistics in parentheses are computed by using two-way clustered standard errors.

When predicting one-year-ahead industry-level stock returns (Table 1.3, Panel A), the highest forecast power arises in the specification simultaneously controlling for B/M, profitability, and asset growth, as suggested by the highest adjusted R^2. All three predictors are significant at the 5% level or above. If looking at the *t*-statistics, the effect of B/M is stronger for industry-level stock returns than for aggregate stock returns (2.41 vs. 1.98). In terms of coefficient magnitude, one-standard-deviation change in profitability or asset growth drives less variation in industry-level stock returns than in aggregate stock returns. For example, one-standard-deviation increase in profitability drives up industry-level stock returns by 1.3% but aggregate stock returns by 6.2%.

Table 1.3, Panel B predicts two-year average industry-level stock returns. The overall explanatory power of the model with three predictors increases from 8% (for one-year-ahead stock return prediction) to 13% and remains the highest among all specifications. Table 1.3, Panel C reports the results of predicting quarterly industry-level stock returns. Asset growth is a strong predictor on its own—one-standard-deviation increase in asset growth would lower quarterly industry stock returns by 0.9%, significant at the 1% level. It also attains an adjusted R^2 of 3%, as high as that by using all three predictors.

1.4.2 Economic Significance of the Equity Premium Forecasts

To illustrate the difference made by using aggregate B/M, profitability, and investment as predictors, we compare their most recent equity premium forecasts with those that we obtain from using B/M alone as predictor. Next, we evaluate the implication of our results for portfolio choice more systematically by computing the certainty equivalent return (CER) gains for different predictive models.

1.4.2.1 Recent Equity Premium Forecasts

We compare the equity premium forecasts—made as at June 2016—to see if the joint use of B/M, profitability, and asset investment as predictors leads to substantially different forecasts, relative to when only the B/M is used.

Table 1.4, Panel A reports the means, standard deviations, and the year 2015 values of the predictors. The last column computes the deviation of the 2015 values from their sample means, measured in standardized units (i.e. the deviations from means are scaled by their standard deviations). Panels B1 and B2 report the annual equity premium forecasts over July 2016-June 2017, and the average annual equity premium forecasts over July 2016-June 2018, respectively.

In June 2016, the aggregate stock market already appeared expensive from a pure valuation perspective—B/M was more than one standard deviation below its sample mean. As a result, when only the B/M is used as predictor, the equity premium forecast over July 2016-June 2017 is given by 2.5%, which is 3.7% lower than the historical average of 6.2%.

Yet, profitability was high in 2015 relative to its historical average, and asset growth was low relative to its average. Thus, when profitability is added to the specification with B/M only, the forecasted equity premium for July 2016-June 2017 increases to 4.6%. When we use B/M, profitability, and asset growth as predictors, the equity premium forecast increases to 11.3%. We now know that, *ex post*, this last forecast is closest to the actual equity premium of 14.7% over this time period.

Of course, a single, superior forecast does not validate a predictive model. The main point of this exercise is to show that the difference our approach makes can be large and highly relevant in practice. To demonstrate the economic significance of our model for portfolio allocation more systematically, we compute its certainty equivalent return (CER) gains below.

1.4.2.2 CER Gains in Portfolio Allocation

This subsection reports the certainty equivalent return (CER) gains from using B/M, profitability, and asset investment instead of only the B/M as equity premium predictors in portfolio allocation. This CER gain represents the value to an investor in her portfolio allocation by switching from a B/M-based OOS predictive model to one that is based on B/M, profitability, and asset investment. The % CER gain can be interpreted as an annual fee that the investor would be willing to pay to switch from a B/M-based to our B/M/profitability/investment-based forecasts.

To obtain the CER of a predictive model, we examine the portfolio choice of a mean-variance investor who optimally allocates her wealth between the value-weighted market portfolio and the risk-free asset, using the OOS forecasts of the predictive model. At the end of period *t*, the investor allocates the weight w_t to the equity portfolio and $1 - w_t$ to the riskless asset. The weight w_t is given by:

$$w_t = \frac{1}{\gamma}\frac{\hat{R}^e_{t+1}}{\hat{\sigma}^2_{t+1}}\,, \tag{1.5}$$

where γ is the risk aversion coefficient, $\hat{R}^e_{t+1}$ is the out-of-sample equity premium forecast obtained from the predictive model (we impose the sign restrictions of Campbell and Thompson (2008) on all OOS forecasts), and $\hat{\sigma}^2_{t+1}$ is the variance forecast for the equity premium, estimated using all available data prior to period t+1 (Ferreira and Santa-Clara 2011; Huang, Jiang, Tu, and Zhou 2015).

The realized portfolio return R^P_{t+1} in period t+1 is

$$R^P_{t+1} = w_t R^e_{t+1} + R^f_{t+1}\,, \tag{1.6}$$

where R^e_{t+1} is the realized excess market return in period t+1, and R^f_{t+1} is the gross risk-free return in period t+1. w_t is winsorized at 0 and 1.5, in order to exclude short sales and leverage that exceeds 50%.

The CER of the portfolio is given by

$$CER_P = \hat{\mu}_P - 0.5\gamma\hat{\sigma}^2_P\,, \tag{1.7}$$

where $\hat{\mu}_P$ and $\hat{\sigma}^2_P$ are the sample mean and variance of the portfolio returns. The CER gain of a predictive model relative to the B/M-based model is the difference between the CER obtained from the predictive model and the CER obtained from using the B/M alone as predictor.

The CER gains for the two-year-average equity premium forecasts are computed analogously. At the end of period *t*, the investor allocates the weight w_t to equities that is based on a predictive model's two-year-average forecast for periods t+1 and t+2:

$$w_t = \frac{1}{\gamma}\frac{\hat{R}^e_{(t+1,t+2)}}{\hat{\sigma}^2_{(t+1,t+2)}}, \tag{1.8}$$

where $\hat{R}^e_{(t+1,t+2)}$ is the OOS forecast for the geometric average of the excess market returns over periods t+1 and t+2, and $\hat{\sigma}^2_{(t+1,t+2)}$ is the variance forecast for two-year average returns, estimated from historical average returns as at the end of period *t*.

The realized average portfolio return over periods t+1 and t+2 is the geometric average $R^P_{(t+1,t+2)} = \sqrt{(w_t R^e{}_{t+1} + R^f_{t+1})(w_t R^e{}_{t+2} + R^f_{t+2})}$,where $R^e{}_{t+i}$ is the excess market return in period t+i (i=1,2). The CER for the average portfolio return is computed as in equation (1.5), with $\hat{\mu}_P$ and $\hat{\sigma}^2_P$ being the sample mean and variance of the average portfolio returns.

To examine whether the CER gain is statistically significant, we carry out the test introduced by DeMiguel, Garlappi, and Uppal (2009). (μ_i, σ_i^2) and (μ_n, σ_n^2), respectively, are the sample means and variances of the realized portfolio returns under forecast strategies *i* and *n*. $\sigma_{i,n}$ is the covariance between the portfolio returns of strategies *i* and *n*. We use υ to denote the vector, $\upsilon = (\mu_i, \mu_n, \sigma_i^2, \sigma_n^2)$, and $\hat{\upsilon}$ its empirical counterpart. The function$f(\upsilon)$, $f(\upsilon) = \left(\mu_i - \frac{\gamma}{2}\sigma_i^2\right) - \left(\mu_n - \frac{\gamma}{2}\sigma_n^2\right)$, calculates the difference in CER between strategies *i* and *n*,. The asymptotic distribution of $f(\upsilon)$ is given by $\sqrt{T}(f(\hat{\upsilon}) - f(\upsilon)) \to N(0, \frac{\partial f}{\partial \upsilon}^{\mathrm{T}} \Theta \frac{\partial f}{\partial \upsilon})$, where $\Theta = \begin{pmatrix} \sigma_i^2 & \sigma_{i,n} & 0 & 0 \\ \sigma_{i,n} & \sigma_n^2 & 0 & 0 \\ 0 & 0 & 2\sigma_i^4 & 2\sigma_{i,n}^2 \\ 0 & 0 & 2\sigma_{i,n}^2 & 2\sigma_n^4 \end{pmatrix}$, and T is the number of observations in the full sample. The null hypothesis is that there is no difference in the CER between the two forecast strategies, i.e., $f(\upsilon) = 0$. The alternative hypothesis is that $f(\upsilon) \neq 0$. The test statistic $\frac{\sqrt{T}f(\hat{\upsilon})}{\sqrt{\left(\frac{\partial f}{\partial \upsilon}^T \Theta \frac{\partial f}{\partial \upsilon}\right)}}$ follows a standard normal distribution.

Table 1.5 reports the CER gains of other predictive models relative to the CER of B/M. We examine models that use B/M plus profitability, or B/M plus profitability plus asset growth as predictors. We consider three different values of risk aversion coefficients ($\gamma = 1, 3,$ or 5).

Table 1.5, Panel A reports CER gains based on one-year-ahead equity premium forecasts. When $\gamma = 1$, the specification with B/M, profitability, and asset growth generates a positive CER gain of 3.23%, with a significance level of 5%. The specification with B/M plus profitability results in a negative CER gain. When γ equals 3 or 5, the specification with all three predictors produces CER gains of 3.61% and 2.23%, respectively, with both being significant at the 1% level. The specification with B/M plus profitability yields positive but statistically insignificant CER gains.

Table 1.5, Panel B reports CER gains based on two-year-average equity premium forecasts. Regardless of the value of the risk aversion coefficient used, the specification of B/M plus profitability does not generate any CER gain (the CER gain is either negative or insignificantly positive). By contrast, the specification of all three predictors always yields positive CER gains that are statistically significant at the 5% level or higher. In terms of magnitude, the CER gains range from 2.97% to 6.88%.

Overall, our results suggest that the benefit to a mean-variance investor in adopting a B/M plus profitability plus asset growth model for portfolio allocation, relative to using the B/M only, is both statistically and economically significant.

1.4.3 Decomposing Asset Growth

In this section, we investigate the source of the predictive power of asset growth by decomposing it into individual components. Following Cooper, Gulen, and Schill (2008), we decompose asset growth from the investment side and the financing side. From the investment side, we decompose asset growth into short-term asset growth (ChgSTAsst), other current asset growth (ChgCurAsst), property, plant and equipment growth (ChgPPE), and other asset growth (ChgOthAsst). The short-term asset component corresponds to Compustat item *CHE*. As discussed in detail by Duchin, Gilbert, Harford, and Hrdlicka (2017), this item represents the sum of the balance sheet accounts “cash and cash equivalents” and “short-term investments”, which include, respectively, financial assets with maturity of up to 90 days at issuance and financial assets that the firm intends to liquidate within a year. From the financing side, asset growth is decomposed into operating liabilities growth (ChgOpLiab), retained earnings growth (ChgRE), stock financing growth (ChgStock), and debt financing growth (ChgDebt).

Table 1.6 reports the predictive power of individual components of asset growth for future excess stock returns. Table 1.6, Panels A and B, respectively, report the one-year-ahead and two-year-average return forecasts. We find that the predictive power of total asset growth for future stock returns is more robust across the two investment horizons than its individual components. At the one-year horizon, the growth in cash and short-term assets has the strongest predictive power by far. The predictive power of the growth rates in longer-term assets is relatively weak. At the two-year horizon, by contrast, the growth in cash and short-term assets—the component of total assets that has the shortest duration—is no longer significant. It is now the growth in longer-term assets that drive the predictive power of total assets.

Arif and Lee (2014) also construct a measure of aggregate investment from firm-level data, and use it to forecast aggregate stock returns. As shown by Arif and Lee (2014), and reproduced in Appendix 1.B below, their investment measure has significant predictive power for aggregate stock returns at the two-year horizon only. Its ability to forecast one-year-ahead stock return is not statistically significant. This finding can be understood in light of our results from this section that long-term asset growth only forecasts long-term (but not short-term) stock returns, and the fact that Arif and Lee's investment measure contains only the longer-term components of total assets. Appendix 1.B presents the details of this analysis.

1.4.4 Predicting Market Volatility

We find that higher B/M, higher profitability, and lower asset investment predict higher future stock returns. In this section, we investigate if this predictive power is related to market volatility risks. Following Huang et al. (2015), we estimate aggregate stock market variance in a time period by the sum of the squared daily returns on the CRSP value-weighted index during the period. In the annual analysis, $LVOL_t$ denotes the annual aggregate stock market volatility over the period from July, year t to June, year t+1. Appendix 1.A contains a more detailed discussion of this variable.

We examine if the aggregate B/M, profitability, and asset growth in period t can predict $LVOL_{t+1}$, after controlling for $LVOL_t$. Table 1.7 reports these results, at annual and quarterly frequencies. B/M and asset growth have significant predictive power for *LVOL*—but with the wrong signs. Higher B/M predicts lower rather than higher future *LVOL*, and higher asset growth predicts higher but not lower future *LVOL*. Since a higher B/M (asset growth rate) forecasts a higher (lower) equity premium, we expect it also forecasts a higher (lower) *LVOL*—if the lower equity premium were to be explained by lower return volatility. Profitability has no forecast power for future *LVOL* at quarterly frequency; it has weak, albeit positive, forecast lower for future *LVOL* at annual frequency, which is also gone after controlling for B/M and asset growth.

1.5 Robustness Checks

We carry out a number of robustness checks on our main results. First, we control for several known predictors of the equity premium. Second, we use cash-based operating profitability as an alternative measure of aggregate profitability. Third, we use our predictors to forecast the CRSP value-weighted index, thereby relaxing the requirement that we only forecast the returns of those firms that are already in our sample when the equity premium forecast is made. Fourth, we forecast non-overlapping two-year-average stock returns. Finally, we examine how the out-of-sample predictive performance of B/M, profitability, and asset growth varies with the sample split year of the training sample.

1.5.1 Controlling for Other Predictors

In this section, we investigate if the predictive power of B/M, profitability, and asset investment comes from their correlations with other known predictors of the equity premium. In particular, we control for the term spread, default spread, T-bill rate, the Baker and Wurgler's (2006, 2007) sentiment index, the Huang, Jiang, Tu, and Zhou's (2015, HJTZ hereafter) partial-least-squares-based sentiment index, CAY (the consumption-wealth ratio constructed by Lettau and Ludvigson 2001), aggregate operating accruals (Hirshleifer, Hou, and Teoh 2009), and the equity share in new issuance (Baker and Wurgler 2000).

Table 1.8 reports these results at annual and quarterly frequencies. At annual frequency, except for the term spread, the HJTZ sentiment index, CAY, and aggregate operating accruals, other control variables do not exhibit significant predictive power for future stock returns in our sample period. The term spread by itself positively predicts one-year-ahead stock returns at the 1% level. This finding is consistent with Campbell and Vuolteenaho (2004) and Campbell, Polk, and Vuolteenaho (2010), among others. After controlling for B/M, profitability, and asset growth, term spread becomes no longer significant and the magnitude of its coefficient drops from .039 to .017. A similar picture emerges at the two-year horizon as well. The term spread by itself significantly predicts two-year-average stock returns—but the predictive power weakens after B/M, profitability, and asset growth have been controlled for.

Consistent with the results presented in Huang, Jiang, Tu, and Zhou (2015), the HJTZ sentiment index significantly predicts future stock returns at the one-year and one-quarter (but not two-year) horizons. At the one-year and one-quarter horizons, the sentiment index by itself is statistically significant at the 5% and 1% levels respectively. In the presence of B/M, profitability, and asset growth, its forecast power becomes weaker, as suggested by a smaller coefficient magnitude and a lower *t*-statistic. When the HJTZ sentiment is controlled for, the explanatory power of B/M and profitability strengthens, whereas the explanatory power of asset growth weakens, especially at the one-quarter horizon—the significance level of asset growth decreases from 1% to 10%.

CAY is another significant predictor for future stock returns. By itself, CAY is positively associated with one-year-ahead returns at the 5% level. This positive relationship between CAY and expected stock returns is explained by Lettau and Ludvigson (2001)—investors who desire smooth consumption over time will cut current consumption in response to forecasts of poor future stock returns. As a result, the consumption-to-wealth ratio positively forecasts future stock returns. We find that the predictive power of CAY becomes stronger as the forecast horizon lengthens—CAY becomes statistically significant at the 1% level and its magnitude rises from .029 to .047—when it is used to predict the two-year-average market returns. At the same time, CAY has no forecast power for aggregate stock returns at the one-quarter horizon. CAY's predictive power for one-year-ahead stock returns is subsumed after B/M, profitability, and asset growth are controlled for—similar to the results for the term spread and the HJTZ sentiment index discussed above. But at the two-year horizon, its predictive power remains relatively unchanged after our predictors being controlled for.

Aggregate operating accruals by itself positive forecasts one-year-ahead aggregate stock returns at the 10% level, but has no predictive power at the other forecast horizons. After controlling for B/M, profitability, and asset growth, its forecast power is subsumed even at the one-year horizon.

The equity share in new issuance is found to be negatively associated with one-quarter-ahead aggregate stock returns at the 10% level, consistent with the result of Baker and Wurgler (2000) that firms time the market when issuing securities. The significance level of the equity share increases to 5% after controlling for our predictors.

Most important, even after controlling for all these predictors, profitability and asset growth remain statistically significant at the 5% level or stronger in all 24 specifications considered (with one exception where asset growth is at the 10% significance level), while B/M is significant at the 10% level or stronger in 14 of the 24 specifications. These results imply that B/M, profitability, and asset growth contain predictive power for the equity premium that is not subsumed by other known predictors.

1.5.2 Using Cash-Based Operating Profitability

In this section, we use cash-based operating profitability as an alternative measure of aggregate profitability to check the robustness of our results against this change. Ball, Gerakos, Linnainmaa, and Nikolaev (2016) find that by excluding accruals from profitability, cash-based operating profitability subsumes accruals in explaining the variations in the cross-sectional stock returns. Table 1.9 reports the results of using B/M, cash-based operating profitability, and asset growth to predict one-year-ahead and two-year-average stock returns.

First of all, cash-based operating profitability is highly correlated with our gross-profits-based profitability measure—the correlation coefficient is 0.89 and significant at the 1% level. It is also negatively correlated with B/M and positively correlated with asset growth. Because of this correlation structure, cash-based operating profitability is not a significant predictor for future aggregate stock returns when it enters the regressions alone. Not surprisingly, it becomes significant at the 10% level or above after B/M has been controlled for. Moreover, the predictive power of cash-based operating profitability reaches the highest when simultaneously controlling for B/M and asset growth—a one-standard-deviation increase in cash-based operating profitability would drive up one-year-ahead or two-year-average stock returns by 5.8%, significant at the 5% level or above. On the other side, unlikely to the cross-section results, cash-based operating profitability does not display stronger forecast power than gross-profits-based profitability for aggregate stock returns—this could be understood from the empirical evidence that aggregate operating accruals also has significantly positive forecast power for aggregate stock returns, as shown by Table 1.8, Panel A. As such, including accruals into aggregate profitability does not hurt its forecast power for future stock returns.

1.5.3 Predicting the CRSP Index Returns

As we discuss above, the relationship implied by equation (1.1) applies to all firms in period t, and firms that only get listed after period t should not be included in the calculation of expected future aggregate variables. For this reason, in all our analyses so far, the market returns (in periods t+1 and t+2) to be forecasted only include those firms that are already in our sample in period t when the equity premium forecast is made. Here, we examine the robustness of our results when we use the CRSP value-weighted index instead to measure aggregate market returns.

Table 1.10 reports these results. Panels A, B, and C of Table 1.10 examines the predictive regressions for one-year-ahead, two-year-average, and one-quarter-ahead stock returns, respectively. The overall explanatory power of B/M, profitability, and asset growth remains robust—the IS adjusted R^2 attains the same value at the one-year horizon, and only declines slightly at the two-year horizon. The forecast power of the three predictors weakens when predicting one-quarter-ahead stock returns, but the specification including all three predictors remains the strongest among all specifications at this horizon.

1.5.4 Non-Overlapping Two-Year-Average Stock Returns

So far, all our forecasts for two-year-average returns are made annually. Since the annual observations for two-year-average returns are overlapping, this approach induces serial correlations across different observations over time. To mitigate the concern that our results are driven by the overlapping observations, we redo our analysis for two-year-average returns—but using non-overlapping, two-year-average returns—with equity premium forecasts made only every other year.

Table 1.11 reports the return forecast results. In terms of the specification including all thee predictors, although the sample size is cut in half, we see an increase rather than a reduction in the explanatory power of the model—both the IS adjusted R^2 and OOS R^2 are higher than those reported in Table 1.2, Panel B. Moreover, the statistical significance of the three predictors remain at the same level as before.

Table 1.12 reports results for the CER gains relative to the standalone B/M specification. We see that the sample size reduction does make the estimation less precise. The magnitude of the CER gains of the three-predictor model becomes smaller in all cases. The CER gain of the three-predictor model becomes insignificant when $\gamma = 1$, but it remains significant at the 10 % or 1% level in the other two cases. Overall, the qualitative conclusion that the use of B/M, profitability, and asset growth as predictors generate significant economic benefits keeps unchanged.

1.5.5 OOS R^2 with Different Sample Split Years

All our OOS analyses carried out so far use the year 1990 to divide the whole sample into a training sample and a test sample. This section examines if the OOS R^2s obtained before are sensitive to the choice of sample split year.

Figure 1.3 plots the OOS R^2s as a function of the sample split for a variety of predictive specifications—with the standalone B/M, B/M plus profitability, B/M plus asset growth, standalone asset growth, or B/M plus profitability plus asset growth used as predictors. Panels A and B take care of the annual and quarterly analyses respectively. We impose Campbell and Thompson's sign restrictions on all specifications. The sample split year ranges from 1982 to 1998.

Regardless of the sample split year chosen, in both the annual and quarterly analyses, the OOS R^2s of the specification that uses all three predictors are uniformly higher than those of the other specifications. In the annual analysis, the specification yields OOS R^2s around 20%-30%. The second best OOS forecast performance is achieved by the specification with standalone asset growth, which stably generates OOS R^2s around 10%-15%. Most of the OOS R^2s generated by standalone B/M are negative. The specification with B/M plus profitability outperforms that with only the B/M prior to the year 1996 and underperforms the latter in 1996-1998. The specification of B/M plus asset growth overlaps that with B/M plus profitability until 1994, from which the two curves deviate from each other with the former going up rapidly and exceeding the one of standalone asset growth in the last three years. In the quarterly analysis, the difference between the B/M/profitability/asset growth specification and the asset growth specification expands since 1985, and this difference becomes smaller after 1995.

1.6 Conclusion

Profitability and asset investment play a special role in cross-sectional asset pricing. Not only are these variables themselves associated with significant return premia, HXZ (2015, 2017) and FF (2016) show that they also help account for a wide range of other anomalies that the CAPM and the FF's (1993) three-factor model fail to capture. Given this unique role played by profitability and investment, showing the robustness of the underlying mechanism that generates their explanatory power is of paramount importance.

While FF and HXZ focus on cross-sectional, firm-specific variations in profitability and investment, we find that variations in profitability and investment that are common across firms can also explain common variations in future stock returns. These results provide out-of-sample empirical support for FF and HXZ—as the same mechanisms that FF and HXZ use to explain firm-specific variations in stock returns can also be used to explain variations that are market-wide in nature.

At the same time, we emphasize the need to simultaneously controlling for B/M, profitability, and asset growth when using these variables to predict aggregate stock returns, which is determined by the correlation structure between these variables. At aggregate level, B/M and profitability are negatively associated but both of them positively predict future stock returns; asset growth and profitability are positively associated but predict future stock returns in the opposite directions. As a result, the predictive power of these variables for future aggregate stock returns may be weakened or disappear completely when these variables are used as predictors separately. We show in this study that a joint use of all three variables improves the IS and OOS forecast performances substantially.

Our second contribution lies in the identification of predictors for aggregate stock returns that are more robust than those used in previous studies. Related to earnings, we find that aggregate profitability displays significant predictive power for aggregate stock returns—especially when used in conjunction with B/M and asset investment—consistent with the implications of FF (2006). With respect to investment, Arif and Lee (2014) construct an aggregate investment measure that focuses on certain components of total asset growth. Their investment measure displays strong predictive power for two-year-ahead (but not one-year-ahead) aggregate stock returns. By contrast, total asset growth, the investment measure used by FF and HXZ and examined here, exhibits predictive power for aggregate stock returns that is robust across both the one- and two-year horizons.

Although FF's valuation model is silent on whether valuations are driven by rational or behavioral factors, our analysis shows that the higher equity premium associated with higher B/M, higher profitability, and lower asset investment is not simply a compensation for higher market volatility risk. Whether it is other sources of risk, changes in the price of risk, or other behavioral factors that drive such variations in the equity premium is left for future research.

Appendix 1.A Variable Descriptions

Firm-level variables are defined as follows:

ln(B/M). The annual log book-to-market ratio ($ln(B_{it}/M_{it})$) equals the log of firm i's book equity in year *t* divided by its market equity at the end of year *t*. Annual book equity equals total assets (Compustat item *AT*), minus total liabilities (Compustat item *LT*), plus balance sheet deferred taxes and investment tax credit (Compustat item *TXDITC*) if available, minus the book value of preferred stocks. We use liquidating value (Compustat item *PSTKL*) if available, or redemption value (Compustat item *PSTKRV*) if available, or carrying value (Compustat item *PSTK*) if available for the book value of preferred stocks. The quarterly book-to-market ratio equals firm *i*'s book equity in quarter *t* divided by its market equity at the end of quarter *t*. We compute quarterly book equity by following Hou, Xue, and Zhang (2015)—it equals shareholders' equity, plus balance sheet deferred taxes and investment tax credit (Compustat item *TXDITCQ*) if available, minus the book value of preferred stock. We use stockholders' equity (Compustat item *SEQQ*) if available, or common equity (Compustat item *CEQQ*) plus the carrying value of preferred stock (Compustat item *PSTKQ*) if available, or total assets (Compustat item *ATQ*) minus total liabilities (Compustat item *LTQ*) as shareholders' equity. We use redemption value (Compustat item *PSTKRQ*) if available, or carrying value for the book value of preferred stock.

GP/B. GP_{it}/B_{it-1} is firm *i*'s profitability in year *t*, defined as its gross profits in year *t* divided by its book equity in year *t*-1. Gross profits is defined as revenues (Compustat item *REVT*) minus cost of goods sold (Compustat item *COGS*). $\sum GP_{it}/B_{it-4}$ is firm *i*'s profitability in quarter *t*, defined as its sum of gross profits in quarters *t*, *t-1*, *t-2*, *t-3* divided by its book equity in quarter *t*-4. Quarterly gross profits is defined as revenues (Compustat item *REVTQ*) minus cost of goods sold (Compustat item *COGSQ*).

OpCash/B. $OpCash_{it}/B_{it-1}$ is firm *i*'s cash-based operating profitability in year *t*, divided by its book equity in year *t*-1. Cash-based operating profitability is constructed by Ball et al. (2016). It equals operating profitability minus the change in accounts receivable (Compustat item *RECT*), minus the change in inventory (Compustat item *INVT*), minus the change in prepaid expenses (Compustat item *XPP*), plus the change in deferred revenue (Compustat item (*DRC+DRLT*)), plus the change in trade accounts payable (Compustat item *AP*), and plus the change in accrued expenses (Compustat item *XACC*). Operating profitability is defined as revenue (Compustat item *REVT*), minus cost of goods sold (Compustat item *COGS*), and minus reported sales, general, and administrative expenses (Compustat item (*XSGA-XRD*)). All the balance sheet items in the computation of cash-based operating profitability are replaced by zero if missing.

dA/A. A_{it} is firm *i*'s total assets (Compustat item *AT*) in year *t*. Asset growth in *t*, dA_{it}/A_{it-1}, equals $(A_{it} - A_{it-1})$ divided by A_{it-1}. Quarterly asset growth dA_{it}/A_{it-4} ($= (A_{it} - A_{it-4})/A_{it-4}$) is defined as the change in total assets (Compustat item *ATQ*) between quarters *t* and *t*-4, divided by the total assets in quarter *t*-4.

Invest$_{AL}$. *Invest$_{AL}$* is an investment measure constructed by Arif and Lee (2014). $Invest_{AL,it}$ is the change in net operating assets (ΔNOA_{it}) plus the capitalized R&D expenditures ($R\&D_{it} - RA_{it}$), scaled by average assets:

$$Invest_{AL,it} = \frac{\Delta NOA_{it} + R\&D_{it} - RA_{it}}{(TA_{it-1} + R\&DC_{it-1} + TA_{it} + R\&DC_{it})/2}, \tag{A1}$$

where ΔNOA_{it} is defined as the change in non-cash assets minus the change in non-debt liabilities. Non-cash assets equal total assets (Compustat item *AT*) less cash and short-term investments (Compustat item *CHE*). Non-debt liabilities equals total liabilities (Compustat item *LT*) plus minority interest (Compustat item *MIB*) less debt (Compustat item *DLTT* plus Compustat item *DLC*). TA_{it} is total assets. $R\&D_{it}$ is R&D expenditures (Compustat item *XRD*). RA_{it} is R&D amortization, defined as the amortized portion of the historical R&D expenditures. $R\&DC_{it}$ is R&D capital, defined as the unamortized portion of the historical R&D expenditures. Both RA_{it} and $R\&DC_{it}$ are computed following Lev and Sougiannis (1996) by using the industry-specific amortization rates estimated by the authors. If the Compustat items *XRD* and *DLC* are missing, we set them to zero.

Market-level variables are defined as follows:

R^e. The annual excess aggregate stock return in *t*+1, R^e_{t+1}, is computed by aggregating firm-level stock returns using the market capitalizations at the end of year *t* as weights, and subtracting the corresponding compounded one-month Treasury bill rates. Firm-level annual stock returns are obtained by compounding monthly stock returns (adjusted for delisting returns) from July in *t*+1 to June in *t*+2. If a firm's delisting return is missing and the delisting is performance related, we assume a -30% delisting return. Otherwise, we set the missing returns to zero. $R^e_{(t+1,t+2)}$ is defined as the geometric average of annual excess stock returns over years *t*+1 and *t*+2.

Term. Term spread ($Term_t$) is the difference between the ten- and the one-year Treasury constant maturity rates, measured as at the end of June in year *t*+1 in Panels A and B of Table 1.8, and as at the end of the month before the forecast period starts in Panel C of Table 1.8. The data are obtained from the Saint Louis Federal Reserve Economic Database.

Def. Default rate (Def_t) is the difference between the Moody's BAA and AAA bond yields, measured as at the end of June in year *t*+1 in Panels A and B of Table 1.8, and as at the end of the month before the forecast period starts in Panel C of Table 1.8. The data are obtained from the Saint Louis Federal Reserve Economic Database.

Tbill. $Tbill_t$ is the thirty-day Treasury bill rate, measured as at the end of June in year *t*+1 in Panels A and B of Table 1.8, and as at the end of the month before the forecast period starts in Panel C of Table 1.8. The data are obtained from Warton Research Data Services (WRDS).

Sent^BW. $Sent_t^{BW}$ is Baker and Wurgler (2006)'s orthogonalized investor sentiment index. We use the value of the index in June of year *t*+1 in Panels A and B of Table 1.8, and the value in the month before the forecast period starts in Panel C of Table 1.8. The monthly index is obtained from Guofu Zhou's website.

Sent^HJTZ. $Sent_t^{HJTZ}$ is Huang, Jiang, Tu, and Zhou (2015)'s partial-least-squares-based investor sentiment index. We use the value of the index in June of year *t*+1 in Panels A and B of Table 1.8, and the value in the month before the forecast period starts in Panel C of Table 1.8. The monthly index is obtained from Guofu Zhou's website.

CAY. CAY_t is the consumption-wealth ratio constructed by Lettau and Ludvigson (2001). We use the value of the ratio in the second quarter of year *t*+1 in Panels A and B of Table 1.8, and the value in the latest quarter prior to the return prediction period in Panel C of Table 1.8. The series is obtained from Martin Lettau's website.

OpAcc. Aggregate operating accruals, $OpAcc_t$, is defined as in Hirshleifer, Hou, and Teoh (2009). It is aggregated from firm-level operating accruals, which equals the change in non-cash current assets (Compustat item *ACT* minus Compustat item *CHE*), minus the change in current liabilities (Compustat item *LCT*) excluding the change in short-term debt (Compustat item *DLC*) and the change in taxes payable (Compustat item *TXP*), minus depreciation and amortization expense (Compustat item *DP*), and scaled by lagged total assets. Quarterly operating accruals is computed as follows: the components in the numerator are computed as the change in values (if applicable) between the current quarter and the fourth lagged quarter; the denominator is the four-quarter lagged total assets.

EquityShare. $EquityShare_t$ is the equity share in new issues constructed by Baker and Wurgler (2000). We use the annual value in year t in Panels A and B of Table 1.8, and the monthly value one month prior to the return prediction period in Panel C of Table 1.8. The annual series over 1962-2007 are obtained from Jeffery Wurgler's website, and extended to 2014 using the data from the Federal Reserve Bulletin. The monthly series over July 1975-April 2008 are obtained from Jeffery Wurgler's website, and extended to April 2017 using the data from the Federal Reserve Bulletin.

LVOL. Annual $LVOL_t$ is the aggregate stock market volatility from July of year t to June of year t+1. It is equal to $log(\sqrt{SVAR_t})$, where $SVAR_t$ is the annual aggregate stock market variance, defined as the sum of squared daily returns on the CRSP value-weighted index during the period,

$$SVAR_t = \sum_{i=1}^{N_t} R_{i,t}^2 \,, \tag{A2}$$

where N_t is the total number of trading days in the measurement period, and $R_{i,t}$ is the excess return of the CRSP value-weighted index on the i^{th} trading day of the measurement period. Quarterly aggregate stock market volatility is computed over the three months prior to the return prediction period.

Appendix 1.B Arif and Lee's (2014) Investment Measure

In this appendix, we examine the predictive power of the investment measure proposed by Arif and Lee (2014, AL hereafter), which we denote as $Invest_{AL}$. AL document that $Invest_{AL}$ has predictive power for two-year-ahead (but not one-year-ahead) aggregate stock returns. We obtain the same results, as shown in Table 1.B.1. From Table 1.B.1, Panel A, we see that $Invest_{AL}$ has no forecast power for one-year-ahead stock returns, with or without controlling for B/M and profitability. However, it is significantly associated with two-year-average returns over years *t*+1 and *t*+2—a one-standard-deviation increase in $Invest_{AL}$ depresses the average return by 5.2%. The corresponding OOS R^2 is 32%, with a forecast accuracy improvement over the historical mean that is statistically significant at the 1% level. When B/M, profitability, and $Invest_{AL}$ are controlled for, all predictors are significantly associated with the two-year-average returns, with an IS adjusted R^2 of 29% and OOS R^2 of 30%.

To understand why the predictive power of asset growth is robust across investment horizons but $Invest_{AL}$ is not, we decompose $Invest_{AL}$ into its components:

$$Invest_{AL,t} = ChgNOA_t + RND_t = ChgAT_t - ChgSTAsst_t - ChgNonDebt_t + RND_t, \quad \text{(B1)}$$

where $ChgNOA_t$ is the change in net operating assets, RND_t is capitalized R&D expense, $ChgAT_t$ is the change in total assets, $ChgSTAsst_t$ is the change in short-term asset (i.e., the change in cash and short-term investments), $ChgNonDebt_t$ is the change in non-debt liabilities. All these variables, including $Invest_{AL,t}$, are scaled by average assets over *t* and *t*-1. The difference between asset growth (dA_t/A_{t-1}) and change in total assets ($ChgAT_t$) is minor—with the former being scaled by total assets in *t*-1, whereas the latter is scaled by average total assets over *t* and *t*-1.

We then use the components of $Invest_{AL,t}$ to predict aggregate stock returns over different time horizons. Table 1.B.2 reports these results. Breaking down $Invest_{AL,t}$ into two components—$ChgNOA_t$ and RND_t—we find that $ChgNOA_t$, analogous to what is observed for $Invest_{AL,t}$, is not significantly related to the stock returns in *t*+1, but exhibits strong predictive power for the returns in *t*+2. RND_t displays marginal predictive power for the stock returns in *t*+1 only and has no significant predictive power for the stock returns in year *t*+2. After breaking $ChgNOA_t$ down further into $ChgAT_t$, $ChgSTAsst_t$, and $ChgNonDebt_t$, it becomes clear that the difference in the predictive power between asset growth and $Invest_{AL}$ comes from two sources—$ChgSTAsst_t$ and $ChgNonDebt_t$. Since both $ChgSTAsst_t$ and $ChgNonDebt_t$ predict one-year-ahead stock returns in the same direction as $ChgAT_t$, but both $ChgSTAsst_t$ and $ChgNonDebt_t$ are being *subtracted* from $ChgAT_t$ to obtain $Invest_{AL,t}$, the predictive power of $ChgSTAsst_t$ and $ChgNonDebt_t$ cancels out the predictive power of $ChgAT_t$, leaving $Invest_{AL,t}$ insignificant when predicting one-year-ahead stock returns. In contrast, since neither $ChgSTAsst_t$ nor $ChgNonDebt_t$ can predict the stock returns in year *t*+2, $Invest_{AL,t}$ inherits the predictive power of $ChgAT_t$ at the two-year horizon.

Table 1.B.1 The predictive power of $Invest_{AL}$

This table reports time-series predictive regression results that use Arif and Lee's (2014) investment measure, $Invest_{AL}$, as predictor. All RHS variables are standardized by their own means and standard deviations. The *t*-statistics in parentheses are computed using Newey-West (1987) standard errors with three lags. Statistical significance at 10%, 5%, and 1% are indicated as *, **, and ***, respectively. Panel A predicts one-year-ahead stock returns; Panel B predicts the average stock returns over years *t*+1 and *t*+2. The training window uses accounting data from 1962-1990, and corresponding stock returns data from July 1963-June 1992 (for one-year-ahead return forecasts) and July 1963-June 1993 (for two-year-average return forecasts). The out-of-sample forecast period is July 1992-June 2016 (for one-year-ahead return forecasts) and July 1993-June 2016 (for two-year-average return forecasts).

Panel A: Predicting one-year-ahead stock returns R^e_{t+1}						
	1	2	3	4	5	6
Constant	0.064***	0.064***	0.064***	0.064***	0.064***	0.064***
	(3.13)	(3.25)	(3.77)	(3.22)	(3.50)	(3.78)
$\ln(B_t/M_t)$	0.034			0.045*	0.029	0.044**
	(1.63)			(1.95)	(1.57)	(2.26)
GP_t/B_{t-1}		0.004		0.025		0.035
		(0.17)		(1.00)		(1.63)
$InvestAL_t$			-0.033		-0.028	-0.036
			(-1.53)		(-1.43)	(-1.63)
No. of Obs.	53	53	53	53	53	53
IS R^2	0.04	0.00	0.04	0.06	0.07	0.11
IS adj. R^2	0.02	-0.02	0.02	0.02	0.04	0.05
			OOS forecast with the sign restrictions			
OOS R^2	-0.03	-0.02	0.08	0.00	0.04	0.10
ENC-NEW	0.20	-0.14	1.29*	0.50	0.93	1.90*

Panel B: Predicting two-year-average stock returns $R^e_{(t+1,t+2)}$						
	1	2	3	4	5	6
Constant	0.056***	0.057***	0.058***	0.056***	0.057***	0.057***
	(3.08)	(3.19)	(4.21)	(3.23)	(3.98)	(4.69)
$\ln(B_t/M_t)$	0.024			0.035	0.014	0.031**
	(1.29)			(1.67)	(1.12)	(2.29)
GP_t/B_{t-1}		0.006		0.023		0.037**
		(0.31)		(1.11)		(2.59)
$InvestAL_t$			-0.052***		-0.050***	-0.057***
			(-3.38)		(-3.44)	(-3.59)
No. of Obs.	52	52	52	52	52	52
IS R^2	0.05	0.00	0.23	0.08	0.25	0.33
IS adj. R^2	0.03	-0.02	0.21	0.04	0.22	0.29
			OOS forecast with the sign restrictions			
OOS R^2	-0.09	-0.11	0.32	-0.11	0.26	0.30
ENC-NEW	-0.65	-0.81	6.43***	-0.75	5.33***	6.25***

Table 1.B.2 The predictive power of individual components of $Invest_{AL}$

This table reports the predictive power of individual components of $Invest_{AL}$ for aggregate stock returns. $Invest_{AL,t}$ is decomposed into: $Invest_{AL,t} = ChgNOA_t + RND_t = ChgAT_t - ChgSTAsst_t - ChgNonDebt_t + RND_t$, where $ChgNOA_t$ is change in net operating assets, RND_t is capitalized R&D expense, $ChgAT_t$ is change in total assets, $ChgSTAsst_t$ is change in short-term asset (change in cash and short-term investments), and $ChgNonDebt_t$ is change in non-debt liabilities. All RHS variables are standardized by their own means and standard deviations. The *t*-statistics in parentheses are computed using Newey-West (1987) standard errors with three lags. Statistical significance at 10%, 5%, and 1% are indicated as *, **, and ***, respectively. Panels A and B predict one-year-ahead and two-year-ahead stock returns respectively. Accounting data are from 1962-2014 and stock returns data are from July 1963-June 2016.

Table 1.B.2 The predictive power of individual components of $Invest_{AL}$ (continued)

Panel A: Predicting one-year-ahead stock returns R^e_{t+1}						
	1	2	3	4	5	6
Constant	0.064***	0.064***	0.064***	0.064***	0.064***	0.064***
	(3.77)	(3.68)	(3.35)	(3.87)	(3.18)	(3.41)
$InvestAL_t$	-0.033					
	(-1.53)					
$ChgNOA_t$		-0.029				
		(-1.29)				
RND_t			-0.039*			
			(-1.92)			
$ChgAT_t$				-0.051***		
				(-3.57)		
$ChgSTAsst_t$					-0.051**	
					(-2.31)	
$ChgNonDebt_t$						-0.039**
						(-2.08)
No. of Obs.	53	53	53	53	53	53
IS R^2	0.04	0.03	0.06	0.10	0.10	0.06
IS adj. R^2	0.02	0.01	0.04	0.08	0.08	0.04

Panel B: Predicting two-year-ahead stock returns R^e_{t+2}						
	1	2	3	4	5	6
Constant	0.064***	0.064***	0.063***	0.064***	0.063***	0.063***
	(4.11)	(4.09)	(3.39)	(3.98)	(3.37)	(3.37)
$InvestAL_t$	-0.065***					
	(-3.90)					
$ChgNOA_t$		-0.064***				
		(-3.61)				
RND_t			-0.030			
			(-1.55)			
$ChgAT_t$				-0.053***		
				(-3.84)		
$ChgSTAsst_t$					-0.011	
					(-0.45)	
$ChgNonDebt_t$						-0.005
						(-0.20)
No. of Obs.	52	52	52	52	52	52
IS R^2	0.17	0.16	0.04	0.11	0.00	0.00
IS adj. R^2	0.15	0.14	0.02	0.09	-0.01	-0.02

Chapter 2
The Crash Risks of Style Investing: Can They Be Internationally Diversified?

2.1 Introduction

Style investing has grown in popularity among investors. Even at the retail level, as of 2008, there are over 2,000 mutual funds and ETFs in the United States that have a market-cap or a value/growth focus.[13] According to statistics reported by Eun, Lai, de Roon, and Zhang (2010), such products are also becoming widely available in other developed countries. With respect to momentum, Jegadeesh and Titman (1993) observe that "a majority of the mututal funds examined by Grinblatt and Titman (1989, 1993) show a tendency to buy stocks that have increased in price over the previous quarter."

Many studies that examine extreme events in the international equity market focus on developing countries (see Forbes and Rigobon 2002, Bae, Karolyi, and Stulz 2003, and Bekaert, Harvey, and Ng 2005, for example), but the recent financial crisis reminds us that even developed stock markets are not immune to crashes and tail risks. Taleb (2007) and Reinhart and Rogoff (2009), together with many others in the financial press, also advise investors to pay more attention to these "rare" events.

Motivated by such growth in the popularity of style investing and the concern for extreme events among investors, we examine the tail risks of style investing in different countries. For the G7 countries (Canada, France, Germany, Italy, Japan, the U.K., and the U.S.) over the 1981-2010 period, we evaluate whether portfolios with different size, value, or momentum tilts—the SMB (small minus big), HML (high minus low), and UMD (past winners minus past losers) portfolios—experience different crash risks, and whether these risks can be mitigated through international diversification.

Using both expected shortfall and return skewness as measures, we find that the left tail risks of UMD are significantly higher than those of SMB and HML.[14] For diversified "world" portfolios (equal-weighted portfolios of the G7 countries), this difference in left tail risks across

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[13] Fund styles are classified according to the Lipper objective codes obtained from the Center for Research in Security Prices (CRSP).

[14] An "expected shortfall" of x% is defined as the average value of those observations that lie below the xth percentile of the empirical returns distribution. This measure is also known as the conditional value at risk (CVaR).

styles is even greater. By calculating conditional correlations (i.e. correlations conditional on returns of different magnitude) and coexceedances (i.e. joint occurrences of extreme returns) across countries, we find that the extreme negative returns on UMD in different markets tend to occur together, whereas those on SMB and HML tend to be country-specific. In fact, for SMB and HML, it is the right-tail events that tend to be more global in nature. These results suggest that momentum crashes cannot be diversified away internationally, and explain why international diversification appears to "magnify" the difference in crash risks between the UMB and the SMB/HML portfolios.

A number of studies, including De Santis and Gerard (1997), Longin and Solnik (2001), and Asness, Israelov, and Liew (2011), examine the crash risks and the effectiveness of international diversification in reducing these risks for aggregate stock market indexes—but not for different investment styles. Eun, Huang, and Lai (2008) and Eun, Lai, de Roon, and Zhang (2010) study the benefits from holding internationally-diversified style portfolios, but have not examined how these portfolios perform during extreme periods. Both Daniel and Moskowitz (2016) and Kadan and Liu (2014) show that momentum exhibits significant left tail risks but have not examined whether these risks can be diversified internationally. Asness, Moskowitz, and Pederson (2013) uncover a common factor structure of value and momentum across markets and asset classes. While our focus is on equities only, we include the size factor, examine crash risks, and evaluate whether these risks can be internationally diversified.

The rest of the paper proceeds as follows. In Section 2.2, we describe our data and discuss the construction of portfolios to be used in subsequent analyses. Section 2.3 reports our empirical results. We provide summary statistics on both the first two moments and the tail risk measures of different style portfolios. We test whether the tail risks on these portfolios are significantly different from those of a normal distribution, and whether the tail risks of momentum are significantly different from those of size and value. Finally, we study the effects of international diversification on the crash risks of different styles. Section 2.4 concludes.

2.2 Data

The data for countries other than the U.S. are obtained from Datastream and Worldscope. The data for the U.S. are from the CRSP and COMPUSTAT databases. Our final sample of portfolio returns covers the period July 1981 to December 2010, 354 months in total.

But in order to sort stocks into different portfolios (see below), data from 1980 are also needed. All stock returns are measured in US dollars.

Following Chui, Titman, and Wei (2010), we only include common stocks that are listed on the major exchange(s) in each country. A cross-listed stock is only included in its home country sample. To mitigate concerns with data quality in Datastream, for each country, we exclude those stocks whose market capitalization is below the fifth percentile of all stocks in each month. Moreover, if a stock's return from Datastream is larger (smaller) than 100% (-95%), we set its return equal to 100% (-95%). If a stock is delisted, we rebalance the portfolio at the end of the delisting month.

Market portfolios are constructed by weighing individual stocks by their previous-month's market capitalization. To be included in a country's size and book-to-market (BM) portfolios for year *t*, firms are required to have book common equity for year *t-1* and stock prices for both December, year *t-1* and June, year *t*. For each country, we rank all such stocks in June of year *t* by their market capitalization, and then use the median to split them into two groups—small and big (S and B). With respect to BM, we divide all stocks in each country into three groups based on the breakpoints for the bottom 30% (Low), middle 40% (Medium), and top 30% (High), where BM is constructed as the ratio between the book equity of year *t-1* and the market equity of December, year *t-1*. We then construct six portfolios (S/L, S/M, S/H, B/L, B/M, B/H) from the intersections of the two size and the three BM groups. Monthly value-weighted returns on the six portfolios are calculated from July of year *t* to June of year *t+1*, with the market capitalizations of June, year *t* being used as weights.

The factor SMB is the difference between the simple average of the monthly returns on the three small-stock portfolios (S/L, S/M, S/H) and the simple average of the monthly returns on the three big-stock portfolios (B/L, B/M, B/H). The factor HML is the difference between the simple average of the monthly returns on the two high-BM portfolios (S/H, B/H) and the simple average of the monthly returns on the two low-BM portfolios (S/L, B/L).

To construct the momentum factor, we rank all the stocks based on their past 6-month cumulative returns at the end of each month. The stocks in the bottom one-third are assigned to the "Down (D)" portfolio and those in the top one-third to the "Up (U)" portfolio. These equally-weighted portfolios are held for six months. To control for the effect of bid-ask bounce, we impose a one-month gap between the ranking period and the holding period. Following Jegadeesh and Titman (1993), we construct overlapping momentum portfolios. For example, the winner portfolio formed in February is the equally-weighted combination of those stocks with cumulative returns in the top one-third over the previous July to December (the U portfolio in December), the previous June to November (the U portfolio in November), and so on up to the previous February to July (the U portfolio in July).

2.3 Empirical Analysis

This section reports results of our empirical analysis. We begin by calculating the first two moments of the style portfolios. We then examine their tail risks within individual countries, and investigate whether these extreme returns tend to be global or country-specific.

2.3.1 Summary Statistics: First and Second Moments

We compute the mean, standard deviation, and Sharpe ratio of different style portfolios in different countries. Table 2.1 reports these statistics. The column labelled “Average” displays the simple average of the seven countries’ statistics. For example, the “Average” standard deviation for SMB is simply the average standard deviation of the seven individual countries’ SMB. The column labelled “World”, on the other hand, displays the statistics of an equal-weighted portfolio over the seven countries.

With the exception of Japan, momentum generates the highest mean returns among the three investment styles. By contrast, the size premium—the excess return of small over large firms—no longer exists in our sample period. Since the standard deviations of different styles are comparable with each other, the higher means of momentum also lead them to have higher Sharpe ratios.

The variance reduction effect of international diversification can be seen through the smaller return standard deviations of the world relative to the country-specific portfolios. This variance reduction tends to raise the Sharpe ratios of the world portfolios above those of individual countries.

2.3.2 Summary Statistics: Tail Risk Measures

We use return skewness and 5% expected shortfall to measure left tail risks. 5% expected shortfall is defined as the average value of those observations that lie below the fifth percentile of the empirical returns distribution. Table 2.2 presents summary statistics of these measures for the market and the three style portfolios. In six of the seven countries, UMD has the most negative skewness among the three style portfolios. UMD also has the most negative expected shortfall in four of the seven markets. If returns are measured in standardized units (i.e. as number of standard deviations away from their respective means), the expected shortfalls of UMD become the most negative among the three styles in all seven markets. This difference between the use of standardized versus non-standardized units in the calculation of expected shortfall is due to the relatively modest standard deviation of UMD relative to those of SMB and HML. In fact, this point is even more apparent for the expected shortfall of the market portfolio. In non-standardized units, the expected shortfalls of the market are always more negative than those of the style portfolios. After standardization, however, only the expected shortfall of the German market portfolio remains higher than its UMD counterpart. Overall, our statistics presented here are consistent with those reported by Daniel and Moskowitz (2016) and Kadan and Liu (2014), who also find that momentum tends to suffer from severe left tail risks.

2.3.3 Statistical Tests

While the summary statistics are informative, we also carry out statistical tests—first to test if the style portfolios exhibit tail risks that are significantly different from those of a normal distribution, and then to test if their tail risks are significantly different from each other.

2.3.3.1 Monte Carlo Simulations

To carry out the first test, we generate null distributions of return skewness and 5% expected shortfall from 5000 random samples. The skewness and expected shortfall of each sample is calculated based on 354 random draws (i.e. the number of monthly observations in our sample) from a standard normal distribution. By comparing the skewness and standardized expected shortfall statistics of a style portfolio with the null distributions, we can obtain the p-values of the statistics and evaluate if they are significantly different from those of a normal distribution.

From Table 2.3, Panel A, we see that the negative skewness of the six negatively-skewed UMD portfolios are all statistically different from that of a normal distribution. Although our focus is on left tail risks, we also note that two (three) of the SMB (HML) portfolios actually exhibit significantly positive return skewness.

Turning to the 5% expected shortfall on standardized portfolio returns reported on Table 2.3, Panel B, we see that all momentum portfolios exhibit expected shortfalls that are statistically lower than that of a standard normal (which has a 5% expected shortfall of -2.06). Note that even though momentum does not enjoy a premium in Japan, it still exhibits significant left tail risks.

2.3.3.2 Bootstrapping

In this section, we use bootstrapping to test if UMD has significantly more severe crash risks than the other two styles. To allow for potential differences across the UMD, SMB, and HML return distributions, we jointly sample from the empirical UMD and SMB (HML) distributions—to construct bootstrap distributions for the *difference* in skewness and for the *difference* in expected shortfall between the UMD and SMB (HML) portfolios. In order to make comparisons across styles (which have different means and standard deviations), we calculate expected shortfalls based on standardized returns.

Each joint bootstrap sample is made up of 354 draws with replacement from the empirical UMD, SMB, and HML distributions. We then calculate the difference in return skewness and 5% expected shortfall between UMD and SMB (HML) for each bootstrap sample. Repeating this procedure 5000 times, we obtain bootstrap distributions for the difference in return skewness and 5% expected shortfall between UMD and SMB (HML). To test the null hypothesis of a zero difference, we center the bootstrap distributions by subtracting their respective means from each draw. By examining the position of the empirical estimates on the centered distributions, we obtain p-values for the difference in return skewness and expected shortfall.

Table 2.4, Panel A (Panel B) reports results of this exercise for the difference in skewness between UMD and SMB (HML). For Canada, Japan, the U.K., and the U.S., we can reject the null hypothesis (with at least 10% significance) that UMD has the same skewness as the SMB and HML portfolios from the same country. For France, we can reject the null with respect to SMB but not HML. For Italy, we can reject the null relative to HML but not SMB. In Germany, the null cannot be rejected in either case.

Table 2.4, Panel C (Panel D) reports test results for the difference in the 5% expected shortfall between UMD and SMB (HML). For France, we can reject the null hypothesis that UMD has the same expected shortfall as those of the SMB and HML portfolios, at the 5% and 10% levels, respectively. For Canada and Italy, we can reject the null at the 5% level relative to HML, but not SMB. For the U.S., we can reject the null at the 10% level with respect to SMB, but not HML. In Germany, Japan, and the U.K., we cannot reject the null in either case.

Of the 28 (four per country) within-country tests reported on Table 2.4, 12 are significant at the 5% level and 15 are significant at the 10% level. These findings provide modest support to the hypothesis that—within individual countries—momentum has higher crash risks than value and size. Next, we investigate if international diversification affects the crash risks of these portfolios.

2.3.4 The Effects of International Diversification

Since markets are imperfectly correlated with each other, it is well known that international diversification can lower portfolio variance. Indeed, from Table 2.1, Panel B, we see that for every style and every market, the "world" portfolio—an equal-weighted portfolio across all seven countries—has a relatively lower return standard deviation. As a result, the "world" Sharpe ratio tends to be higher than that of an average country—with the exception of that on the SMB portfolio, which has a negative mean return and thus a negative Sharpe ratio.

From Table 2.2, Panel B, we see that world portfolios do have higher (less negative) non-standardized expected shortfalls than their country-specific counterparts for all styles—so diversification can alleviate crash risks in an absolute sense. But when we use measures that account for the reduction in portfolio variance as well, the effect of international diversification on tail risks becomes less clear-cut. When measured by return skewness (Table 2.2, Panel A) and standardized 5% expected shortfall (Table 2.2, Panel C), the left tail risks of both the world

UMD and world market portfolio tend to exceed those of individual countries. By contrast, the return skewness and expected shortfall on both the SMB and HML portfolios tend to increase as a result of international diversification.

2.3.4.1 Momentum Crashes tend to be Global: Statistical Significance

The statistical significance of the tendency for UMD crashes to be more global (relative to their SMB and HML counterparts) is evident from the bootstrapping results reported on Table 2.4. From the "World" column, we see that all p-values on the difference between the world UMD and the world SMB (HML) crash risks are smaller than 5%—whether it is skewness or 5% expected shortfall that is used as a measure of crash risk. By contrast, as discussed in Section 2.3.3.2 above, less than half (11 out of 28) of the corresponding p-values at the individual-country level are significant at the 5% level.

2.3.4.2 Momentum Crashes tend to be Global: Economic Significance

In this section, we show that our finding of momentum crashes being globally more correlated and less diversifiable (relative to HML and SMB crashes) can have economic significance to investors.

To quantify the cost of "crash risks" to investors, we make use of the preference specification explored by Mitton and Vorkink (2007). Equation (2) of Mitton and Vorkink (2007), reproduced here, specifies the preference of an investor who not only cares about mean and variance, but also skewness: $U(W) = E(W) - \frac{1}{2\tau}Var(W) + \frac{1}{3\phi}Skew(W)$. W represents future wealth and τ denotes the coefficient of risk aversion. The coefficient ϕ measures the investor's preference for skewness, with positive values indicating a preference for positive skewness. When $\phi \rightarrow \infty$, we get back Markowitz's (1959) mean-variance model.

When countries are considered in isolation, momentum does display more negative skewness than HML—but the difference is only modest. Under the "Average" column of Table 2.2, Panel A, we see that this difference in skewness has an average of -1.26 (-0.92-0.34) across the G7 countries. To an investor whose preference parameters are given by $\tau = 2.5$ and $\phi = 2.5$—following the values of Mitton and Vorkink's (2007) calibration—the "disutility" of having to bear this lower skewness is equivalent to a reduction in mean return of 0.168% (1.26/(3*2.5)). This utility cost of negative skewness is comparable to the actual average difference in mean returns of 0.17% between UMD and HML (as reported under the "Average" column of Table 2.1, Panel A).

In contrast, when investors hold diversified world portfolios, the tendency for momentum (but not value) to crash together across countries increases the gap between their portfolio skewness. Under the "World" column of Table 2.2, Panel A, we see that this difference in skewness is now -2.46 (-1.39-1.07). Using the same preference parameters as before, the corresponding disutility in terms of mean return reduction is given by 0.328% (2.46/(3*2.5))—which is substantially higher than in the case when countries are considered in isolation. In particular, the higher mean return of 0.17% on the world UMD portfolio can no longer make it worthwhile for the investor in question to bear the lower skewness of the world UMD relative to the world HML portfolio.

To further understand the difference in the effect of international diversification across styles, we use the next two sections to examine the conditional correlations and the coexceedances of extreme returns.

2.3.4.3 Conditional Correlations

In calculating conditional correlations, we follow Longin and Solnik (2001) and report return correlations that are conditioned on signed values, rather than absolute values. As shown by Boyer, Gibson, and Loretan (1999) and Forbes and Rigobon (2002), estimated correlations conditioned on absolute values trivially increase with the threshold. But this is no longer the case when the conditioning is done on signed extremes.[15]

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[15] Longin and Solnik (2001, p. 654) discuss the intuition for why different conditioning produces different results: "If we condition on the absolute value of realized returns, the conditional correlation of a bivariate normal distribution trivially increases with the threshold … As the normal distribution is symmetric, the truncated distribution retains the same mean as the total distribution. But a large positive (respectively negative) return in one series tends to be associated with a large positive (respectively negative) return in the other series, so the estimated conditional correlation is larger than the "true" constant correlation … Here, we condition on signed extremes (e.g, positive or negative). The mean of the truncated distribution is not equal to the mean of the total distribution. As indicated above, the conditional correlation of a multivariate normal distribution decreases with the threshold and reaches zero for extreme returns. A false intuition would be that extreme returns in two series appear highly correlated as they are large compared with the mean of all returns. Extreme value theory says that two extreme returns are not necessarily correlated, as they may not always be large compared with the mean of extreme returns."

Table 2.5 reports return correlations between the U.S. and the other six markets, conditional on the returns in the U.S. being at least 1.5, 1.0, or 0.5 signed (i.e. both positive and negative) standard deviations away from its mean, or simply, on US returns being above/below its mean. For the market and UMD portfolios, the conditional correlations when US returns are smaller than μ-1.5σ are always larger than those when US returns are larger than μ+1.5σ, where μ and σ, respectively, denote the mean and standard deviation of the return distribution. The same conclusion also holds for comparisons of other signed thresholds (i.e. μ-σ correlations higher than μ+σ correlations, and so on), with only two exceptions.

By contrast, for SMB and HML, the correlations associated with below-mean thresholds do not appear to exceed those associated with above-mean ones. If anything, the asymmetry seems to have reversed—the correlations associated with above-mean thresholds tend to be higher. Overall, these results suggest that market crashes and momentum crashes tend to be global—explaining our previous finding that international diversification does not help much in alleviating the crash risks on these portfolios. On the other hand, the fact that SMB and HML crashes tend to be idiosyncratic causes the world SMB and HML portfolios to have lower crash risks than their country-specific counterparts.

One caveat in the interpretation of the aforementioned patterns is the substantially smaller number of observations available at the extremes. As shown in the first row of each panel on Table 2.5, the number of months that fall into the μ-1.5σ or μ+1.5σ categories is often less than 20. In particular, the big jumps that appear between μ+σ and μ+1.5σ for the market and the UMD portfolios in certain countries may be due, in part, to the fact that the μ+1.5σ conditional correlations for these portfolios are estimated from only 15 and 11 observations, respectively.

2.3.4.4 Coexceedances

Bae, Karolyi, and Stulz (2003) define negative (positive) return exceedances as extreme returns that lie below the 5th (above the 95th) percentile of the marginal return distribution. There is a close link between this definition and the concept of expected shortfall—the 5% expected shortfall of a returns series is simply the average over all its negative return exceedances.

Bae, Karolyi, and Stulz (2003) also define a negative (positive) coexceedance as a joint occurrence of negative (positive) return exceedances. As a measure of the extent to which extreme returns occur together across countries, we calculate "coexceedance counts". A coexceedance count of *i* units in a given month represents a joint occurrence of return exceedances in *i* different countries for that month. Table 2.6 reports these results. Under the columns *i*=0 to *i*=7, the row "Total" reports the total number of months in our sample that have a coexceedance count of *i*. The rows for individual countries report the number of times a country contributes to the coexceedance count of *i*. For example, consider the negative coexceedances on the market portfolios as reported on Table 2.6, Panel A. Of the 354 months from July 1981 to December 2010, six of which have negative coexceedances that involve exactly three countries (*i*=3). Among these six incidences of negative coexceedances, Italy participated in five and the U.S. in one.

We also calculate the average excess returns for the months with coexceedance counts larger than 3(*i*>3) and larger than 5(*i*>5). To draw comparisons across portfolios with different standard deviations, we report results when returns are measured in "standardized units"—as the number of standard deviations away from the series' own mean. The non-standardized and standardized results are reported in Columns 2-3 and Columns 4-5 of Table 2.6, respectively. These calculations allow us to gauge the magnitude of portfolio returns in months with significant joint occurrences of extreme returns. In this sense, these measures can be viewed as multivariate counterparts to the expected shortfalls obtained for individual series.

The results we present in Table 2.6, Panels G and H show that, for UMD, it is more likely for negative rather than positive exceedances to be global in nature. In fact, there is no positive coexceedance that involves more than five countries. At the same time, in the event that such extreme returns do occur, the negative exceedances tend to have a larger magnitude than the positive ones. In months with negative coexceedance counts larger than 3(*i*>3), UMD is on average 2.41 standard deviations below its own mean. By contrast, in months with positive coexceedance counts higher than 3, UMD is only 1.61 standard deviations above its mean on average. From Table 2.6, Panels A and B, we can reach the same conclusion for the market portfolio.

By contrast, this pattern is reversed when we examine SMB and HML. For SMB (HML), in months with positive coexceedance counts larger than 3, it is on average 2.08 (2.21) standard deviations above its own mean. By contrast, in months with negative coexceedance counts higher than 3, SMB (HML) is on average 1.47 (1.69) standard deviations below its mean.

These results indicate that, for UMD and the market portfolios, negative coexceedances tend to have more extreme returns than positive coexceedances. For SMB and HML, by contrast, the magnitude of the returns on positive coexceedances tends to be greater. For UMD, there are months with negative coexceedance counts higher than 5—with a mean standardized return of -3.23, but no months with positive coexceedance counts that exceed 5. This finding suggests that global momentum crashes do occur, consistent with our earlier result that international diversification does not lower the (standardized) expected shortfall of the UMD portfolio. On the other hand, there are months in which HML has positive coexceedance counts i>5—with a mean standardized return of 3.23, but no months with negative coexceedance counts that exceed 5. This result suggests that the HML portfolios in different countries have a greater tendency to be jointly "euphoric", rather than to crash together.

To examine whether the number of coexceedances we report on Table 2.6 is statistically different from the case when extreme events occur independently across countries, we make use of the binomial distribution. Our null hypothesis is that the negative (positive) exceedances of individual countries are independent from each other. In the tests, the Bernoulli experiment refers to one negative (positive) exceedance occurring in an individual country. Based on our definition of negative (positive) exceedance as extreme returns that lie below the 5th (above the 95th) percentile of the return distribution, the probability of "success" in each Bernoulli experiment is 0.05, and the different coexceedance count i can be represented as the total number of "success" in a string of seven Bernoulli experiments. For example, the event "i = 0" refers to the scenario that there is no negative (positive) exceedance occurring in any of the seven countries. If the extreme returns in the seven markets occur independently, the probability for the event "i = 0" is equal to $C_0^7 * 0.05^0 * 0.95^7 = 0.698$, where C_k^n denotes the number of k-combinations from a set of n elements. Given our sample size of 354, we expect to see 247 ($354 * 0.698$) observations of such an event—if the null of independence were true. Using the same reasoning, the probability for the event "i = k" is given by $C_k^7 * 0.05^k * 0.95^{7-k}$ under the null hypothesis, and the number of observations we expect to see for the events i = 0, …, 7 (based on our sample size of 354) are therefore 247, 91, 14, 1, 0, 0, 0, and 0, respectively.

For each panel on Table 2.6, the row labeled "Total" reports the total number of months that have a coexceedance count of i, where i ranges from 0 to 7. These "Total" numbers are then compared against the right tail of an appropriate binomial cumulative distribution function (i.e. one with 354 trials and probability $C_i^7 * 0.05^i * 0.95^{7-i}$)—to conduct the one-sided test of whether the observed numbers are larger than what one would expect under the null hypothesis of independent extreme returns. The p-values for this test are reported in parentheses on the last row of each panel. A p-value of 0.05 or lower suggests that the observed number is significantly larger than what is expected under the null at the 5% level. We find that this is the case for the left tails of the market and UMD portfolios—consistent with results reported earlier. At the same time, we also see that the number of months with $i = 0$ is also significantly higher than in the case when extreme returns occur independently across countries. When extreme returns are globally correlated, there are also more "quiet" months—during which no extreme returns arise anywhere.

2.4. Concluding Remarks

Consistent with results reported by Daniel and Moskowitz (2016), we find that momentum tends to suffer from more severe crashes relative to size and value. For the G7 countries over the 1981-2010 period, we reach this conclusion by using return skewness and expected shortfall as measures of crash risk. Daniel and Moskowitz (2016) go on to investigate the predictability and potential causes of momentum crashes, and use this predictability to develop a *dynamic* momentum strategy. This dynamic strategy adopts a time-varying weight on the *static* momentum strategy (i.e. UMD)—where the weight varies over time as a function of the conditional mean and variance of UMD. Daniel and Moskowitz (2016) show that this strategy is no longer exposed to static momentum crashes, can be used to generate a higher Sharpe ratio (relative to the static momentum strategy), and has robust performance across different markets.

By contrast, we focus on the static (rather than dynamic) momentum strategy. We examine the extent to which static momentum crashes are internationally diversifiable and how this diversifiability compares to those of value and size. We find that a diversified, world UMD portfolio tends to be more left-skewed and has a more negative expected shortfall than the momentum portfolios of individual countries. By contrast, both the skewness and expected shortfall of the world SMB and HML portfolios tend to be less negative than their country-specific counterparts. By calculating conditional correlations and coexceedances across countries, we confirm that these differences are due to the UMD portfolios being more correlated across countries at their left tails, whereas the SMB and HML portfolios tend to be more correlated at their right tails.

Chapter 3
The Fama-French Three Factors in the Chinese Stock Market

3.1 Introduction

The Chinese stock market has a few special features that potentially affect the application of the Fama-French three-factor model to Chinese stock returns. First, before April 2005, about two-thirds of outstanding shares in Chinese listed firms were held by government agencies or government-related enterprises, and were non-tradable in the public market. The Chinese government started the Share-Structure Reform in April 2005 to legally convert non-tradable shares to be tradable. Almost all Chinese listed firms completed the reform by the end of 2006. Figure 3.1 shows the aggregate tradable market value and the aggregate total market value (both in RMB Yuan) for all A-shares of Chinese listed firms at the end of each month from December 1991 to December 2012. The tradable market value of a listed firm is the end-of-month market price times the number of tradable A-shares, while the total market value is the end-of-month market price times the number of all outstanding shares (including both tradable and non-tradable shares). We aggregate over all Chinese listed firms. As shown in Figure 3.1, the proportion of the aggregate tradable market value increases from about 30% in 1995 to above 80% in 2012. Figure 3.2 shows the five percentiles (5th, 25th, 50th, 75th and 90th) of the cross-sectional distribution in the proportion of tradable shares across all Chinese listed firms in each month from December 1991 to December 2012. By the end of 2012, all outstanding shares are tradable for more than 25% of firms, but still for another one quarter of firms, more than 60% of shares are non-tradable. The first issue we examine is whether the Fama-French three factors should be based on tradable shares or all outstanding shares.

Second, China has two main boards of listing public firms, the Shanghai Stock Exchange and the Shenzhen Stock Exchange. In addition, the Small Medium Enterprise Board (SME) and the Growth Enterprise Board (GEB) were set up in May 2004 and October 2009, respectively; both are hosted by the Shenzhen Stock Exchange. Table 3.1 shows the total number of Chinese listed firms and the number of firms listed on the SME and GEB boards in each year from 1991 to 2012. At the end of 2012, there are 1,383 firms listed on the Shanghai and Shenzhen main boards and 1,049 firms listed on the SME and GEB boards. Fama and French (1992) use NYSE-listed firms to determine the breakpoints between small and big firms, in order to avoid the overwhelming influence of the large number of small Nasdaq firms. It is unclear whether we should follow the same practice to exclude the GEB and SME listed firms in determining the breakpoints for the size factor in China.

Third, more than 170 Chinese listed firms have issued multiple class shares that have the same cash flow and voting rights but are traded in different markets. Some have A-shares and B-shares, others have A- and H-shares, and the rest have A-shares and shares in other foreign markets.[16] Because these shares share the same cash flow and voting rights, they usually have the same claim on the firm's book value of equity. Hence, for Chinese domestic investors who invest in only A-shares, to obtain the book-to-market-value ratio per A-share of a firm with multiple class shares, it is incorrect to divide the firm's total book value of equity from its balance sheet by the total market value of A-shares. The correct way is to calculate the book value of equity per share divided by the A-share price.

In this paper, we closely follow Fama and French (1993) to construct the market, size, and value factors based on Chinese stock returns, with a particular focus on how the above-mentioned special features affect the three factors and the performance of the three-factor model. We find that these features considerably affect the three factors and also influence the explanatory power of the three-factor model. Specifically, our main findings are the following.

First, the return on the market portfolio crucially depends on whether or not the non-tradable shares are included in the market portfolio. Over the period between July 1996 and June 2003 inclusively, the monthly average excess return on the market portfolio including only tradable shares is 0.94%, while the monthly average excess return on the market portfolio including both tradable and non-tradable shares is only 0.75%. The difference of 19 basis points in monthly returns is economically significant.

Second, the explanatory power of the market model also depends on the definition of the market portfolio. The adjusted R squared of the market model is on average 82.9% when the market portfolio includes only tradable shares, and decreases to 76.6% when the market portfolio includes both non-tradable and tradable shares.

[16] Both A and B shares are listed in Chinese domestic exchanges. A-shares are denominated and traded in Yuan while B-shares are denominated and traded in USD or HKD. Foreign individual investors cannot buy A-shares. H-shares are listed in the Hong Kong Stock Exchange. Other foreign countries in which Chinese firms listed their shares include the U.S., the U.K., Singapore, Germany, etc.

Third, value firms earn significantly higher returns than growth firms in China. The monthly average return on the HML factor is 0.54% in China over the period between July 1996 and June 2003. By comparison, based on the three factors from Kenneth French's website, the average return on the HML factor is only 0.33% in the U.S. over the period between July 1991 and June 2011.

Fourth, small firms earn significantly higher returns than large firms in China. The monthly average return on the SMB factor is 0.82% in China over the period between July 1996 and June 2003. By comparison, based on the three factors from Kenneth French's website, the average return on the SMB factor is only 0.26% in the U.S. over the period between July 1991 and June 2011.[17]

Last but not least, the average adjusted R squared of the three-factor model is greater than 93%, which is a substantial improvement over the explanatory power of the market model. The best performance of the three-factor model is achieved when the three factors are constructed by using the market portfolio that includes only tradable shares, using the total market value to divide firms into size groups, including the SME and GEB stocks to determine portfolio breakpoints, and using the book-value-to-price ratio instead of the book-to-market-value ratio.

The rest of the paper is organized as follows. Section 3.2 gives a brief review of the relevant literature. Section 3.3 explains our data and methodology. Section 3.4 presents our empirical results, and Section 3.5 concludes the paper.

3.2 Related Literature

The capital asset pricing model (CAPM) is a fundamental theory in modern finance. One key prediction of the CAPM is that a stock's systematic risk, captured by the slope coefficient (i.e., β) in the time-series regression of the stock's excess return on the market excess return, is the only factor that explains its expected return (Sharpe (1964) and Lintner (1965)). However, academic studies have documented ample evidence that β alone cannot

[17] Asness, Frazzini, and Pedersen (2017) find that the average monthly return on the SMB factor is 0.28% in the U.S. between 1956 and 2012, but the alpha is 0.64% in the regression of the SMB factor return on the market excess return, the HML factor return, the UMD factor return, and the QMJ factor return.

adequately explain the variation in stock returns (see, e.g., Fama and French (1992) and references in Campbell (2000)).

Other asset pricing theories, such as the Intertemporal Capital Asset Pricing Model (Merton (1973)) and the Arbitrage Pricing Theory (Ross (1976)), suggest that there may be multiple systematic factors. These theories however do not specify the factors explicitly. Many studies attempt to identify pricing factors empirically, for example, Connor and Korajczyk (1988), Lehmann and Modest (1988), Chen, Roll, and Ross (1986), etc. Fama and French (1993) develop an empirical asset pricing model that includes three factors – the market factor, one factor related to firm size, and the other factor related to the ratio of the book value of equity to the market value of equity. They find that the three-factor model explains the variation in stock returns better than the CAPM and is able to explain several well-documented return anomalies. Since then, the three-factor model has been widely used in finance research (Campbell (2000) and the Scientific Background on the Nobel Prize Winners in Economics 2013).

In the following, we review a few studies that apply the Fama-French three-factor model to Chinese stock returns. We do not intend to give a comprehensive review of all studies that use the three-factor model for the China market. Our purpose is to highlight the lack of consistency in the construction of the three factors for Chinese stock returns.

Liao and Shen (2008) use the Fama-French three-factor model to examine stock price reaction to Chinese listed firms' completion of the split-share structure reform that was initiated in April 2005. To construct the size factor, they separate small and large stocks by the median of their tradable shares' market value, which is defined as the number of tradable shares at the beginning of each year multiplied by share price. To construct the value factor, they sort stocks into three groups by their book-to-market-value (BE/ME) ratio. The ratio is computed as the net assets per share divided by share price. The intersection of the two size groups with the three BE/ME groups produces six portfolios. The portfolio returns are value-weighted by the tradable shares' market value, which implicitly assumes that the portfolios include only tradable shares.

Liu and Yang (2010) examine the explanatory power of the Fama-French three-factor model for Chinese bond returns. They find that the two factors, SMB and HML, do not contribute significantly to explain Chinese bond returns. To construct the size factor, they sort stocks by their total market value into two groups. They sort stocks by their price-to-book ratio into three groups. The portfolio returns are value-weighted by the total market value.

Chen (2004) examines the performance of the Fama-French three-factor model for Chinese A-shares. He sorts stocks by the tradable shares' market value into three size groups, using the breakpoints at the 30% and 70% percentiles. He sorts stocks by their BE/ME ratio into two groups. The portfolio returns are value-weighted by the tradable shares' market value.

Mao, Chen, and Yang (2008) apply the Fama-French three-factor model to study the long-run return performance after Chinese listed firms completed rights offering. To construct the three factors, they sort stocks into two size groups by the tradable shares' market value and sort stocks into three groups by their BE/ME ratio. It is unclear how they calculate the value-weighted portfolio returns.

3.3 Data and Methodology

We follow Fama and French (1993) and use the CRSP/Compustat database to construct the three factors for the U.S. market. For China data, we use the CSMAR databases. The annual book value of equity is from the CSMAR China Stock Market Financial Statements Database. The monthly trading data including closing price, total market value, tradable market value and stock returns with cash dividend reinvested are from the CSMAR China Stock Market Trading Database. The change in the total number of shares outstanding is also from this database. We use the 3-month RMB deposit rates provided by the Industrial and Commercial Bank of China as the risk free rate of return.[18]

We examine the performance of two asset pricing models – the CAPM model and the Fama-French three-factor model. We estimate the CAPM model as follows:

$$R_t - r_{ft} = \alpha + \beta(R_{mt} - r_{ft}) + e_t \ , \tag{3.1}$$

where R_t is the return on testing portfolios, R_{mt} is the market return, and r_{ft} is the risk-free rate. Although the Sharp-Lintner version of the CAPM stipulates the intercept to be zero, an

[18] The risk free rate of return that is available from CSMAR database is based on one-year fixed-term deposit rate or one-year treasury note issued by the Chinese government. We choose the 3-month deposit rate to match the monthly returns under our study. We cannot find a long series of the market-based interest rate such as SHIBOR that covers the whole time period under our study.

intercept is usually included in empirical finance studies (Campbell, Lo, and MacKinlay (1997, Chapter 5)).

The Fama-French three-factor model is specified by the following equation

$$R_t - r_{ft} = \alpha + \beta_1 (R_{mt} - r_{ft}) + \beta_2 SMB_t + \beta_3 HML_t + e_t \ , \tag{3.2}$$

where R_t is the return on testing portfolios, R_{mt} is the market return, r_{ft} is the risk-free rate, SMB_t is the return on the size factor, and HML_t is the return on the book-to-market factor. Fama and French (1993) construct the SMB factor as the return on a portfolio long in small stocks and short in large stocks, and the HML factor as the return on a portfolio long in stocks of high book-to-market-value ratio and short in stocks of low book-to-market-value ratio.

We construct the Fama and French three factors for the Chinese stock market as follows. First, at the end of June of year t, we sort stocks by their total market value and divide them into two size groups: small (S) and big (B) firms. Fama and French (1993) determine the size breakpoint based on NYSE-listed firms, in order to avoid the overwhelming influence of the large number of small firms listed on the Nasdaq. We do not know how the stocks listed on the Chinese SME and GEB boards influence the three factors in China. Thus, we choose the size breakpoint in two ways: one is the median size including the SME/GEB stocks and the other is the median size excluding the SME/GEB stocks.

Next, we note that for Chinese firms that have shares listed on different stock exchanges, for example, A-shares listed in the Chinese mainland, H-shares listed in Hong Kong and N-shares listed in New York, it is incorrect to measure the book-to-market-value (BE/ME) ratio of A-shares as the firm's total book value of equity from its balance sheet divided by the market value of A shares. Instead, we use the B/P ratio of A-shares as the book value of equity per share divided by the end-of-year closing price of A-shares. The book value of equity per share is equal to the total book value of equity divided by the total number of shares outstanding; both figures are available in the annual report. Table 3.2 shows the mean, median and standard deviation of the B/P ratio, the BE/ME ratio, and the difference between the B/P ratio and the BE/ME ratio across all Chinese listed firms in each year from 1992 to 2012. The number of firms for which the B/P ratio differs from the BE/ME ratio gradually increases from

18 in 1992 to 174 in 2012.[19] To form the HML factor, we sort stocks by the B/P ratio at the end of December of year t-1 and divide them into three groups: low (L), medium (M) and high (H) firms. The breakpoints for the three groups are the 30th and 70th percentiles of the B/P ratios.

After these two steps, at the end of June of year t, we have two size groups and three B/P groups. The intersection of them forms six non-overlapping portfolios, denoted as (S, L), (S, M), (S, H), (B, L), (B, M), and (B, H). The portfolios remain the same from July of year t to June of year t+1. At the end of June of year t+1, we reconstruct the portfolios. We calculate the value-weighted monthly returns (with cash dividends reinvested) of each portfolio at the end of month t with their tradable (or total) market value at the end of month t-1. The tradable market value is the end-of-month market price times the number of tradable A-shares, while the total market value is the end-of-month market price times the number of all outstanding shares (including both tradable and non-tradable shares).

Finally, we obtain the Fama-French three factors as follows. The market factor is equal to the value-weighted returns of all A-shares minus the risk free rate. The factor SMB is then computed as the simple average of the monthly value-weighted returns of the three small-firm portfolios, (S, L), (S, M) and (S, H), minus the simple average of the monthly value-weighted returns of the three big-firm portfolios, (B, L), (B, M) and (B, H). Similarly, the HML factor is computed as the simple average of the monthly value-weighted returns of the two high-B/P groups, (S, H) and (B, H), minus the simple average of the monthly value-weighted returns of the two low-B/P groups, (S, L) and (B, L).

3.4 Empirical Results

To understand the details of constructing the Fama-French three factors and gain confidence in our programming and empirical work, we at first use the CRSP/Compustat data to replicate the Fama and French three factors in the U.S. We compare the three factors we obtained with those on Kenneth French's website for the time period from July 1991 to June 2011. Table 3.3 shows descriptive statistics of the three factors for the U.S. stock returns. Figure 3.3 shows the time-series plot of the monthly cumulated value of one dollar invested in

[19] The proportion of such firms dropped from 34.6% in 1992 to 7.2% in 2012, as the total number of listed firms increases significantly over these years.

each of the three factors at the end of June 1991 and compounded at the monthly returns on the respective factor. We obtain almost exactly the same market factor as the one provided by Kenneth French, while there are small discrepancies in the SMB and HML factors. Figure 3.3 shows that all three of our factors track the changes in the respective factors from Kenneth French's website very closely.

Next, we study the three factors for Chinese stock returns. We experiment with four ways of constructing the three factors to investigate the impact of the special features in the Chinese stock market. Almost all Chinese listed firms went through the Share-Structure Reform in 2005 and 2006, which legally converted non-tradable shares to tradable. Figure 3.1 shows that the proportion of the tradable market value to the total market value increases from about 30% in 1996 to above 80% in 2012. We examine three time periods: the whole period from July 1996 to June 2013, the sub-period from July 1996 to December 2004, and the sub-period from July 2007 to June 2013. Hence, the two sub-periods allow us to observe potential differences in the three factors before and after the reform. Our analysis starts from July 1996 because we want to ensure that there are a sufficient number of stocks in each portfolio; Table 3.1 shows the number of firms is small in the early years. Table 3.4 reports the descriptive statistics of the three factors under the four different methods in the three time periods. Figures 3.4.1, 3.4.2, and 3.4.3 show the time-series plots of the cumulated value of one dollar invested at the end of June 1996 and compounded at the monthly returns on the three factors.

To assess how well the three factors explain Chinese stock returns, we follow Fama and French (1993) to construct 25 portfolios and regress the excess returns of the 25 portfolios on the three factors. To form the 25 portfolios at the end of June of year t, we sort stocks into five equal-size groups based on their total market value at the end of June of year t, and independently sort stocks into five equal-size groups based on their B/P ratio at the end of December of year t-1. The intersection of these groups forms the 25 non-overlapping portfolios. The value-weighted monthly return of each portfolio in month t is equal to the sum of the monthly returns on the constituent stocks multiplied by their tradable market value at the end of month t-1. The excess return of each portfolio is equal to the value-weighted return of each portfolio minus the risk free rate of return.

We first run regressions of the 25 portfolios based on the market model in Equation (3.1). The regression results are shown in Tables 3.5.1 and 3.5.2. In Table 3.5.1, we use the tradable market value as weights to calculate the value-weighted market returns. In Table 3.5.2, we use the total market value as weights to calculate the value-weighted market returns. The coefficients for the market factor are all highly significant at the 1% level in both tables. The average adjusted R squared across the 25 portfolios is 82.9% when the market portfolio includes only tradable shares, whereas the average adjusted R squared is 76.6% when the market portfolio includes both non-tradable and tradable shares. However, the market model does not explain small firms' returns properly as the intercepts are significantly positive for four of the five small firm portfolios.

Next, we run regressions of the 25 portfolios on the three factors as in Equation (3.2). Table 3.6.1 reports the regression results by using a firm's tradable market value as portfolio weights in the calculation of value-weighted returns and including the SME and GEB stocks to determine the portfolio breakpoints. In Table 3.6.1, the coefficients for the SMB and market factors are all significant at the 5% level; the coefficients for the HML factors are significant at the 5% level except for three portfolios. The average adjusted R squared is equal to 93.6%. The intercepts are significant at the 5% level for 2 out of the 25 portfolios.

Table 3.6.2 shows the regression results by using a firm's tradable market value as portfolio weights in the calculation of value-weighted returns and excluding the SME and GEB stocks to determine the portfolio breakpoints. The results are very similar to those in Table 3.6.1. The average adjusted R squared in Table 3.6.2 is equal to 93.7%.

Table 3.6.3 shows the regression results by using a firm's total market value as portfolio weights in the calculation of value-weighted returns, including the SME and GEB stocks to determine the portfolio breakpoints, while Table 3.6.4 shows the results by using a firm's total market value as portfolio weights, excluding the SME and GEB stocks to determine the portfolio breakpoints. The average adjusted R squares are equal to 92.3% and 92.4% in Tables 3.6.3 and 3.6.4, which are lower than in Tables 3.6.1 and 3.6.2.

Overall, these results demonstrate that the Fama-French three-factor model explains the variation in Chinese stock returns very well. It does not affect the explanatory power of the three-factor model whether or not the SME and GEB stocks are included to determine the portfolio breakpoints. The explanatory power of the three-factor model is higher when the market portfolio includes only tradable shares than when the market portfolio includes both non-tradable and tradable shares.

Furthermore, we explore whether the U.S. factors have any impact on Chinese stock returns. In Table 3.7, we report the results that include the Fama-French three factors of both China and the U.S. in the regressions of the 25 testing portfolio returns. By comparing the results in Table 3.7 with those in Table 3.6.1, we do not find evidence that the U.S. factors affect Chinese stock returns. The average adjusted R squared is equal to 93.6%.

3.5 Conclusion

We investigate the Fama-French three factors in the Chinese stock market and find that the three-factor model can explain more than 93% of the variation in the portfolio returns on Chinese A-shares. We experiment with different ways of constructing the three factors in order to evaluate the effect of several special features in China. Our results demonstrate that the formation of the three factors can have a big impact in empirical studies that apply the Fama-French three-factor model to Chinese stock returns. We recommend that the three factors be constructed by using the market portfolio that includes only tradable shares, using the total market value to divide firms into size groups, including the SME and GEB stocks to determine the portfolio breakpoints, and using the book-value-to-price ratio instead of the book-to-market-value ratio.

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Figure 1.1 The difference in cumulative squared forecast errors—Annual frequency

This figure displays the difference in cumulative squared forecast errors (CSFE) between the historical mean and different forecast models in one-year-ahead stock return forecasts. In each year of the OOS forecast period, we compute the difference between the squared forecast error of the historical mean and the squared forecast error of a forecast model. We then add up these differences cumulatively at each point in time over the entire OOS forecast period. The OOS equity premium forecasts are computed by imposing Campbell and Thompson's (2008) sign restrictions. The training period uses accounting data from 1962-1990, and corresponding stock returns data from July 1963-June 1992. The out-of-sample forecast period for one-year-ahead stock returns is July 1992-June 2016. The forecast models used are specifications with B/M only (Panel A), B/M plus profitability (Panel B), B/M plus asset growth (Panel C), asset growth (Panel D), and B/M plus profitability plus asset growth (Panel E).

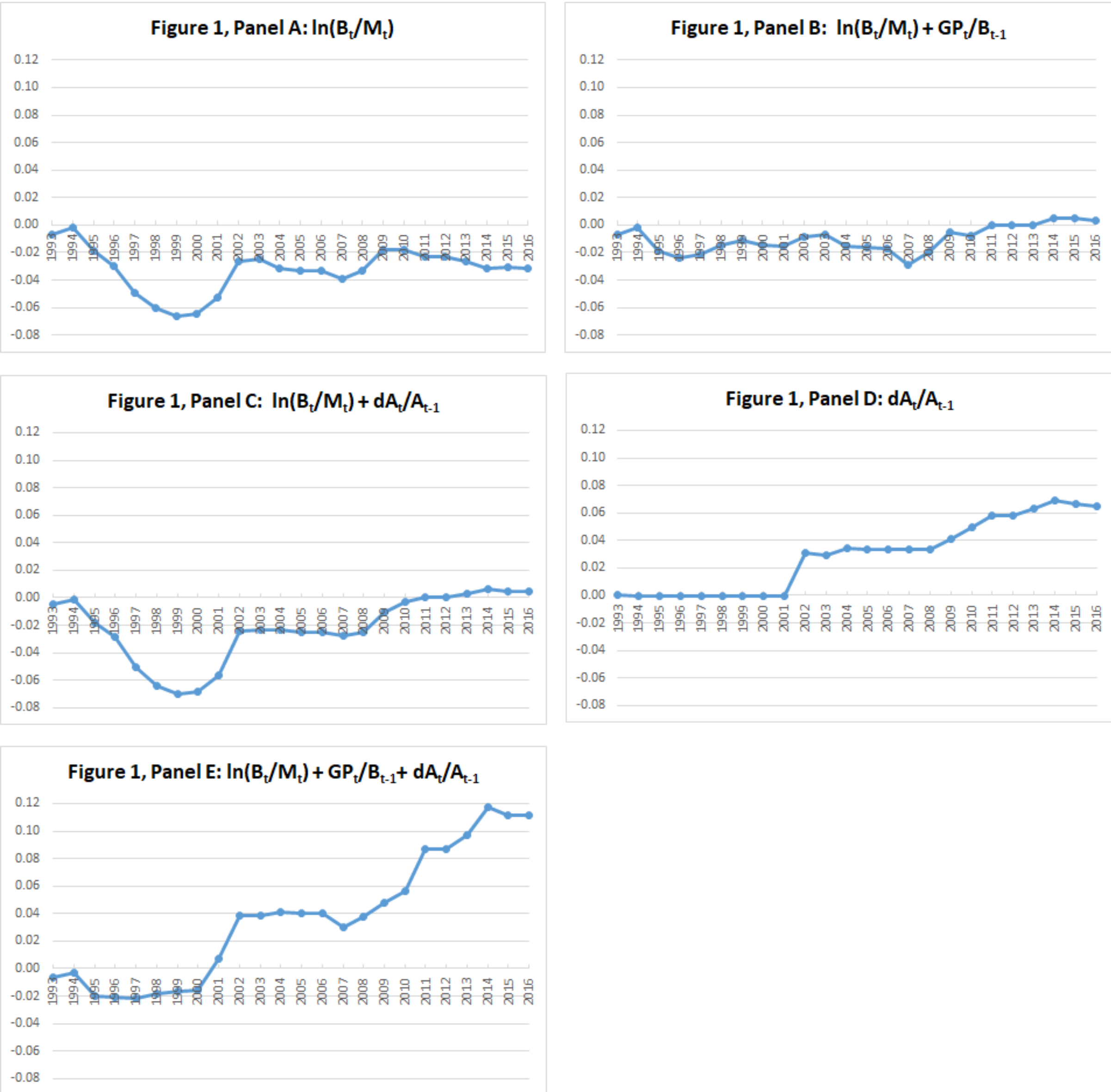

Figure 1.2 The difference in cumulative squared forecast errors—Quarterly frequency

This figure displays the difference in cumulative squared forecast errors (CSFE) between the historical mean and different forecast models in one-quarter-ahead stock return forecasts. In each quarter of the OOS forecast period, we compute the difference between the squared forecast error of the historical mean and the squared forecast error of a forecast model. We then add up these differences cumulatively at each point in time over the entire OOS forecast period. The OOS equity premium forecasts are computed by imposing Campbell and Thompson's (2008) sign restrictions. The training period uses accounting data from 1975Q1-1990Q4, and corresponding stock returns data from August 1975-July 1991. The out-of-sample forecast period for one-quarter-ahead stock returns is August 1991-July 2017. The forecast models used are specifications with B/M only (Panel A), B/M plus profitability (Panel B), B/M plus asset growth (Panel C), asset growth (Panel D), and B/M plus profitability plus asset growth (Panel E).

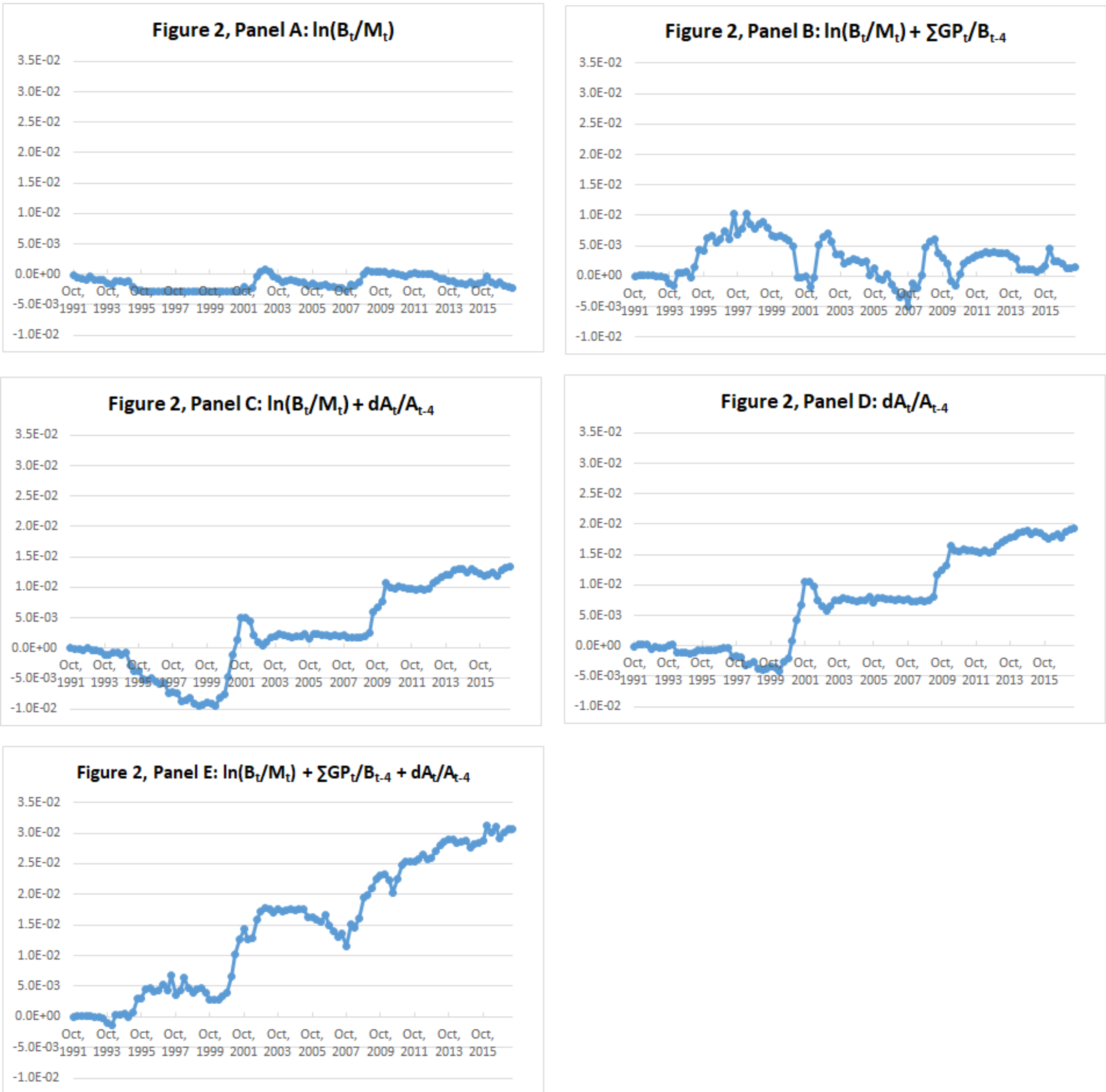

Figure 1.3 OOS R^2 by sample split year/quarter

This figure displays OOS R^2s as a function of sample split years/quarters, with Panels A and B applied to the annual and quarterly analyses, respectively. The sample split year/quarter is used to divide the whole sample (1962-2014, or, 1975Q1-2016Q4, based on the timing of the accounting variables) into a training sample and a test sample. The OOS R^2s are computed by imposing Campbell and Thompson's (2008) sign restrictions on the equity premium forecasts. The specifications examined include those that use the standalone B/M, B/M plus profitability, B/M plus asset growth, standalone asset growth, or B/M plus profitability plus asset growth as predictors.

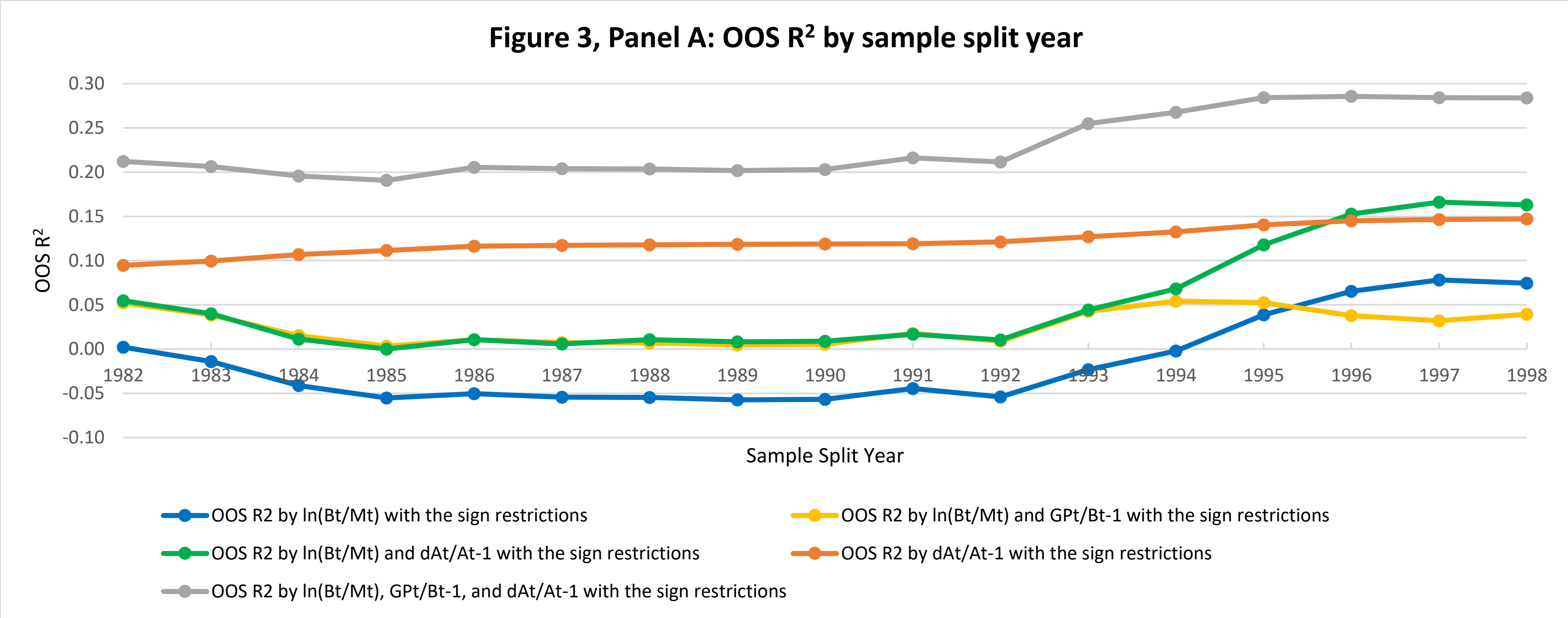

Figure 1.3 OOS R^2 by sample split year/quarter (continued)

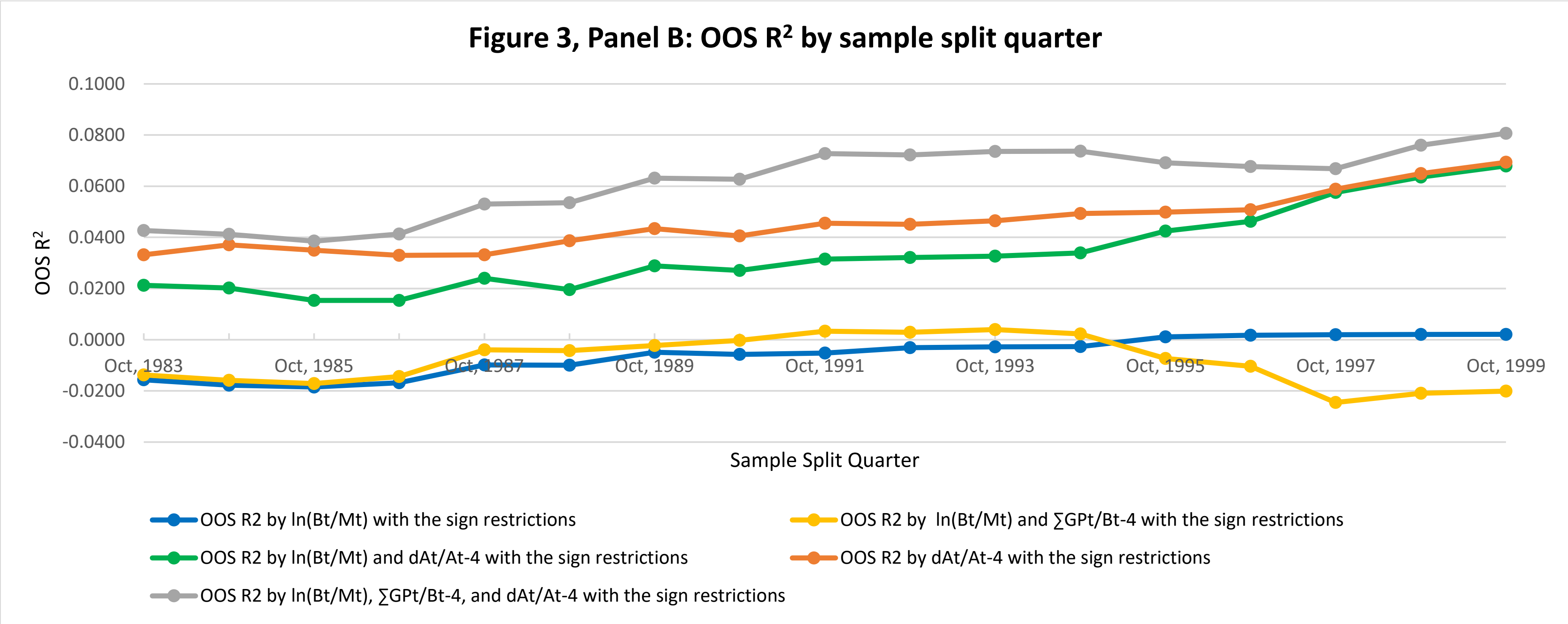

Figure 3.1 Market value

This figure shows the total market value and the tradable market value in aggregate for all A-shares in China. The left axis is the amount of market value. The right asix is the ratio of the tradable market value to the total market value.

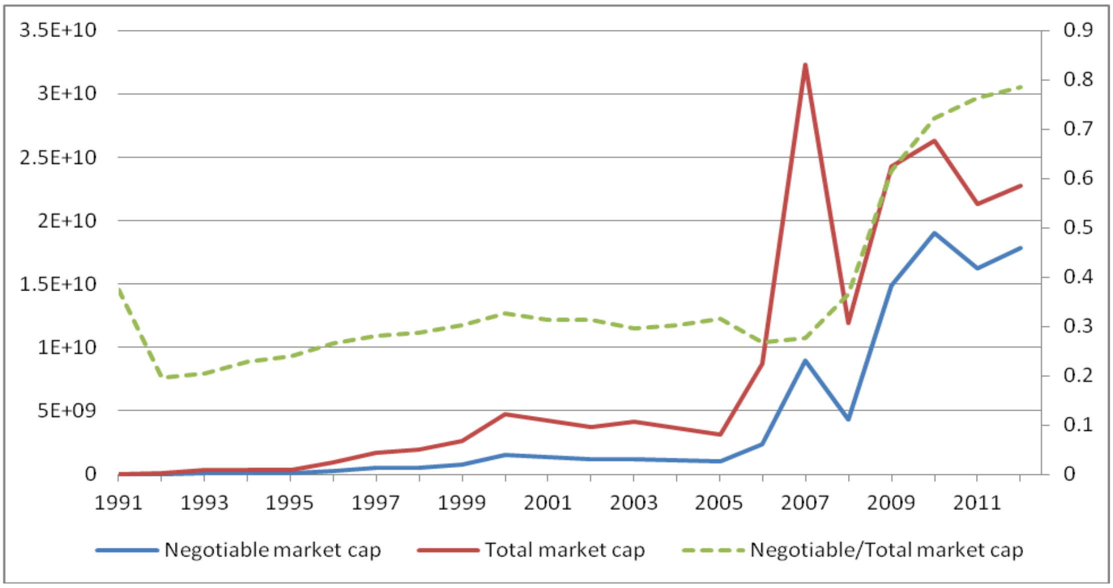

Figure 3.2 Percentiles of the ratio of tradable to total market value

This figure shows the five percentiles (5%, 25%, 50%, 75%, 90%) of the firm-level ratio of tradable market value to total market value for all A-shares in China.

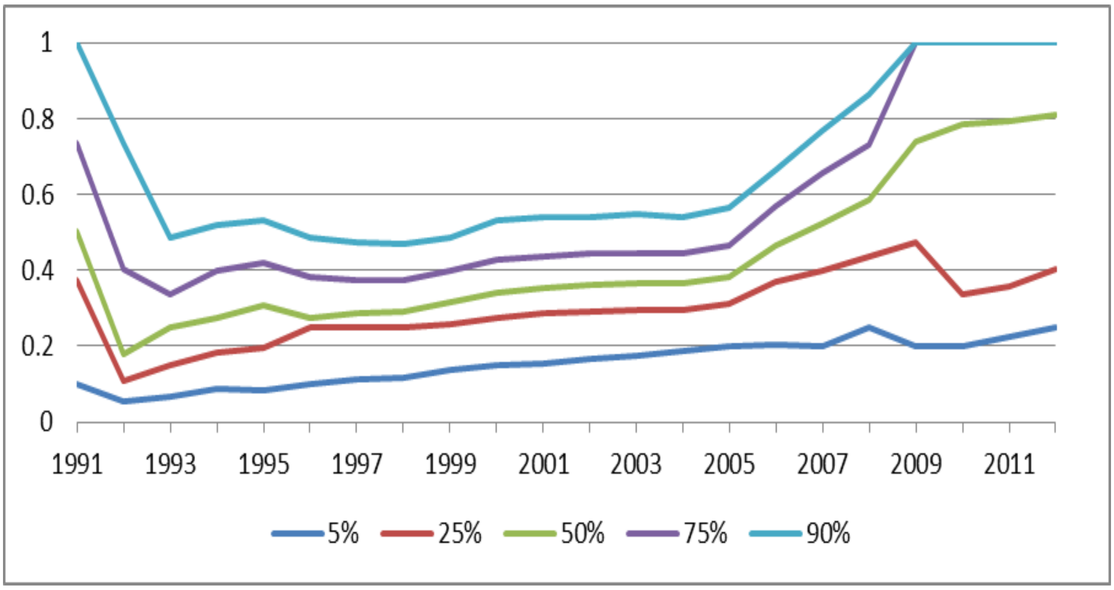

Figure 3.3 Cumulative value of the three factors in the U.S.

This figure plots the monthly cumulated value of one dollar invested at the end of June 1991 and compounded at the monthly returns of the three factors in the U.S. market. The solid lines represent the three factors from Kenneth French's website. The dashed lines represent the three factors we replicated. The time period is from July 1991 to June 2011.

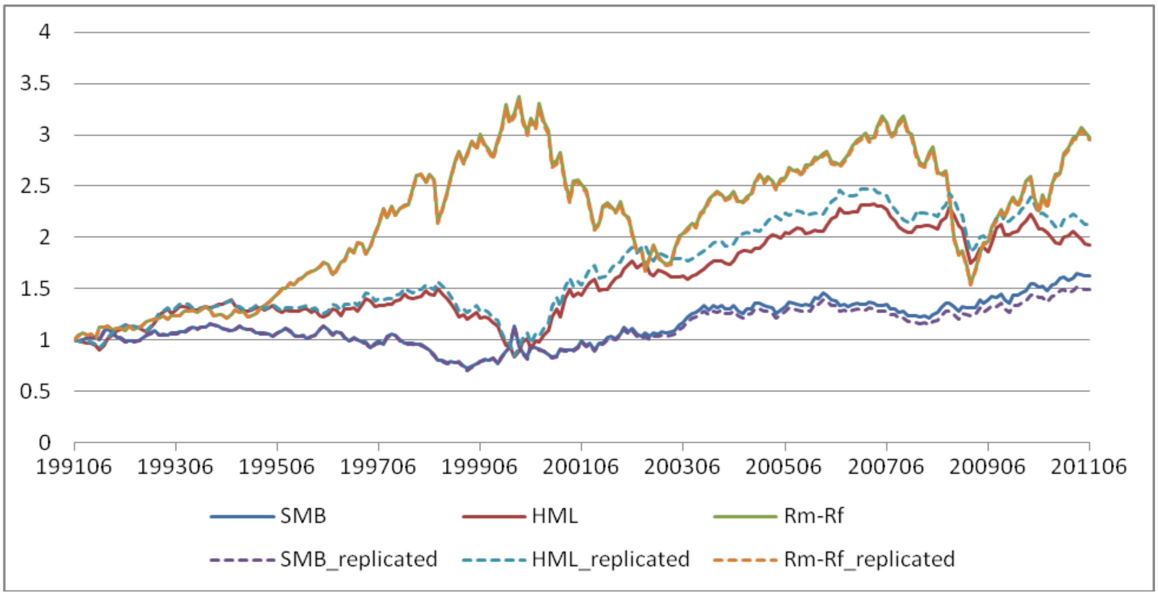

Figure 3.4.1 Cumulative value of the size factor in China

The figure shows the time-series plot of the monthly cumulated value of one dollar invested at the end of June 1996 and compounded at the monthly returns of the size factor in China. The time period is from July 1996 to June 2013. Method 1 includes the SME and GEB stocks to determine the median firm size and uses a firm's tradable market value as portfolio weights. Method 3 includes the SME and GEB stocks to determine the median firm size and uses a firm's total market value as portfolio weights.

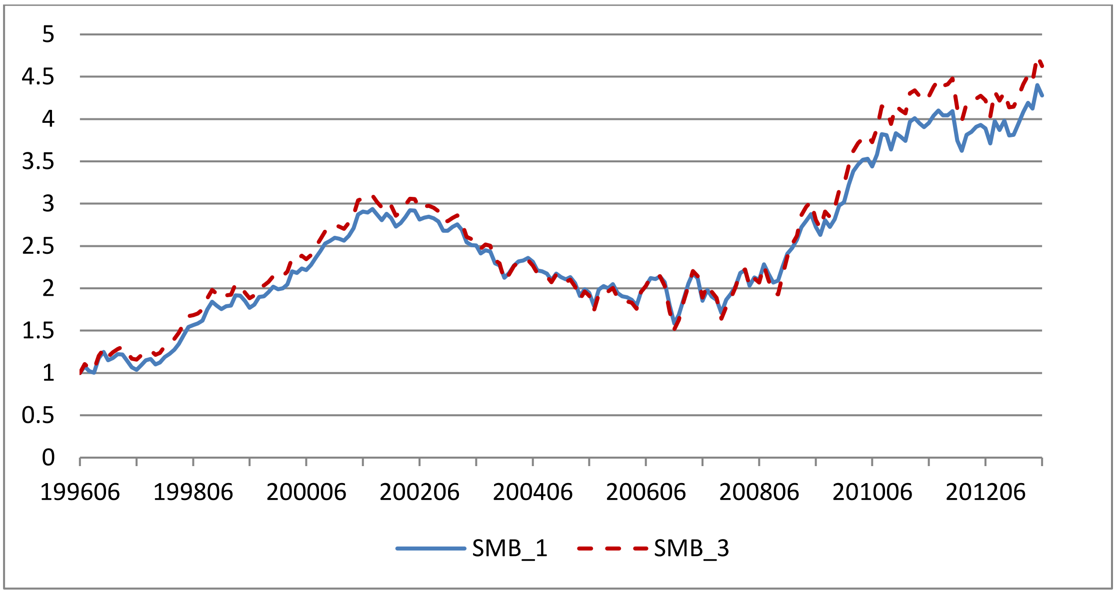

Figure 3.4.2 Cumulative wealth of the value factor in China

The figure shows the time-series plot of the monthly cumulated value of one dollar invested at the end of June 1996 and compounded at the monthly returns of the value factor in China. The time period is from July 1996 to June 2013. Method 1 includes the SME and GEB stocks to determine the median firm size and uses a firm's tradable market value as portfolio weights. Method 3 includes the SME and GEB stocks to determine the median firm size and uses a firm's total market value as portfolio weights.

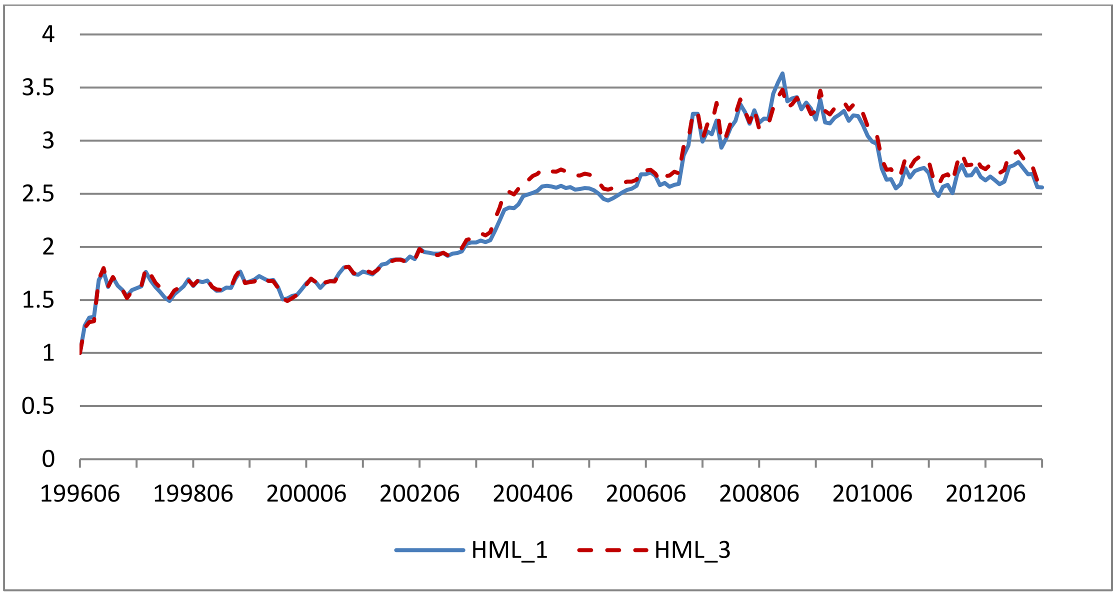

Figure 3.4.3 Cumulative value of the market factor in China

The figure shows the time-series plot of the monthly cumulated value of one dollar invested at the end of June 1996 and compounded at the monthly returns of the market factor in China. The time period is from July 1996 to June 2013. Method 1 includes the SME and GEB stocks to determine the median firm size and uses a firm's tradable market value as portfolio weights. Method 3 includes the SME and GEB stocks to determine the median firm size and uses a firm's total market value as portfolio weights.

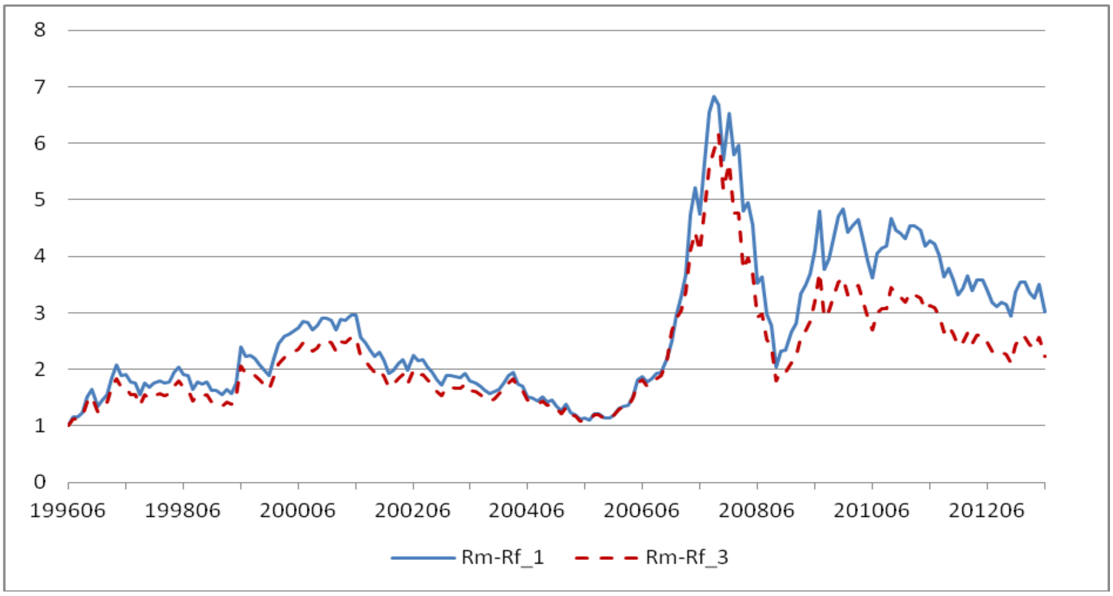

Table 1.1 Summary statistics of the aggregate variables at annual frequency

This table reports the summary statistics of the aggregate variables (Panels A and B) at annual frequency, which are obtained by weighing firm-level variables by each firm's end-of-year market capitalization. Firm-level variables (except for stock returns) are first winsorized at the 0.5 and 99.5 percentiles for each year before being aggregated. $ln(B_t/M_t)$ is the aggregate log book-to-market ratio. GP_t/B_{t-1} is aggregate profitability. $OpCash_t/B_{t-1}$ is aggregate cash-based operating profitability. dA_t/A_{t-1} is aggregate asset growth. $Invest_{AL,t}$ denotes the investment measure proposed by Arif and Lee (2014). $Term_t$ is the term spread measured as of the end of June in year *t*+1, defined as the difference between the ten- and the one-year Treasury constant maturity rates. Def_t is the default spread measured as of the end of June in year *t*+1, defined as the difference between the Moody's BAA and AAA bond yields. $Tbill_t$ is the thirty-day Treasury bill rate measured as of the end of June in year *t*+1. $Sent_t^{BW}$ is Baker and Wurgler (2006)'s orthogonalized investor sentiment index measured in June of year *t*+1. $Sent_t^{HJTZ}$ is Huang, Jiang, Tu, and Zhou's (2015) investor sentiment index in June of year *t*+1. CAY_t is the consumption-wealth ratio constructed by Lettau and Ludvigson (2001), measured at the second quarter of year *t*+1. $OpAcc_t$ is aggregate operating accruals, as defined by Hirshleifer, Hou, and Teoh (2009), and aggregated from firm-level operating accruals at the end of year *t*. $EquityShare_t$ is the equity share in new issues in year *t*. $LVOL_t$ is the annual aggregate stock market volatility from July of year *t* to June of year *t*+1, computed by using daily returns on the CRSP value-weighted index. R_{t+1}^e is the annual excess stock return in *t*+1, computed by aggregating firm-level stock returns and subtracting the corresponding compounded one-month Treasury bill rates. $R_{(t+1,t+2)}^e$ is the geometric average of annual excess stock returns over years *t*+1 and *t*+2. Appendix 1.A contains detailed definitions of these variables. For stock returns, the sample period is July 1963-June 2016. For other variables except Sent^{BW} and Sent^{HJTZ}, the sample period (based on the time subscript *t*) is 1962-2014. For Sent^{BW} and Sent^{HJTZ}, the sample period is 1965-2013. Panel A reports the summary statistics of the aggregate variables. Panel B (Panel C) reports Pearson correlation coefficients between the main aggregate (industry-level) variables, with the p-values presented in parentheses. In Panel C, firm-level variables are aggregated to the industry level at the end of each year. Fama-French 48-industry definitions are used. Each variable is demeaned by their industry-specific mean over the sample period. $ln(B_t/M_t)$ is the aggregate log book-to-market ratio at quarterly frequency. $\sum GP_{it}/B_{it-4}$ is aggregate profitability. dA_t/A_{t-4} is aggregate asset growth. All these variables are computed by using quarterly accounting data. R_{t+1}^e is the quarterly excess stock return in *t*+1. For stock returns, the sample period is August 1975-July 2017. For accounting variables, the sample period (based on the time subscript *t*) is 1975Q1-2016Q4.

Table 1.1 Summary statistics of the aggregate variables (continued)

Panel A: Summary Statistics of Aggregate Variables

	No. of Obs.	Mean	Std Dev	Q1	Median	Q3
$\ln(B_t/M_t)$	53	-0.780	0.395	-1.036	-0.850	-0.438
GP_t/B_{t-1}	53	0.822	0.122	0.748	0.798	0.891
$OpCash_t/B_{t-1}$	53	0.480	0.087	0.420	0.467	0.545
dA_t/A_{t-1}	53	0.138	0.069	0.106	0.120	0.148
$InvestAL_t$	53	0.069	0.029	0.051	0.061	0.091
$Term_t$	53	0.010	0.011	0.002	0.010	0.018
Def_t	53	0.010	0.004	0.008	0.009	0.012
$Tbill_t$	53	0.004	0.003	0.003	0.004	0.005
$Sent^{BW}_t$	49	-0.011	0.964	-0.381	-0.081	0.394
$Sent^{HJTZ}_t$	49	0.117	0.963	-0.456	-0.153	0.274
CAY_t	53	-0.003	0.020	-0.013	-0.003	0.012
$OpAcc_t$	53	-0.048	0.012	-0.053	-0.047	-0.043
$EquityShare_t$	53	0.172	0.085	0.116	0.150	0.217
$LVOL_{t+1}$	53	-2.038	0.391	-2.280	-2.124	-1.828
R^e_{t+1}	53	0.062	0.160	-0.013	0.061	0.179
$R^e_{(t+1,t+2)}$	52	0.056	0.107	0.008	0.049	0.118

Panel B: Pearson Correlation Coefficients at Aggregate Level

	$\ln(B_t/M_t)$	GP_t/B_{t-1}	$OpCash_t/B_{t-1}$	dA_t/A_{t-1}	$InvestAL_t$	R^e_{t+1}	$R^e_{(t+1,t+2)}$
$\ln(B_t/M_t)$	1	-0.52	-0.52	-0.40	-0.15	0.19	0.19
		(0.00)	(0.00)	(0.00)	(0.27)	(0.16)	(0.17)
GP_t/B_{t-1}		1	0.89	0.50	0.23	0.07	0.13
			(0.00)	(0.00)	(0.10)	(0.64)	(0.37)
$OpCash_t/B_{t-1}$			1	0.31	-0.03	0.13	0.24
				(0.02)	(0.83)	(0.34)	(0.09)
dA_t/A_{t-1}				1	0.76	-0.29	-0.44
					(0.00)	(0.04)	(0.00)
$InvestAL_t$					1	-0.21	-0.48
						(0.14)	(0.00)
R^e_{t+1}						1	0.72
							(0.00)
$R^e_{(t+1,t+2)}$							1

Table 1.1 Summary statistics of the aggregate variables (continued)

Panel C: Pearson Correlation Coefficients At Industry Level					
	$\ln(B_t/M_t)$	dA_t/A_{t-1}	GP_t/B_{t-1}	R^e_{t+1}	$R^e_{(t+1,t+2)}$
$\ln(B_t/M_t)$	1	-0.18	-0.35	0.18	0.21
		(0.00)	(0.00)	(0.00)	(0.00)
dA_t/A_{t-1}		1	0.18	-0.21	-0.28
			(0.00)	(0.00)	(0.00)
GP_t/B_{t-1}			1	0.03	0.05
				(0.20)	(0.01)
R^e_{t+1}				1	0.71
					(0.00)
$R^e_{(t+1,t+2)}$					1

Table 1.2 Predicting aggregate stock returns

This table reports time-series predictive regression results that use B/M, profitability, and asset growth as predictors. All RHS variables are standardized by their own means and standard deviations. Panel A predicts one-year-ahead stock returns. Panel B predicts average stock returns over years t+1 and t+2. Panel C predicts one-quarter-ahead stock returns. The t-statistics in parentheses are computed using Newey-West (1987) standard errors with three lags in Panels A and B, and with four lags in Panel C. For Panels A and B, the training window uses accounting data from 1962-1990, and corresponding stock returns data from July 1963-June 1992 (for one-year-ahead return forecasts) and July 1963-June 1993 (for two-year-average return forecasts). The out-of-sample forecast period is July 1992-June 2016 (for one-year-ahead return forecasts) and July 1993-June 2016 (for two-year-average return forecasts). For Panel C, the training window uses accounting data from 1975Q1-1990Q4, and corresponding stock returns data from August 1975-July 1991. The out-of-sample forecast period is August 1991-July 2017. The Clark and McCracken (2001)'s ENC-NEW statistic is used to test whether the forecast accuracy improvement of a model relative to the historical mean is significantly positive. The OOS R^2s and the ENC-NEW statistics are computed by imposing Campbell and Thompson's (2008) sign restrictions on the OOS equity premium forecasts. Statistical significance at 10%, 5%, and 1% are indicated as *, **, and ***, respectively.

Table 1.2 Predicting aggregate stock returns (continued)

	1	2	3	4	5	6
Panel A: Predicting one-year-ahead stock returns R^e_{t+1}						
Constant	0.062***	0.062***	0.062***	0.062***	0.062***	0.062***
	(3.11)	(3.24)	(3.58)	(3.26)	(3.41)	(4.13)
$\ln(B_t/M_t)$	0.031			0.050**	0.015	0.038*
	(1.56)			(2.13)	(0.82)	(1.98)
GP_t/B_{t-1}		0.011		0.036		0.062***
		(0.40)		(1.42)		(3.01)
dA_t/A_{t-1}			-0.046***		-0.040***	-0.062***
			(-3.99)		(-3.09)	(-4.46)
No. of Obs.	53	53	53	53	53	53
Prob>F	0.125	0.689	0.000	0.095	0.001	0.000
IS R^2	0.04	0.00	0.08	0.08	0.09	0.18
IS adj. R^2	0.02	-0.02	0.06	0.04	0.05	0.13
OOS forecast with the sign restrictions						
OOS R^2	-0.06	-0.04	0.12	0.01	0.01	0.20
ENC-NEW	-0.09	0.08	1.90**	0.60	0.61	4.00**
Panel B: Predicting two-year-average stock returns $R^e_{(t+1,t+2)}$						
	1	2	3	4	5	6
Constant	0.056***	0.056***	0.056***	0.056***	0.056***	0.056***
	(3.09)	(3.20)	(3.49)	(3.37)	(3.45)	(4.87)
$\ln(B_t/M_t)$	0.021			0.039*	0.001	0.025*
	(1.19)			(1.82)	(0.10)	(1.69)
GP_t/B_{t-1}		0.014		0.035		0.061***
		(0.61)		(1.65)		(4.45)
dA_t/A_{t-1}			-0.047***		-0.047***	-0.068***
			(-5.83)		(-4.55)	(-6.41)
No. of Obs.	52	52	52	52	52	52
Prob>F	0.241	0.547	0.000	0.124	0.000	0.000
IS R^2	0.04	0.02	0.20	0.11	0.20	0.40
IS adj. R^2	0.02	0.00	0.18	0.08	0.16	0.36
OOS forecast with the sign restrictions						
OOS R^2	-0.13	-0.15	0.21	-0.15	0.06	0.29
ENC-NEW	-1.04	-0.52	3.63***	-0.86	1.46*	5.97***

Table 1.2 Predicting aggregate stock returns (continued)

Panel C: Predicting one-quarter-ahead stock returns R^e_{t+1}						
	1	2	3	4	5	6
Constant	0.017***	0.017***	0.017***	0.017***	0.017***	0.017***
	(3.00)	(3.00)	(3.28)	(3.11)	(3.27)	(3.47)
$\ln(B_t/M_t)$	0.004			0.017**	-0.000	0.014*
	(0.60)			(2.07)	(-0.05)	(1.71)
$\sum GP_t/B_{t-4}$		0.004		0.017**		0.020***
		(0.60)		(2.31)		(2.78)
dA_t/A_{t-4}			-0.015***		-0.015***	-0.016***
			(-4.11)		(-3.67)	(-3.35)
No. of Obs.	168	168	168	168	168	168
Prob>F	0.546	0.550	0.000	0.053	0.000	0.001
IS R^2	0.00	0.00	0.04	0.03	0.04	0.07
IS adj. R^2	0.00	0.00	0.04	0.02	0.03	0.06
OOS forecast with the sign restrictions						
OOS R^2	-0.01	-0.02	0.05	0.00	0.03	0.07
ENC-NEW	-0.05	1.03	3.33**	1.94*	2.55*	5.73***

Table 1.3 Predicting industry-level stock returns

This table reports the industry-level panel regression results. Firm-level B/M, profitability, and asset growth are aggregated to the industry level and used to predict industry-level stock returns. Panel A predicts one-year-ahead industry-level stock returns. Panel B predicts two-year average industry-level stock returns. Panel C predicts one-quarter-ahead stock returns. Fama-French 48 industry definitions are used with the financial industries (44-47) excluded. We run the panel regressions with industry fixed effects by value-weighting each industry every year. All the RHS variables are scaled by their own aggregate standard deviation. The sample period of the accounting variables is 1962-2014 for Panel A, 1962-2013 for Panel B, and 1975Q1-2016Q4 for Panel C. The corresponding sample period of the stock returns is July 1963-June 2016 in Panels A and B, and August 1975-July 2017 in Panel C. The *t*-statistics in parentheses are computed based on two-way clustered standard errors. Statistical significance at 10%, 5%, and 1% are indicated as *, **, and ***, respectively.

Panel A: Predicting one-year-ahead stock returns R^e_{t+1}						
	1	2	3	4	5	6
$\ln(B_t/M_t)$	0.036**			0.042***	0.029*	0.037**
	(-2.31)			(2.62)	(1.95)	(2.41)
GP_t/B_{t-1}		0.003		0.010***		0.013***
		(-0.80)		(2.63)		(3.21)
dA_t/A_{t-1}			-0.026***		-0.022***	-0.024***
			(-3.57)		(-3.54)	(-3.99)
No. of Obs.	2,315	2,315	2,315	2,315	2,315	2,315
R^2	0.03	0.00	0.04	0.04	0.07	0.08
Adj. R^2	0.03	0.00	0.04	0.04	0.06	0.08
Industry Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Panel B: Predicting two-year-average stock returns $R^e_{(t+1,t+2)}$						
	1	2	3	4	5	6
$\ln(B_t/M_t)$	0.028**			0.035***	0.021**	0.029***
	(2.43)			(2.82)	(2.21)	(2.84)
GP_t/B_{t-1}		0.004		0.010***		0.013***
		(1.24)		(2.95)		(3.42)
dA_t/A_{t-1}			-0.023***		-0.021***	-0.022***
			(-4.48)		(-4.78)	(-5.39)
No. of Obs.	2,271	2,271	2,271	2,271	2,271	2,271
R^2	0.04	0.00	0.08	0.06	0.10	0.13
Adj. R^2	0.04	0.00	0.08	0.06	0.10	0.13
Industry Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes

Table 1.3 Predicting industry-level stock returns (continued)

Panel C: Predicting one-quarter-ahead stock returns R^e_{t+1}						
	1	2	3	4	5	6
$\ln(B_t/M_t)$	0.007			0.010*	0.004	0.008
	(1.62)			(1.94)	(1.00)	(1.63)
$\sum GP_t/B_{t-4}$		0.001		0.003**		0.004***
		(1.04)		(2.23)		(2.93)
dA_t/A_{t-4}			-0.009***		-0.009***	-0.009***
			(-4.86)		(-4.41)	(-4.71)
No. of Obs.	7,235	7,235	7,235	7,235	7,235	7,235
R^2	0.01	0.00	0.03	0.01	0.03	0.03
Adj. R^2	0.01	0.00	0.03	0.01	0.03	0.03
Industry Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes

Table 1.4 Forecasting the equity premium as at June 2016

This table reports the equity premium forecasts—made as at June 2016—by using the B/M, profitability, and asset growth as predictors. Panel A reports the means, standard deviations, and the year 2015 values of the predictors. The last column computes the deviation of the 2015 values from their sample means, measured in standardized units. Panel B1 reports the annual equity premium forecasts over July 2016-June 2017, and Panel B2 reports the average annual equity premium forecasts over July 2016-June 2018.

Panel A: Summary statistics of the predictors

Predictors	Mean	Std Dev	Value in 2015	Deviation of the value in 2015 from the mean (in standardized unit)
$\ln(B_t/M_t)$	-0.789	0.396	-1.254	-1.174
GP_t/B_{t-1}	0.825	0.123	0.967	1.164
dA_t/A_{t-1}	0.137	0.069	0.111	-0.378

Panel B1: Forecasting the return premium of 2016 (July 2016 - June 2017)

Predictor(s)			Estimated intercept	Value of the first predictor in 2015	Coefficient estimate of the first predictor	Value of the second predictor in 2015	Coefficient estimate of the second predictor	Value of the third predictor in 2015	Coefficient estimate of the third predictor	Forecasted return premium of 2016
$\ln(B_t/M_t)$	-	-	0.124	-1.254	0.079	-	-	-	-	0.025
$\ln(B_t/M_t)$	GP_t/B_{t-1}	-	-0.084	-1.254	0.127	0.967	0.298	-	-	0.046
$\ln(B_t/M_t)$	dA_t/A_{t-1}	GP_t/B_{t-1}	-0.153	-1.254	0.098	0.111	-0.888	0.967	0.504	0.113

Panel B2: Forecasting the geometric average of the return premia over 2016-2017 (July 2016 - June 2018)

Predictor(s)			Estimated intercept	Value of the first predictor in 2015	Coefficient estimate of the first predictor	Value of the second predictor in 2015	Coefficient estimate of the second predictor	Value of the third predictor in 2015	Coefficient estimate of the third predictor	Forecasted geometric average of the return premia over 2016-2017
$\ln(B_t/M_t)$	-	-	0.097	-1.254	0.053	-	-	-	-	0.031
$\ln(B_t/M_t)$	GP_t/B_{t-1}	-	-0.098	-1.254	0.100	0.967	0.280	-	-	0.049
$\ln(B_t/M_t)$	dA_t/A_{t-1}	GP_t/B_{t-1}	-0.169	-1.254	0.064	0.111	-0.966	0.967	0.496	0.123

Table 1.5 Certainty equivalent return (CER) gains

This table reports the certainty equivalent return (CER) gains from jointly using B/M, profitability, and asset investment instead of only using the B/M as equity premium predictors in portfolio allocation. This CER gain represents the value to an investor in her portfolio allocation by switching from a B/M-based OOS predictive model to one that is based on B/M, profitability, and asset investment. The % CER gain can be interpreted as an annual fee that the investor would be willing to pay to switch from a B/M-based to a B/M/profitability/investment-based forecast. The CER gains reported here are computed by imposing Campbell and Thompson's (2008) sign restrictions on the OOS equity premium forecasts. Panel A reports CER gains based on one-year-ahead equity premium forecasts, and Panel B reports CER gains based on two-year-average equity premium forecasts. In each panel, the risk aversion coefficient γ can take on values of 1, 3, or 5. The training window uses accounting data from 1962-1990, and corresponding stock returns data from July 1963-June 1992 (for one-year-ahead return forecasts) and July 1963-June 1993 (for two-year-average return forecasts). The out-of-sample forecast period is July 1992-June 2016 (for one-year-ahead return forecasts) and July 1993-June 2016 (for two-year-average return forecasts). Statistical significance at 10%, 5%, and 1% are indicated as *, **, and ***, respectively.

Panel A: Portfolio allocation considering one-year-ahead stock returns					
Predictor(s)			**CER (%)**	**CER gain (%)**	**Test statistic for CER gain**
Panel A1: Risk aversion coefficient γ = 1					
$\ln(B_t/M_t)$	-	-	9.32	-	-
$\ln(B_t/M_t)$	GP_t/B_{t-1}	-	9.10	-0.22	-0.14
$\ln(B_t/M_t)$	dA_t/A_{t-1}	GP_t/B_{t-1}	12.55	3.23	2.35**
Panel A2: Risk aversion coefficient γ = 3					
$\ln(B_t/M_t)$	-	-	5.05	-	-
$\ln(B_t/M_t)$	GP_t/B_{t-1}	-	5.66	0.61	0.62
$\ln(B_t/M_t)$	dA_t/A_{t-1}	GP_t/B_{t-1}	8.66	3.61	2.91***
Panel A3: Risk aversion coefficient γ = 5					
$\ln(B_t/M_t)$	-	-	4.04	-	-
$\ln(B_t/M_t)$	GP_t/B_{t-1}	-	4.38	0.34	0.56
$\ln(B_t/M_t)$	dA_t/A_{t-1}	GP_t/B_{t-1}	6.27	2.23	2.91***
Panel B: Portfolio allocation considering two-year average stock returns					
Predictor(s)			**CER (%)**	**CER gain (%)**	**Test statistic for CER gain**
Panel B1: Risk aversion coefficient γ = 1					
$\ln(B_t/M_t)$	-	-	10.78	-	-
$\ln(B_t/M_t)$	GP_t/B_{t-1}	-	10.85	0.07	0.08
$\ln(B_t/M_t)$	dA_t/A_{t-1}	GP_t/B_{t-1}	13.76	2.97	2.49**
Panel B2: Risk aversion coefficient γ = 3					
$\ln(B_t/M_t)$	-	-	5.30	-	-
$\ln(B_t/M_t)$	GP_t/B_{t-1}	-	6.79	1.49	1.35
$\ln(B_t/M_t)$	dA_t/A_{t-1}	GP_t/B_{t-1}	12.18	6.88	5.33***
Panel B3: Risk aversion coefficient γ = 5					
$\ln(B_t/M_t)$	-	-	4.02	-	-
$\ln(B_t/M_t)$	GP_t/B_{t-1}	-	3.67	-0.35	-0.28
$\ln(B_t/M_t)$	dA_t/A_{t-1}	GP_t/B_{t-1}	9.94	5.92	4.95***

Table 1.6 Predictive power of individual components of asset growth

This table reports the predictive power of individual components of asset growth. We decompose asset growth from the investment side and the financing side. From the investment side, asset growth is decomposed into short-term asset growth (ChgSTAsst), other current asset growth (ChgCurAsst), property, plant and equipment growth (ChgPPE), and other asset growth (ChgOthAsst). From the financing side, asset growth is decomposed into operating liabilities growth (ChgOpLiab), retained earnings growth (ChgRE), stock financing growth (ChgStock), and debt financing growth (ChgDebt). Panel A reports one-year-ahead return forecasts, and Panel B reports two-year-average return forecasts. All RHS variables are standardized by their own means and standard deviations. The *t*-statistics in parentheses are computed using Newey-West (1987) standard errors with three lags. Statistical significance at 10%, 5%, and 1% are indicated as *, **, and ***, respectively. This analysis uses accounting data from 1962-2014 and stock returns data from July 1963-June 2016.

Table 1.6 Predictive power of individual components of asset growth (continued)

Panel A: Predicting one-year-ahead stock returns R^e_{t+1}											
	1	2	3	4	5	6	7	8	9	10	11
Constant	0.063***	0.063***	0.063***	0.063***	0.063***	0.063***	0.063***	0.063***	0.063***	0.063***	0.063***
	(3.75)	(3.33)	(3.67)	(3.78)	(3.31)	(3.90)	(3.31)	(3.30)	(3.49)	(3.57)	(3.53)
dA_t/A_{t-1}	-0.048***										
	(-4.89)										
$ChgSTAsst_t$		-0.051***				-0.081**					
		(-3.57)				(-2.02)					
$ChgCurAsst_t$			-0.023			0.005					
			(-1.09)			(0.29)					
$ChgPPE_t$				-0.033		-0.045*					
				(-1.46)		(-1.86)					
$ChgOthAsst_t$					-0.033*	0.033					
					(-1.72)	(0.91)					
$ChgOpLiab_t$							-0.014				-0.001
							(-1.08)				(-0.05)
$ChgRE_t$								-0.003			0.004
								(-0.24)			(0.25)
$ChgStock_t$									-0.028		-0.019
									(-1.32)		(-0.55)
$ChgDebt_t$										-0.032	-0.025
										(-1.54)	(-1.14)
No. of Obs.	53	53	53	53	53	53	53	53	53	53	53
R^2	0.09	0.10	0.02	0.04	0.04	0.17	0.01	0.00	0.03	0.04	0.05
Adj. R^2	0.07	0.09	0.00	0.03	0.02	0.11	-0.01	-0.02	0.01	0.02	-0.03

Table 6. Predictive power of individual components of asset growth (continued)

Panel B: Predicting two-year-ahead stock returns R^e_{t+2}

	1	2	3	4	5	6	7	8	9	10	11
Constant	0.063***	0.063***	0.063***	0.063***	0.063***	0.063***	0.063***	0.063***	0.063***	0.063***	0.063***
	(3.75)	(3.51)	(4.06)	(3.76)	(3.40)	(3.73)	(3.46)	(3.42)	(3.62)	(3.64)	(3.61)
dA_t/A_{t-1}	-0.043***										
	(-3.33)										
$ChgSTAsst_t$		-0.015				0.002					
		(-0.78)				(0.08)					
$ChgCurAsst_t$			-0.035**			-0.002					
			(-2.25)			(-0.07)					
$ChgPPE_t$				-0.045**		-0.042					
				(-2.22)		(-1.33)					
$ChgOthAsst_t$					-0.028*	-0.026					
					(-1.75)	(-0.83)					
$ChgOpLiab_t$							-0.014				-0.004
							(-0.91)				(-0.12)
$ChgRE_t$								-0.004			0.005
								(-0.33)			(0.24)
$ChgStock_t$									-0.029**		-0.014
									(-2.22)		(-0.53)
$ChgDebt_t$										-0.043***	-0.038*
										(-2.89)	(-2.01)
No. of Obs.	52	52	52	52	52	52	52	52	52	52	52
R^2	0.08	0.01	0.05	0.09	0.03	0.11	0.01	0.00	0.04	0.08	0.09
Adj. R^2	0.06	-0.01	0.03	0.07	0.01	0.04	-0.01	-0.02	0.02	0.06	0.01

Table 1.7 Predicting market volatility

This table reports the predictability of market volatility ($LVOL_{t+1}$), as measured by the sum of the squared daily returns on the CRSP value-weighted index over a year in Panel A (from July, year *t*+1 to June, year *t*+2) or a quarter (Panel B). Panel A predicts one-year-ahead market volatility. Panel B predicts one-quarter-ahead market volatility. All RHS variables are standardized by their own means and standard deviations. The *t*-statistics in parentheses are computed using Newey-West (1987) standard errors with three lags in Panel A, and four lags in Panel B. Statistical significance at 10%, 5%, and 1% are indicated as *, **, and ***, respectively. Panel A (Panel B) uses accounting data from 1962-2014 (1975Q1-2016Q4) and stock returns data from July 1963-June 2016 (August 1975-July 2017).

Panel A: Predicting one-year-ahead market volatility $LVOL_{t+1}$

	1	2	3	4	5	6	7	8	9
Constant	-2.038***	-2.038***	-2.038***	-2.038***	-2.038***	-2.038***	-2.038***	-2.038***	-2.038***
	(-44.78)	(-28.22)	(-44.86)	(-30.60)	(-46.31)	(-32.46)	(-48.56)	(-32.57)	(-47.06)
$LVOL_t$	0.200***		0.191***		0.175***		0.170***		0.166***
	(4.34)		(4.35)		(3.68)		(4.52)		(4.18)
$\ln(B_t/M_t)$		-0.104*	-0.084**					-0.025	-0.042
		(-1.75)	(-2.08)					(-0.44)	(-0.89)
GP_t/B_{t-1}				0.136*	0.083*			0.066	0.022
				(1.89)	(1.78)			(0.71)	(0.37)
dA_t/A_{t-1}						0.155***	0.109***	0.112*	0.083
						(3.82)	(2.93)	(1.74)	(1.63)
No. of Obs.	53	53	53	53	53	53	53	53	53
R^2	0.26	0.07	0.31	0.12	0.30	0.16	0.33	0.19	0.35
Adj. R^2	0.25	0.05	0.28	0.10	0.27	0.14	0.31	0.14	0.30

Table 1.7 Predicting market volatility (continued)

Panel B: Predicting one-quarter-ahead market volatility $LVOL_{t+1}$									
	1	2	3	4	5	6	7	8	9
Constant	-2.724***	-2.724***	-2.724***	-2.724***	-2.724***	-2.724***	-2.724***	-2.724***	-2.724***
	(-117.56)	(-50.94)	(-117.63)	(-49.17)	(-117.58)	(-52.02)	(-118.37)	(-53.65)	(-117.72)
$LVOL_t$	0.276***		0.265***		0.272***		0.260***		0.254***
	(10.79)		(10.22)		(10.36)		(9.04)		(8.89)
$\ln(B_t/M_t)$		-0.110***	-0.042**					-0.116*	-0.046
		(-2.62)	(-2.11)					(-1.68)	(-1.32)
$\sum GP_t/B_{t-4}$				0.071	0.027			-0.049	-0.019
				(1.61)	(1.42)			(-0.71)	(-0.53)
dA_t/A_{t-4}						0.129***	0.054***	0.109***	0.048***
						(4.68)	(3.86)	(3.49)	(3.03)
No. of Obs.	168	168	168	168	168	168	168	168	168
R^2	0.45	0.07	0.46	0.03	0.45	0.10	0.46	0.14	0.47
Adj. R^2	0.45	0.07	0.45	0.02	0.45	0.09	0.46	0.12	0.46

Table 1.8 Controlling for other predictors

This table reports results of predictive regressions that include other predictors as controls. Panel A reports one-year-ahead equity premium forecasts. Panel B reports two-year-average equity premium forecasts. Panel C reports one-quarter-ahead equity premium forecasts. The control variables include the term spread (Term), default spread (Def), Treasury bill rate (Tbill), the Baker and Wurgler's sentiment index ($Sent^{BW}$), the Huang, Jiang, Tu, and Zhou's (2015) sentiment index ($Sent^{HJTZ}$), the Lettau and Ludvigson's (2001) consumption-wealth ratio (CAY), aggregate operating accruals (OpAcc), and equity share in new issuance (EquityShare). All RHS variables are standardized by their own means and standard deviations. The *t*-statistics in parentheses are computed using Newey-West (1987) standard errors with three lags in Panels A and B, and four lags in Panel C. Statistical significance at 10%, 5%, and 1% are indicated as *, **, and ***, respectively. In Panels A and B, the sample period is July 1963-June 2016 for the stock returns, is 1962-2014 (based on the time subscript *t*) for other variables except $Sent^{BW}$ and $Sent^{HJTZ}$, and is 1965-2013 for $Sent^{BW}$ and $Sent^{HJTZ}$ (with the last observation corresponding to the June 2014 values of the variables). In Panel C, the sample period is August 1975-July 2017 for stock returns, is 1975Q1-2016Q4 (based on the time subscript *t*) for other variables except CAY, $Sent^{BW}$, and $Sent^{HJTZ}$, is 1975Q1-2016Q2 for CAY, and is 1975Q1-2014Q2 for $Sent^{BW}$ and $Sent^{HJTZ}$. Appendix 1.A contains more detailed descriptions of these variables.

Table 1.8 Controlling for other predictors (continued)

Panel A: Predicting one-year-ahead stock returns R^e_{t+1}	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
Constant	0.062***	0.062***	0.062***	0.062***	0.062***	0.062***	0.062***	0.062***	0.062***	0.062***	0.062***	0.054***	0.053***	0.062***	0.062***	0.062***
	(3.61)	(3.18)	(3.21)	(2.88)	(2.84)	(3.49)	(3.22)	(3.16)	(4.19)	(4.08)	(4.03)	(3.35)	(2.96)	(4.25)	(3.94)	(4.09)
$Term_t$	0.039***								0.017							
	(2.82)								(0.93)							
Def_t		0.017								-0.002						
		(0.92)								(-0.09)						
$Tbill_t$			-0.016								-0.035					
			(-0.82)								(-1.44)					
$Sent^{BW}_t$				-0.015								-0.000				
				(-0.52)								(-0.01)				
$Sent^{HJTZ}_t$					-0.060**								-0.045**			
					(-2.54)								(-2.12)			
CAY_t						0.029**								0.011		
						(2.02)								(0.81)		
$OpAcc_t$							0.037*								0.016	
							(2.00)								(0.90)	
$EquityShare_t$								0.015								0.009
								(0.80)								(0.41)
$\ln(B_t/M_t)$									0.039**	0.040*	0.064**	0.054**	0.056**	0.034*	0.030	0.034
									(2.06)	(1.80)	(2.31)	(2.40)	(2.36)	(1.73)	(1.29)	(1.62)
GP_t/B_{t-1}									0.054**	0.062***	0.060***	0.085***	0.076***	0.056**	0.056**	0.063***
									(2.28)	(3.09)	(2.74)	(3.96)	(3.45)	(2.56)	(2.64)	(2.92)
dA_t/A_{t-1}									-0.054***	-0.061***	-0.046**	-0.059***	-0.041**	-0.061***	-0.060***	-0.063***
									(-3.17)	(-4.36)	(-2.66)	(-3.95)	(-2.41)	(-4.24)	(-4.38)	(-4.23)
No. of Obs.	53	53	53	49	49	53	53	53	53	53	53	49	49	53	53	53
R^2	0.06	0.01	0.01	0.01	0.13	0.03	0.05	0.01	0.19	0.18	0.21	0.21	0.27	0.19	0.19	0.18
Adj. R^2	0.04	-0.01	-0.01	-0.01	0.11	0.01	0.04	-0.01	0.12	0.11	0.14	0.14	0.21	0.12	0.12	0.12

Table 1.8 Controlling for other predictors (continued)

Panel B: Predicting two-year-average stock returns $R^e_{(t+1,t+2)}$

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
Constant	0.057***	0.056***	0.056***	0.057***	0.057***	0.054***	0.056***	0.056***	0.056***	0.056***	0.056***	0.051***	0.050***	0.055***	0.056***	0.056***
	(3.81)	(3.13)	(3.14)	(2.98)	(3.02)	(3.48)	(3.16)	(3.02)	(5.02)	(4.83)	(4.83)	(4.63)	(4.06)	(5.27)	(4.78)	(4.68)
$Term_t$	0.035***								0.009							
	(2.81)								(0.76)							
Def_t		0.014								0.005						
		(0.82)								(0.37)						
$Tbill_t$			-0.010								-0.005					
			(-0.58)								(-0.33)					
$Sent^{BW}_t$				0.002								0.020*				
				(0.10)								(1.71)				
$Sent^{HJTZ}_t$					-0.027								-0.006			
					(-1.52)								(-0.48)			
CAY_t						0.047***								0.034***		
						(3.70)								(3.75)		
$OpAcc_t$							0.022								0.001	
							(1.41)								(0.07)	
$EquityShare_t$								0.016								0.017
								(1.01)								(1.07)
$\ln(B_t/M_t)$									0.025*	0.022	0.029	0.034**	0.035**	0.014	0.025	0.017
									(1.74)	(1.34)	(1.46)	(2.06)	(2.09)	(1.23)	(1.29)	(0.95)
GP_t/B_{t-1}									0.056***	0.060***	0.060***	0.075***	0.074***	0.044***	0.060***	0.063***
									(3.99)	(4.24)	(4.39)	(4.92)	(5.56)	(4.01)	(3.85)	(4.40)
dA_t/A_{t-1}									-0.063***	-0.068***	-0.065***	-0.073***	-0.064***	-0.064***	-0.067***	-0.069***
									(-6.44)	(-6.26)	(-6.02)	(-6.21)	(-4.75)	(-5.91)	(-6.17)	(-6.01)
No. of Obs.	52	52	52	49	49	52	52	52	52	52	52	49	49	52	52	52
R^2	0.11	0.02	0.01	0.00	0.06	0.18	0.04	0.02	0.40	0.40	0.40	0.46	0.43	0.48	0.40	0.42
Adj. R^2	0.09	0.00	-0.01	-0.02	0.04	0.16	0.02	0.00	0.35	0.35	0.35	0.41	0.38	0.43	0.35	0.37

Table 1.8 Controlling for other predictors (continued)

Panel C: Predicting one-quarter-ahead stock returns R^e_{t+1}	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
Constant	0.017***	0.017***	0.017***	0.017***	0.017***	0.017***	0.017***	0.017***	0.017***	0.017***	0.017***	0.017***	0.017***	0.017***	0.017***	0.017***
	(3.01)	(2.98)	(3.01)	(2.78)	(2.93)	(2.92)	(2.97)	(3.00)	(3.46)	(3.43)	(3.52)	(3.21)	(3.34)	(3.34)	(3.45)	(3.58)
$Term_t$	0.004								0.002							
	(0.74)								(0.35)							
Def_t		0.001								0.002						
		(0.12)								(0.29)						
$Tbill_t$			-0.003								-0.008					
			(-0.58)								(-0.91)					
$Sent^{BW}_t$				-0.004								-0.004				
				(-0.51)								(-0.68)				
$Sent^{HJTZ}_t$					-0.015***								-0.014***			
					(-2.97)								(-2.65)			
CAY_t						0.009								0.005		
						(1.55)								(0.94)		
$OpAcc_t$							-0.004								-0.008	
							(-0.47)								(-1.16)	
$EquityShare_t$								-0.011*								-0.016**
								(-1.69)								(-2.28)
$\ln(B_t/M_t)$									0.016*	0.014	0.022**	0.015	0.019**	0.012	0.019**	0.025**
									(1.88)	(1.51)	(2.06)	(1.65)	(2.04)	(1.23)	(2.10)	(2.44)
$\sum GP_t/B_{t-4}$									0.020***	0.020***	0.022***	0.021***	0.023***	0.018**	0.022***	0.024***
									(2.95)	(2.83)	(3.21)	(2.87)	(3.24)	(2.22)	(3.12)	(3.04)
dA_t/A_{t-4}									-0.015***	-0.016***	-0.013**	-0.016***	-0.011*	-0.016***	-0.015***	-0.014**
									(-2.74)	(-3.37)	(-2.28)	(-3.13)	(-1.96)	(-3.15)	(-2.77)	(-2.57)
No. of Obs.	168	168	168	158	158	166	168	168	168	168	168	158	158	166	168	168
R^2	0.00	0.00	0.00	0.00	0.04	0.01	0.00	0.03	0.07	0.07	0.08	0.07	0.11	0.08	0.08	0.12
Adj. R^2	0.00	-0.01	0.00	0.00	0.04	0.01	0.00	0.02	0.05	0.05	0.06	0.05	0.08	0.05	0.06	0.09

Table 1.9 Cash-based operating profitability

This table reports time-series predictive regression results that use B/M, cash-based operating profitability, and asset growth as predictors. All RHS variables are standardized by their own means and standard deviations. Panel A predicts one-year-ahead stock returns. Panel B predicts average stock returns over years *t*+1 and *t*+2. The *t*-statistics in parentheses are computed using Newey-West (1987) standard errors with three lags. The training window uses accounting data from 1962-1990, and corresponding stock returns data from July 1963-June 1992 (for one-year-ahead return forecasts) and July 1963-June 1993 (for two-year-average return forecasts). The out-of-sample forecast period is July 1992-June 2016 (for one-year-ahead return forecasts) and July 1993-June 2016 (for two-year-average return forecasts). The Clark and McCracken (2001)'s ENC-NEW statistic is used to test whether the forecast accuracy improvement of a model relative to the historical mean is significantly positive. The OOS R^2s and the ENC-NEW statistics are computed by imposing Campbell and Thompson's (2008) sign restrictions on the OOS equity premium forecasts. Statistical significance at 10%, 5%, and 1% are indicated as *, **, and ***, respectively.

Table 1.9 Cash-based operating profitability (continued)

Panel A: Predicting one-year-ahead stock returns R^e_{t+1}						
	1	2	3	4	5	6
Constant	0.063***	0.063***	0.063***	0.063***	0.063***	0.063***
	(3.05)	(3.24)	(3.57)	(3.23)	(3.37)	(3.93)
$\ln(B_t/M_t)$	0.031			0.060**	0.014	0.045*
	(1.48)			(2.14)	(0.72)	(1.84)
$OpCash_t/B_{t-1}$		0.018		0.052*		0.058**
		(0.67)		(1.87)		(2.38)
dA_t/A_{t-1}			-0.046***		-0.040***	-0.047***
			(-3.68)		(-2.75)	(-3.07)
No. of Obs.	53	53	53	53	53	53
Prob>F	0.146	0.505	0.001	0.082	0.001	0.001
IS R^2	0.04	0.01	0.08	0.10	0.08	0.17
IS adj. R^2	0.02	-0.01	0.06	0.07	0.05	0.12
OOS forecast with the sign restrictions						
OOS R^2	-0.05	-0.04	0.12	0.07	0.01	0.19
ENC-NEW	-0.12	0.36	1.84**	1.51**	0.68	3.86**
Panel B: Predicting two-year-average stock returns $R^e_{(t+1,t+2)}$						
	1	2	3	4	5	6
Constant	0.056***	0.056***	0.056***	0.056***	0.056***	0.056***
	(3.02)	(3.22)	(3.46)	(3.39)	(3.47)	(4.81)
$\ln(B_t/M_t)$	0.018			0.047*	-0.004	0.026
	(0.96)			(1.79)	(-0.28)	(1.47)
$OpCash_t/B_{t-1}$		0.025		0.051**		0.058***
		(1.19)		(2.47)		(3.54)
dA_t/A_{t-1}			-0.049***		-0.051***	-0.057***
			(-5.81)		(-4.73)	(-5.25)
No. of Obs.	52	52	52	52	52	52
Prob>F	0.341	0.238	0.000	0.051	0.000	0.000
IS R^2	0.03	0.05	0.20	0.17	0.20	0.38
IS adj. R^2	0.01	0.03	0.18	0.14	0.16	0.34
OOS forecast with the sign restrictions						
OOS R^2	-0.13	-0.06	0.20	0.00	0.05	0.31
ENC-NEW	-1.07	0.95*	3.26***	1.18	1.25	7.57***

Table 1.10 Predicting the CRSP index returns

This table predicts the CRSP value-weighted index returns. Panels A, B, and C predict one-year-ahead, two-year-average, and one-quarter-ahead returns on the CRSP index respectively. All RHS variables are standardized by their own means and standard deviations. The *t*-statistics in parentheses are computed using Newey-West (1987) standard errors with three lags in Panels A and B, and with four lags in Panel C. Statistical significance at 10%, 5%, and 1% are indicated as *, **, and ***, respectively. This analysis uses accounting data from 1962-2014 (1975Q1-2016Q4) and stock returns data from July 1963-June 2016 (August 1975-July 2017) in Panels A and B (Panel C).

Panel A: Predicting one-year-ahead stock returns R^e_{t+1}

	1	2	3	4	5	6
Constant	0.063***	0.063***	0.063***	0.063***	0.063***	0.063***
	(3.02)	(3.17)	(3.42)	(3.18)	(3.25)	(3.87)
$\ln(B_t/M_t)$	0.034			0.055**	0.018	0.043**
	(1.64)			(2.27)	(0.85)	(2.04)
GP_t/B_{t-1}		0.012		0.041		0.067***
		(0.46)		(1.47)		(2.87)
dA_t/A_{t-1}			-0.048***		-0.041***	-0.065***
			(-3.99)		(-3.00)	(-4.82)
No. of Obs.	53	53	53	53	53	53
R^2	0.04	0.01	0.08	0.08	0.09	0.18
Adj. R^2	0.02	-0.01	0.06	0.04	0.05	0.13

Panel B: Predicting two-year-average stock returns $R^e_{(t+1,t+2)}$

	1	2	3	4	5	6
Constant	0.055***	0.055***	0.055***	0.055***	0.055***	0.055***
	(2.85)	(2.94)	(3.22)	(3.09)	(3.18)	(4.40)
$\ln(B_t/M_t)$	0.022			0.042*	0.001	0.027
	(1.22)			(1.80)	(0.09)	(1.67)
GP_t/B_{t-1}		0.014		0.036		0.065***
		(0.56)		(1.40)		(3.48)
dA_t/A_{t-1}			-0.051***		-0.051***	-0.073***
			(-6.54)		(-5.11)	(-7.03)
No. of Obs.	52	52	52	52	52	52
R^2	0.04	0.01	0.19	0.10	0.19	0.38
Adj. R^2	0.02	-0.01	0.17	0.07	0.16	0.34

Table 1.10 Predicting the CRSP index returns (continued)

Panel C: Predicting one-quarter-ahead stock returns R^e_{t+1}						
	1	2	3	4	5	6
Constant	0.019***	0.019***	0.019***	0.019***	0.019***	0.019***
	(3.18)	(3.17)	(3.36)	(3.26)	(3.33)	(3.45)
$\ln(B_t/M_t)$	0.007			0.017**	0.004	0.015*
	(1.08)			(1.98)	(0.60)	(1.73)
$\sum GP_t/B_{t-4}$		0.000		0.014*		0.016*
		(0.08)		(1.69)		(1.74)
dA_t/A_{t-4}			-0.012**		-0.011**	-0.012*
			(-2.31)		(-2.07)	(-1.76)
No. of Obs.	168	168	168	168	168	168
R^2	0.01	0.00	0.03	0.02	0.03	0.05
Adj. R^2	0.00	-0.01	0.02	0.01	0.02	0.03

Table 1.11 Non-overlapping two-year-average stock returns: predictive regressions

This table reports predictive regression results for non-overlapping, two-year-average stock returns. The training sample contains only the even years in 1962-1990, and the OOS period contains only the even years in 1992-2016. All RHS variables are standardized by their own means and standard deviations. The *t*-statistics in parentheses are computed using Newey-West (1987) standard errors with three lags. Statistical significance at 10%, 5%, and 1% are indicated as *, **, and ***, respectively.

Predicting two-year-average stock returns $R^e_{(t+1,t+2)}$						
	1	2	3	4	5	6
Constant	0.057***	0.057***	0.057***	0.057***	0.057***	0.057***
	(3.04)	(3.45)	(3.18)	(3.32)	(3.08)	(4.67)
$\ln(B_t/M_t)$	0.021			0.034*	0.003	0.022*
	(1.57)			(1.87)	(0.19)	(1.74)
GP_t/B_{t-1}		0.011		0.028		0.059***
		(0.58)		(1.41)		(3.72)
dA_t/A_{t-1}			-0.046***		-0.045***	-0.069***
			(-4.59)		(-3.86)	(-5.22)
No. of Obs.	26	26	26	26	26	26
IS R^2	0.05	0.01	0.23	0.11	0.23	0.47
IS adj. R^2	0.01	-0.03	0.20	0.04	0.17	0.40
			OOS forecast with the sign restrictions			
OOS R^2	-0.09	-0.11	0.23	-0.12	0.09	0.32
ENC-NEW	-0.31	-0.15	2.05**	-0.32	0.96	3.36**

Table 1.12 Non-overlapping two-year-average stock returns: CER gains

This table reports the certainty equivalent return (CER) gains from jointly using B/M, profitability, and asset investment instead of only the B/M as equity premium predictors for portfolio allocation, based on non-overlapping, two-year-average equity premium forecasts. The training sample contains only the even years in 1962-1990, and the OOS period contains only the even years in 1992-2016. Statistical significance at 10%, 5%, and 1% are indicated as *, **, and ***, respectively.

Predictor(s)			CER (%)	CER gain (%)	Test statistic for CER gain
			Panel A: Risk aversion coefficient γ = 1		
$\ln(B_t/M_t)$	-	-	12.33	-	-
$\ln(B_t/M_t)$	GP_t/B_{t-1}	-	12.33	0.00	0.00
$\ln(B_t/M_t)$	dA_t/A_{t-1}	GP_t/B_{t-1}	14.62	2.30	1.28
			Panel B: Risk aversion coefficient γ = 3		
$\ln(B_t/M_t)$	-	-	8.18	-	-
$\ln(B_t/M_t)$	GP_t/B_{t-1}	-	8.48	0.30	0.17
$\ln(B_t/M_t)$	dA_t/A_{t-1}	GP_t/B_{t-1}	11.85	3.67	1.80*
			Panel C: Risk aversion coefficient γ = 5		
$\ln(B_t/M_t)$	-	-	4.96	-	-
$\ln(B_t/M_t)$	GP_t/B_{t-1}	-	5.47	0.51	0.31
$\ln(B_t/M_t)$	dA_t/A_{t-1}	GP_t/B_{t-1}	10.64	5.68	3.29***

Table 2.1 Summary statistics: First and second moments

This table reports the means, standard deviations, and Sharpe ratios of the market and style portfolio returns in the G7 countries. Style portfolios analyzed are the long-short, zero-net-investment size (Small-minus-Big or SMB), value (High-minus-Low or HML), and momentum (Up-minus-Down or UMD) portfolios. All returns are measured in US dollars. The market returns are measured in excess of the US one-month Treasury bill rate. The column "Average" reports the simple average of the seven individual countries' statistics. The column "World" reports statistics on an equal-weighted portfolio of the seven countries. The sample period is from July 1981 to December 2010.

				Panel A: Mean					
	Canada	France	Germany	Italy	Japan	UK	US	Average	World
Market	0.55	0.83	0.65	0.49	0.30	0.65	0.56	0.57	0.57
SMB	0.27	-0.06	-0.54	-0.38	0.05	-0.21	0.12	-0.11	-0.11
HML	0.54	0.65	0.65	0.83	0.65	0.52	0.38	0.60	0.60
UMD	0.90	0.95	1.02	0.87	-0.01	1.08	0.58	0.77	0.77
				Panel B: Standard deviation					
	Canada	France	Germany	Italy	Japan	UK	US	Average	World
Market	5.41	5.92	5.92	7.05	6.47	5.30	4.62	5.81	4.60
SMB	3.20	3.43	3.56	3.45	3.92	3.74	3.18	3.50	2.05
HML	3.22	3.86	3.67	3.63	2.87	2.97	3.14	3.34	1.91
UMD	3.41	3.12	3.48	3.25	3.37	2.68	3.69	3.29	2.23
				Panel C: Sharpe ratio					
	Canada	France	Germany	Italy	Japan	UK	US	Average	World
Market	0.10	0.14	0.11	0.07	0.05	0.12	0.12	0.10	0.12
SMB	0.08	-0.02	-0.15	-0.11	0.01	-0.06	0.04	-0.03	-0.05
HML	0.17	0.17	0.18	0.23	0.23	0.17	0.12	0.18	0.32
UMD	0.26	0.31	0.29	0.27	0.00	0.40	0.16	0.24	0.35

Table 2.2 Summary statistics: Tail risk measures

This table reports statistics for the tail risks of stock returns, as measured by skewness and 5% expected shortfall. 5% expected shortfall is the average value of those observations that lie below the fifth percentile of the empirical returns distribution. Panel A reports portfolio skewness. Panel B reports the 5% expected shortfall on portfolio returns. Panel C reports the 5% expected shortfall on standardized portfolio returns. Portfolio returns are standardized by subtracting the series' mean and then dividing by the series' standard deviation. The sample period is from July 1981 to December 2010.

	Canada	France	Germany	Italy	Japan	UK	US	Average	World
Panel A: Skewness of portfolio returns									
Market	-0.61	-0.41	-0.31	0.14	0.32	-0.36	-0.79	-0.29	-0.63
SMB	0.28	0.15	-0.12	-0.22	0.04	0.04	0.80	0.14	0.07
HML	-0.01	-0.06	0.69	0.66	-0.09	1.15	0.04	0.34	1.07
UMD	-0.57	-0.96	0.07	-0.29	-1.07	-1.47	-2.12	-0.92	-1.39
Panel B: 5% Expected shortfall on portfolio returns									
	Canada	France	Germany	Italy	Japan	UK	US	Average	World
Market	-12.48	-13.96	-13.93	-14.37	-12.64	-11.55	-10.88	-12.83	-11.28
SMB	-6.83	-6.82	-9.14	-8.09	-8.83	-8.84	-6.29	-7.83	-4.60
HML	-6.26	-7.40	-7.01	-6.08	-5.80	-6.09	-6.79	-6.49	-3.25
UMD	-7.81	-7.71	-7.37	-7.37	-9.06	-6.54	-9.80	-7.95	-5.81
Panel C: 5% Expected shortfall on standardized portfolio returns									
	Canada	France	Germany	Italy	Japan	UK	US	Average	World
Market	-2.41	-2.50	-2.46	-2.11	-2.00	-2.30	-2.48	-2.32	-2.58
SMB	-2.22	-1.97	-2.41	-2.23	-2.26	-2.31	-2.01	-2.20	-2.19
HML	-2.11	-2.09	-2.08	-1.91	-2.25	-2.22	-2.28	-2.14	-2.02
UMD	-2.55	-2.78	-2.41	-2.53	-2.69	-2.84	-2.81	-2.66	-2.95

Table 2.3 Statistical tests: Monte Carlo simulations

The tail risk measures of each style portfolio (SMB, HML, or UMD) are reported, with p-values against the null hypothesis that they are from a normal distribution shown in parentheses. The null distributions of return skewness and 5% expected shortfall are constructed from 5000 random samples, with each sample consisting of 354 random draws (i.e. the number of monthly observations in our sample) from a standard normal distribution. The p-values of the statistics are obtained by comparing the skewness and standardized expected shortfall statistics of the style portfolios with the null distributions. Panel A reports results of this exercise for the skewness of portfolio returns. Panel B reports results for the 5% expected shortfall of standardized portfolio returns.

Panel A: Skewness of portfolio returns								
	Canada	France	Germany	Italy	Japan	UK	US	World
SMB	0.28	0.15	-0.12	-0.22	0.04	0.04	0.80	0.07
	(0.985)	(0.877)	(0.188)	(0.048)	(0.609)	(0.632)	(1.000)	(0.711)
HML	-0.01	-0.06	0.69	0.66	-0.09	1.15	0.04	1.07
	(0.456)	(0.317)	(1.000)	(1.000)	(0.246)	(1.000)	(0.627)	(1.000)
UMD	-0.57	-0.96	0.07	-0.29	-1.07	-1.47	-2.12	-1.39
	(0.000)	(0.000)	(0.705)	(0.013)	(0.000)	(0.000)	(0.000)	(0.000)
Panel B: 5% Expected shortfall on standardized portfolio returns								
	Canada	France	Germany	Italy	Japan	UK	US	World
SMB	-2.22	-1.97	-2.41	-2.23	-2.26	-2.31	-2.01	-2.19
	(0.119)	(0.758)	(0.006)	(0.103)	(0.073)	(0.040)	(0.646)	(0.173)
HML	-2.11	-2.09	-2.08	-1.91	-2.25	-2.22	-2.28	-2.02
	(0.351)	(0.424)	(0.435)	(0.890)	(0.083)	(0.116)	(0.055)	(0.630)
UMD	-2.55	-2.78	-2.41	-2.53	-2.69	-2.84	-2.81	-2.95
	(0.000)	(0.000)	(0.006)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)

Table 2.4 Statistical tests: Bootstrapping

The differences in skewness and 5% expected shortfall on standardized returns between UMD and SMB (HML) are reported, with p-values shown in parentheses below each estimate. For every country and an equal-weighted world portfolio, the null distributions of the difference in return skewness and 5% expected shortfall between UMD and SMB (HML) are generated from 5000 bootstrap samples—each made up of 354 jointly sampled draws with replacement from the empirical UMD and SMB (HML) distributions. To test the null hypothesis of a zero difference, the bootstrap distributions are centered by subtracting their respective means from each draw. The p-values are deduced from the position of the empirical estimates on the null distributions. Panels A and B report results for the differences in skewness. Panels C and D report results for the differences in the 5% expected shortfall.

Panel A: Difference in Skewness between UMD and SMB							
Canada	France	Germany	Italy	Japan	UK	US	World
-0.86	-1.12	0.19	-0.08	-1.11	-1.52	-2.93	-1.46
(0.064)	(0.002)	(0.633)	(0.415)	(0.041)	(0.013)	(0.002)	(0.002)
Panel B: Difference in Skewness between UMD and HML							
Canada	France	Germany	Italy	Japan	UK	US	World
-0.56	-0.90	-0.62	-0.95	-0.98	-2.62	-2.17	-2.46
(0.017)	(0.147)	(0.116)	(0.004)	(0.012)	(0.037)	(0.002)	(0.000)
Panel C: Difference in 5% expected shortfall between UMD and SMB							
Canada	France	Germany	Italy	Japan	UK	US	World
-0.33	-0.81	0.00	-0.30	-0.42	-0.54	-0.80	-0.76
(0.139)	(0.022)	(0.485)	(0.145)	(0.138)	(0.102)	(0.082)	(0.040)
Panel D: Difference in 5% expected shortfall between UMD and HML							
Canada	France	Germany	Italy	Japan	UK	US	World
-0.44	-0.69	-0.33	-0.63	-0.44	-0.62	-0.53	-0.93
(0.034)	(0.073)	(0.142)	(0.011)	(0.118)	(0.101)	(0.155)	(0.026)

Table 2.5 Conditional correlations of portfolio returns

This table reports return correlations between the U.S. and six other markets, conditional on the returns in the U.S. being above/below its mean, or being at least 1.5, 1.0, or 0.5 signed standard deviations (s.d.) away from its mean. Panels A to D report results for the market, SMB, HML, and UMD portfolios, respectively. The first row in each panel reports the number of observations used in the corresponding calculations. The sample period is from July 1981 to December 2010.

Panel A: Conditional correlations of market portfolios

	<-1.5 s.d.	<-s.d.	<-0.5 s.d.	<mean	>mean	>0.5 s.d.	>s.d.	>1.5 s.d.
No. of Obs.	**25**	**46**	**102**	**150**	**204**	**109**	**44**	**15**
Canada	0.81	0.80	0.72	0.72	0.57	0.52	0.35	0.38
France	0.60	0.67	0.62	0.65	0.38	0.34	0.20	-0.04
Germany	0.56	0.62	0.66	0.65	0.27	0.21	-0.10	-0.52
Italy	0.43	0.51	0.48	0.44	0.33	0.26	0.01	-0.42
Japan	0.40	0.31	0.33	0.38	0.24	0.16	0.19	0.24
UK	0.65	0.68	0.70	0.69	0.47	0.45	0.19	0.12

Panel B: Conditional correlations of SMB portfolios

	<-1.5 s.d.	<-s.d.	<-0.5 s.d.	<mean	>mean	>0.5 s.d.	>s.d.	>1.5 s.d.
No. of Obs.	**14**	**44**	**95**	**190**	**164**	**90**	**40**	**18**
Canada	0.33	0.34	0.33	0.36	0.37	0.42	0.46	0.56
France	0.23	0.09	0.17	0.19	0.14	0.16	0.23	0.49
Germany	-0.40	-0.30	-0.15	0.01	-0.10	-0.13	-0.13	-0.03
Italy	-0.20	-0.10	0.03	0.05	0.00	-0.03	0.00	0.17
Japan	0.17	0.07	0.14	0.07	-0.03	0.02	0.09	0.34
UK	0.41	0.35	0.36	0.28	0.20	0.15	0.25	0.48

Panel C: Conditional correlations of HML portfolios

	<-1.5 s.d.	<-s.d.	<-0.5 s.d.	<mean	>mean	>0.5 s.d.	>s.d.	>1.5 s.d.
No. of Obs.	**18**	**45**	**97**	**184**	**170**	**88**	**49**	**22**
Canada	0.49	0.45	0.17	0.19	0.37	0.32	0.33	0.25
France	0.57	0.55	0.34	0.24	0.53	0.56	0.69	0.74
Germany	0.10	0.27	0.28	0.25	0.39	0.48	0.61	0.70
Italy	-0.43	-0.18	0.01	0.01	0.15	0.09	0.35	0.46
Japan	0.33	0.26	0.22	0.19	0.10	-0.01	0.17	0.52
UK	0.47	0.29	0.31	0.20	0.35	0.40	0.47	0.30

Panel D: Conditional correlations of UMD portfolios

	<-1.5 s.d.	<-s.d.	<-0.5 s.d.	<mean	>mean	>0.5 s.d.	>s.d.	>1.5 s.d.
No. of Obs.	**20**	**30**	**66**	**151**	**203**	**73**	**29**	**11**
Canada	0.65	0.40	0.42	0.49	0.16	0.04	-0.08	-0.13
France	0.55	0.57	0.65	0.59	0.36	0.42	0.35	-0.30
Germany	0.53	0.51	0.49	0.45	0.37	0.43	0.35	-0.08
Italy	0.19	0.32	0.34	0.30	0.23	0.31	0.22	-0.07
Japan	0.37	0.42	0.27	0.30	0.00	-0.03	-0.06	-0.31
UK	0.27	0.35	0.48	0.49	0.37	0.53	0.39	-0.29

Table 2.6 Coexceedances of portfolio returns

This table reports statistics on the return coexceedances of the market and style portfolios. Negative (positive) return exceedances are defined as extreme returns that lie below the 5th (above the 95th) percentile of the return distribution. A negative (positive) coexceedance is a joint occurrence of negative (positive) return exceedances. A coexceedance count of *i* units in a given month represents a joint occurrence of return exceedances in *i* different countries for that month. Under the columns *i*=0 to *i*=7, the row "Total" reports the total number of months that have a coexceedance count of i. These "Total" numbers are then compared against the right tail of a binomial cumulative distribution function with 354 trials and probability $C_i^7 * 0.05^i * 0.95^{7-i}$—to conduct the one-sided test of whether the observed numbers are larger than what one would expect under the null hypothesis of independent extreme returns. The p-values for this test are reported in parentheses on the last row of each panel. The rows for individual countries report the number of times a country contributes to the coexceedance count of *i*. The mean excess returns for months with coexceedance counts larger than 3(*i*>3) and larger than 5(*i*>5) are reported in Columns 2-3 (non-standardized returns) and Columns 4-5 (standardized returns), respectively. The sample period is from July 1981 to December 2010.

Panel A: Negative coexceedances for market portfolios

	Mean of portfolio returns		Mean of standardized portfolio returns		Negative coexceedance count (*i*)							
	i>3	*i*>5	*i*>3	*i*>5	*i*=7	*i*=6	*i*=5	*i*=4	*i*=3	*i*=2	*i*=1	*i*=0
Canada	-12.95	-13.18	-2.31	-2.35	2	2	1	1	2	0	4	300
France	-12.40	-14.02	-2.22	-2.49	2	2	5	1	6	5	1	300
Germany	-13.49	-15.42	-2.40	-2.73	2	2	5	1	4	4	2	300
Italy	-14.40	-14.67	-2.56	-2.60	2	2	5	2	5	5	9	300
Japan	-10.23	-10.58	-1.85	-1.90	2	1	3	1	0	5	9	300
UK	-12.66	-12.18	-2.26	-2.18	2	1	2	2	0	1	1	300
US	-11.73	-12.60	-2.10	-2.25	2	2	4	0	1	0	1	300
Total	-12.55	-13.23	-2.24	-2.36	2	2	5	2	6	10	27	300
(p-value)					(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.854)	(1.000)	(0.000)

Panel B: Positive coexceedances for market portfolios

	Mean of portfolio returns		Mean of standardized portfolio returns		Positive coexceedance count (*i*)							
	i>3	*i*>5	*i*>3	*i*>5	*i*=7	*i*=6	*i*=5	*i*=4	*i*=3	*i*=2	*i*=1	*i*=0
Canada	9.75	17.89	1.57	2.96	0	2	1	0	1	3	1	280
France	12.71	12.30	2.07	2.00	0	2	2	2	6	3	2	280
Germany	9.59	12.08	1.54	1.97	0	2	1	1	5	4	6	280
Italy	13.28	15.41	2.17	2.53	0	2	1	2	6	6	17	280
Japan	9.58	9.24	1.54	1.48	0	1	2	1	1	5	15	280
UK	12.24	14.36	1.99	2.35	0	2	2	2	1	2	6	280
US	8.69	8.89	1.39	1.42	0	1	1	0	1	1	2	280
Total	10.83	12.88	1.75	2.10	0	2	2	2	7	12	49	280
(p-value)					(1.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.683)	(1.000)	(0.000)

Table 2.6 Coexceedances of portfolio returns (continued)

	Panel C: Negative coexceedances for SMB portfolios											
	Mean of portfolio returns		Mean of standardized portfolio returns		Negative coexceedance count (*i*)							
	i>3	*i*>5	*i*>3	*i*>5	*i*=7	*i*=6	*i*=5	*i*=4	*i*=3	*i*=2	*i*=1	*i*=0
Canada	-7.75	-	-2.17	-	0	0	1	1	1	5	3	266
France	-4.69	-	-1.30	-	0	0	1	1	0	5	4	266
Germany	-6.69	-	-1.87	-	0	0	1	1	4	6	11	266
Italy	-5.47	-	-1.53	-	0	0	1	0	3	8	14	266
Japan	-2.43	-	-0.66	-	0	0	0	0	1	4	18	266
UK	-7.72	-	-2.17	-	0	0	1	1	5	6	10	266
US	-2.10	-	-0.57	-	0	0	0	0	1	4	2	266
Total	-5.27	-	-1.47	-	0	0	1	1	5	19	62	266
(p-value)					(1.000)	(1.000)	(0.000)	(0.002)	(0.002)	(0.089)	(1.000)	(0.012)
	Panel D: Positive coexceedances for SMB portfolios											
	Mean of portfolio returns		Mean of standardized portfolio returns		Positive coexceedance count (*i*)							
	i>3	*i*>5	*i*>3	*i*>5	*i*=7	*i*=6	*i*=5	*i*=4	*i*=3	*i*=2	*i*=1	*i*=0
Canada	14.35	-	4.12	-	0	0	0	2	3	6	4	269
France	7.53	-	2.17	-	0	0	0	2	4	10	8	269
Germany	1.06	-	0.33	-	0	0	0	1	6	1	6	269
Italy	3.01	-	0.89	-	0	0	0	0	0	6	7	269
Japan	2.98	-	0.88	-	0	0	0	0	2	10	15	269
UK	10.72	-	3.08	-	0	0	0	2	2	4	9	269
US	10.64	-	3.06	-	0	0	0	1	1	5	7	269
Total	7.19	-	2.08	-	0	0	0	2	6	21	56	269
(p-value)					(1.000)	(1.000)	(0.998)	(0.000)	(0.000)	(0.034)	(1.000)	(0.004)

Table 2.6 Coexceedances of portfolio returns (continued)

	Mean of portfolio returns		Mean of standardized portfolio returns		Negative coexceedance count (*i*)							
Panel E: Negative coexceedances for HML portfolios												
	i>3	*i*>5	*i*>3	*i*>5	*i*=7	*i*=6	*i*=5	*i*=4	*i*=3	*i*=2	*i*=1	*i*=0
Canada	-7.31	-	-2.36	-	0	0	2	1	3	4	15	273
France	-12.45	-	-3.89	-	0	0	2	1	5	4	8	273
Germany	-2.42	-	-0.90	-	0	0	1	0	5	4	10	273
Italy	3.24	-	0.79	-	0	0	0	1	2	4	7	273
Japan	-1.72	-	-0.69	-	0	0	1	0	3	3	6	273
UK	-6.13	-	-2.01	-	0	0	2	0	2	4	5	273
US	-8.54	-	-2.73	-	0	0	2	1	4	9	3	273
Total	-5.05	-	-1.69	-	0	0	2	1	8	16	54	273
(p-value)					(1.000)	(1.000)	(0.000)	(0.002)	(0.000)	(0.275)	(1.000)	(0.001)

	Mean of portfolio returns		Mean of standardized portfolio returns		Positive coexceedance count (*i*)							
Panel F: Positive coexceedances for HML portfolios												
	i>3	*i*>5	*i*>3	*i*>5	*i*=7	*i*=6	*i*=5	*i*=4	*i*=3	*i*=2	*i*=1	*i*=0
Canada	6.97	7.91	1.90	2.18	0	2	0	3	2	4	8	272
France	11.39	16.17	3.22	4.64	0	2	1	2	2	5	11	272
Germany	11.48	19.41	3.24	5.61	0	2	1	2	3	6	8	272
Italy	5.14	8.42	1.35	2.33	0	2	1	0	0	6	17	272
Japan	1.26	4.97	0.19	1.30	0	0	0	0	1	0	8	272
UK	11.02	9.88	3.11	2.77	0	2	1	3	1	1	5	272
US	8.93	13.17	2.48	3.75	0	2	1	2	0	4	3	272
Total	8.03	11.42	2.21	3.23	0	2	1	3	3	13	60	272
(p-value)					(1.000)	(0.000)	(0.000)	(0.000)	(0.039)	(0.578)	(1.000)	(0.001)

Table 3.1 Number of Chinese listed firms

The table below shows the number of Chinese listed firms in each year from 1991 to 2012. The Small Medium Enterprise Board (SME) and the Growth Enterprise Board (GEB) were set up in May 2004 and October 2009 respectively, both in Shenzhen. The non SME/GEB stocks are listed on either the Shanghai Stock Exchange or the Shenzhen Stock Exchanges.

Year	Total	SME&GEB	Non SME/GEB
1991	13	0	13
1992	52	0	52
1993	176	0	176
1994	288	0	288
1995	312	0	312
1996	515	0	515
1997	720	0	720
1998	825	0	825
1999	924	0	924
2000	1060	0	1060
2001	1136	0	1136
2002	1193	0	1193
2003	1259	0	1259
2004	1350	38	1312
2005	1340	50	1290
2006	1363	102	1261
2007	1440	200	1240
2008	1559	273	1286
2009	1662	363	1299
2010	1990	682	1308
2011	2267	922	1345
2012	2432	1049	1383

Table 3.2 Comparing the B/P ratio with the BE/ME ratio

This table reports descriptive statistics of the book-value-to-price (B/P) ratio, the book-value-to-market-value-of-equity (BE/ME) ratio, and the difference between the B/P ratio and the BE/ME ratio across firms in each year from 1992 to 2012.

		B/P ratio			BE/ME ratio			Difference (= B/P – BE/ME)			
Year	Total # of firms	Median	Mean	Std	Median	Mean	Std	Absolute diff. > 0.001		Mean	Std
								# of firms	% of total		
1992	52	0.141	0.155	0.066	0.157	0.175	0.083	18	34.6%	-0.020	0.038
1993	176	0.253	0.257	0.084	0.272	0.276	0.099	38	21.6%	-0.019	0.043
1994	288	0.448	0.463	0.212	0.462	0.496	0.236	63	21.9%	-0.034	0.080
1995	312	0.512	0.561	0.256	0.551	0.606	0.285	70	22.4%	-0.045	0.100
1996	515	0.271	0.294	0.113	0.287	0.317	0.142	83	16.1%	-0.023	0.061
1997	720	0.261	0.271	0.111	0.266	0.290	0.141	93	12.9%	-0.019	0.058
1998	821	0.268	0.294	0.132	0.274	0.312	0.159	98	11.9%	-0.019	0.060
1999	913	0.259	0.276	0.135	0.266	0.291	0.155	99	10.8%	-0.015	0.051
2000	1046	0.180	0.194	0.096	0.184	0.203	0.109	101	9.7%	-0.009	0.034
2001	1117	0.248	0.265	0.128	0.255	0.278	0.143	112	10.0%	-0.013	0.046
2002	1173	0.339	0.354	0.172	0.349	0.370	0.186	113	9.6%	-0.015	0.056
2003	1229	0.422	0.438	0.189	0.436	0.455	0.200	115	9.4%	-0.017	0.063
2004	1316	0.524	0.552	0.244	0.540	0.572	0.260	115	8.7%	-0.020	0.079
2005	1284	0.665	0.712	0.337	0.686	0.738	0.362	114	8.9%	-0.026	0.108
2006	1314	0.474	0.506	0.270	0.485	0.526	0.288	120	9.1%	-0.020	0.079
2007	1409	0.190	0.212	0.114	0.196	0.224	0.172	139	9.9%	-0.012	0.126
2008	1521	0.521	0.563	0.305	0.532	0.594	0.468	144	9.5%	-0.031	0.346
2009	1612	0.236	0.263	0.141	0.243	0.280	0.290	146	9.1%	-0.017	0.244
2010	1954	0.245	0.290	0.185	0.248	0.309	0.408	158	8.1%	-0.019	0.350
2011	2236	0.425	0.470	0.255	0.430	0.493	0.478	160	7.2%	-0.023	0.388
2012	2414	0.466	0.504	0.266	0.471	0.529	0.519	174	7.2%	-0.025	0.428

Table 3.3 The Fama-French three factors for the U.S. market

This table reports descriptive statistics of the monthly returns on the Fama-French three factors in the U.S. market. Panel A is for the three factors from Kenneth French's website, and Panel B is for the three factors that we construct from the CRSP/Compustat data. The Sharpe ratio is equal to the mean divided by the standard deviation. The cumulative wealth is the cumulated value of one dollar invested at the end of June 1991 and compounded at the monthly returns of each factor until the end of June 2011.

Panel A: *The three factors from Kenneth French's website between July 1991 and June 2011*			
	SMB	**HML**	**Rm-Rf**
Mean (%)	0.26	0.33	0.55
Standard Deviation (%)	3.50	3.39	4.42
Sharpe Ratio	0.07	0.10	0.12
Cumulative Wealth	1.63	1.93	2.98
Panel B: *The three factors from our replication between July 1991 and June 2011*			
	SMB	**HML**	**Rm-Rf**
Mean (%)	0.23	0.37	0.55
Standard Deviation (%)	3.56	3.43	4.40
Sharpe Ratio	0.06	0.11	0.13
Cumulative Wealth	1.49	2.12	2.95

Table 3.4 The Fama-French three factors for Chinese stock returns

This table reports descriptive statistics of the monthly returns on the Fama-French three factors in China. The four panels represent the four different methods we use to construct the three factors, as indicated by the title of each panel. We examine three time periods: the whole period from July 1996 to June 2013, the first sub-period from July 1996 to December 2004, and the second sub-period from July 2007 to June 2013. The Sharpe ratio is equal to the mean divided by the standard deviation. The cumulative wealth is the cumulated value of one dollar invested at the end of June 1996 and compounded at the monthly returns of each factor until the end of June 2013.

	Whole period *(1996/07-2013/06)*			***Sub-period*** *(1996/07-2004/12)*			***Sub-period*** *(2007/07-2013/06)*		
	SMB	**HML**	**Rm-Rf**	**SMB**	**HML**	**Rm-Rf**	**SMB**	**HML**	**Rm-Rf**
Panel A: *Including SME and GEB stocks and using tradable market value as portfolio weights*									
Mean (%)	0.82	0.54	0.94	0.82	1.02	0.61	1.26	-0.16	-0.14
Standard Deviation (%)	4.50	4.01	8.96	3.90	4.53	8.08	4.29	3.38	9.76
Sharpe Ratio	0.18	0.13	0.10	0.21	0.23	0.07	0.29	-0.05	-0.01
Cumulative Wealth	4.28	2.56	3.02	2.13	2.57	1.35	2.31	0.86	0.64
Panel B: *Excluding SME and GEB stocks and using tradable market value as portfolio weights*									
Mean (%)	0.79	0.54	0.94	0.82	1.02	0.61	1.17	-0.14	-0.14
Standard Deviation (%)	4.53	4.07	8.96	3.89	4.53	8.08	4.44	3.54	9.76
Sharpe Ratio	0.17	0.13	0.10	0.21	0.23	0.07	0.26	-0.04	-0.01
Cumulative Wealth	4.03	2.56	3.02	2.13	2.57	1.35	2.16	0.87	0.64
Panel C: *Including SME and GEB stocks and using total market value as portfolio weights*									
Mean (%)	0.87	0.55	0.75	0.80	1.09	0.54	1.37	-0.14	-0.39
Standard Deviation (%)	4.90	4.14	8.49	3.91	4.80	7.63	5.04	3.41	9.36
Sharpe Ratio	0.18	0.13	0.09	0.21	0.23	0.07	0.27	-0.04	-0.04
Cumulative Wealth	4.63	2.61	2.22	2.10	2.73	1.30	2.44	0.87	0.54
Panel D: *Excluding SME and GEB stocks and using total market value as portfolio weights*									
Mean (%)	0.85	0.55	0.75	0.80	1.09	0.54	1.31	-0.15	-0.39
Standard Deviation (%)	4.95	4.20	8.49	3.90	4.80	7.63	5.16	3.59	9.36
Sharpe Ratio	0.17	0.13	0.09	0.21	0.23	0.07	0.25	-0.04	-0.04
Cumulative Wealth	4.41	2.57	2.22	2.10	2.73	1.30	2.32	0.86	0.54

Table 3.5.1 The market model in China (I)

This table shows the results of regressing the excess returns of the 25 testing portfolios on the market excess return in China. The market return are value-weighted by each firm's tradable market value.

Size quintiles	**Value quintiles**					**Value quintiles**				
	Low	2	3	4	High	Low	2	3	4	High
	Estimate					**t-statistic**				
	Panel A: Intercept									
Small	0.675	0.849	0.966	1.187	1.103	1.779	2.358	2.595	2.750	2.710
2	0.050	0.519	0.502	0.718	0.828	0.141	1.660	1.600	1.865	2.467
3	-0.110	0.166	0.326	0.435	0.492	-0.352	0.570	1.242	1.416	1.430
4	0.057	-0.063	0.129	-0.045	0.110	0.206	-0.240	0.584	-0.200	0.488
Big	-0.482	-0.520	-0.262	-0.047	0.207	-1.691	-2.358	-1.111	-0.228	0.861
	Panel B: Coefficient on Rm-Rf									
Small	1.053	1.053	1.088	1.175	1.188	24.939	26.294	26.292	24.478	26.245
2	1.037	1.048	1.064	1.128	1.155	26.157	30.156	30.515	26.343	30.932
3	0.987	1.055	1.097	1.123	1.155	28.384	32.545	37.587	32.920	30.202
4	0.973	1.003	1.047	1.085	1.137	31.581	34.225	42.774	43.421	45.185
Big	0.900	0.962	1.002	0.989	0.990	28.403	39.233	38.241	42.998	37.046
	Panel C: Adjusted R-squared									
Small	0.754	0.773	0.773	0.747	0.772					
2	0.771	0.817	0.821	0.773	0.825					
3	0.799	0.839	0.874	0.842	0.818					
4	0.831	0.852	0.900	0.903	0.910					
Big	0.799	0.883	0.878	0.901	0.871					

Table 3.5.2 The market model in China (II)

This table shows the results of regressing the excess returns of the 25 testing portfolios on the market excess return in China. The market return are value-weighted by each firm's total market value.

Size quintiles	**Value quintiles**					**Value quintiles**				
	Low	2	3	4	High	Low	2	3	4	High
	Estimate					**t-statistic**				
	Panel A: Intercept									
Small	0.893	1.018	1.183	1.480	1.378	2.044	2.432	2.725	3.027	2.931
2	0.330	0.706	0.764	0.942	1.020	0.800	1.909	1.993	2.119	2.528
3	0.094	0.369	0.548	0.713	0.728	0.252	1.072	1.709	1.905	1.751
4	0.121	0.071	0.338	0.162	0.317	0.385	0.246	1.214	0.538	1.071
Big	-0.344	-0.397	-0.094	0.012	0.413	-1.340	-1.971	-0.387	0.047	1.562
	Panel B: Coefficient on Rm-Rf									
Small	1.037	1.042	1.088	1.162	1.187	20.168	21.158	21.297	20.210	21.464
2	1.033	1.043	1.066	1.132	1.144	21.318	23.963	23.645	21.650	24.102
3	0.986	1.041	1.097	1.126	1.151	22.502	25.722	29.110	25.565	23.548
4	0.986	1.003	1.055	1.084	1.129	26.688	29.448	32.163	30.657	32.395
Big	0.940	0.986	1.001	1.002	1.011	31.132	41.636	35.088	34.155	32.539
	Panel C: Adjusted R-squared									
Small	0.667	0.688	0.690	0.667	0.694					
2	0.691	0.738	0.733	0.697	0.741					
3	0.713	0.765	0.807	0.763	0.732					
4	0.778	0.810	0.836	0.822	0.838					
Big	0.827	0.895	0.858	0.852	0.839					

Table 3.6.1 The Fama-French three-factor model in China (I)

This table shows the results of regressing excess stock returns of the 25 portfolios on the Fama-French three factors in China. SME and GEB stocks are included to determine the portfolio breakpoints. The Fama-French three factors are constructed by using tradable market value as portfolio weights.

Size quintiles	Value quintiles					Value quintiles				
	Low	2	3	4	High	Low	2	3	4	High
	Estimate					t-statistic				
	Panel A: Intercept									
Small	0.056	0.299	0.208	0.200	0.169	0.306	1.766	1.261	1.017	0.886
2	-0.301	0.047	-0.105	-0.130	0.058	-1.564	0.281	-0.664	-0.645	0.356
3	-0.441	-0.261	0.060	-0.182	-0.292	-2.214	-1.393	0.304	-0.920	-1.782
4	0.031	-0.319	-0.095	-0.422	-0.224	0.142	-1.392	-0.503	-2.418	-1.186
Big	0.039	-0.144	0.025	0.014	0.240	0.216	-0.868	0.119	0.073	1.400
	Panel B: Coefficient on SMB									
Small	1.086	1.026	1.087	1.134	1.025	26.167	26.823	29.117	25.513	23.788
2	0.889	0.856	0.885	0.963	0.792	20.435	22.487	24.667	21.132	21.687
3	0.745	0.737	0.552	0.660	0.696	16.510	17.383	12.319	14.722	18.752
4	0.381	0.450	0.389	0.414	0.284	7.770	8.688	9.111	10.496	6.651
Big	-0.320	-0.296	-0.340	-0.252	-0.374	-7.832	-7.925	-7.125	-5.992	-9.623
	Panel C: Coefficient on HML									
Small	-0.377	-0.437	-0.060	0.390	0.448	-8.017	-10.066	-1.413	7.751	9.180
2	-0.668	-0.337	-0.073	0.353	0.458	-13.556	-7.800	-1.802	6.836	11.066
3	-0.473	-0.240	-0.305	0.324	0.648	-9.261	-5.006	-6.006	6.373	15.413
4	-0.571	-0.159	-0.131	0.179	0.297	-10.287	-2.708	-2.714	4.012	6.141
Big	-0.667	-0.374	-0.095	0.278	0.544	-14.403	-8.816	-1.756	5.844	12.344
	Panel D: Coefficient on Rm-Rf									
Small	0.986	0.999	0.986	1.019	1.036	47.095	51.711	52.355	45.440	47.656
2	1.021	0.999	0.983	0.993	1.026	46.528	52.000	54.295	43.204	55.613
3	0.964	1.007	1.075	1.022	1.014	42.347	47.116	47.534	45.186	54.142
4	0.998	0.975	1.023	1.024	1.076	40.353	37.323	47.462	51.394	49.919
Big	1.005	1.033	1.047	0.984	0.968	48.763	54.707	43.436	46.419	49.355
	Panel E: Adjusted R-squared									
Small	0.944	0.952	0.957	0.949	0.952					
2	0.936	0.949	0.956	0.940	0.961					
3	0.921	0.936	0.931	0.936	0.960					
4	0.900	0.892	0.929	0.943	0.939					
Big	0.922	0.937	0.905	0.923	0.936					

Table 3.6.2 The Fama-French three-factor model in China (II)

This table shows the results of regressing excess stock returns of the 25 portfolios on the Fama-French three factors in China. SME and GEB stocks are excluded to determine the portfolio breakpoints. The Fama-French three factors are constructed by using tradable market value as portfolio weights.

Size quintiles	Value quintiles					Value quintiles				
	Low	2	3	4	High	Low	2	3	4	High
	Estimate					t-statistic				
Panel A: Intercept										
Small	0.080	0.307	0.221	0.192	0.135	0.436	1.792	1.324	0.994	0.698
2	-0.193	0.091	-0.079	-0.136	0.110	-0.991	0.570	-0.512	-0.677	0.718
3	-0.542	-0.262	0.088	-0.186	-0.305	-2.675	-1.425	0.435	-0.998	-1.932
4	0.032	-0.403	-0.130	-0.488	-0.247	0.150	-1.812	-0.725	-2.875	-1.364
Big	0.016	-0.106	-0.005	0.062	0.225	0.088	-0.630	-0.022	0.345	1.284
Panel B: Coefficient on SMB										
Small	1.064	1.011	1.053	1.142	1.017	25.847	26.335	28.194	26.407	23.545
2	0.841	0.821	0.853	0.973	0.771	19.264	22.990	24.789	21.687	22.448
3	0.743	0.701	0.566	0.618	0.679	16.387	17.041	12.536	14.834	19.199
4	0.375	0.444	0.348	0.368	0.259	7.781	8.928	8.651	9.683	6.393
Big	-0.334	-0.312	-0.361	-0.266	-0.382	-8.065	-8.238	-7.505	-6.564	-9.731
Panel C: Coefficient on HML										
Small	-0.351	-0.393	-0.016	0.380	0.476	-7.570	-9.097	-0.388	7.809	9.796
2	-0.634	-0.322	-0.059	0.380	0.491	-12.888	-8.002	-1.512	7.513	12.686
3	-0.450	-0.209	-0.302	0.354	0.661	-8.813	-4.508	-5.947	7.549	16.599
4	-0.571	-0.136	-0.137	0.237	0.333	-10.529	-2.433	-3.030	5.538	7.288
Big	-0.639	-0.369	-0.055	0.295	0.546	-13.680	-8.653	-1.016	6.486	12.356
Panel D: Coefficient on Rm-Rf										
Small	0.989	1.000	0.989	1.004	1.022	46.921	50.864	51.715	45.317	46.219
2	1.014	1.004	0.978	0.991	1.021	45.320	54.882	55.515	43.104	58.014
3	0.948	0.993	1.071	1.029	1.007	40.794	47.107	46.283	48.237	55.592
4	1.000	0.982	1.040	1.043	1.064	40.542	38.507	50.493	53.563	51.172
Big	1.006	1.032	1.050	0.957	0.970	47.397	53.267	42.546	46.202	48.241
Panel E: Adjusted R-squared										
Small	0.944	0.951	0.956	0.950	0.950					
2	0.932	0.954	0.958	0.941	0.964					
3	0.917	0.936	0.928	0.944	0.962					
4	0.901	0.899	0.936	0.948	0.943					
Big	0.917	0.933	0.903	0.923	0.934					

Table 3.6.3 The Fama-French three-factor model in China (III)

This table shows the results of regressing excess stock returns of the 25 portfolios on the Fama-French three factors in China. SME and GEB stocks are included to determine the portfolio breakpoints. The Fama-French three factors are constructed by using total market value as portfolio weights.

Size quintiles	Value quintiles					Value quintiles				
	Low	2	3	4	High	Low	2	3	4	High
	Estimate					t-statistic				
	Panel A: Intercept									
Small	0.095	0.309	0.218	0.306	0.247	0.469	1.650	1.289	1.522	1.217
2	-0.219	0.095	-0.025	-0.116	0.041	-1.038	0.490	-0.140	-0.589	0.243
3	-0.429	-0.204	0.012	-0.124	-0.279	-2.009	-1.039	0.063	-0.608	-1.536
4	-0.097	-0.280	-0.083	-0.434	-0.241	-0.423	-1.308	-0.409	-2.153	-1.121
Big	0.056	-0.190	0.085	-0.116	0.288	0.307	-1.011	0.357	-0.505	1.421
	Panel B: Coefficient on SMB									
Small	1.160	1.113	1.168	1.194	1.099	27.883	28.902	33.521	28.886	26.343
2	1.018	0.941	0.999	1.051	0.946	23.443	23.591	26.736	25.985	27.413
3	0.896	0.849	0.773	0.827	0.835	20.404	21.062	19.573	19.699	22.367
4	0.569	0.585	0.582	0.606	0.501	12.103	13.273	13.910	14.624	11.300
Big	-0.143	-0.129	-0.192	-0.070	-0.204	-3.832	-3.338	-3.930	-1.490	-4.884
	Panel C: Coefficient on HML									
Small	-0.286	-0.393	0.050	0.447	0.518	-5.737	-8.541	1.196	9.032	10.385
2	-0.571	-0.309	-0.034	0.442	0.457	-10.984	-6.467	-0.757	9.132	11.050
3	-0.420	-0.235	-0.183	0.359	0.701	-7.988	-4.876	-3.874	7.143	15.697
4	-0.507	-0.252	-0.099	0.225	0.327	-9.006	-4.782	-1.983	4.534	6.168
Big	-0.598	-0.215	-0.051	0.387	0.607	-13.384	-4.644	-0.863	6.853	12.176
	Panel D: Coefficient on Rm-Rf									
Small	0.962	0.982	0.978	1.009	1.036	39.974	44.104	48.492	42.204	42.915
2	1.001	0.990	0.979	0.992	1.013	39.830	42.895	45.284	42.374	50.694
3	0.948	0.989	1.046	1.015	1.004	37.300	42.388	45.805	41.761	46.489
4	0.987	0.976	1.013	1.006	1.051	36.277	38.287	41.853	41.968	40.987
Big	1.015	1.020	1.024	0.969	0.967	46.937	45.504	36.176	35.450	40.119
	Panel E: Adjusted R-squared									
Small	0.931	0.940	0.955	0.946	0.945					
2	0.922	0.931	0.942	0.943	0.957					
3	0.909	0.926	0.933	0.932	0.951					
4	0.887	0.900	0.916	0.923	0.917					
Big	0.916	0.911	0.869	0.879	0.909					

Table 3.6.4 The Fama-French three-factor model in China (IV)

This table shows the results of regressing excess stock returns of the 25 portfolios on the Fama-French three factors in China. SME and GEB stocks are excluded to determine the portfolio breakpoints. The Fama-French three factors are constructed by using total market value as portfolio weights.

Size quintiles	Value quintiles					Value quintiles				
	Low	2	3	4	High	Low	2	3	4	High
	Estimate					t-statistic				
Panel A: Intercept										
Small	0.122	0.316	0.211	0.320	0.226	0.607	1.633	1.198	1.619	1.091
2	-0.115	0.122	0.014	-0.127	0.095	-0.536	0.661	0.080	-0.651	0.599
3	-0.548	-0.180	0.010	-0.149	-0.297	-2.565	-0.946	0.050	-0.753	-1.674
4	-0.088	-0.334	-0.132	-0.457	-0.270	-0.390	-1.570	-0.669	-2.241	-1.290
Big	0.037	-0.176	0.040	-0.063	0.297	0.199	-0.935	0.164	-0.278	1.432
Panel B: Coefficient on SMB										
Small	1.144	1.099	1.142	1.190	1.088	27.926	27.884	31.906	29.626	25.778
2	0.973	0.910	0.964	1.060	0.919	22.358	24.128	26.759	26.776	28.500
3	0.881	0.801	0.774	0.795	0.820	20.259	20.672	19.517	19.776	22.712
4	0.556	0.580	0.542	0.553	0.479	12.097	13.395	13.562	13.320	11.233
Big	-0.165	-0.140	-0.213	-0.088	-0.206	-4.401	-3.639	-4.324	-1.915	-4.900
Panel C: Coefficient on HML										
Small	-0.264	-0.349	0.085	0.440	0.539	-5.413	-7.441	1.998	9.216	10.734
2	-0.544	-0.291	-0.013	0.471	0.499	-10.508	-6.481	-0.310	9.992	13.029
3	-0.402	-0.206	-0.172	0.391	0.713	-7.769	-4.479	-3.642	8.177	16.604
4	-0.501	-0.237	-0.089	0.280	0.359	-9.158	-4.594	-1.876	5.683	7.069
Big	-0.573	-0.201	-0.011	0.411	0.610	-12.812	-4.417	-0.193	7.533	12.177
Panel D: Coefficient on Rm-Rf										
Small	0.962	0.983	0.977	0.994	1.023	40.029	42.477	46.500	42.185	41.275
2	1.003	0.993	0.977	0.986	1.010	39.238	44.860	46.196	42.406	53.346
3	0.930	0.975	1.041	1.017	0.996	36.436	42.860	44.720	43.129	47.010
4	0.990	0.981	1.028	1.028	1.039	36.662	38.602	43.784	42.208	41.507
Big	1.014	1.019	1.024	0.948	0.965	45.929	45.276	35.367	35.185	39.009
Panel E: Adjusted R-squared										
Small	0.932	0.936	0.951	0.947	0.942					
2	0.919	0.936	0.944	0.944	0.961					
3	0.907	0.928	0.931	0.936	0.952					
4	0.889	0.902	0.922	0.923	0.920					
Big	0.913	0.911	0.864	0.879	0.905					

Table 3.7 Regressing the portfolio returns on the Fama-French three factors

This table shows the results by regressing the returns of the 25 testing portfolios on the Fama-French three-factors in both China and the U.S.

Size	Value quintiles					Value quintiles				
	Low	2	3	4	High	Low	2	3	4	High
	Estimate					t-statistic				
Panel A: Intercept										
Small	0.079	0.352	0.170	0.173	0.203	0.426	2.054	1.045	0.863	1.051
2	-0.303	0.052	-0.099	-0.146	0.066	-1.568	0.300	-0.615	-0.712	0.402
3	-0.448	-0.245	0.079	-0.154	-0.309	-2.214	-1.287	0.392	-0.771	-1.855
4	0.008	-0.300	-0.080	-0.441	-0.205	0.038	-1.294	-0.424	-2.476	-1.067
Big	0.063	-0.152	0.060	-0.021	0.213	0.341	-0.908	0.277	-0.112	1.217
Panel B: Coefficient on Chinese SMB										
Small	1.085	1.016	1.108	1.136	1.018	25.950	26.291	30.193	25.091	23.312
2	0.893	0.857	0.887	0.956	0.796	20.496	22.075	24.304	20.689	21.388
3	0.751	0.740	0.546	0.667	0.703	16.448	17.200	11.959	14.783	18.704
4	0.401	0.454	0.398	0.414	0.282	8.299	8.667	9.344	10.316	6.500
Big	-0.319	-0.287	-0.344	-0.254	-0.367	-7.678	-7.588	-7.091	-5.965	-9.296
Panel C: Coefficient on Chinese HML										
Small	-0.368	-0.441	-0.051	0.390	0.450	-7.815	-10.131	-1.239	7.639	9.147
2	-0.676	-0.334	-0.075	0.347	0.461	-13.780	-7.647	-1.815	6.669	10.999
3	-0.475	-0.240	-0.309	0.325	0.649	-9.239	-4.962	-6.013	6.389	15.325
4	-0.570	-0.163	-0.134	0.176	0.291	-10.488	-2.758	-2.785	3.883	5.968
Big	-0.666	-0.370	-0.098	0.274	0.549	-14.238	-8.695	-1.798	5.703	12.349
Panel D: Coefficient on Chinese Rm-Rf										
Small	0.981	1.004	0.983	1.017	1.036	46.102	51.057	52.657	44.171	46.612
2	1.029	0.998	0.986	0.994	1.026	46.428	50.526	53.070	42.229	54.179
3	0.968	1.011	1.078	1.027	1.014	41.621	46.160	46.428	44.752	52.974
4	1.003	0.982	1.030	1.025	1.082	40.812	36.855	47.529	50.142	49.061
Big	1.008	1.033	1.052	0.983	0.963	47.675	53.687	42.548	45.363	47.952
Panel E: Coefficient on U.S. SMB										
Small	-0.071	-0.071	0.160	0.023	-0.086	-1.322	-1.415	3.374	0.398	-1.531
2	0.109	-0.010	0.033	-0.027	0.014	1.931	-0.202	0.707	-0.453	0.297
3	0.087	0.041	-0.038	0.073	0.074	1.477	0.745	-0.649	1.261	1.528
4	0.211	0.078	0.118	0.027	0.023	3.377	1.146	2.150	0.525	0.419
Big	0.010	0.078	-0.016	0.009	0.032	0.185	1.603	-0.251	0.156	0.627
Panel F: Coefficient on U.S. HML										
Small	-0.090	-0.034	-0.037	0.044	-0.051	-1.597	-0.658	-0.755	0.718	-0.872
2	0.045	-0.022	-0.005	0.073	-0.037	0.764	-0.420	-0.101	1.184	-0.739
3	0.009	-0.031	0.008	-0.065	0.004	0.146	-0.538	0.136	-1.074	0.070
4	-0.012	-0.013	-0.028	0.054	0.012	-0.185	-0.190	-0.496	0.995	0.205
Big	-0.042	-0.028	-0.025	0.089	-0.005	-0.760	-0.554	-0.385	1.551	-0.088
Panel G: Coefficient on U.S. Rm-Rf										
Small	0.044	-0.041	-0.016	0.017	0.013	1.092	-1.113	-0.462	0.383	0.318
2	-0.089	0.008	-0.032	0.016	-0.010	-2.130	0.218	-0.906	0.367	-0.287
3	-0.049	-0.044	-0.015	-0.075	-0.018	-1.130	-1.067	-0.352	-1.734	-0.503
4	-0.091	-0.081	-0.096	-0.006	-0.058	-1.980	-1.626	-2.347	-0.149	-1.395
Big	-0.034	-0.023	-0.045	0.022	0.034	-0.855	-0.639	-0.979	0.539	0.914
Panel H: Adjusted R-squared										
Small	0.945	0.952	0.959	0.949	0.952					
2	0.937	0.948	0.955	0.940	0.960					
3	0.921	0.935	0.930	0.937	0.960					
4	0.905	0.892	0.931	0.943	0.939					
Big	0.921	0.937	0.904	0.923	0.936					