Essays on Empirical Asset Pricing

Gormsen, Niels Joachim

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Essays on Empirical Asset Pricing

Niels Joachim Christfort Gormsen

A thesis presented for the degree of
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Ph.D. School in Economics and Management
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The PhD School in Economics and Management is an active national and international research environment at CBS for research degree students who deal with economics and management at business, industry and country level in a theoretical and empirical manner.

Abstract

This thesis concerns the empirical relation between risk and return in equities. It studies why the expected return on stocks as a whole varies over time and why there are predictable cross-sectional differences in the return on individual stocks. The thesis consists of three chapters which can be read independently.

The first chapter addresses why the expected return on the market portfolio varies over time. The market portfolio is a claim to all future cash flows earned by the firms in the stock market. I study the expected return to these future cash flows individually. I find that the expected return to the distant-future cash flows increases by more in bad times than the expected return to near-future cash flows does. This new stylized fact is important for understanding why the expected return on the market portfolio as a whole varies over time. In addition, it has strong implications for which economic model that drives the return to stocks. Indeed, I find that none of the canonical asset pricing models can explain this new stylized fact while also explaining the previously documented facts about stock returns.

The second chapter, called Conditional Risk, studies how the expected return on individual stocks is influenced by the fact that their riskiness varies over time. We introduce a new "conditional-risk factor", which is a simple method for determining how much of the expected return to individual stocks that can be explained by time variation in their market risk, i.e. market betas. Using this new factor, we find that around 20% of the cross-sectional variation in expected stock returns worldwide can be explained by such time variation in market betas.

The third chapter studies why stocks with low market betas have high risk-adjusted returns. To shed light on this low-risk effect, we decompose all stocks' market betas into their volatility and their correlation with the market portfolio. We find that both stocks with lower volatility and stocks with lower correlation have higher risk-adjusted returns. The last fact, that stocks with low correlation have high risk-adjusted returns, is particularly important

because it helps distinguish between competing theories of the low-risk effect. Indeed, the high risk-adjusted returns to low-correlation stocks are consistent with leverage based theories of the low-risk effect, but it is not immediately implied by competing behavioral theories we consider in the paper.

Acknowledgements

Writing this thesis has put me in debt to more people than I can mention here. The biggest debt is to Lasse Heje Pedersen who trained me as a financial economist and showed me how to do research, something I am profoundly grateful for. Working with Lasse has been the great privilege of my education.

I am also indebted to much of the finance faculty at Harvard University. Most importantly, John Y. Campbell sponsored a one-year visit to Harvard and taught me asset pricing, and Robin Greenwood took me under his wings during the stay, which resulted in a great co-authorship and friendship.

Finally, my fiancée Joanna deserves special thanks. Joanna has been far more involved in this finance thesis than any anthropologist would ever want to be. I am nonetheless glad she was, because it made writing this thesis a much greater pleasure than it would otherwise have been.

With that said, the last four years of my life in Copenhagen can easily be summarized: David Lando built the FRIC center and made Copenhagen a great place to be a student of finance. Thomas Kjær Poulsen kept me in good standing with the PhD administration. My co-author Christian and I argued over everything we wrote. Friends and family made the time fly by. I could not have asked for four better years.

Introduction and Summaries

The starting point for this thesis is the following two empirical observations: (1) the expected return on the market portfolio of stocks varies over time,[1] and (2) the expected return on individual stocks varies cross-sectionally.[2] Much of modern asset pricing is about understanding this time series and cross-sectional variation in expected returns, which are often referred to as discount rates (Cochrane, 2011). All three chapters in this thesis document new empirical facts that help us understand this expected return variation in equities. The first paper improves our understanding of the economics behind time series variation in expected returns. The second and third paper improve our understanding of cross-sectional variation in expected returns. The next pages provide summaries of the individual papers in English and Danish. These summaries clarify the individual papers' contribution.

1 Summaries in English

Time Variation of the Equity Term Structure

This paper studies the equity term structure, which is a novel way of studying the market portfolio. Usually we study the return to buying the market portfolio as a whole, which is really the return to buying the right to all future dividends. In contrast, when we study the equity term structure, we study the return to buying individual dividends on their own, which in turn allows us to get deeper insights into the economics of stock returns.

More precisely, the equity term structure refers to how the expected return to dividends depends on how far into the future these dividends are paid out. The previous literature focuses on the average equity term premium, which is the average difference in return on claims on long- and short-maturity dividends. This literature finds that the equity term

[1]See e.g. Campbell and Shiller (1988); Fama and French (1988); Campbell and Thompson (2008).

[2]See Bondt and Thaler (1985); Fama and French (1992, 2015); Pastor and Stambaugh (2003); Acharya and Pedersen (2005); Novy-Marx (2013) and more.

premium has historically been negative, which means that claims on dividends that are paid out in the near future have earned a higher average return than claims on dividends that are paid out in the distant future.[3] This result is surprising, because it is inconsistent with leading asset pricing models.[4]

In my paper, I document a large cyclical variation in the equity term premium: the premium is negative in good times but positive in bad times. This counter-cyclical variation in the equity term premium is robust across four different countries, different sample periods, and different ways of measuring the return to buying dividends.

The counter-cyclical variation in the equity term structure is important for multiple reasons. First, it improves our understanding of why the expected return on the market portfolio varies over time. Previous research has documented that the expected return on the market goes up in bad times,[5] and the counter-cyclical equity term premium tells us more about why this is the case. Indeed, the counter-cyclical equity term premium implies that the expected return on the market goes up in bad times mainly because the expected return on dividends that are paid out far into the future goes up. This new fact, in turn, improves our understanding of the economics that drive stock returns.

Second, I show that the counter-cyclical equity term premium is a puzzle when combined with the previously documented fact that the premium is negative on average. Indeed, I show that the leading asset pricing models cannot produce an equity term premium that is both negative on average and counter-cyclical. I therefore present a new model than can explain both of the stylized facts.

Conditional Risk

The Capital Asset Pricing Model (CAPM) is one of the fundamental models in asset pricing. The model dictates that the expected return of a stock should be a linear function of how much market risk the stock is exposed to. But measuring market risk of a stock is challenging, particularly because it varies over time. Therefore researchers usually ignore time variation in market risk when they implement the model, and instead they look at average

[3]See Binsbergen, Brandt, and Koijen (2012) and Binsbergen and Koijen (2017).

[4]The negative term premium is inconsistent with leading asset pricing models such as Campbell and Cochrane (1999); Bansal and Yaron (2004); Gabaix (2012).

[5]Campbell and Shiller (1988); Fama and French (1988)

(unconditional) market risk. The unconditional market risk of a stock is easy to estimate, but using unconditional market risk when implementing the CAPM has a drawback, namely that the estimate of the expected return becomes biased (see e.g. Jagannathan and Wang (1996)).

We contribute to this research by introducing a new method for implementing the CAPM that takes time variation in market risk into account. We derive a new "conditional-risk" factor, which is a factor that can be used in factor regressions along with the market portfolio to estimate the expected return on any given asset. We then use this new factor to study stock returns.

Using our new conditional-risk factor, we document that time variation in risk – or, conditional risk – is a pervasive feature of the data. In a global sample covering 23 developed countries, part of the return to all the major trading strategies can be explained by our conditional risk factor, which is to say that part of their return can be explained by the fact that the strategies' riskiness varies over time. On average, our conditional-risk factor explains around 20% of the CAPM alpha of trading strategies. In addition, our conditional-risk factor explains all the alpha to time-series strategies such as volatility-managed portfolios (Moreira and Muir, 2017) or time series momentum (Moskowitz, Ooi, and Pedersen, 2012).

Finally, we also analyze why market risk varies over time. Doing so, we find evidence that the conditional risk arises from trading activities of constrained arbitrageurs.

Betting Against Correlation: Testing Theories of the Low-Risk Effect

The last chapter also takes the CAPM as the starting point. One of the major stylized facts on the CAPM is the observation that assets with low market risk (market betas) have high alpha (Black, Jensen, and Scholes, 1972). Researchers usually refer to this stylized fact as the low-risk effect. While the effect is well documented empirically, the literature offers different views on the underlying economic drivers of the low-risk effect and the best empirical measures. In short, the debate is whether (a) the low-risk effect is driven by leverage constraints and risk should be measured using systematic risk vs. (b) the low-risk effect is driven by behavioral effects and risk should be measured using idiosyncratic risk.

In the paper, we further test the extent to which the low-risk effect is driven by leverage constraints or behavioral demand. We do so by using broad global data, controlling for more existing factors, using measures of the economic drivers, and using new factors that we call betting against correlation and scaled MAX that help solve the problem that the existing low-risk factors are highly correlated. The results suggest that both leverage constraints and behavioral demand may play a role in the low-risk effect.

The results on the betting against correlation factor are particularly important. The betting against correlation factor buys low-correlation stocks and sells high-correlation stocks. We find that this new factor has high risk-adjusted returns. This result has important economic implications for the driver of the low-risk effect. Indeed, the leverage constraints theory directly implies that low-correlation stocks should, ceteris paribus, have high risk-adjusted returns whereas the behavioral theories do not immediately imply so.[6] Accordingly, the high risk-adjusted return to the betting against correlation factor is strong evidence that leverage constraints play a role in the low-risk effect, which is something recent studies have questioned (Bali, Brown, Murray, and Tang, 2017; Liu, Stambaugh, and Yuan, 2017).

[6]For leverage constraints theory see Black (1972); Frazzini and Pedersen (2014). For behavioral theories see Barberis and Huang (2008).

2 Summaries in Danish

Time Variation of the Equity Term Structure

Denne artikel studerer egenkapitalens løbetidsstruktur, hvilket er en ny måde at studere aktier på. Når man køber en aktie, køber man retten til alle fremtidige dividender, der bliver udbetalt af det pågældende firma, og når man studerer aktieafkast, studerer man således det afkast man får, hvis man køber alle fremtidige dividender. Når vi studerer egenkapitalens løbetidsstruktur, studerer vi i stedet det afkast man får, hvis man køber et givent års dividende individuelt. På den måde kan man studere, om der er forskel i afkast på tværs af dividender, og man kan derved opnå en dybere forståelse for økonomien bag aktiepriser.

For at være mere præcis, så refererer egenkapitalens løbetidsstruktur til sammenhængen mellem en dividendes afkast, og hvor langt inde i fremtiden den bliver udbetalt. Den eksisterende litteratur fokuserer på den gennemsnitlige løbetidspræmie for egenkapital, hvilket er forskellen i det gennemsnitlige afkast på lang- og kortsigtede dividender. Denne litteratur finder, at den gennemsnitlige løbetidspræmie er negativ, hvilket betyder, at dividender der udbetales i den nærmere fremtid, i gennemsnit har højere afkast, end dividender der udbetales i den fjerne fremtid. Dette er overraskende, eftersom det er inkonsistent med ledende modeller indenfor værdiansættelse.

I min artikel dokumenterer jeg en stor konjunkturvariation i egenkapitalens løbetidspræmie: løbetidspræmien er negativ i gode tider, men positiv i dårlige tider. Denne konjunkturvariation i løbetidspræmien er robust på tværs af fire forskellige lande, forskellige tidsperioder, og forskellige måder at måle dividendeafkast på.

Konjunkturvariationen i løbetidspræmien er vigtig af flere årsager. For det første styrker den vores forståelse af, hvorfor det forventede afkast på aktier varierer over tid. Tidligere forskning har vist, at det forventede afkast på aktier går op i dårlige tider, og konjunkturvariationen i løbetidspræmien fortæller os mere om, hvorfor dette er tilfældet: konjunkturvariationen i løbetidspræmien indebærer, at det forventede afkast på aktier går op i dårlige tider, fordi at det forventede afkast på dividender der er langt ude i fremtiden går op. Dette nye faktum er vigtigt for at forstå økonomien bag aktieafkast.

Den anden årsag til at konjunkturvariationen i løbetidspræmien er vigtig, er at den er svær at forene med det faktum, at løbetidspræmien i gennemsnit er negativ. Jeg viser at ingen af de ledende økonomiske modeller for aktiepriser kan producere en løbetidspræmie, der både er negativ i gennemsnit og har den konjunkturvariation, jeg dokumenter i min artikel. Jeg præsenterer derfor en struktur for en ny model, der kan forklare begge disse empiriske fakta.

Conditional Risk

The Capital Asset Pricing Model (CAPM) er en af værdiansættelsens fundamentale modeller. Modellen siger, at det forventede afkast på en aktie er en lineær funktion af mængden af markedsrisiko, som det givne aktiv er eksponeret overfor. Men det er vanskeligt at måle hvor meget markedsrisiko der er i en aktie, eftersom dette varierer over tid. Derfor plejer forskere at ignorere tidsvariation i markedsrisiko når de implementerer CAPM modellen, og de kigger i stedet blot på den gennemsnitlige (ubetingede) markedsrisiko. Denne ubetingede markedsrisiko er nem at estimere, men problemet ved at bruge den ubetingede markedsrisiko når man implementerer CAPM modellen er, at man får et bias i ens estimat af det forventede afkast.

Vi bidrager til denne litteratur ved at introducere en ny metode for at implementere CAPM model, som tager tidsvariation i markedsrisiko med i betragtning. Vi udleder en ny "conditional-risk factor", som er en risikofaktor der kan bruges i faktorregressioner sammen markedsafkastet til at estimere det forventede afkast på en aktie. Vi bruger dernæst denne nye faktor til at studere aktieafkast.

Ved hjælp af vores nye faktor dokumenterer vi, at tidsvariation in markedsrisiko – hvilket vi kalder betinget risiko – spillet en stor rolle i aktieafkast. Vi dokumenterer, i et globalt datasæt der dækker 23 udviklede lande, at afkastet på alle store handelsstrategier kan beskrives delvist ved hjælp af vores nye risikofaktor, hvilket vil sige, at afkastet på disse strategier kan forklares delvist ved det faktum, at deres markedsrisiko varierer over tid. I gennemsnit kan vores nye risikofaktor beskrive 20% af CAPM merafkastet på disse handelsstrategier. Derudover kan vi beskrive hele afkastet på tidsrækkestrategier såsom volatility-managed portfolios (Moreira and Muir, 2017) eller time series momentum (Moskowitz, Ooi, and Pedersen, 2012).

Afslutningsvis studerer vi hvorfor markedsrisiko varier over tid. I denne analyse kommer vi frem til, at betinget risiko muligvis opstår som et produkt af begrænsede arbitragørers handelsaktiviteter.

Betting Against Correlation: Testing Theories of the Low-Risk Effect

Det sidste kapitel i afhandlingen omhandler også CAPM. Et af de mest kendte fakta om CAPM er, at aktier med lav markedsrisiko (markedsbeta) har højt risikojusteret afkast (Black, Jensen, and Scholes, 1972). Forskere refererer normalt til dette faktum som lavrisikoeffekten. Lavrisikoeffekten er empirisk veldokumenteret, men litteraturen er uenig omkring hvad der er den underlæggende økonomiske drivkraft bag den, og omkring hvordan man bedst måler lavrisikoeffekten. I hovedtræk handler debatten om, hvorvidt (a) at lavrisikoeffekten er drevet af lånebegrænsninger, og at risiko derfor skal måles ved hjælp af beta, versus (b) at lavrisikoeffekten er drevet af adfærdsmæssige effekter, og at risiko derfor skal måles ved hjælp af idiosynkratisk risiko.

I denne artikel tester vi yderligere hvorvidt lavrisikoeffekten er drevet af lånebegrænsninger eller adfærdsmæssige effekter. Vi gør dette ved at bruge et globalt datasæt, ved at kontrollere for flere eksisterende risikofaktorer, ved at bruge mål for de økonomiske drivkræfter, og ved at bruge nye faktorer som vi kalder betting against correlation (BAC) og SMAX, som hjælper med at løse det problem, at de eksisterende lavrisikofaktorer er højt korrelerede. Resultaterne antyder, at både lånebegrænsninger og adfærdsmæssige effekter potentielt set spiller en rolle i lavrisikoeffekten.

Analysen af afkastet på BAC er især vigtig. BAC køber aktier der har høj markedskorrelation og sælger aktier der har lav markedskorrelation. Vi finder, at denne nye faktor har højt risikojusteret afkast. Dette resultat har vigtige implikationer for hvilken økonomisk drivkraft der ligger bag lavrisikoeffekten: Lånebegrænsningsteorien indebærer at lavkorrelationsaktier, alt andet lige, burde have højt risikojusteret afkast, hvorimod de adfærdsteorier vi betragter, ikke direkte implementere dette. Derfor er det høje risikojusterede afkast for BAC stærkt bevismateriale for, at lånebegrænsninger er vigtige for at forstå lavrisikoeffekten, hvilket tidligere studier har sat spørgsmålstegn ved (Bali, Brown, Murray, and Tang, 2017; Liu, Stambaugh, and Yuan, 2017).

Contents

Chapter 1

Time Variation of the Equity Term Structure

Abstract:
I document that the term structure of holding-period equity returns is counter-cyclical: it is downward sloping in good times, but upward sloping in bad times. This new stylized fact implies that long-maturity risk plays a central role in asset price fluctuations, consistent with theories of long-run risk and habit, but these theories cannot explain the average downward slope. At the same time, the cyclical variation is inconsistent with recent models constructed to match the average downward slope. I present the theoretical source of the puzzle and suggest a new model as a resolution. My model also shows that the counter-cyclical term structure has implications for real activity, which I verify empirically: in bad times, long-duration firms decrease their investment and capital-to-labor ratio relative to short-duration firms.

Keywords: asset pricing, equity term structure, time-varying discount rates.

JEL classification: G10, G12.

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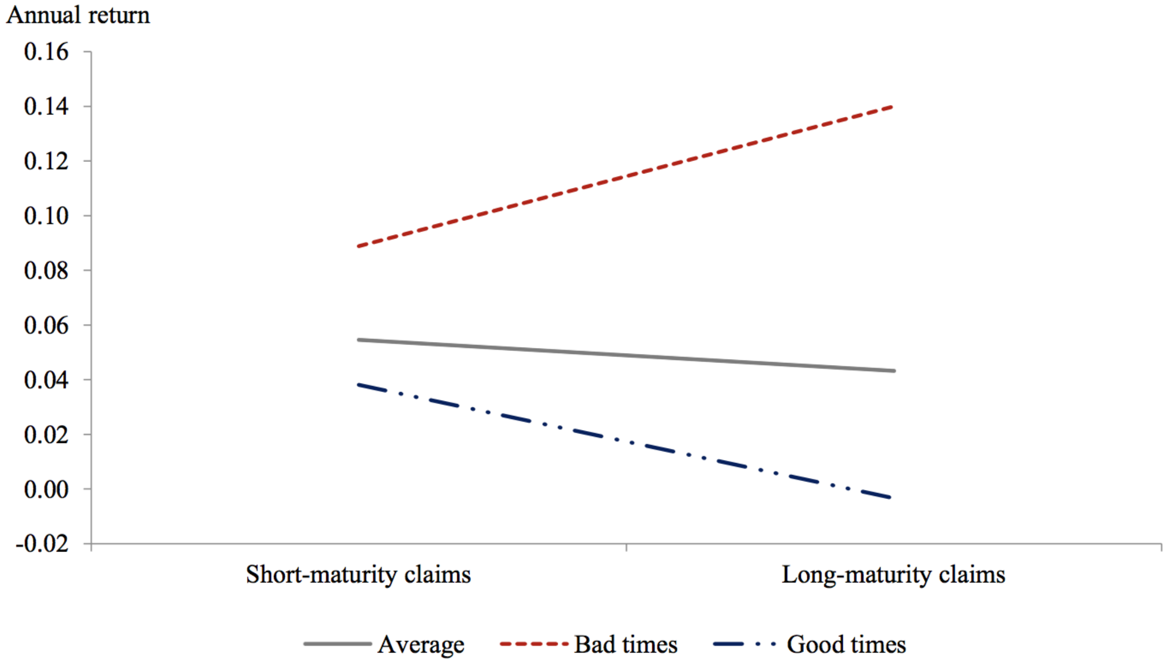
I study the term structure of equity returns and document a large cyclical variation. This cyclical variation is important for understanding which risks drive fluctuations in asset prices. Indeed, the cyclical variation documented in this paper suggests that price fluctuations are driven mainly by long-maturity risks such as persistent changes in dividend growth, and only less by short-maturity risks such as disaster risks. As such, the results are consistent with classical asset pricing models such as Campbell and Cochrane (1999) or Bansal and Yaron (2004), but they are inconsistent with the newer models that are designed to have downward sloping equity term structures. In addition, the cyclical variation of the equity term structure has important real consequences because it directly influences when capital flows to long-maturity firms such as biotech firms or short-maturity firms such as automobile firms and the extent to which these firms invest in production plants, R&D, or labor.

By way of background, the previous research on the equity term structure has focused on its average slope, finding that it is downward sloping on average (Binsbergen, Brandt, and Koijen, 2012), as indicated by the solid line in my Figure 1. This result is inconsistent with traditional models of long-run risk and habit which have upward sloping term structures. Addressing this challenge to traditional asset pricing models has become one of the most active areas in macro-finance (Cochrane, 2017) and has led to the development of new models with average downward sloping term structures.[1]

I contribute to the literature on the equity term structure by studying its time variation. My main result is that the equity term structure of holding-period returns is counter-cyclical: it is downward sloping in good times but upward sloping in bad times. As shown in Figure 1, this counter-cyclical variation is economically large. In good times, long-maturity equity has 4 percent lower expected annual return than short-maturity equity, but in bad times it has 5 percent higher expected return, meaning that the equity term premium varies by 9 percentage points between good and bad times.

As shown in Figure 2, I document this new stylized fact using several different measures of term premia, sample periods, data sources, and by also using futures returns as opposed

[1]The reference model for a downward sloping term structure is Lettau and Wachter (2007), which precedes the empirical literature on the downward sloping equity term structure. More recent models include Eisenbach and Schmalz (2013); Andries, Eisenbach, and Schmalz (2015); Nakamura, Steinsson, Barro, and Ursúa (2013); Belo, Collin-Dufresne, and Goldstein (2015); Croce, Lettau, and Ludvigson (2014); Hasler and Marfe (2016). Binsbergen and Koijen (2017) review the new theoretical models that have been motivated by the downward sloping terms structure.



Figre 1: The Term Structure of One-Year Equity Returns

This figure shows the term structure of holding-period equity returns for the S&P 500. The figure shows the unconditional average return (solid line), the average return in bad times (dashed line), and the average return in good times (dash-dotted line). Good and bad times are defined by the ex ante dividend-price ratio. Short-maturity equity claims is the average return to dividend futures of 1 to 7 years maturity. The long-maturity claim is the average return to the market portfolio. Returns are annual spot returns, 2005 – 2016.

to spot returns. Using dividend futures with maturities up to seven years, I find a positive relation between the ex ante dividend price ratio and the ex post one-year return difference between long- and short-maturity dividend futures (Panel A). The result also holds when using the market portfolio as the long-maturity claim, when considering Sharpe ratios instead of returns, when excluding the financial crisis, and when using other measures of bad times such as the CAPE ratio and the cay variable. The result holds in the U.S. for the S&P 500 and it holds internationally for Nikkei 225, Euro Stoxx 50, and the FTSE 100. Going beyond dividend futures, the result also holds when measuring the equity term structure using option implied dividend prices (Panel B) or the cross-section of stocks (Panel C).[2]

As shown in the first two columns of Table 1, the counter-cyclical equity term premia represent a puzzle for asset pricing theory: none of our canonical asset pricing models are able to produce both the counter-cyclical variation documented in this paper and the

[2]I estimate a term-premium mimicking portfolio in the cross-section of stocks by projecting the excess returns of characteristics-sorted portfolios onto the realized return difference between long- and short-maturity claims.

negative slope documented by Binsbergen, Brandt, and Koijen (2012). The counter-cyclical variation is consistent with the traditional macro-finance models such as Campbell and Cochrane (1999) and Bansal and Yaron (2004), but inconsistent with the new models with average downward sloping term structures. Hence, traditional models explain the time-variation in the term premium, but not its average value, and vice versa for the newer models.

The puzzle applies more generally than just the models in Table 1. To underline the generality of the puzzle and to identify its source, I study the cyclicality of term premia through a simple, essentially affine model that is sufficiently general to capture most of the dynamics of log-normal models. In the model, the term structure of returns may be either upward or downward sloping; but I show that if it is upward sloping it is counter-cyclical and if it is downward sloping it is pro-cyclical. To see the intuition behind this result, consider for instance a downward sloping model. The downwards sloping term structure suggests that short-maturity equity is riskier than long-maturity equity and commands a premium, meaning that the equity term premium is negative. In bad times, this premium on short-maturity equity increases because the price of risk increases and the term premium thus becomes even more negative, not positive as is observed empirically.

To understand what is needed to resolve the puzzle and explain the stylized facts, I introduce a new model with a term premium that is both counter-cyclical *and* negative on average. In the model, investors trade off a demand for hedging investment opportunities with an aversion towards long-run risk: the required return on long-maturity equity is pushed down by investors' demand for hedging investment opportunities, but it is pushed up by their aversion for long-run risk. The relative strength of the two effects varies over time, and the model is specified such that demand for hedging dominates on average, meaning that the equity term premium is negative on average; but in bad times the aversion against long-run risk dominates so that the equity term premium becomes positive. The model is thus able to capture the two stylized facts of the equity term structure. The model is based on an exogenous stochastic discount factor and rooting it in a micro-foundation remains an interesting topic for future research.

The counter-cyclical term premia documented in this paper may be surprising given the pro-cyclical "equity yield curve" documented by Binsbergen, Hueskes, Koijen, and Vrugt (2013). An equity yield is the current dividends divided by the price of future dividends of a given maturity, meaning that it is closely related to hold-to-maturity returns.[3] The authors document that the yield curve is steeply downward sloping in bad times, which might lead one to believe that during bad times, long-maturity claims are expected to have low returns relative to short maturity claims, i.e. that the one-period equity term premium is lower than usually. However, I directly study the one-period term premium and find that it is higher in bad times, even though the yield curve is downward sloping.

To better understand this negative relation between equity term premia and the slope of the yield curve, I test an expectations hypothesis. The hypothesis is that equity term premia are constant, meaning that the expected development in yields can be inferred from the yield curve. I find that equity yields move in the direction suggested by the yield curve, but they move by *more* than suggested by the expectations hypothesis. I show that this excess movement in yields implies that the slope of the equity yield curve must be negatively correlated with equity term premia, thus reconciling my results with Binsbergen, Hueskes, Koijen, and Vrugt (2013). The result that yields move too much in the direction of what the yield curve suggests is surprising because it contrasts the results from the bond literature: for bonds, the expectations hypothesis is rejected because yields move in the *opposite* direction of what the yield curve suggests[4].

In addition, the test of the expectations hypothesis represents another tension between theory and the data. As shown in the third column of Table 1, none of the asset pricing models I consider are able to generate as strong a relation between the yield spread and future changes in yields as that observed in the data. The models fail in this regard because their term premium is pro-cyclical or because the models create too little predictability in equity yields relative to term premia.

Finally, the counter-cyclical equity term structure is also important for understanding the cost of capital and how real resources are allocated in the economy. To better understand these real dynamics, I study firms' investment decisions in my model of the equity term structure. In the model, some firms have long-maturity cash flows and some have short-maturity. These firms are differently affected by the equity term structure: in bad times, the counter-cyclical equity term structure incentivizes long-maturity firms to invest less and to apply less capital relative to labor compared to short-maturity firms because the long-maturity firms find capital relatively more expensive.

[3] Equity yields are equivalent to hold-to-maturity returns minus the hold-to-maturity growth rates.

[4] See e.g. Shiller (1979); Shiller, Campbell, and Schoenholtz (1983) and Campbell and Shiller (1991).

I verify the real implications of the model empirically, as summarized in Figure 3. I find that, in bad times, the long-maturity firms invest less in capital equipment and R&D than short-maturity firms do. On the other hand, they increase spending on wages relative to short-maturity firms. Taken together, the long-maturity firms thus decrease their capital to labor ratio relative to short-maturity firms. This pattern is consistent with long-maturity firms finding capital relatively more expensive than short-maturity firms do in bad times because the equity term structure is more upward sloping.

In conclusion, this paper documents a new stylized fact that gives new insight into the drivers of the equity risk premium. The counter-cyclical term structure implies that the variation in the equity risk premium mainly comes from variation in long-term risk. Together with the observation that the equity term structure is downward sloping, the counter-cyclical term structure represents a puzzle for existing macro-finance models. I show theoretically that the canonical models are not able to reproduce both facts, and as a response I introduce a new model that can. Finally, I show empirically and theoretically that the cyclicality of the equity term structure is linked to the cylicality in real investments: in bad times where the equity term structure is upward sloping, long-maturity firms invest less than short-maturity firms.

The paper proceeds as follows. Section I introduces a model of the equity term structure with implications for firm investment. Section II describes data sources. Section III documents the counter-cyclical equity term structure. Section IV tests the expectation hypothesis. Section V studies real consequences of the equity term structure. Section VI studies calibrations of several canonical asset pricing models individually as well as my model introduced in section II. Section VII concludes.

1 Motivating Theory

In this section, I introduce a simple extension of the model of the equity term structure by Lettau and Wachter (2007). In the special case of the original Lettau and Wachter model, I show that there is a link between the sign and cyclicality of the term premium in the sense that term premia are either positive on average and counter-cyclical or negative on average and pro-cyclical (Proposition 1.a). In the more general version of the model, one can capture the empirical regularities that I uncover, that is, one can have term premia that are negative on average and counter-cyclical (Proposition 1.b). Finally, I study the link between the equity term structure and the investment decisions of individual firms, finding that long-maturity firms use less capital to labor when the equity term structure is more upward sloping (Proposition 2).

1.1 Model

The economy has an aggregate equity claim with dividends at time t denoted by D_t, where $d_t = \ln(D_t)$ evolves as

$$\Delta d_{t+1} = \mu_g + z_t + \sigma_d \epsilon_{d,t+1} \tag{1.1}$$

Here $\mu_g \in \mathbb{R}$ is the unconditional mean dividend growth and z_t drives the conditional mean:

$$z_{t+1} = \varphi_z z_t + \sigma_z \epsilon_{z,t+1} \tag{1.2}$$

where $0 < \varphi_z < 1$. Further, $\epsilon_{d,t+1}$ and $\epsilon_{z,t+1}$ are normally distributed mean-zero shocks with unit variance and σ_d, σ_z are their volatilities.

The risk-free rate r^f is constant and the stochastic discount factor is given by

$$M_{t+1} = \exp\left(-r^f - \frac{1}{2}x_t^2 - x_t \epsilon_{d,t+1} - a\left(\frac{1}{2}a + x_t \rho_{dx} + \epsilon_{x,t+1}\right)\right) \tag{1.3}$$

where $a \in \mathbb{R}$ and the state variable x_t drives the price of risk:

$$x_{t+1} = (1 - \varphi_x)\bar{x} + \varphi_x x_t + \sigma_x \epsilon_{x,t+1} \tag{1.4}$$

The parameter $\bar{x} \in \mathbb{R}^+$ is the long-run average, $0 < \varphi_x < 1$, and $\epsilon_{x,t+1}$ is a normally distributed mean-zero shock with unit variance and σ_x is the volatility. The three shocks have correlations denoted ρ_{dx}, ρ_{dz}, and ρ_{zx}, where $\rho_{zx} = 0$, $\rho_{dx}\sigma_x \leq \varphi_x$, and $\rho_{dz}\sigma_z < \sigma_d(1 - \varphi_z)$. The first assumption is also made by Lettau and Wachter (2007) and the latter two hold in their empirical calibration.

To understand the intution behind the stochastic discount factor, consider first the case where $a = 0$ as in Lettau and Wachter (2007). In this case, investors are averse towards shocks to dividends, $\epsilon_{d,t+1}$. A negative shock to dividends increases the marginal utility and thus increases the value of the stochastic discount factor. The effect of a given shock on the stochastic discount factor depends on the price-of-risk variable x_t, which in this sense can be interpreted as a risk aversion variable. In addition, shocks to the price of risk and the conditional growth rate z_t are only priced to the extent that they are correlated with the dividend shock, which is consistent with, for instance, the habit model.

In the more general case where $a \neq 0$, the price-of-risk shock is priced even if it is uncorrelated with the dividend shock. If, for instance, $a < 0$, investors are averse towards increases in the price of risk. The intuition behind such a specification is that an increase in the price of risk causes a capital loss today, which increases marginal utility. The shock to the price of risk is scaled by a and not by the price of risk, meaning that the aversion towards the price-of-risk shocks are constant over time.[5]

1.2 Equity Term Premia and Their Cyclicality

The analysis is centered around the prices and returns on n-maturity dividend claims. The price of an n-maturity claim at time t is denoted P_t^n and the log-price is denoted $p_t^n = \ln(P_t^n)$. Since an n-maturity claim becomes and $n-1$ maturity claim next period, we have the following relation for prices:

$$P_t^n = E_t\left[M_{t+1}P_{t+1}^{n-1}\right] \tag{1.5}$$

with boundary condition $P_t^0 = D_t$ because the dividend is paid out at maturity. To solve the model, I conjecture and verify that the price dividend ratio is log-linear in the state variables z_t and x_t:

$$\frac{P_t^n}{D_t} = \exp\left(A^n + B_z^n z_t + B_x^n x_t\right) \tag{1.6}$$

[5]These dynamics are reminiscent of the long-run risk model. In the long-run risk model, the counterpart to x_t is the conditional variance of cash flow shocks; and in the long-run risk model's stochastic discount factor, shocks to cash flows are scaled by this conditional variance but shocks to the conditional variance are scaled by a constant. In the long-run risk model, the shocks to the conditional mean growth rate of dividends also enter the stochastic discount factor, scaled by the conditional variance. For simplicity, I do not include the shock to the conditional growth rate in the stochastic discount factor, but as long as the shock is positively correlated with the dividend shock, the terms in the expected returns on equity, which is presented later, remain largely the same. Despite the discrepancy between the stochastic discount factor in the long-run risk model and this paper, the cyclicality of the term-structure is similar to the models that have $a = 0$ because investors are averse to all shocks in the model (i.e. $a < 0$).

The price dividend ratio can then be written as

$$\frac{P_t^n}{D_t} = E_t\left[M_{t+1}\frac{D_{t+1}}{D_t}\frac{P_{t+1}^{n-1}}{D_{t+1}}\right] = E_t\left[M_{t+1}\frac{D_{t+1}}{D_t}\exp\left(A^{n-1} + B_z^{n-1}z_{t+1} + B_x^{n-1}x_{t+1}\right)\right] \quad (1.7)$$

Matching coefficients of (1.6) and (1.7), using (1.1) and (1.4), gives

$$\begin{aligned}
A^n &= A^{n-1} - r^f + \mu_g - a\rho_{dx}\sigma_d + B_x^{n-1}\left((1-\varphi_x)\bar{x} - a\sigma_x\right) + \frac{1}{2}V^{n-1}\\
B_x^n &= B_x^{n-1}\left(\varphi_x - \rho_{dx}\sigma_x\right) - \sigma_d + B_z^{n-1}\rho_{dz}\sigma_z\\
B_z^n &= \frac{1-(\varphi)_z^n}{1-\varphi_z}
\end{aligned}$$

where $B_x^0 = 0$, $A^0 = 0$, and

$$V^{n-1} = \operatorname{var}\left(\sigma_d\epsilon_{d,t+1} + B_z^{n-1}\sigma_z\epsilon_{z,t+1} + B_x^{n-1}\sigma_x\epsilon_{x,t+1}\right),$$

which provides the solution to the model and verifies the conjecture.

The term B_z^n is positive for all values of $n > 0$, meaning that the price increases relative to dividends when the expected growth rate of dividends increases. Similarly, B_x^n is negative for all values of $n > 0$, meaning that the price relative to dividends decrease when the price of risk is higher.

The simple return on the n maturity claim is denoted $R_{t+1}^n = P_{t+1}^{n-1}/P_t^n - 1$ and the log-return is $r_{t+1}^n = \ln\left(1 + R_{t+1}^n\right)$. The expected excess return is

$$\begin{aligned}
E_t\left[r_{t+1}^n - r^f\right] + &\frac{1}{2}\operatorname{var}_t(r_{t+1}^n) && (1.8)\\
&= -\operatorname{cov}_t(r_{t+1}^n; m_{t+1}) && (1.9)\\
&= (\sigma_d + B_x^{n-1}\rho_{dx}\sigma_x + B_z^{n-1}\rho_{dz}\sigma_z)x_t + a\left(\rho_{dx}\sigma_d + B_x^{n-1}\sigma_x\right) && (1.10)
\end{aligned}$$

The n-vs-1 term premium, $\theta_t^{n,1}$, is defined as the difference in expected return between the n- and the 1-period claim:

$$\theta_t^{n,1} = E_t[r_{t+1}^n] + \frac{1}{2}\operatorname{var}_t(r_{t+1}^n) - E_t[r_{t+1}^1] - \frac{1}{2}\operatorname{var}_t(r_{t+1}^1), \quad (1.11)$$

Using (1.10), we see that

$$\theta_t^{n,1} = aB_x^{n-1}\sigma_x + (B_x^{n-1}\rho_{dx}\sigma_x + B_z^{n-1}\rho_{dz}\sigma_z)x_t \tag{1.12}$$

which shows how the equity term premium arises. The term premium arises because the short- and the long-maturity claims are differently exposed to shocks to the price of risk and to the conditional growth rate. These two channels are summarized by B_x^{n-1} and B_z^{n-1} in expression (1.12), as these govern how much more the long-maturity claim loads on these shocks relative to the short-maturity claim. The impact of these two channels on the term premium depends on assumptions about how the shocks covary with the dividend shock.

Having defined equity term premia and discussed how they arise, I next address how they vary over time. The following Proposition summarizes their cyclicality:

Proposition 1 (cyclicality of equity term premia).
(a) *For $a = 0$, positive term premia are counter-cyclical and negative term premia are pro-cyclical. More precisely, the average sign of the term premium is the same as the sign of minus the covariance between the term premium and the price dividend ratio of the market portfolio:*

$$\text{sign}\left(E[\theta_t^{n,1}]\right) = \text{sign}\left(\text{cov}(d_t - p_t; \theta_t^{n,1})\right)$$

(b) *There exist values of $a \neq 0$ such that*

$$\text{sign}\left(E[\theta_t^{n,1}]\right) \neq \text{sign}\left(\text{cov}(d_t - p_t; \theta_t^{n,1})\right)$$

meaning that the cyclicality of the term premium is not determined by its average sign. Proof is in the appendix.

When $a = 0$, the cyclicality of the term premium is given by the sign of the average premium (Proposition 1.a). To understand why, note that the term premium arises as a result of the different exposures of short- and long-maturity firms to the price-of-risk shock and the conditional-growth-rate shock. Because the size of these shocks are constant over time, the time variation in the premium is determined by the time variation in the aversion towards these shocks, which is summarized by the price-of-risk variable x_t. When this aversion increases, as it does in bad times, the size of the term premium is amplified. A negative term premium thus becomes more negative; a positive term premium becomes more positive. The assumption $a = 0$ captures much of the dynamics of standard asset pricing models and Proposition 1.a can therefore help us understand why none of the canonical asset pricing models can generate term premia that are both negative and counter-cyclical.

In the more general version of the model where $a \neq 0$, the average sign of the term premium no longer determines the premium's cyclicality (Proposition 1.b). The important difference relative to the scenario where $a = 0$ is that the price-of-risk shock now also influences the term premium by the constant a. If a is sufficiently large, the price-of-risk shocks dominates the average term premium. However, the cyclicality of the term premium is still driven by the aversion towards the shocks to both the price of risk and the conditional growth rate. If the conditional-growth-rate shocks dominate the price-of-risk shocks, the cyclicality is thus driven by the aversion towards the conditional-growth-rate shocks.[6] Accordingly, the average term premium might reflect the aversion towards the price-of-risk shock, while the cyclicality reflects the aversion towards the conditional-growth-rate shock, and the average and the cyclicality are therefore no longer mechanically linked.

To see this result on a more mechanical level, note that the premium in (1.12) is influenced by a, but that variation in prices of the dividends are not. Accordingly, a does not influence the covariance between the term premium and the dividend price ratio of the dividends:

$$\mathrm{cov}(d_t - p_t^n; \theta_t^{n,1}) = -B_x^{\mathrm{n}}(B_x^{n-1}\rho_{dx}\sigma_x + B_z^{n-1}\rho_{dz}\sigma_z)\mathrm{var}(x_t) \tag{1.13}$$

Accordingly, by changing a one influences the average sign of the term premium but not its cyclicality. In the last section of the paper, I calibrate a model with $a > 0$ that has negative and counter-cyclical term premia and as such addresses the puzzle documented in this paper. In addition, the model is also able to match the equity premium and other asset pricing moments such as the time variation in the dividend price ratio.

[6]Or, if the price-of-risk shock is uncorrelated with the dividend shock, the cyclicality is driven only by the conditional-growth-rate shock.

1.3 Equity Term Premia and Real Investments

I next analyze how the variation in equity term premia influences the investment of firms with different cash-flow maturities. A firm of type n produces claims to dividends with maturity n by using labor L_t^n and capital K_t^n according to the following production function

$$F(K_t^n, L_t^n) = b \times (L_t^n)^\alpha (K_t^n)^\beta \tag{1.14}$$

where $(\alpha, \beta) \in \{x \in \mathbb{R}_+^2 | x_1 + x_2 < 1\}$ are the output elasticities of labor and capital and b is the total factor productivity. The firm uses one period to produce the claim which can be thought of as a patent that allows one to get the n-maturity dividends at time $t+n$. Specifically, at time $t+1$ the firm is done producing $F(K_t^n, L_t^n)$ patents, which yield a dividend at time $t+n$ equal to $F(K_t^n, L_t^n)D_{t+n}/D_{t+1}$ (i.e. the dividend growth is the same as the rest of the economy). The firm maximizes the present value of profits given labor cost w and cost of renting capital $E_t[R_{t+1}^n]$:

$$\max_{K_t^n, L_t^n} E_t\left[M_{t+1}\frac{P_{t+1}^{n-1}}{D_{t+1}}F_t(K_t^n, L_t^n)\right] - wL_t^n - E_t[R_{t+1}^n]K_t^n \tag{1.15}$$

The first order conditions for capital and labor are

$$E_t\left[M_{t+1}\frac{P_{t+1}^{n-1}}{D_{t+1}}\right] b\beta(L_t^n)^\alpha (K_t^n)^{\beta-1} = E_t[R_{t+1}^n] \tag{1.16}$$

$$E_t\left[M_{t+1}\frac{P_{t+1}^{n-1}}{D_{t+1}}\right] b\alpha(L_t^n)^{\alpha-1} (K_t^n)^{\beta} = w \tag{1.17}$$

The following Proposition shows the variation in capital choice for short- and long-maturity firms, where the capital to labor ratio is defined as $k_t^n = K_t^n/L_t^n$. I also define $n > m$.

Proposition 2 (capital choice and the equity term structure).
(a) *The term premium determines the difference between the capital-to-labor ratios of long- vs short-maturity firms*

$$\ln(k_t^n) - \ln(k_t^m) = -\left(\ln E_t[R_{t+1}^n] - \ln E_t[R_{t+1}^m]\right)$$

(b) *The difference in capital between an n and a one-period firm is given by (suppressing constants)*

$$\ln(K_t^n) - \ln(K_t^1) = \frac{1}{1-\alpha-\beta}\Big((B_z^n - B_z^1)z_t + (B_x^n - B_x^1)x_t + (\alpha - 1)\left(\ln E_t[R_{t+1}^n] - \ln E_t[R_{t+1}^m]\right)\Big)$$

Proof is in the appendix.

As seen in Proposition 2.a, long-maturity firms increase their capital to labor ratio relative to short-maturity firms when the term premium decreases because capital becomes relatively cheaper. Accordingly, time variation in this difference in the capital to labor ratio is given by the time variation in the equity term premium: if the equity term premium is counter-cyclical, the capital to labor ratio for long-maturity firms relative to the ratio for short-maturity firms is pro-cyclical.

The term premium also influences the time variation in the total amount of capital applied by long-maturity firms relative to short-maturity firms. As seen in Proposition 2.b, long-maturity firms use more capital when the term premium is lower because capital is relatively cheaper. In addition, long-maturity firms also use more capital when the conditional dividend growth rate, z_t, is high or the price of risk, x_t, is low. The long-maturity firms increase capital based on these state variables because the high growth rate and low price of risk increases the present value of producing the dividend claim, thereby incentivizing the long-maturity firms to produce more by allocating more capital and labor to the production. If the term premium is counter-cyclical, long-maturity firms thus use less capital relative to short-maturity firms in bad times because the relative cost of capital increases and the relative present value of dividends drops.

2 Data and Methodology

I use a range of different data sources for the empirical analysis:

Dividend futures: The main data source for the equity term structure is dividend futures. I use proprietary data from a major investment bank for S&P 500, Nikkei 225, FTSE 100, and Euro Stoxx 50. The prices are daily prices on dividend claims that are tied to the calendar year. The payoff on the contract is the declared dividends that go ex-dividend during the given calendar year. The contracts are forward contracts, meaning everything is settled at the expiration date. For example, on February 11th 2011, the 2013 forward contract for S&P 500 trades at $31. In this contract, the buyer agrees to pay the seller $31 by the end of December 2013, and the seller agrees to pay the buyer the sum of the dividends that have gone ex-dividend between January 1st 2013 and the end of December 2013.

Because the expiration dates of the contracts are fixed in calendar time, the maturity of the available contracts varies over the calendar year. To get constant maturity prices I thus interpolate across the prices of different contracts each month, following the norm in the literature on dividend futures prices (see e.g. Binsbergen, Hueskes, Koijen, and Vrugt (2013); Binsbergen and Koijen (2017); Cejnek and Randl (2016b,a)).

Option implied equity term premium: Binsbergen, Brandt, and Koijen (2012) make their estimated time series of dividend prices and returns available online. The dividend prices are for the S&P 500 and the sample runs from 1996-2009. Binsbergen, Brandt, and Koijen (2012) estimate both the return to buying next year's dividends and the return to buying the dividend two years ahead, which they call the dividend steepener. The first strategy's returns are based on the collected dividends whereas the second strategy's returns are pure capital gains. Because dividend returns and capital gains are taxed differently, I use the dividend steepener because these returns are more easily compared to the returns to the market portfolio and to the returns in the remainder of the paper (see Schulz (2016) for an analysis of the impact of taxes on the returns to dividends).

Cross-section of equity: Stock returns are from the union of CRSP and the XpressFeed Global Database. For companies traded in multiple markets, I use the primary trading vehicle identified by XpressFeed. Fundamentals are from the XpressFeed Global Database. I consider standard characteristics that may be related to the duration of cash-flow. I measure book-to-market, profitability, and investment following Fama and French (2015). Portfolio breakpoints are calculated each June using the most recent characteristics starting from the end of the previous year. Portfolios are rebalanced at the end of each calendar month. Portfolio breakpoints are based on NYSE firms and returns are equal-weighted.

Dividends: The dividends for the S&P 500 index are from Shiller's webpage. For the international indexes, I get dividends from Bloomberg. I measure dividends as the running annual dividends instead of end of year dividends. I do so to avoid omitting easily available information about the final annual dividends.

Returns: I measure equity term premia in log-returns to mitigate measurement error issues, as advocated by Boguth, Carlson, Fisher, and Simutin (2012). In addition, the expectations hypothesis makes assumptions about log-returns, and using log-returns in the entire analysis thereby ensures consistency. The results are not sensitive to this choice.

3 Counter-Cyclical Term Premia: A New Stylized Fact

In this section, I document that equity term premia are counter-cyclical. I first show this using the full sample of dividend futures. I afterwards document the robustness using other sample periods, other measures of cyclicality, and other measures of equity term premia.

I study the cyclicality of equity term premia by regressing the realized return difference between long- and short-maturity equity on the ex ante dividend price ratio. That is, for each index, I run the following regression for different maturity pairs n and m, where $n > m$:

$$r^n_{t,t+12} - r^m_{t,t+12} = \beta^{n,m}_0 + \beta^{n,m}_1 (d_t - p_t) + \epsilon_{t,t+12} \tag{1.18}$$

where $r^n_{t,t+12}$ is the log-return on the n maturity claim between period t and $t+12$, and $d_t - p_t$ is the log of the dividend price ratio of the index at time t. The regression is implemented on the monthly level using rolling one-year log returns.[7] Accordingly, I use Newey-West standard errors corrected for 18 lags.

Panel A in Table 2 shows the estimates of $\beta^{n,m}_1$ for the S&P 500. The parameter estimates are positive for all maturity pairs. The positive parameter estimates suggest that term premia are larger when the dividend price ratio is high, which is to say that the term premia are counter-cyclical. The estimates are highly significant for low n and m but the significance becomes weaker as n and m increases.

The estimates of $\beta^{n,m}_1$ are large in magnitude. Consider for instance the premium of the five-year claim in excess of the two-year claim. The loading on the dividend price ratio is around 0.2, suggesting that the term premium increases by 20 percentage points annually

[7] Throughout the analysis I work with rolling annual returns. Working with an annual horizon allows me to calculate realized Sharpe ratios and easily compare with the results on the expectations hypothesis. The results are similar when using quarterly horizon (Table A2), but the statistical significance is lower partly because of noise in the dividend futures data.

when the log dividend price ratio increases with 1. In the sample, the log dividend price ratio varies by 0.6, implying that this one-year term premium varies by more than 12 percentage points over the sample.

The results in the international sample are similar to those in the U.S.. Across almost all indexes and maturity pairs, the parameter estimates are positive. The exception is the long premium in excess of the three-year claim for FTSE 100 and Euro Stoxx 50; the estimate for these term premia are negative.

In the rightmost column, I include the market portfolio as the long-maturity claim. Because the return to the market portfolio is not a futures contract, I must correct for the effect of interest rates. Following Binsbergen and Koijen (2017), I subtract from the market portfolio the 30 year bond return over the same period. Across the four indexes, the term premia that have the market as the long-maturity claim are all counter-cyclical, except for the term premium in excess of the three year claim for Euro Stoxx 50. The statistical significance is highest in the U.S. and highest at low m.

Together, the results provide both statistically and economically significant evidence that equity term premia are counter-cyclical. Given that equity term premia are negative on average (Binsbergen, Brandt, and Koijen, 2012; Binsbergen and Koijen, 2017), the results thus reject a large class of model (see Proposition 1.a and Section VI).

I consider several robustness checks. First, one possible concern is that the results are driven by the financial crisis during which prices on dividends may have deviated from fundamentals. To address this concern, I run the regression again, excluding observations starting in 2008 and 2009. Table 3 reports these results. The parameter estimates are still positive, and they are generally larger and more statistically significant, underlining that the results are not driven by the financial crisis.

Another way to see that the results are not driven by the financial crisis is by considering the time series of the term premium and the dividend price ratio in Figure 4. The figure shows on each date the dividend price ratio and the future realized return difference between long- and short-maturity claims. Consider for instance Euro Stoxx 50 in Panel C. As can be seen on its dividend price ratio, the Euro Stoxx 50 goes through two crises: the financial crisis in 2008 and the sovereign debt crisis in 2011. In both instances, the term premium increases substantially. The results are similar for Nikkei 225 and FTSE 100, both of which also see an increase in the dividend price ratio around 2011. Finally, Panel A shows the

S&P 500, for which the time series goes all the way back to 1996. The figure shows that the term premium also tracked the dividend price ratio through the tech bubble and the subsequent recession, again underlining the generality of the counter-cyclical term premium. The pre-2005 S&P 500 results are based on implied dividend prices from options, which I analyze in depth in Section 3.1.

I next test the cyclicality of the equity term premia using the cay measure (Lettau and Ludvigson, 2001a) instead to ensure that the cyclicality is not driven by the choice of conditioning variable. The results, reported in Table 4, are similar: the term premia are highly counter cyclical. The cylicality is slightly weaker in the sample excluding the financial crisis, but term premia remain counter-cyclical.

Binsbergen and Koijen (2017) document that both expected returns and Sharpe ratios on equity claims are downward sloping in maturity. In a similar spirit, I study how the Sharpe ratios of the term premia vary over time. To this end, I calculate the time-varying realized variance using 12 months of monthly returns and use it to estimate realized Sharpe ratios as:[8]

$$SR^{n,m}_{t,t+12} = \frac{r^n_{t,t+12} - r^m_{t,t+12}}{\mathrm{var}_t(r^{n-m}_{t,t+12})} = \frac{r^n_{t,t+12} - r^m_{t,t+12}}{\sqrt{\frac{1}{12-1}\sum_{i=1}^{12}\left((r^n_{t+i} - r^m_{t+i}) - (\bar{r}^n_{t,t+12} - \bar{r}^m_{t,t+12})\right)^2}} \tag{1.19}$$

I next regress the Sharpe ratio on the ex ante dividend price ratio to estimate the cyclicality. The results of this regression are reported in Table 5. For the S&P 500 in Panel A, the term premia are all counter-cyclical. The cyclicality is statistically significant for almost all maturity pairs, but the statistical significance decreases as m increases. Panels B through D of Table 5 report similar results for the international indexes: the Sharpe ratios are generally counter-cyclical, and the effect is strongest for the term premia with low m. The exception is the Sharpe ratios of term premia measured in excess of the three-year claim for Euro Stoxx 50 and FTSE 100; these parameter coefficients are negative but statistically insignificant.

The counter-cyclical Sharpe ratios are consistent with the model covered earlier. In the model, changes in the term premium come from changes in the price of risk and not from changes in volatility. Accordingly, we would expect higher term premia to be associated with higher Sharpe ratios, which is indeed what Table 5 suggests.

[8]These are not technically Sharpe ratios because they are based on log-returns to ensure consistency with the rest of the paper. The results are, however, similar when using simple returns.

For additional robustness, I next confirm that my results are similar when using other measures of equity term premia over other sample periods. In particular, I estimate the equity term premium by using implied dividend prices from Binsbergen, Brandt, and Koijen (2012) and by using the cross-section of stock returns. Neither of these measures are as direct as the dividend futures, but using them allows me to consider a sample that goes as far back as 1964.

3.1 The Equity Term Premium Implied from Options Prices

Binsbergen, Brandt, and Koijen (2012) use options prices to estimate the present value of future dividends. The intuition behind their method is simple. When you buy the index you get next year's dividends plus next year's resale price. By going short a call option and buying a put option you can hedge the resale price such that you are certain only to get next year's dividends. The price of buying the stock and hedging the resale price thus reflects the price of the dividends.

To measure the equity term premium, I compare the return to these implied dividends with the return to the market portfolio. To measure the cyclicality, I again regress the rolling one-year realized return difference between long- and short-maturity claims onto the ex ante dividend price ratio.

The results are shown in the first two columns of Table 6. The term premium estimated from options prices is highly counter-cyclical. The realize return difference has a loading of 1 on the dividend price ratio, which is approximately twice as large as the loadings in Table 2 that are based on the dividend futures. The results thus support the notion that term premia are highly counter-cyclical.

The second column shows that the results are robust to controlling for the five Fama and French (2015) factors as well as the yield spread and the short yield. Because the returns used in this regression are spot returns and not future returns, I include the treasury yield spread and the treasury short yield to control for potential interest rate effects.

3.2 The Equity Term Premium Implied from the Cross-Section of Equities

I next use the cross-section of equities to study the cyclicality of the term premium. I first identify a portfolio that mimicks the equity term premium that I observe in the 1996-2015 sample. I then study the cyclicality of this portfolio in the full sample running from

1964 to 2015. Consistent with the previous results, I find that the mimicking portfolio has counter-cyclical abnormal returns.

I use 30 characteristics-sorted portfolios as the foundation of the mimicking portfolio. I use characteristics-sorted portfolios rather than individual equities because the duration of characteristics-sorted portfolios is more stable than the duration of individual stocks.[9] I use ten portfolios sorted on book-to-market, ten portfolios sorted on profitability, and ten portfolios sorted on investment. The portfolios are based on NYSE breakpoints and returns are equal-weighted.

To construct the mimicking portfolio, I first project the equity term premium onto the 30 characteristics-sorted portfolios. I do so by regressing the monthly excess return to these portfolios onto the equity term premium between 1996 and 2015. Before 2005 I use option implied dividend returns, from 2005 to 2009 I use the average of the option implied dividend returns and the dividend futures returns, and after 2009 I use the dividend futures returns.[10]

I then use these betas to construct the mimicking portfolio. For each style (e.g. book-to-market), I rank the ten portfolios based on the term premium betas. I assign the two portfolios with highest betas to the long-duration portfolio and I assign the two portfolios with the lowest betas to the short-duration portfolio. I then equal weight the six low-beta portfolios into a short-duration portfolio and I equal weight the six high-beta portfolios into a long-duration portfolio. The mimicking portfolio is then long the long-duration portfolio and short the short-duration portfolio.

The term premium betas generally line up with expectations. For instance, the literature argues that value stocks have short cash-flow maturity, and, consistent with this, I find that value stocks have low term premium betas and growth stocks have high term premium betas.[11] I also find that term premium betas are decreasing in profitability and increasing in investment. The term premium betas are, however, not linearly correlated with characteristics. For instance, the portfolio with highest book-to-market does not have a particularly low term premium beta, which suggests that the characteristics pick up other signals than only duration.

[9] Indeed, over the life-cycle, stocks may start as growth stocks with long cash flow duration and evolve into value stocks with short cash flows duration.

[10] I use the $(\text{mkt}, 2)$ premia as the monthly term premium because this term premium is available both for dividend futures and option implied dividend prices.

[11] It is worth noting, however, that a long cash-flow maturity does not mean that the term premium beta must be high (for instance, Hansen, Heaton, and Li (2008) find that short-maturity value stocks behave like long-maturity claims in the sense that they load highly on long-run consumption shocks).

Table 6 reports results on cyclicality of the mimicking portfolio. The third column reports results from a regression of the mimicking portfolio on the ex ante dividend price ratio. The parameter estimate is positive, suggesting that the returns to the mimicking portfolio are counter-cyclical. The effect is, however, statistically insignificant.

In the fourth column, I augment the regression with a series of controls. I control for the five Fama and French (2015) factors, the one-year treasury yield, and the treasury yield spread. I control for the five Fama and French factors to ensure that I do not pick up well-documented cyclicality to one of the other factors. For instance, the mimicking portfolio has a positive beta, and since the market returns are counter-cyclical, one might worry that the counter-cyclical returns simply come from this positive beta. Controlling for the market, and the other factors, mitigates such concerns.[12] Because the returns are spot and not forward returns, I also include the treasury yield spread and the short treasury yield to control for potential interest rate effects.

As can be seen in the fourth column, the returns to the mimicking portfolio remain counter-cyclical even after including the controls. Including the controls mainly decrease the standard error of the parameter estimate on the dividend price ratio. Accordingly, the parameter estimate is now statistically significant with a t-statistic of 3.67. The parameter estimate is, however, an order of magnitude smaller than when using the equity term premium from options (also Table 6) or when using the dividend futures (Table 2). One reason for this could be that the actual maturity of the short-maturity firms are not as short as the short-maturity claims in Table 2. Indeed, the average firm has a maturity above 20 years, which is substantially higher than the maturities of the dividends futures.

In the fifth and sixth columns, I separate the sample into two parts: before and after 1996. Recall that the mimicking portfolio is identified in the 1996-2015 sample, so the returns should be counter-cyclical in this sample almost by construction because the term premium it mimicks is counter-cyclical. As can be seen in the fifth column, the term premium is indeed counter-cyclical in this sample. More interestingly, the mimicking portfolio is also counter-cyclical in the pre 1996 sample. As can be seen in the sixth column, the parameter estimate on the dividend price ratio is the same in the early sample as it is in the full sample,

[12]Yogo (2006) for instance argues that the value premium can be explained by cyclical properties that are unrelated to duration and the equity term premium. In addition, Asness, Liew, Pedersen, and Thapar (2017) argue that the time-variation in the value premium mostly comes from potentially behavioral drivers, which are also unrelated to duration. More generally, Gormsen and Greenwood (2017) document that most risk factors related to fundamentals have counter-cyclical returns.

although the statistical significance is only around half.

3.3 Measurement Error Concerns

The research on the equity term structure is based on prices of either option implied dividends or dividend futures, which one might worry are measured with error. One concern in this regard is that potential measurement error will bias returns upwards, as argued by Blume and Stambaugh (1983): when computing returns, one divides end-of-period price with beginning-of-period price, and if there is white noise measurement error in the beginning-of-period price, then the average returns will be biased upwards because the inverse of the price is convex over positive prices. This potential upward bias is a serious concern when working with option implied dividend prices (se e.g. Boguth, Carlson, Fisher, and Simutin (2012)).[13] One-month returns on option implied dividends are indeed highly volatile and have negative autocorrelation, which suggest that there might be measurement error in prices.

Such measurement error does, however, not influence the main results in this paper. Indeed, while measurement error influence average returns, they do not influence the covariance with the dividend price ratio. The parameter estimate on the dividend price ratio is thus unbiased, even when working with noisy data.[14] A second advantage of the method in this paper is related to inference in the relatively short time-series of available data. As pointed out by Merton (1980), estimating average returns requires longer horizons than estimating covariances. The reason is that dividing the sample into shorter parts increases the precision of the estimate of covariances while it generally does not improve the estimate of the average returns. However, this advantage of estimating covariances only partly applies, because one of the variables, the dividend price ratio, is quite persistent, thereby making estimating the covariance more like estimating a mean.

[13] Schulz (2016) and Song (2016) also underline potential tax and microstructure issues related to the option implied dividend prices.

[14] To see this, consider a normally distributed measurement error $\varepsilon \sim N(\mu, \sigma_\varepsilon)$ in returns such that the observed returns $\hat{r}_t$ is equal to the true return r_t plus the measurement error. Assuming the dividend price ratio for the market portfolio is observed correctly, the observed parameter estimate is thus

$$\hat{\beta} = \frac{\text{cov}(r_{t+1} + \epsilon_{t+1}; d_t - p_t)}{\text{var}(d_t - p_t)} \tag{1.20}$$

$$= \beta + \frac{\text{cov}(\epsilon_{t+1}; d_t - p_t)}{\text{var}(d_t - p_t)} = \beta \tag{1.21}$$

where β is the true parameter coefficient in regression (1.18).

Finally, the methodology in this paper potentially produces a Stambaugh bias. Stambaugh (1999) shows that regression coefficients are upwards biased when one predicts returns with a persistent predictor that has innovations that are negatively correlated with realized returns. The Stambaugh bias is, however, not as serious in the regressions in this paper as in usual predictive regressions for two reasons. First, realized return differences between long- and short-maturity claims are not as strongly linked to innovations in the dividend yield as the realizations of the market portfolio are, because the equity term premia are both long and short an equity claim. Second, the dividend price ratio is much less persistent in this sample compared to the full 1930-2017 U.S. sample.[15] Accordingly, I find that the biases are insufficiently small to significantly alter the inference. For the results reported in Table 2, the bias is around 20 percent for $m = 1$ and it quickly decays to a few percent for $m = 3$ (see Table A4).

4 The Expectations Hypothesis

I next address how the counter-cyclical term premia influence the relation between the equity yield curve and the future development of equity yields. The benchmark for this relation is the expectations hypothesis. The expectations hypothesis is that equity term premia are constant, and that the future development of yields therefore can be inferred from the equity yield curve. The expectations hypothesis is rejected given that term premia exhibit cyclical variation. However, by studying the expectations hypothesis we can learn how the counter-cyclical equity term premium influences the relation between the equity yield curve and the expected development in yields, and we can learn how term premia are related to the equity yield curve.

4.1 Defining Equity Yields and the Expectations Hypothesis

I define the time t equity yield e_t^n for maturity n as the difference between log-dividends d_t at time t and the log-forward price, f_t^n, of the time $t+n$ dividends:

$$e_t^n = \frac{1}{n}\left(d_t - f_t^n\right) \tag{1.22}$$

[15] Of course, a persistent process always looks less persistent in a subsample than in the full sample (Kendall, 1954). However, the dividend price ratio is less persistent in this subsample even when compared to the full sample mean.

where n is the maturity of the dividend claim.

To understand the information content in equity yields, note that equity yields can be written as the average of future returns and future growth rates:

$$e_t^n = \frac{1}{n}(d_t - f_t^n) = \frac{1}{n}\sum_{i=1}^{n} r_{t+i}^{n+1-i} - \frac{1}{n}\sum_{i=1}^{n} g_{t+i} \tag{1.23}$$

where g_{t+1} is the log growth rate on dividends between period t and $t+1$. I do not empirically decompose the equity yields into expected growth rates and returns. It is possible to test the expectations hypothesis and study its implications for equity term premia without decomposing yields into growth rates and returns, and I prefer to do so to avoid the uncertainty arising from such an empirical decomposition.

To motivate the expectations hypothesis, note that the yield of an n maturity claim can be decomposed into future short yields and future term premia by rewriting (1.23):

$$e_t^n = \frac{1}{n}\sum_{i=0}^{n-1} E_t\left[e_{t+i}^1\right] + \frac{1}{n}\sum_{i=0}^{n-1} E_t\left[r_{t+1+i}^{n-i} - r_{t+1+i}^1\right] \tag{1.24}$$

The expression in (1.24) underlines the intuition in the expectations hypothesis: if term premia are constant, the variation in the long yield only comes from variation in the expected future short yields, and the long yield therefore summarizes these expectations. Before presenting the next Proposition that summarizes the testable implications of the expectations hypothesis, I define the equity yield spread $s_t^{n,m} = e_t^n - e_t^m$.

Proposition 3 (The expectations hypothesis).
If equity term premia are constant, i.e. there exist constants $c^{n,m}$ such that $E_t[r_{t+1}^n] - E_t[r_{t+1}^m] = c^{n,m}$ for all m, n, then the following holds:
(a) *The regression coefficient is $\gamma_1^{n,m} = 1$ in*

$$e_{t+m}^{n-m} - e_t^n = \gamma_0^{n,m} + \gamma_1^{n,m} s_t^{n,m} \frac{m}{n-m} + \epsilon_{t+m} \tag{1.25}$$

(b) *The regression coefficient is $\phi_1^{n,m} = 1$ in*

$$\sum_{i=1}^{k-1}\left(1 - \frac{i}{n}\right)\left(e_{t+im}^m - e_{t+(i-1)m}^m\right) = \phi_0^{n,m} + \phi_1^{n,m} s_t^{n,m} + \eta_{t+n} \tag{1.26}$$

The expression in (1.25) specifies the relation between the yield spread and the development in the yield of the long-maturity claim. The expression suggests that when the yield spread is higher than usual, the yield on the long-maturity claim must increase over the lifetime of the short-maturity claim. The intuition behind this relation is simple: under the expectations hypothesis, the long and the short yields are the same period by period (up to a constant), so the relatively high long yield must come from the fact the long yield is expected to be high in the future, after the short yield has matured.

The expression in (1.26) specifies the relation between the yield spread and future changes in the short yield. The expression suggests that when the yield spread is higher than usual, the weighted average of future changes in the short yield must be positive as well. The intuition behind this relation follows from the relation above: when the yield spread is positive, the yield on the long-maturity claim is expected to go up, but the long-maturity claim eventually becomes a short-maturity claim, and the short yield must therefore also increase.

4.2 Testing the Expectations Hypothesis

Before formally testing the expectations hypothesis, it is constructive to visualize the time variation in equity yields. Figure 6 plots the time-series of equity yields with different maturities for the S&P 500, Nikkei 225, Euro Stoxx 50, and the FTSE 100. I consider the two-, five-, and seven-year maturity claim.

The top left graph shows the results for S&P 500. From 2005 to the beginning of 2008, the yield curve is upward sloping as the yield of the two-year claim is constantly below the yield of the five-year claim which is constantly below the yield of the seven-year claim. During 2008 and 2009 the yield curve flips and is downward sloping. Finally, from 2010 and forward the yield curve is upwards sloping again.

The steeply downward sloping yield curve observed during the financial crisis can can be interpreted in two ways: either yields were expected to come down or the term premium was lower than usual. Under the expectations hypothesis, it must be the case that yields were expected to go down because term premia are constant.

The graph does show a drop in yields following the crisis, consistent with the expectations hypothesis. After the financial crisis, the yields on all maturities come down substantially from their high crisis levels. The yield curve thus suggests that investors to a large extent expected the quick rebound in price levels that occurred after the financial crisis. More generally, Figure 6 suggests that when the yield curve is upward sloping, yields subsequently increase, and when the yield curve is downward sloping, yields subsequently decrease. This relationship suggests that the expectations hypothesis has some validity: the yield curve predicts changes in yields.

I next address the relation between the yield spread and the development in yields more formally by testing the expressions in Proposition 3.a and 3.b. In 3.b, each observation lasts for n years, whereas each observation only lasts for m years in 3.a. When studying the spread between, for instance, an $n = 7$ and a $m = 2$ year claim, the regression in 3.b thus requires that one disposes of seven years of observations whereas the regression in 3.a only requires that one disposes of two years of observations. This fact makes the regression in 3.a better suited for the short sample of dividend futures.

Panel A of Table 7 presents the results from regression 3.a for the S&P 500. The first row shows estimates of $\gamma_1^{n,m}$ for $m = 1$. The parameter estimate is 1.00 at the short horizon ($n = 2$) and it increases steadily to 1.5 at the long horizon. The parameter estimates are all statistically indifferent from 1. The next rows show the parameter estimates for the spread in excess of the two- and three-year yields. These are all above one and they are all statistically significant at the five percent level, which is evidence against the expectations hypothesis.

Panels B through D in Table 7 show the estimates of $\gamma_1^{n,m}$ in the international samples. For all three indexes, the estimates of $\gamma_1^{n,m}$ tend to be bigger than one. The estimates are generally statistically indifferent from one, but for all indexes, at least one estimate is statistically different from one.

The positive gammas reported in Table 7 suggest that yields on long-maturity claims move in the direction suggested by the yield curve, but the fact that the gammas are higher than one suggests that the yields go up by more than the expectations hypothesis can justify. In addition, the large gammas have direct implications for the relation between the yield spread and term premia. To see this, note that the expression for yields in (1.23) can be written as

$$r_{t,t+m}^{n} - r_{t,t+m}^{m} = m(e_t^n - e_t^m) - (n-m)(e_{t+m}^{n-m} - e_t^n) \tag{1.27}$$

which inserted in (1.25) gives (suppressing constants):

$$E_t[r^n_{t,t+m} - r^m_{t.t+m}]\frac{1}{m} = (1 - \hat{\gamma}^{n,m}_1)s^{n,m}_t \tag{1.28}$$

From (1.28) it is evident that when $\gamma^{n,m}_1$ is larger than one, the term premium is negatively related to the yield spread. Accordingly, the high estimates of $\gamma^{n,m}_1$ in Table 7 suggest that a higher yield spread predicts *lower* equity term premia.

The negative relation between the yield spread and the term premium is a result of the counter-cyclical term structure. Indeed, the yield curve is naturally pro-cyclical: in bad times, yields are high and expected to mean-revert back down, and the yield curve is therefore downward sloping (Binsbergen, Hueskes, Koijen, and Vrugt, 2013). The fact that equity term premia are counter-cyclical and the yield curve is pro-cyclical implies that the yield spread is negatively related to term premia.

While, as explained earlier, the regression in Proposition 3.a allows for the longest sample, it is also subject to bias in the presence of measurement error. For any given maturity, the yield e^n_t is on both the right and the left hand side but with different signs. When there is measurement error in the yields, the parameter estimate $\gamma^{n,m}_1$ is thus biased downwards as shown by Stambaugh (1988). Because I calculate yields based on prices that are interpolated across maturities, the yields are likely subject to at least some measurement error. It is thus likely that the true $\gamma^{n,m}_1$ are larger than the ones reported in the Table 7. I therefore next consider the results of the regression in Proposition 3.b, which do not suffer from this bias.

Table 8 reports the parameter estimates $\phi^{n,m}_1$ from the regression in Proposition 3.b. For the S&P 500 in Panel A, the parameter estimates are higher than 1 for all m and n except one, and around half the estimates are statistically different from 1. The high estimates of $\phi^{n,m}_1$ imply that future short yields increase when the yield spread is high, as dictated by the expectations hypothesis. But the fact that the parameter estimates are higher than one implies that the short yields increase by more than dictated by the expectations hypothesis. Panels B to D of Table 8 report similar results in the international sample: $\phi^{n,m}_1$ is higher than one and generally statistically significant. The exception is for Nikkei 225 in Panel B, as the estimates do not provide evidence against the expectations hypothesis – the parameter estimates are all close to one.

The results of the test of the expectations hypothesis are in direct contrast to the results from the bond literature. For U.S. treasuries, Shiller (1979), Shiller, Campbell, and Schoenholtz (1983), and Campbell and Shiller (1991) find $\gamma_1^{n,m}$ to be negative in general. Accordingly, for U.S. treasuries, a higher yield spread predicts a higher return on long-term bonds in excess of the return on short-term bonds (see also Fama and Bliss (1987)). This positive relationship between yields and excess returns is also seen elsewhere in the literature. Indeed, in most cases in asset pricing, low prices (that is, high yields) predict high excess returns and not changes in fundamentals. Cochrane (2011) refers to this tendency as a pervasive phenomenon: for the cross-section of stocks, the time-series of the stock indexes, fixed income, currencies, and commodities, a low price predicts high relative returns.[16]

In conclusion, the counter-cyclical term structure causes the expectations hypothesis to be rejected. More precisely, the counter-cyclical term structure causes the equity yield curve to underestimate the future development in equity yields. For S&P 500, this effect is statistically significant for almost all maturity pairs n, m. In the international sample, the statistical significance is weaker, but for all exchanges, the expectations hypothesis is rejected for at least one maturity pair.

5 Real Effects: Cyclicality in the Relative Investments by Long- and Short-Maturity Firms

In this section, I test if firm investments are related to the term structure of equity returns. As shown in Proposition 2, the counter-cyclical term structure causes short-maturity firms to employ more capital and higher capital-to-labor ratios in bad times. Consistent with this, I find that, in bad times, short-duration firms have a higher capital-to-labor ratio, invest more, and do more R&D than long-duration firms.

I analyze investment in the cross-section of stocks by using the short- and long-duration portfolios constructed earlier in Section 3.2. I calculate different investment characteristics for the short- and long-duration portfolio and analyze how they covary with the dividend price ratio in the following regression:

$$X_t^i = b_0 + b_1(d_t - p_t) + \text{controls} + e_t \tag{1.29}$$

[16]For the time-series of the market portfolio see Fama and French (1988), for the cross-section of equities see the literature on the value premium (Bondt and Thaler, 1985; Fama and French, 1992), for currencies see Hansen and Hodrick (1980). Asness, Moskowitz, and Pedersen (2013) summarize evidence from commodities, fixed income, currencies, and international stock indexes.

where X_t^i is the investment characteristic at time t, measured in cross-sectional percentiles.

I consider five different investment characteristics: (1) the capital to labor ratio; (2) capital expenditures relative to the value of plant, property, and equipment; (3) change in capital expenditure; (4) change in research and development costs; (5) change in total salary expenses. I particularly focus on the capital to labor because the difference between in capital to labor between a short- and a long-duration firm is determined by the equity term premium alone (Proposition 2.a).

Panel A in Table 9 presents the results on the capital to labor ratio. The first two columns show the cyclicality of the capital-to-labor ratio of short- and long-duration firms. Consistent with the short-duration firms having a relatively cheaper cost of capital, the short-duration firms apply more capital to labor in bad times. Similarly, long-duration firms apply less capital to labor in bad times. The third column considers the net capital to labor ratio of the long-short portfolio. Consistent with Proposition 2.a, the long-short portfolio applies less capital to labor in bad times, which is to say that the ratio is pro-cyclical. In the fourth column, I control for the treasury yield, the treasury yield spread, and a regression dummy. None of these are statistically significant on their own.

In the fifth and the sixth column I split the sample into pre and post 1996. The capital to labor of the long-short portfolio is pro-cyclical in both samples. Recall that the mimicking portfolio is estimated only based on the late sample. The use of the mimicking portfolio in the early sample is thus based on the assumption that the term premium betas are constant for the characteristics-based portfolios. The fact that the investment cyclicality of the portfolio remains pro-cyclical in both samples brings confidence that his assumption indeed holds and that the portfolio is indeed mimicking the term premium in both the late and the early sample.

In addition, the sample split suggests that some of the cyclicality comes from a time-series trend. Indeed, the parameter estimate on the dividend price ratio is larger in the full sample than in either of the subsamples, suggesting that part of the large effect in the full sample comes from the fact that, over the sample, the dividend price ratio has trended down and the capital to labor ratio has trended up. The trend is not too problematic if it is a prolonged change in the equity term premium that has caused the capital to labor ratio to increase. But to the extent that the trend reflects secular changes in production technology, the results might overstate the effect of the equity term premium on the capital to labor ratio.

One way to address this problem is by detrending the dividend price ratio and the capital to labor ratio. I do so using either the HP filter (Hodrick and Prescott, 1997) or first differences. The results of these regressions are reported in Panel B of Table 9. The sign of all the parameter estimates remains the same, which means that the capital to labor ratio for the long-short portfolio remains pro-cyclical. For the HP filter, the results remain statistically significant on the five-percent level in the full sample and on the ten percent level in the two subsamples. For the regression in first differences, however, the parameter estimate only appears to be statistically significant in the late sample from 1996-2015.

Panel C of Table 9 considers the cyclicality of two investment characteristics. The first three columns show the cyclicality of the investment rate measured as capital expenditure to property, plant, and equipment. Consistent with Proposition 2.b, the short duration firms invest more in bad times and the long-duration firms invest less. The effect is statistically significant even after controlling for the treasury yields and a regression dummy. The fourth to sixth column reports similar results when using the change in capital expenditure as measure of investments: relative to the cross-sectional average, short-duration firms increase their capital expenditure and long-duration firms decrease their capital expenditure.

Panel D of Table 9 considers two labor-related measures of real activity, namely the change in R&D related salary and the change in total salary expenses. The cyclicality of the R&D salary is different for long- and short-duration firms. Relative to the cross-sectional average, short-duration firms increase their R&D related salaries and long-duration firms decrease it. The fourth through sixth columns show that the change in total salary is not strongly related to the duration of the firms, suggesting that much of the dynamics in the capital to labor ratio comes from the capital side.

Taken together, the results show that the real activities of short- and long-duration firms have different cyclical properties and that these properties are potentially driven by the equity term structure. Indeed, the cyclical properties of the real activities are consistent with Proposition 2 and with the idea that the equity term premium increases in bad times and causes long-duration firms to apply less capital.

6 Testing Asset Pricing Models: Theory vs. Stylized Facts

In this section, I relate my empirical findings to canonical asset pricing models individually. I calculate, either analytically or through simulations, the parameters from the regressions in the empirical analysis and compare these theoretical parameters to those observed empirically.

The results are summarized in Table 10. The main challenge for the models is, as mentioned, that they cannot produce an equity term premium that is both negative on average *and* counter-cyclical. Rather, if the equity term premium is positive on average, it is counter-cyclical; if the term premium is negative on average, it is pro-cyclical. In addition, none of the models are able to get the test of the expectations hypothesis right: none of them have parameter estimates that are higher than one. The parameter estimates are too low because the equity term premia are positively related to the yield spread, not negatively as in the data.

While much of the paper has focused on the qualitative results – that is, whether the sign on the cyclicality is correct – the results in Table 10 highlight another problem for the models: none of the models are quantitatively close to matching the observed time variation. Indeed, the Campbell and Cochrane (1999) model and the Bansal and Yaron (2004) model both have counter-cyclical slopes, but the cyclicality is not sufficiently strong. Empirically, the parameter estimates for the regression of the $(Mkt, 2)$ premium on the dividend price ratio, $\beta_1^{Mkt,2}$, is around 0.35. However, in the habit and the long-run risks model, the estimate of $\beta_1^{Mkt,2}$ is only around 0.1 and 0.03.

In the end of this section, I propose a model that addresses the main challenge to existing models, but before doing so I address the canonical models individually.

6.1 The Habit Model by Campbell and Cochrane (1999)

In the habit model by Campbell and Cochrane (1999), the term structure arises because the short- and long-maturity claims are differently exposed to discount rate risk. In the habit model, discount rate risk requires a premium because discount rate shocks are conditionally perfectly negatively correlated with consumption. The negative correlation arises because a negative shock to consumption increases risk aversion and therefore the required rate of return.

The dynamics of the habit model are largely captured by setting $a = 0$ in the model from the theoretical section, meaning that Proposition 1.a applies to the model. Given the fact that the term structure is upward sloping on average, it is therefore also counter-cyclical. The economic intuition is that, in bad times, the higher price of risk causes investors to increase the required compensation for the discount rate risk inherent in long-maturity dividends, thereby making the term structure more upward sloping.

This economic intuition is confirmed in simulation studies. As can be seen in Table 10, the paramamter estimate for $\beta^{Mkt,2}$ in simulation studies is 0.12. This estimate is positive, as is the empirically observed value. While the parameter estimate is well below the empirical estimate, it is still large in absolute terms. Indeed, the model is calibrated to have a standard deviation of the dividend price ratio of 0.26, which means that a one standard deviation change in the dividend price ratio changes the term premium by around 3 percentage points. Finally, the model has the wrong sign on the parameter estimates in the expectations hypothesis. Both γ and ϕ are negative, which is evidence that equity yields spread positively predicts equity term premia.

6.2 The Long-Run Risk Model by Bansal and Yaron (2004)

I analyze the long-run risk model by Bansal and Yaron (2004). Alternatively, using Bansal, Kiku, and Yaron (2012) does not fundamentally change the results. The long-run risk model has a non-degenerate treasury term structure, and I therefore subtract the corresponding bond return to get forward returns (see Binsbergen and Koijen (2017) for a decomposition of spot returns into forward and bond returns).

The Bansal and Yaron model has an upward sloping equity term structure. The term structure arises because long-maturity dividends are more exposed to the long-run dividend growth risk and discount rate risk. Investors are averse towards both shocks, and long-maturity claims therefore require a premium to compensate for the additional discount rate and dividend growth rate risk.

The long-run risk model is captured by setting $a < 0$ in the model from the theory section, meaning that Proposition 1.b applies to the long-run risk model. As such, the model could in principle have a positive and pro-cyclical equity term premium, but the model's parameters imply that it has a counter-cyclical equity term premium. In the model, periods with a high dividend price ratio are generally periods with a high price of risk, and this high price of risk causes investors to require a higher premium on the long-run risk inherent in long-maturity dividends.

Again, the counter-cyclical term structure is confirmed in simulations. Table 10 shows that the parameter estimate for $\beta^{Mkt,2}$ is 0.03. The parameter estimate is again well below the empirical estimate, but it is economically large. The reason β is lower for long-run risk than for the habit model is not that the term structure dynamics are less volatile for the long-run risk model, but rather that the dividend price ratio of the market portfolio is not determined solely by the price of risk; rather, in the long-run risk model, the dividend price ratio may be low because long-run growth rates are high, and these growth rates do not influence the term structure of expected returns.[17] Finally, the long-run risk model also has the wrong signs for γ and ϕ. The negative signs suggest that the equity yield spread positively predicts equity premia, not negatively as in the data.

6.3 The Model by Lettau and Wachter (2007)

The model by Lettau and Wachter (2007) has a downward sloping term structure of expected returns and as such it has so far been the most successful model in explaining the equity term structure. The model has a downward sloping term structure because a negative shock to dividends causes a positive shock to dividend growth rates. This long-run insurance makes long-maturity dividends less risky than short-maturity dividends, because a negative shock to dividends over time is canceled out by a higher growth rate.

The Lettau and Wachter model is captured by setting $a = 0$ in the theory section, meaning that Proposition 1.a applies to the model. Given that the equity term structure is downward sloping on average, it is therefore also pro-cyclical. When the dividend price ratio is low, the price of risk is on average high and investors therefore require a higher premium for holding the risky short-maturity dividends. The term premium thus increases in absolute size which is to say that it becomes more negative and the slope becomes more downward sloping. Consistent with this intuition, the value of $\beta^{Mkt,2}$ is -0.08 in the model.

With regards to γ and ϕ from the test of the expectations hypothesis, the model by Lettau and Wachter (2007) does better than the habit model and the long-run risk model. The reason is that, unlike for the two latter, the term premium and the expected changes in the yields have the same impact on the yield curve in the Lettau and Wachter (2007)

[17]See Beeler and Capmbell (2012) for a discussion of the relationship between the dividend price ratio and future dividend growth in the long-run risk model.

model. Accordingly, both γ and ϕ are positive.

6.4 The Disaster Model by Gabaix (2012)

The spot term structure of equity returns is flat and constant in the disaster model by Gabaix (2012). The equity term structure is flat because a disaster hits all equity claims similarly. The treasury term structure is, however, upward sloping because long-maturity bonds are exposed to inflation risk. Accordingly, the forward term premium on equity is downward sloping and the slope varies over time as the slope of the bond term structure varies.

For the Gabaix model, I report in Table 10 the results for the spot equity term structure instead of the results for the forward equity term structure. I do so because the spot dynamics are more representative of the risk-dynamics in the Gabaix model and because the empirical results for β, γ, and ϕ qualitatively are the same irrespectively of whether I consider spot or forward prices on dividend strips. Under the spot dynamics, the term structure of equities is constant and flat, which implies that the expectations hypothesis holds and γ and ϕ are equal to 1.

6.5 Reconciling the Facts: A Model with Negative and Counter-Cyclical Term Premia

In this section, I calibrate the earlier model such that it can explain the two most important stylized facts, i.e. that equity term premia are negative on average and counter-cyclical. The model does so by having two competing drivers of term premia: long-run risk in dividend growth and a demand for hedging investment opportunities. Investors dislike long-maturity stocks because they are exposed to long-run risk in dividend growth, but they also like them because they hedge deteriorations in investment opportunities. The strength of these two competing forces varies over time in such a way that term premia are negative on average but counter-cyclical.

More concretely, I assume that $a > 0$, $\rho_{dx} = 0$, and $\rho_{dz} > 0$. The assumptions imply that price-of-risk shocks are uncorrelated with dividend shocks and enter the stochastic discount factor negatively. In addition, the positive correlation between shock to dividend and growth rates imply that there is long-run risk in dividends.

The positive value of a implies a high demand for hedging deteriorations in investment opportunities. Indeed, the high a means that states where the price of risk drops are bad states where the stochastic discount factor is high. Intuitively, investors consider the drop in the price of risk a bad thing because their investment opportunities deteriorate. Investors are therefore willing to accept lower return on assets that hedge such deteriorations in investment opportunities. Long-maturity assets are such assets, because these realize a large capital gain when the price of risk drops.

A demand for hedging deteriorations in investment opportunities features in many models in financial economics.[18] The idea in these models is exactly that investors find losses that occur due to discount rate shocks less unpleasant than losses that occur due to cash flow shocks. They do so because losses that occur due to discount rate shocks are partly offset by higher future expected returns. However, these models rarely have a positive value of a. Indeed, while losses that occur due to discount rate shocks are less unpleasant than losses that occur due to cash flow shocks, they are nonetheless still unpleasant. Accordingly, a is negative, but less so than the coefficient in front of cash flow shocks. Indeed, Campbell (1993) shows that Epstein-Zin investors generally dislike discount rate shocks, although they dislikes them less than cash flow shocks if they have a risk aversion paramter $\gamma > 1$. Consistent with this insight, shocks to the price of risk (or, equivalently, the conditional variance of dividends), enter the stochastic discount factor of Bansal and Yaron (2004) scaled by a constant, but the constant is positive which is to say that $a < 0$ in the long-run risk model. The positive a is also difficult to align with the habit model because its price of risk is conditionally perfectly negatively correlated with consumption. Indeed, Santos and Veronesi (2010) show that habit models imply a high premium on discount rate risk.

A positive a could, however, arise from underfunded pension funds. Indeed, if an underfunded pension fund plans to hold its assets to maturity, the fund is not worried about losses that occur due to discount rate shocks. However, when the discount rate goes up, the underfunded pension fund needs less additional funding to become fully funded because the additional funding offers a higher return. Accordingly, states where the price of risk goes up are considered good states for underfunded pension funds, which means that a could be positive.

Given the positive value of a, and the additional assumptions above, the term premia

[18]See Merton (1973); Campbell and Vuolteenaho (2004) for the original ICAPM and Bansal, Kiku, Shaliastovich, and Yaron (2014); Campbell, Giglio, Polk, and Turley (2017) for an ICAPM with stochastic volatility.

are given by:

$$\theta_t^{n,1} = \underbrace{aB_x^{n-1}\sigma_x}_{\text{negative (demand for hedging)}} + \underbrace{B_z^{n-1}\rho_{dz}\sigma_z}_{\text{positive (long-run risk in dividends)}} x_t \tag{1.30}$$

The first term in the term premium reflects that investors are willing to accept a lower return on long-maturity equity because it hedges deteriorations in investment opportunities. The second term reflects that investors want a higher return on long-maturity equity because it is more exposed to long-run risk. The net effect can be either positive or negative depending on the specification of the model.

In the term premium, the effect of the demand for hedging is constant but the effect of long-run risk depends on the price of risk: when the price of risk increases, the compensation demanded for long-run risk increases as well. Accordingly, the equity term premium is counter-cyclical.

I calibrate the model to fit the 1996-2016 sample where I have data on dividend prices. In this sample, the annual dividend growth rate is 3.57 percent per year with an annualized quarterly standard deviation of 0.05. I use those inputs and specify the following quarterly variables to fit the data: $\sigma_x = 0.022$, $\sigma_z = 0.001$, $\rho_{dz} = 0.16$, $\varphi_x = \varphi_z = 0.65$, $\bar{x} = 0.85$, and $a = 0.2$.

The moments of the model are summarized in Table 11. Qualitatively, the model has the right regression coefficients in the three tests covered in this paper: it has a counter-cyclical term structure and it has regression coefficients in the tests of the expectations hypothesis above 1. In addition, the equity term premium is negative on average. The results of the model is summarized in Figure 7.

7 Conclusion

I document a new stylized fact about the equity term structure, namely that the equity term premium is counter-cyclical. The result is robust: (1) it holds in the post-2005 sample across four different indexes when measuring the equity term premia using dividend futures; (2) it holds when excluding the financial crisis from the sample; (3) it holds in the U.S. sample from 1996 when using equity term premia implied from options prices; and (4) it holds in the U.S. from 1963 when using the cross-section of equities to measure equity term premia. In addition, the variation in the equity term premia is large: in the post 2005 sample, the equity term premium varies with nine percentage points between good and bad times.

A series of recent studies documents the importance of short-maturity risks in understanding *average* risk premia in equities, bonds, variance-swaps, housing markets, and currencies (Binsbergen and Koijen, 2017; Duffee, 2011; Dew-Becker, Giglio, Le, and Rodriguez, 2017; Giglio, Maggiori, and Stroebel, 2015; Giglio, Maggiori, Stroebel, and Weber, 2015; Lustig, Stathopoulos, and Verdelhan, 2013). Given these previous studies, the counter-cyclical equity term structure is surprising because it suggests that long-maturity risks are the main drivers of *variation* in risk premia. Accordingly, the short-maturity risk appears important for explaining average risk premia, but long-maturity risk appears the most important for explaining the variation in these risk premia, at least for equities. This pattern is puzzling. Indeed, none of the standard asset pricing models that I study can generate this pattern, i.e. a term premium that is negative on average and counter-cyclical: the recent downward sloping models have pro-cyclical term premia; the traditional upward sloping models have counter-cyclical term premia.

I present a new model as a potential solution to the puzzle. In my model, investors trade off a demand for hedging investment opportunities with an aversion towards long-run risk in dividend growth. In good times, investors require a lower return on long-maturity dividends than on short-maturity dividends because they want to hedge deteriorations in investment opportunities. In bad times, investors require a higher return on long-maturity dividends than on short-maturity dividends because they are averse to the increased long-run risk in dividend growth. The model is, however, not grounded in a utility function, and doing so remains an interesting avenue for future research.

In addition to having strong implications for macro-finance models, the counter-cyclical term structure also has real effects. The equity term structure influences the difference in cost of capital between firms with different cash-flow maturity. In bad times, when the equity term premia are higher, long-maturity firms find capital relatively more expensive than short-maturity firms and therefore use relatively more labor and less capital. In this sense, the equity term structure has important consequences for individual firms and for workers in different industries.

8 Proofs

Proof of proposition 1.a

Note first that the price-dividend ratio of the market portfolio is given by the following sum:

$$\frac{P_t}{D_t} = \sum_{i=1}^{\infty} \frac{P_t^i}{D_t} = \sum_{i=1}^{\infty} \exp\left(A^i + B_z^i z_t + B_x^i x_t\right) \tag{1.31}$$

where P_t is the price of the market portfolio at time t.

We first establish that the price dividend ratio and the negative of the price of risk, $-x_t$, are positively quadrant dependent (Lehmann, 1966) and have positive covariance. To see this, define first the random variable $y_t = -x_t$ and note that the dividend price ratio P_t/D_t is an increasing, monotone function of z_t and y_t, i.e.

$$\frac{P_t}{D_t} = f(z_t, y_t)$$

where $f : \mathbb{R}^2 \to \mathbb{R}$ is nondecreasing in both z_t and y_t. Similarly, define the function $g(y_t) = -x_t$ where $g : \mathbb{R} \to \mathbb{R}$ is nondecreasing in y_t. Because z_t and y_t are independent, $f(z_t, y_t)$ and $g(y_t)$ have positive covariance and the two are positively quadrant dependent. The positive quadrant dependence means that the positive covariance between the two functions caries over through monotonic transformations of the two variables (see e.g. Oliveira, 2012). Accordingly, we can write

$$\text{cov}(P/D_t; -x_t) = \text{cov}\Bigg(f(z_t, y_t); g(y_t)\Bigg) > 0 \tag{1.32}$$

and

$$\text{cov}(p_t - d_t; -x_t) = \text{cov}\Bigg(\ln\left(f(z_t, y_t)\right); g(y_t)\Bigg) > 0 \tag{1.33}$$

The sign of the covariance between the dividend price ratio and the term premium is therefore determined as

$$\text{sign}\left(\text{cov}(d_t - p_t; \theta_t^{n,1})\right) = \text{sign}\left((B_x^{n-1}\rho_{dx}\sigma_x + B_z^{n-1}\rho_{dz}\sigma_z)\right) \tag{1.34}$$

Next, the average term premium is given by:

$$E[\theta_t^{n,1}] = (B_x^{n-1}\rho_{dx}\sigma_x + B_z^{n-1}\rho_{dz}\sigma_z)\bar{x} \tag{1.35}$$

Because $\bar{x}$ is positive, the sign is given by

$$\text{sign}\left(E[\theta_t^{n,1}]\right) = \text{sign}\left((B_x^{n-1}\rho_{dx}\sigma_x + B_z^{n-1}\rho_{dz}\sigma_z)\right) \tag{1.36}$$

which proves the proposition. □

Proof of proposition 1.b

The asset pricing model in this paper is an example where $a \neq 0$ and $\text{sign}\left(E[\theta_t^{n,1}]\right) \neq \text{sign}\left(\text{cov}(d_t - p_t; \theta_t^{n,1})\right)$ which proves the proposition. □

Proof of proposition 2.a

Note first that taking the natural logarithm of (1.16) and (1.17) and subtracting (1.17) from (1.16) gives the following expression for the capital to labor ratio:

$$\ln(k_t^n) = -\ln(E_t[R_{t+1}^n]) + \ln w + \ln\beta - \ln\gamma \tag{1.37}$$

Subtracting (1.37) for an m-maturity claim from (1.37) for an n-maturity claim gives

$$\ln(k_t^n) - \ln(k_t^m) = -\left(\ln(E_t[R_{t+1}^n] - E_t[R_{t+1}^m])\right) \qquad \square$$

Proof of proposition 2.b

Note first that

$$E_t\left[M_{t+1}\frac{P_{t+1}^{n-1}}{D_{t+1}}F_t(K_t^n, L_t^n)\right] = \exp(\tilde{A}^n + (B_x^n + \sigma_d)x_t + B_z^n z_t)F_t(K_t^n, L_t^n) \tag{1.38}$$

where $\tilde{A}^n$ is a constant. Inserting this expression in (1.16) and (1.17), taking the natural logarithm, and solving for K_t^n gives (supressing constants):

$$\ln(K_t^n) = \frac{1}{1-\alpha-\beta}\left(B_z^n z_t + (B_x^n + \sigma_d)x_t + (\alpha - 1)\left(\ln E_t[R_{t+1}^n]\right)\right) \tag{1.39}$$

Subtracting a one-period claim from the expression in (1.39) gives the expression in proposition 2.b. □

Table 1

The Equity Term Structure: Stylized Facts versus Theory

The equity term premium $E_t[TP_t] = E_t[r_{t+1}^{long} - r_{t+1}^{short}]$ is the conditional expected annual return to long-maturity equity minus the annual return to short maturity equity. The cyclicality of the equity term premium is measured by a linear projection of the realized term premium on the ex ante dividend price ratio of the market portfolio. The expectations hypothesis refers to the relation between the equity yield spread and future equity yields. The hypothesis is evaluated in a regression of future yield changes on the yields spread multiplied by a maturity modification. A parameter estimate of one implies that the yields develop exactly as the yield curve suggests under the expectations hypothesis. The habit model refers to the Campbell & Cochrane (1999) model. The long-run risk model refers to the Bansal & Yaron (2004) model.

Paper	Average slope (van Binsbergen, Brandt, Koijen, 2012)	Cyclicality (this paper)	Expectations Hypothesis (this paper)
Data			
Measured as	$E[TP] = E[r_{t+1}^{long} - r_{t+1}^{short}]$	$TP_t = \beta_0 + \beta_1 D_t/P_t + e_t$	$\Delta \text{yield}_{t+1} = \gamma_0 + \gamma_1 \text{yield spread}_t + \epsilon_{t+1}$
Result	Downward sloping $E[TP] < 0$	Counter-cyclical $\beta_1 > 0$	Yield spread predicts change in yield $\gamma_1 > 1$
Theories			
Habit	Upward	Counter-cyclical	$\gamma_1 < 0$
Long-run risk	Upward	Counter-cyclical	$\gamma_1 < 0$
Lettau Wacther (2007)	Downward	Pro-cyclical	$\gamma_1 \in (0;1)$
Gabaix (2012)	Flat	Constant	$\gamma_1 = 1$
Hasler Marfe (2016)	Downward	Pro-cyclical	$\gamma_1 \in (0;1)$
My model	Downward	Counter-cyclical	$\gamma_1 > 1$

Table 2
Counter-Cyclical Equity Term Premia

This table shows the relation between term premia and the dividend price ratio of the market portfolio. The table reports the parameter estimate from the following regression:

$$r_{t;t+12}^{n} - r_{t;t+12}^{m} = \beta_0^{n,m} + \beta_1^{n,m}(d_t - p_t) + \epsilon_{t,t+12}$$

where $d_t - p_t$ is the dividend price ratio of the market portfolio and $r_{t,t+12}^{n}$ is the twelve-month forward return to the dividend claim with n year maturity. The regression is based on monthly rolling regressions. The *t*-statistics are based on Newey and West (1987) standard errors corrected for 18 lags. The maturities *n* and *m* are both measured in years. The row *m=mean(1-7)* refers to the average return to the one- through seven-year maturity dividend claim. The sample is from 2005 to 2016.

	Maturity of long-maturity claim (*n*)						
	2	3	4	5	6	7	Mkt
Panel A: S&P 500							
m=1	0.12	**0.18**	**0.25**	**0.34**	**0.41**	**0.45**	**0.59**
	(1.95)	(2.61)	(3.35)	(3.97)	(4.24)	(4.50)	(4.39)
m=2		**0.05**	**0.12**	**0.21**	**0.26**	**0.29**	**0.35**
		(2.41)	(3.64)	(4.26)	(4.19)	(3.98)	(2.40)
m=3			**0.05**	0.09	0.11	0.13	**0.27**
			(1.96)	(1.33)	(1.21)	(1.28)	(1.99)
m=mean(1-7)							0.25
							(1.89)
Panel B: Nikkei 225							
m=1	**0.40**	**0.69**	**0.77**	**0.81**	**0.84**	**0.87**	**0.75**
	(5.15)	(3.54)	(3.19)	(2.92)	(2.69)	(2.57)	(2.58)
m=2		**0.21**	**0.30**	**0.36**	**0.40**	**0.43**	0.39
		(2.95)	(2.61)	(2.44)	(2.27)	(2.13)	(1.83)
m=3			0.06	0.09	0.09	0.07	0.04
			(1.46)	(1.24)	(0.94)	(0.57)	(0.28)
m=mean(1-7)							0.40
							(0.52)
Panel C: EuroStoxx 50							
m=1	**0.23**	**0.39**	**0.41**	**0.40**	**0.39**	**0.36**	**0.37**
	(1.98)	(2.63)	(2.69)	(2.76)	(2.68)	(2.39)	(2.33)
m=2		0.07	0.07	0.05	0.02	0.01	0.03
		(0.95)	(0.67)	(0.43)	(0.23)	(0.05)	(0.22)
m=3			-0.03	-0.06	-0.09	**-0.12**	-0.05
			(-1.13)	(-1.51)	(-1.89)	(-2.32)	(-0.49)
m=mean(1-7)							0.04
							(0.41)

continued...

Panel D: FTSE 100							
m=1	**0.30**	**0.44**	**0.47**	**0.46**	**0.43**	**0.40**	**0.52**
	(2.61)	(3.32)	(3.69)	(3.38)	(2.92)	(2.48)	(2.34)
m=2		0.07	0.09	0.07	0.04	0.00	0.12
		(1.12)	(0.96)	(0.61)	(0.28)	(0.01)	(0.48)
m=3			0.01	-0.02	-0.06	-0.09	0.01
			(0.15)	(-0.32)	(-0.64)	(-0.87)	(0.03)
m=mean(1-7)							0.09
							(0.53)

Table 3
Counter-Cyclical Equity Term Premia: Excluding the Financial Crisis

This table shows the relation between term premia and the dividend price ratio of the market portfolio. The table reports the parameter estimate from the following regression:

$$r^n_{t;t+12} - r^m_{t;t+12} = \beta_0^{n,m} + \beta_1^{n,m}(d_t - p_t) + \epsilon_{t,t+12}$$

where $d_t - p_t$ is the dividend price ratio of the market portfolio and $r^n_{t,t+12}$ is the twelve-month forward return to the dividend claim with n year maturity. The regression is based on monthly rolling regressions. The t-statistics are based on Newey and West (1987) standard errors corrected for 18 lags. The maturities n and m are both measured in years. The row *m=mean(1-7)* refers to the average return to the one- through seven-year maturity dividend claim. The sample is from 2005 to 2016 excluding the years 2008 and 2009.

	Maturity of long-maturity claim (n)						
	2	3	4	5	6	7	Mkt
Panel A: S&P 500							
m=1	**0.33**	**0.67**	**0.84**	**1.05**	**1.23**	**1.34**	**2.24**
	(4.24)	(9.21)	(9.42)	(8.69)	(8.25)	(7.59)	(3.60)
m=2		**0.25**	**0.43**	**0.60**	**0.70**	**0.77**	**1.29**
		(3.70)	(5.22)	(5.46)	(4.23)	(3.66)	(2.12)
m=3			0.06	0.03	0.03	0.07	0.82
			(0.59)	(0.13)	(0.08)	(0.19)	(1.63)
m=mean(1-7)							**0.97**
							(2.05)
Panel B: Nikkei 225							
m=1	**0.34**	**0.66**	**0.82**	**0.92**	**0.98**	**1.05**	**0.92**
	(10.24)	(6.00)	(5.05)	(4.55)	(4.16)	(4.02)	(2.17)
m=2		**0.25**	**0.41**	**0.50**	**0.57**	**0.61**	0.53
		(5.00)	(4.44)	(4.23)	(4.00)	(3.74)	(1.86)
m=3			**0.10**	0.15	0.16	0.15	0.06
			(2.25)	(1.90)	(1.53)	(1.08)	(0.27)
m=mean(1-7)							0.05
							(0.34)
Panel C: EuroStoxx 50							
m=1	0.08	0.31	**0.37**	**0.37**	**0.35**	0.32	**0.46**
	(1.20)	(1.94)	(2.20)	(2.41)	(2.30)	(1.92)	(1.99)
m=2		0.11	0.13	0.11	0.09	0.06	0.19
		(1.30)	(1.17)	(0.89)	(0.67)	(0.45)	(0.91)
m=3			-0.02	-0.05	-0.08	-0.12	0.05
			(-0.39)	(-0.75)	(-1.03)	(-1.41)	(0.32)
m=mean(1-7)							0.15
							(1.06)

Continued...

Panel D: FTSE 100							
m=1	**0.38**	**1.09**	**1.45**	**1.60**	**1.68**	**1.73**	**2.13**
	(4.02)	(4.50)	(5.94)	(7.12)	(8.26)	(9.16)	(5.99)
m=2		**0.45**	**0.70**	**0.81**	**0.86**	**0.89**	**1.19**
		(2.34)	(2.64)	(2.76)	(2.76)	(2.80)	(2.18)
m=3			**0.20**	**0.28**	0.31	0.34	0.57
			(2.30)	(2.10)	(1.94)	(1.95)	(1.38)
m=mean(1-7)							0.56
							(1.62)

Table 4
Counter-Cyclical Equity Term Premia: Using cay as Measure of Cyclicality

This table shows the relation between term premia and the ex ante value of cay (Lettau and Ludvigson, 2001). The table reports the parameter estimate from the following regression:

$$r^n_{t,t+4} - r^m_{t,t+4} = \beta_0^{n,m} + \beta_1^{n,m}\text{cay}_t + \epsilon_{t,t+4}$$

where $r^n_{t,t+4}$ is the four-quarter forward return to the dividend claim with n year maturity. The regression is based on quarterly rolling regressions. The t-statistics are based on Newey and West (1987) standard errors corrected for 6 lags. The maturities n and m are both measured in years. The row *m=mean(1-7)* refers to the average return to the one- through seven-year maturity dividend claim. The sample is from 2005 to 2016.

	Maturity of long-maturity claim (n)						
	2	3	4	5	6	7	Mkt
Panel A: S&P 500							
m=1	1.47	2.69	**3.98**	**5.26**	**6.26**	**6.32**	**8.22**
	(1.25)	(1.91)	(2.76)	(3.60)	(4.20)	(4.57)	(4.36)
m=2		**1.01**	**2.34**	**3.65**	**4.42**	**4.45**	**5.12**
		(2.27)	(4.55)	(5.29)	(5.31)	(3.89)	(2.73)
m=3			**1.28**	**2.47**	**3.19**	**3.20**	**4.08**
			(4.92)	(3.82)	(3.63)	(2.74)	(2.30)
m=mean(1-7)							2.96
							(1.54)
Panel B: S&P 500 (excluding 2008-2009)							
m=1	**2.94**	**5.00**	**6.27**	**7.55**	**8.53**	**8.15**	**9.47**
	(3.06)	(5.53)	(6.36)	(6.09)	(5.52)	(4.32)	(4.31)
m=2		**1.78**	**3.07**	**4.41**	**5.12**	**4.75**	4.78
		(3.35)	(4.33)	(4.01)	(3.56)	(2.38)	(1.92)
m=3			**1.32**	**2.72**	**3.46**	3.10	3.10
			(3.99)	(2.72)	(2.48)	(1.66)	(1.34)
m=mean(1-7)							2.28
							(0.89)

Table 5
Counter-Cyclical Sharpe Ratios

This table shows the relation between the sharpe ratios for term premia and the dividend price ratio of the market portfolio. The table reports the parameter estimate from the following regression:

$$SR^{n,m}_{t;t+12} = \beta_0^{n,m} + \beta_1^{n,m}(d_t - p_t) + \epsilon_{t,t+12}$$

where $d_t - p_t$ is the dividend price ratio of the market portfolio and $SR^{n,m}_{t,t+12}$ is the one-year log-Sharpe ratio of the log-return to the n maturity claim minus the return to the m maturity claim. The regression is based on monthly rolling regressions. The t-statistics are based on Newey and West (1987) standard errors corrected for 18 lags. The maturities n and m are both measured in years. The sample is from 2005 to 2016.

	Maturity of long-maturity claim (n)						
	2	3	4	5	6	7	Mkt
Panel A: S&P 500							
m=1	**3.18**	**3.27**	**3.70**	**4.19**	**4.15**	**3.74**	**3.43**
	(2.84)	(3.44)	(4.47)	(5.43)	(5.58)	(5.79)	(6.69)
m=2		**1.54**	**2.87**	**3.67**	**3.67**	**3.10**	**1.78**
		(2.65)	(5.27)	(6.60)	(5.51)	(6.19)	(2.61)
m=3			**2.17**	**2.13**	1.83	1.46	**1.40**
			(3.10)	(2.20)	(1.54)	(1.52)	(2.11)
m=mean(1-7)							**1.57**
							(2.16)
Panel B: Nikkei 225							
m=1	**5.28**	**5.43**	**5.91**	**6.04**	**5.79**	**5.41**	**4.65**
	(6.91)	(5.88)	(5.35)	(4.84)	(4.34)	(3.91)	(2.81)
m=2		**3.66**	**4.31**	**4.34**	**4.02**	**3.59**	2.48
		(3.55)	(3.03)	(2.74)	(2.43)	(2.12)	(1.77)
m=3			2.89	2.48	2.00	1.46	0.50
			(1.63)	(1.41)	(1.19)	(0.88)	(0.60)
m=mean(1-7)							0.71
							(1.09)
Panel C: EuroStoxx 50							
m=1	**1.92**	**2.38**	**2.61**	**2.54**	**2.64**	**2.46**	**2.00**
	(2.42)	(2.45)	(2.64)	(2.59)	(2.78)	(2.70)	(2.89)
m=2		1.52	0.92	0.48	0.63	0.55	0.50
		(1.18)	(0.93)	(0.53)	(0.62)	(0.57)	(0.63)
m=3			-0.68	-0.93	-0.76	-0.74	0.35
			(-0.79)	(-1.09)	(-0.85)	(-0.87)	(0.58)
m=mean(1-7)							1.06
							(1.72)

Continued...

Panel D: FTSE 100							
m=1	**4.02**	**4.32**	**4.64**	**4.60**	**4.43**	**4.12**	**3.20**
	(3.81)	(3.80)	(3.81)	(3.88)	(4.03)	(3.83)	(3.85)
m=2		2.17	2.11	1.75	1.57	1.25	0.88
		(1.47)	(1.27)	(1.01)	(0.99)	(0.78)	(0.74)
m=3			0.57	0.17	-0.05	-0.30	0.22
			(0.38)	(0.11)	(-0.04)	(-0.22)	(0.24)
m=mean(1-7)							0.77
							(0.99)

Table 6
Counter-Cyclical Equity Term Premia: Alternative Measures

This table shows the relation between term premia and the dividend price ratio of the market portfolio. The term premia are measured in two different ways: (1) as the implied term premium from equity options (van Binsbergen, Brandt, and Koijen, 2012) and (2) as the return to a term premium mimicking portfolio from the cross-section of equities. The term premium mimicking portfolio is long a portfolio with long duration firms and short a portfolio with short duration firms. To construct the long and short duration portfolios, I run a regression of the excess return to 30 portfolios sorted on book-to-market, profitability, and investment onto the realized return difference between long- and short-maturity equity claims between 1996 and 2015. For each style, I rank portfolios in ascending order based on their beta with respect to long- minus short-maturity return difference. I assign the two portfolios with highest (lowest) beta to the long (short) duration portfolio. Within the long (short) duration portfolio I equal weight the excess return. I include as independent variables the ex ante dividend price ratio of the market portfolio, the five Fama and French (20015) factors, the ex ante one-year treasury yield, and the ex ante treasury yield spread (five-year yield in excess of one-year yield). The yields are from Fama and Bliss (1987). All returns are measured in rolling one-year log returns. I report *t*-statistics below the parameter estimates. The *t*-statistics are based on Newey and West (1987) standard errors corrected for 18 lags. The results are from the U.S.

Panel A: Alternative measures of the equity term premium

	Option implied term premium		Cross-sectional term premium			
Period	1996-2009	1996-2009	1963-2015	1963-2015	1996-2015	1963-1996
d_t - p_t	**1.04**	**0.90**	0.04	**0.07**	0.13	0.07
	(2.55)	(5.93)	(0.92)	(3.68)	(1.54)	(1.68)
Mkt		0.30		**0.10**	-0.03	**0.11**
		(0.91)		(3.23)	(-0.51)	(3.09)
SMB		**-0.65**		**0.25**	**0.23**	**0.25**
		(-2.41)		(7.09)	(2.85)	(4.83)
HML		-0.45		**-0.34**	**-0.20**	**-0.38**
		(-1.32)		(-7.41)	(-3.14)	(-7.03)
RMW		-0.79		**-0.59**	**-0.89**	**-0.43**
		(-1.44)		(-9.24)	(-9.46)	(-5.01)
CMA		0.26		-0.09	-0.03	-0.05
		(0.55)		(-1.13)	(-0.20)	(-0.51)
Bond yield		0.05		**-0.01**	0.00	**-0.01**
		(1.31)		(-2.92)	(-0.19)	(-3.76)
Bond yield spread		0.10		**-0.02**	-0.01	**-0.02**
		(1.28)		(-3.40)	(-0.86)	(-3.00)

Panel B: Alternative measures of cyclicality

	Option implied term premium				Cross-sectional term premium	
Period	1996-2009	1996-2009	1996-2009	1996-2009	1963-2015	1963-2015
$CAPE_t$	0.59	**0.96**			**0.05**	
	(1.46)	(5.17)			(2.42)	
cay_t			3.07	-2.78		**0.81**
			(0.61)	(-0.61)		(1.99)
Mkt		0.30		0.98	**0.10**	**0.10**
		(0.88)		(1.78)	(3.02)	(3.28)
SMB		**-0.73**		-1.14	**0.26**	**0.18**
		(-2.51)		(-1.64)	(7.09)	(2.37)
HML		**-0.64**		-0.81	**-0.32**	-0.13
		(-2.35)		(-1.50)	(-6.48)	(-1.12)
RMW		-0.77		0.22	**-0.62**	-0.08
		(-1.43)		(0.48)	(-9.66)	(-0.55)
CMA		0.15		0.69	-0.15	0.13
		(0.37)		(0.55)	(-1.74)	(0.72)
Bond yield		**0.11**		-0.03	**-0.01**	0.00
		(2.11)		(-0.52)	(-2.01)	(-0.96)
Bond yield spread		0.13		0.04	**-0.02**	-0.02
		(1.39)		(0.33)	(-3.09)	(-1.74)

Table 7
The Expectations Hypothesis: The Yield Spread and Long-Yield Changes

This table shows the relation between long-yield changes and the equity yield spread. The table reports the parameter estimate from the following regression:

$$e_{t+m}^{n-m} - e_t^n = \gamma_0^{n,m} + \gamma_1^{n,m} s_t^{n,m} \frac{m}{n-m} + \epsilon_{t+m}$$

The expectations hypothesis is that $\gamma_1^{n,m} = 1$ for all maturity pairs n,m. The t-statistics for this hypothesis are reported below the parameter estimates. The t-statistics are based on Newey and West (1987) standard errors corrected for $1.5m$ lags. The maturities n and m are both measured in years. The sample is from 2005 to 2016.

	Maturity of long-maturity claim (n)					
	2	3	4	5	6	7
Panel A: S&P 500						
m=1	1.00	1.08	1.18	1.27	1.36	1.38
	(-0.00)	(0.17)	(0.46)	(0.70)	(0.93)	(1.07)
m=2		**1.61**	**1.77**	**1.87**	**1.95**	**2.04**
		(2.08)	(2.16)	(2.51)	(2.91)	(3.32)
m=3			**1.73**	**1.94**	**2.09**	**2.15**
			(3.04)	(3.25)	(3.09)	(3.29)
Panel B: Nikkei 225						
m=1	1.62	1.59	1.30	1.17	1.07	0.99
	(1.02)	(0.92)	(0.53)	(0.32)	(0.14)	(-0.02)
m=2		1.05	0.97	0.85	0.79	0.74
		(0.11)	(-0.07)	(-0.33)	(-0.46)	(-0.59)
m=3			1.23	1.29	1.19	1.14
			(0.34)	(0.37)	(0.26)	(0.19)
Panel C: EuroStoxx 50						
m=1	**2.72**	**3.86**	**3.10**	**2.79**	**2.62**	**2.53**
	(2.03)	(5.37)	(5.91)	(5.92)	(5.76)	(5.58)
m=2		**1.61**	**1.58**	1.46	1.36	1.33
		(2.80)	(2.05)	(1.78)	(1.59)	(1.52)
m=3			1.04	1.13	1.01	0.93
			(0.09)	(0.25)	(0.03)	(-0.19)
Panel D: FTSE 100						
m=1	**-1.20**	1.71	2.04	**2.03**	**1.96**	**1.88**
	(-3.50)	(0.85)	(1.55)	(2.05)	(2.41)	(2.56)
m=2		1.56	1.71	1.59	1.52	1.47
		(1.90)	(1.74)	(1.70)	(1.68)	(1.66)
m=3			1.26	1.19	1.03	0.95
			(1.06)	(0.58)	(0.10)	(-0.17)

Table 8
The Expectations Hypothesis: The Yield Spread and Short-Yield Changes

This table shows the relation between short-yield changes and the equity yield spread. The table reports the parameter estimate from the following regression:

$$\sum_{i=1}^{k-1}\left(1-\frac{i}{n}\right)\left(e_{t+m}^{m}-e_{t+(i-1)m}^{m}\right)=\phi_{o}^{n,m}+\phi_{1}^{n,m}s_{t}^{n,m}+\eta_{t+n}$$

The expectations hypothesis is that $\phi_1^{n,m}=1$ for all maturity pairs n,m. The t-statistics for this hypothesis are reported below the parameter estimates. The t-statistics are based on Newey and West (1987) standard errors corrected for $1.5m$ lags. The maturities n and m are both measured in years. The sample is from 2005 to 2016.

	Maturity of long-maturity claim (n)				
	2	3	4	5	6
Panel A: S&P 500					
m=1	1.00	1.23	**1.23**	**1.25**	**1.26**
	(-0.00)	(1.41)	(1.98)	(2.58)	(2.02)
m=2			**1.38**		**1.37**
			(2.24)		(3.60)
Panel B: Nikkei 225					
m=1	1.31	1.15	0.98	1.06	1.07
	(0.92)	(0.70)	(-0.10)	(0.35)	(0.37)
m=2			0.98		1.13
			(-0.07)		(0.63)
Panel C: EuroStoxx 50					
m=1	**1.86**	**2.07**	**1.49**	**1.30**	**0.72**
	(3.07)	(6.18)	(3.81)	(3.55)	(-3.82)
m=2			**1.29**		**1.12**
			(2.66)		(2.09)
Panel D: FTSE 100					
m=1	**-0.10**	1.43	1.37	**1.34**	1.17
	(-4.58)	(1.45)	(1.84)	(2.68)	(1.69)
m=2			1.36		**1.20**
			(1.79)		(2.07)

Table 9
Cyclicality of the Investment Duration

This table reports the results from a regression of investment characteristics on the dividend price ratio of the market portfolio plus controls. I consider the investment rates for three portfolios: a portfolio with short-duration firms, a portfolio with long-duration firms, and a long/short portfolio. To construct the long- and short-duration portfolio, I run a regression of the excess return to 30 portfolios sorted on book-to-market, profitability, and investment onto the realized return difference between long- and short-maturity equity claims between 1996 and 2015. For each style, I rank portfolios in ascending order based on their beta with respect to long- minus short-maturity return difference. I assign the two portfolios with highest (lowest) beta to the long (short) duration portfolio. Within the long (short) duration portfolio I equal-weight the characteristics. Capital to labor is measured as capital expenditures to total salary. Investment is measured as capital expenditure to plant, property, and equipment. Change in Capex is the change in capital expenditure. R&D is the annual change in salary spend on R&D activities. Total salary expenses is the annual change in total salaries. All characteristics are measured in cross-sectional percentiles. In the regressions, I use as the independent variables the ex ante dividend price ratio of the market portfolio, the one-year treasury yield, the treasury yield spread (five-year in excess of one-year), and a dummy variable for NBER recessions. I report *t*-statistics below the parameter estimates. The *t*-statistics are based on Newey and West (1987) standard errors corrected for 18 lags. The sample is U.S. equities from 1963-2015.

Panel A: Capital to labor

Portfolio	Short duration	Long duration	Long- minus short duration			
Period	1963-2015	1963-2015	1963-2015	1963-2015	1996-2015	1963-1996
$d_t - p_t$	**2.85**	**-4.03**	**-6.88**	**-6.86**	**-0.54**	-4.08
	(10.93)	(-9.09)	(-10.56)	(-5.50)	(-2.64)	(-1.76)
Bond yield$_t$				0.01	**-0.31**	**0.38**
				(0.04)	(-8.99)	(1.96)
Bond yield spread$_t$				0.91	**-0.57**	**1.38**
				(1.52)	(-4.27)	(2.92)
Recession dummy$_t$				1.35	0.22	0.20
				(1.70)	(1.74)	(0.23)

Panel B: Detrended capital to labor

	Capital to labor (HP filter)			Capital to labor (first difference)		
Portfolio	Long-short	Long-short	Long-short	Long-short	Long-short	Long-short
Period	1963-2015	1996-2015	1963-2015	1963-2015	1996-2015	1963-1996
$d_t - p_t$ *(HP filter)*	**-2.00**	-0.45	-3.78			
	(-2.02)	(-1.70)	(-1.92)			
$d_t - p_t$ *(first differenced)*				-1.14	**-0.97**	-1.33
				(-0.95)	(-2.18)	(-0.60)
Bond yield$_t$	0.02	-0.08	0.03	0.05	-0.04	0.14
	(0.67)	(-1.58)	(0.39)	(1.36)	(-0.62)	(1.47)
Bond yield spread$_t$	-0.16	-0.26	-0.26	0.10	-0.24	0.21
	(-0.93)	(-1.63)	(-1.12)	(0.49)	(-1.60)	(0.73)
Recession dummy$_t$	0.35	-0.01	0.51	0.21	0.21	0.11
	(1.13)	(-0.03)	(1.16)	(0.44)	(0.83)	(0.16)

Panel C: Investment

Investment measure	Investment (Capex to PPE)			Change in CapEx		
Portfolio	Short duration	Long duration	Long-short	Short duration	Long duration	Long-short
Period	1963-2015	1963-2015	1963-2015	1963-2015	1963-2015	1963-2015
d_t - p_t	**1.84** (3.27)	**-3.48** (-4.13)	**-9.13** (-4.16)	**2.54** (4.86)	**-4.17** (-4.85)	**-10.14** (-4.51)
Bond yield$_t$			**0.74** (2.12)			0.66 (1.91)
Bond yield spread$_t$			1.68 (1.87)			1.10 (1.11)
Recession dummy$_t$			**2.58** (2.64)			1.90 (1.57)

Panel D: R&D and Salary

Characteristic:	R&D			Total Salary Expenses		
Portfolio	Short duration	Long duration	Long-short	Short duration	Long duration	Long-short
Period	1963-2015	1963-2015	1963-2015	1963-2015	1963-2015	1963-2015
d_t - p_t	**2.74** (6.37)	**-5.85** (-9.96)	**-9.26** (-6.12)	0.07 (0.22)	**0.83** (2.15)	0.82 (1.21)
Bond yield$_t$			0.10 (0.40)			0.06 (0.53)
Bond yield spread$_t$			0.67 (1.01)			**0.77** (2.60)
Recession dummy$_t$			1.88 (1.77)			-0.38 (-0.75)

Table 10
Asset Pricing Theories versus Stylized Facts

This table shows the result of simulations of different asset pricing models. I simulate the models and estimate the following regressions:

$$r_{t;t+12}^{n} - r_{t;t+12}^{m} = \beta_0^{n,m} + \beta_1^{n,m}(d_t - p_t) + \epsilon_{t,t+12}$$

$$e_{t+m}^{n-m} - e_t^{n} = \gamma_0^{n,m} + \gamma_1^{n,m} s_t^{n,m} \frac{m}{n-m} + \epsilon_{t+m}$$

$$\sum_{i=1}^{k-1}\left(1 - \frac{i}{n}\right)\left(e_{t+m}^{m} - e_{t+(i-1)m}^{m}\right) = \phi_o^{n,m} + \phi_1^{n,m} s_t^{n,m} + \eta_{t+n}$$

where r_{t+12}^{n} is the forward log-return on the *n* maturity claim between month *t* and *t+12*, $d_t - p_t$ is the log dividend price ratio of the market portfolio, e_t^{n} is the yield on the *n* maturity dividend at time *t*, and $y_t^{n,m}$ is the yield spread between the *n* and the *m* maturity dividend at time *t*. Maturities *n* and *m* are measured in years. The habit model is the Campbell and Cochrane (1999) model. The model is simulated using the series method of Wachter (2005). The long-run risk model is the model by Bansal and Yaron (2004) that features stochastic volatility.

	$E[r_{t+12}^{mkt} - r_{t+12}^{2}]$	$\beta_1^{mkt,2}$	$\gamma_1^{5,1}$	$\phi_1^{5,1}$
Data				
Empirical observation	-0.035	0.35	1.27	1.25
Theories				
Habit	0.038	0.12	-1.32	-0.80
Long-run risk	0.029	0.03	-0.95	-0.03
Lettau & Wacther (2007)	-0.067	-0.08	0.32	0.72
Disaster (Gabaix, 2012)	0	0	1	1
My model	-0.01	0.10	2.4	1.6

Table 11

Reconciling Theory with the Empirical Facts: Simulated Results in an Asset Pricing Model

This table shows results of simulations in my model. The results are based on 100,000 years of artificial data. The model is simulated to fit the U.S. data in the 1996-2016 period. The model is simulated on the quarterly horizon. Expected returns and standard deviations are annualized (multiplied by 4 and 2).

	Data	Model
Stock market moments		
$E[R^m_{t+1} - R^f]$	0.07	0.07
$\sigma[R^m_{t+1} - R^f]$	0.18	0.23
$E[P_t/D_t]$	57.3	49.7
$\sigma(p_t - d_t)$	0.22	0.28
AR1$(p_t - d_t)$	0.92	0.90
Term structure of equity results		
$E[r^{mkt}_{t+12} - r^2_{t+12}]$	-0.035	-0.01
$\beta_1^{mkt,2}$	0.35	0.10
$\gamma_1^{5,1}$	1.27	2.4
$\phi_1^{5,1}$	1.25	1.6

Figure 1
The Term Structure of One-Year Equity Returns

This figure shows the term structure of holding-period equity returns for the S&P 500. The figure shows the unconditional average return (solid line), the average return in bad times (dashed line), and the average return in good times (dash-dotted line). Good and bad times are defined by the ex ante dividend price ratio. Short-maturity equity claims is the average return to dividend futures of 1 to 7 years maturity. The long-maturity claim is the average return to the market portfolio. Returns are annual spot returns, 2005 – 2016.

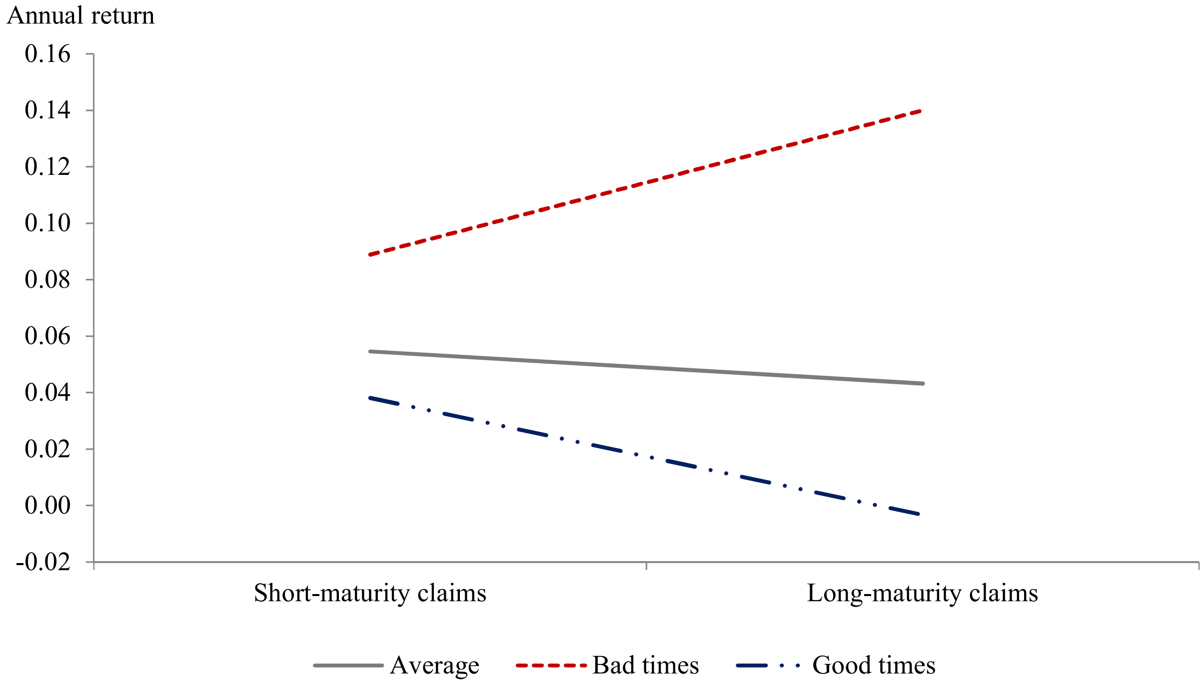
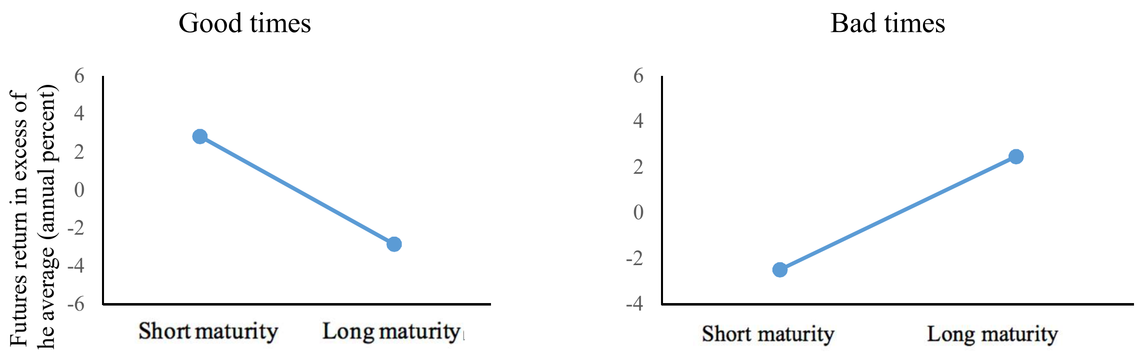


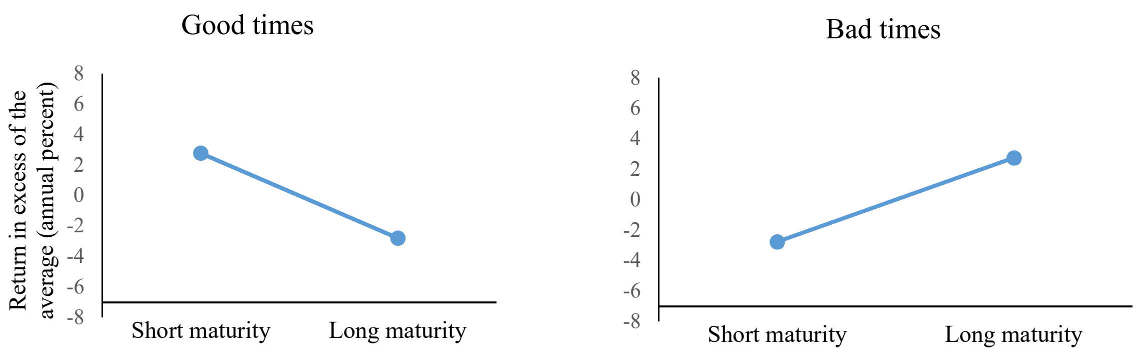
Figure 2
The Equity Term Structure in Good and Bad Times

This figure shows the term structure of one-year equity returns in good and bad times. Panel A shows the equity term structure estimated using dividend futures. The short-maturity return is the return to the one- and two-year dividend claims and the long-maturity return is the return to the six- and seven-year claims – all measured in excess of the cross-sectional and time-series averages. Panel B shows the equity term structure estimated using option implied dividends. The short-maturity claim is the return to the two-year dividend and the long-maturity claim is the return to the market portfolio, measured in excess of the cross-sectional and time-series averages. Panel C shows the term structure estimated using the cross-section of stocks. The duration of stocks is measured by a regression of excess returns on the realized long- minus short-maturity return in the 1996-2016 sample. Returns are measured as annual alpha in the five-factor model. Good (bad) times are months where the dividend price ratio is below (above) the median.

Panel A: Estimated using dividend futures (2005-2016)



Panel B: Estimated using option implied dividend prices (1996-2009)



Panel C: Estimated using the cross-section of stocks (1963-2015)

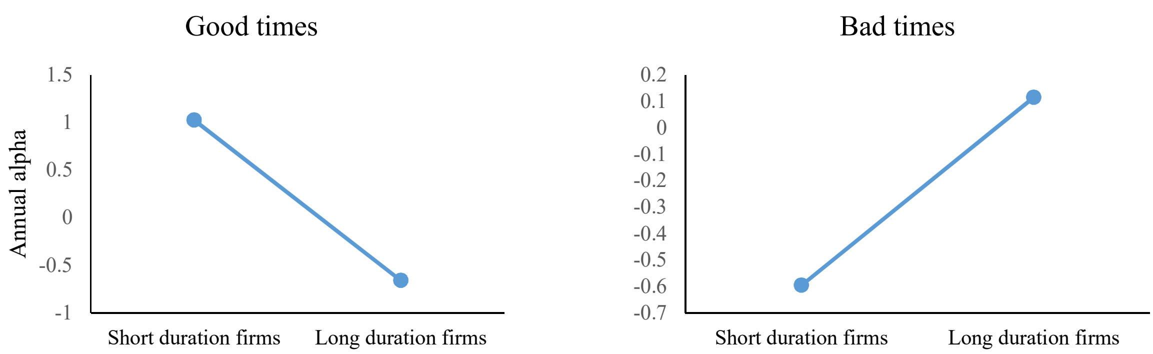
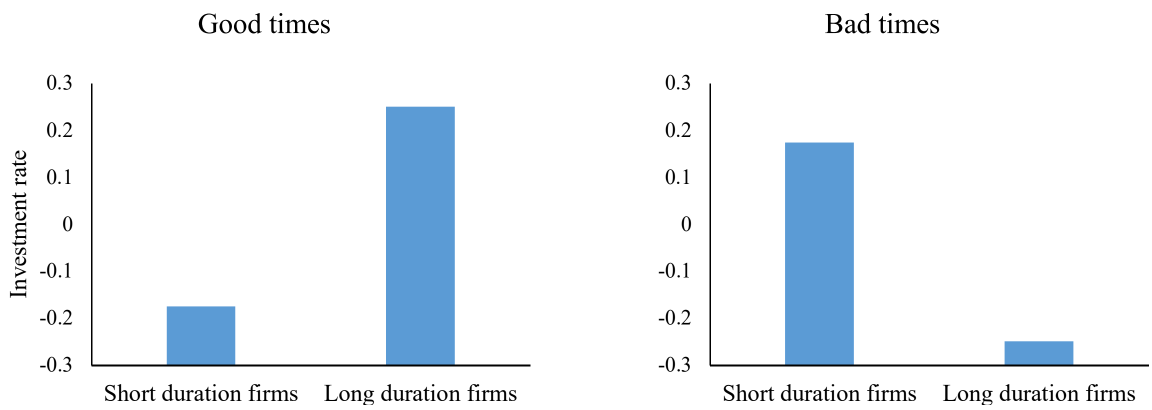


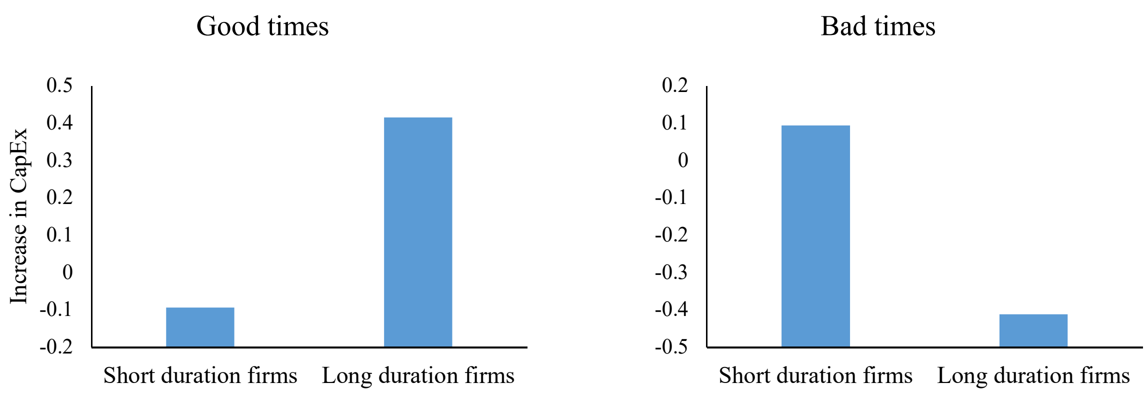
Figure 3
Real Effects of the Equity Term Structure

This figure shows average firm characteristics in good and bad times for firms with different duration of cash flows. Panel A shows the investment rate measured as CAPEX over the value of property, plant, and equipment. Panel B shows the annual change in capital expenditure. Panel C shows the capital to labor ratio measured as CAPEX to salaries. All characteristics are measured as cross-sectional percentiles in excess of the given portfolios time-series average. Duration is measured by sensitivity to the equity term premium. Good (bad) times are months where the dividend price ratio is below (above) the median. The sample is from 1964-2015.

Panel A: Investment (CAPEX/PPE)



Panel B: Investment (increase in capital expenditure)



Panel C: Capital to Labor Ratio

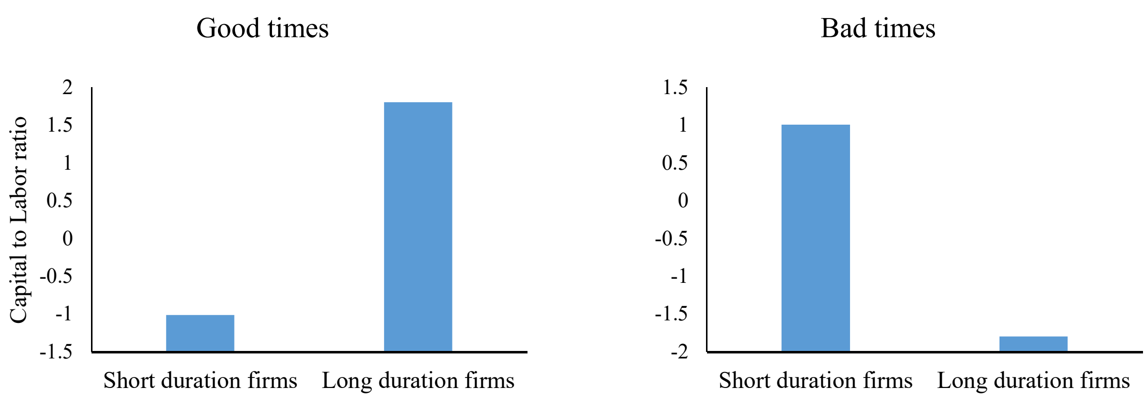


Figure 4
Realized Long-minus-Short Return and Dividend Price Ratios

This figure shows, for four different indexes, the ex ante log dividend price ratio and the realized return difference between long- and short-maturity claims. The future long-minus-short return is the average two-year log-return to the six- and seven-year dividend claim minus the average two-year log-return to the one- and two-year dividend claim. The graph indicates the starting date of the two-year period. After 2005 returns are based on dividend futures. Before 2005, the U.S. term premium is the two-year return difference between the two- and the one-year option implied dividend returns.

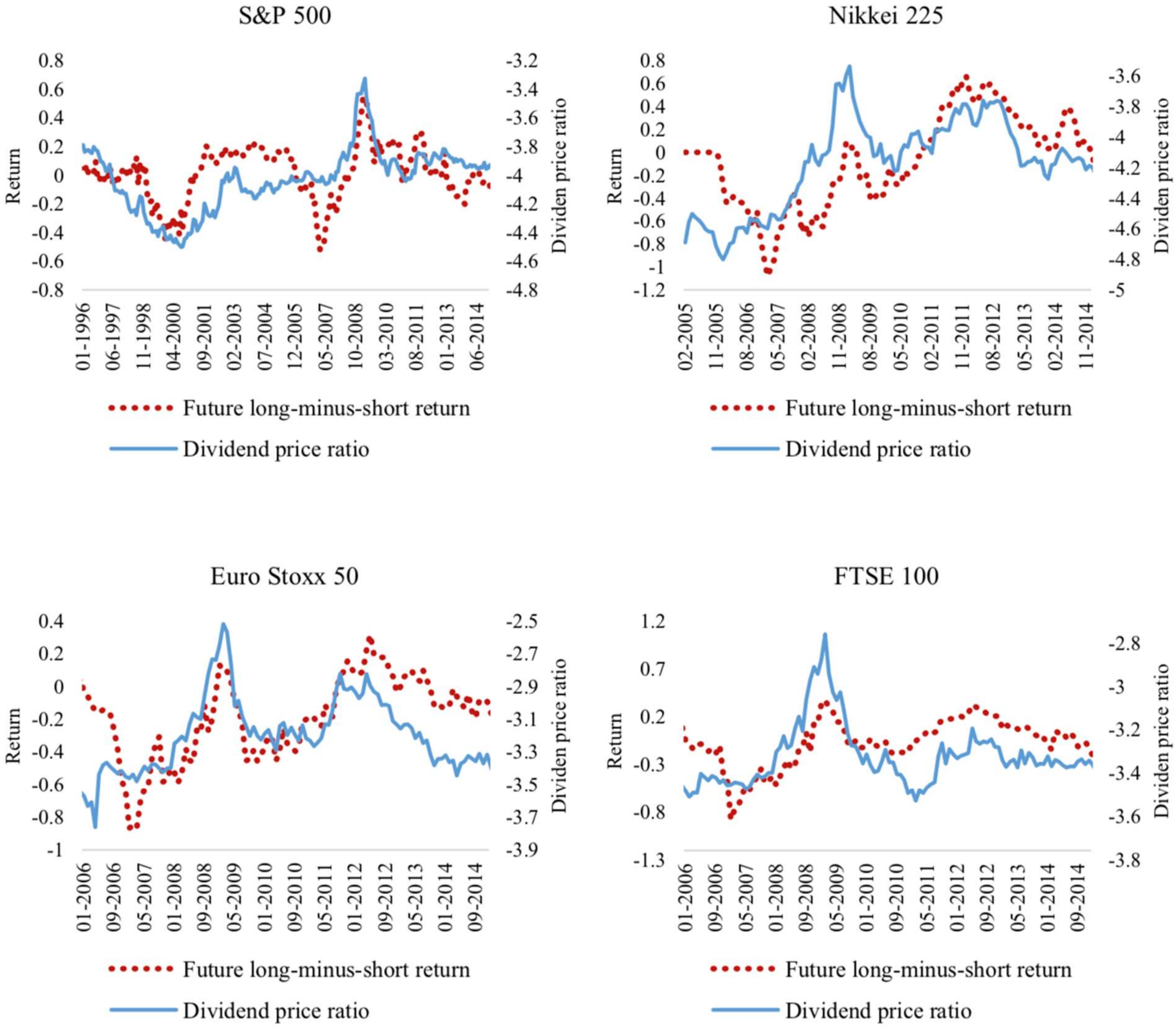


Figure 5
Realized Long-minus-Short Return

This figure shows for four different indexes the ex ante value of the cay variable and the realized return difference between long- and short-maturity claims. The future long-minus-short return is the average two-year log-return to the six- and seven-year dividend claim minus the average two-year log-return to the one- and two-year dividend claim. The graph indicates the starting date of the two-year period. After 2005 returns are based on dividend futures. Before 2005, the U.S. term premium is the two-year return difference between the two- and the one-year option implied dividend returns. The figure shows the U.S. cay variable for all indexes.

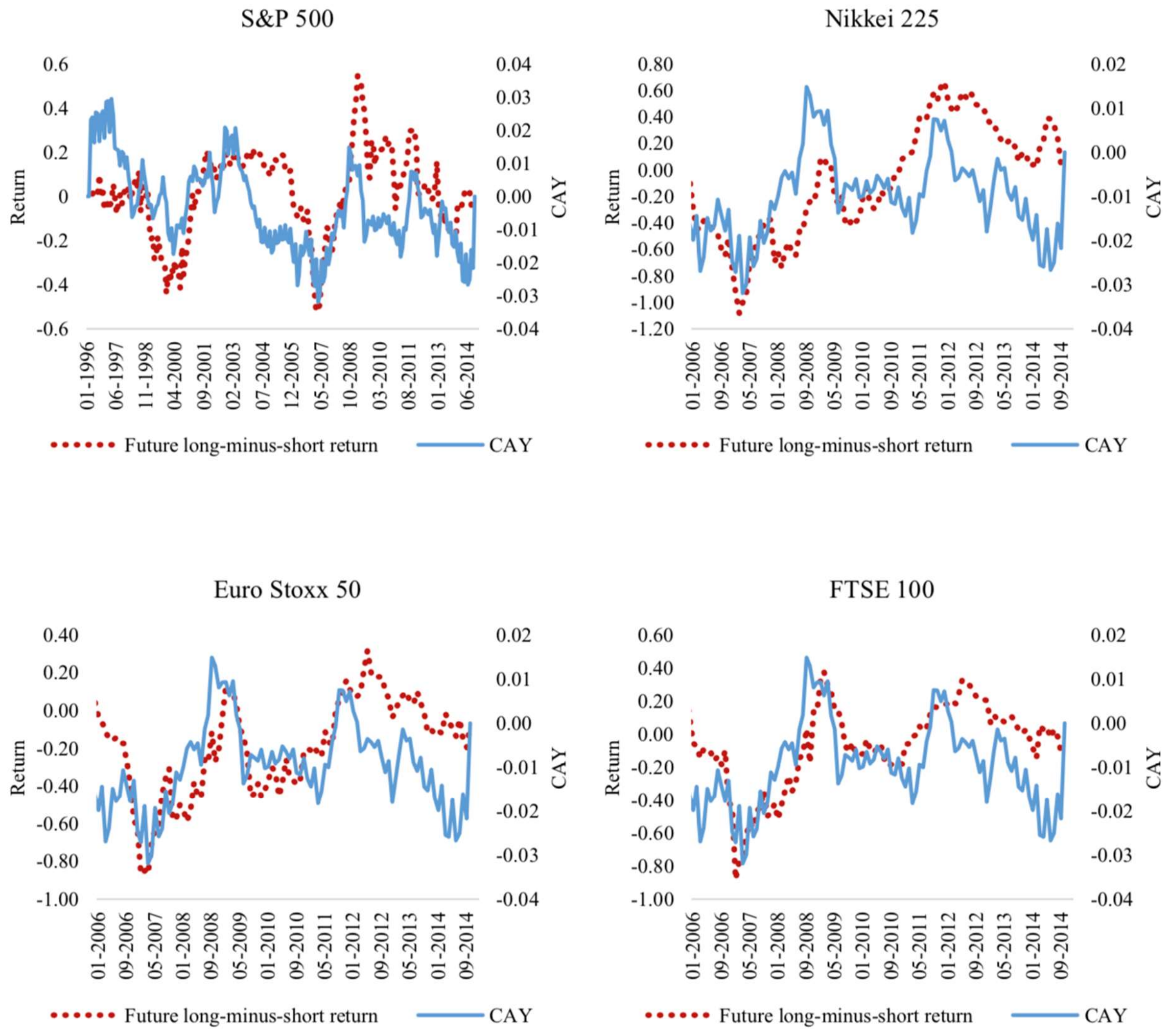


Figure 6
Time Variation in The Term Structure of Equity Yields

This figure shows the time variation in the term structure of equity yields. The figure shows the yield for the two-, five-, and seven-year dividend claim. The equity yield for dividends that are paid out at time *t*+*n* are defined as:

$$e_t^n = \frac{1}{n}(d_t - f_t^n)$$

where d_t is the rolling annual dividends at time *t* and f_t^n is the forward price of the *n* maturity claim at time t.

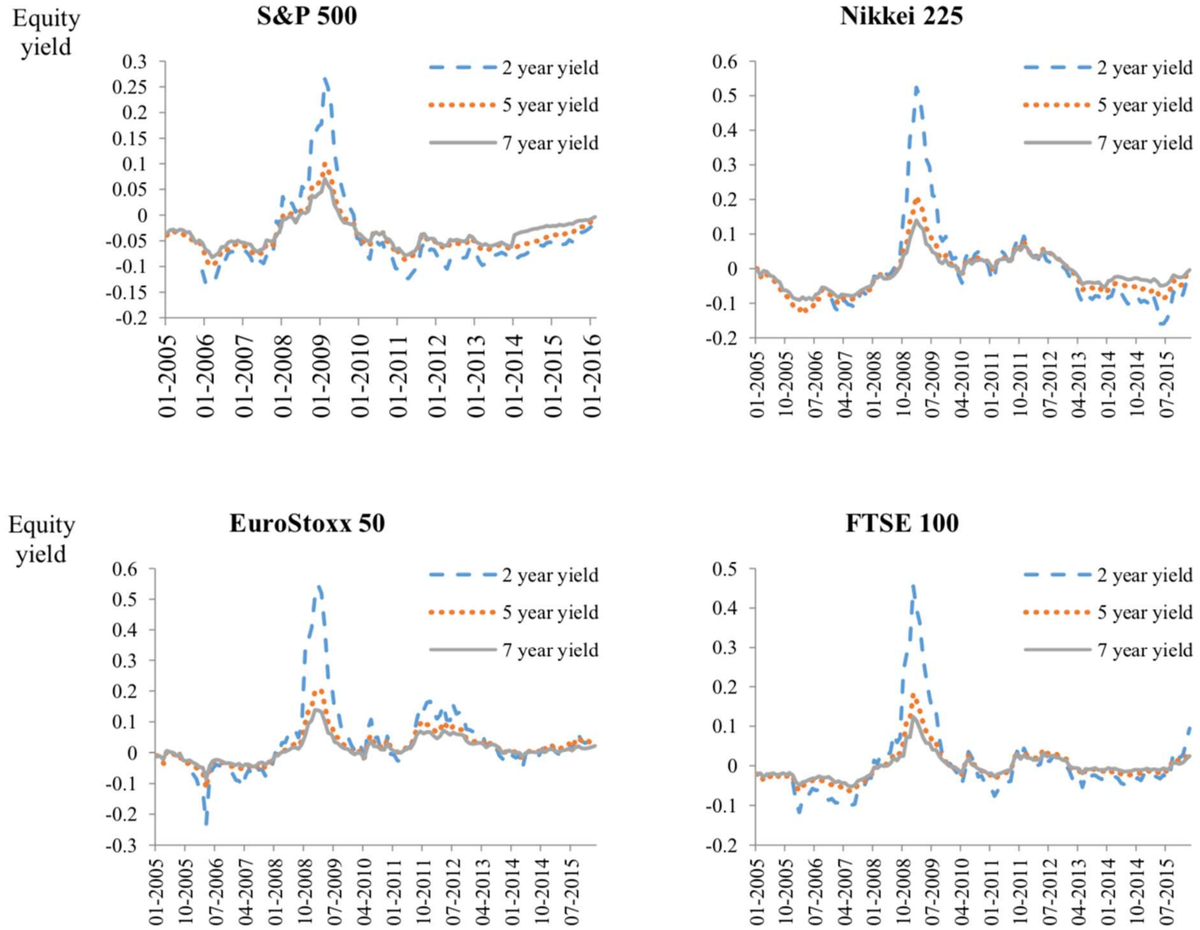


Figure 7

Reconciling the Facts in an Asset Pricing Model: Equity Term Premia in Good and Bad Times

This figure shows equity term premia $\theta_t^{n,1}$ in the asset pricing model on average, in good times, and in bad times. The term premia are plotted as a function of the long-maturity claims (the x-axis). Good (bad) times are periods where the ex ante dividend price ratio of the market portfolio is below (above) the time series median. The results are based on 100,000 years of artificial quarterly data.

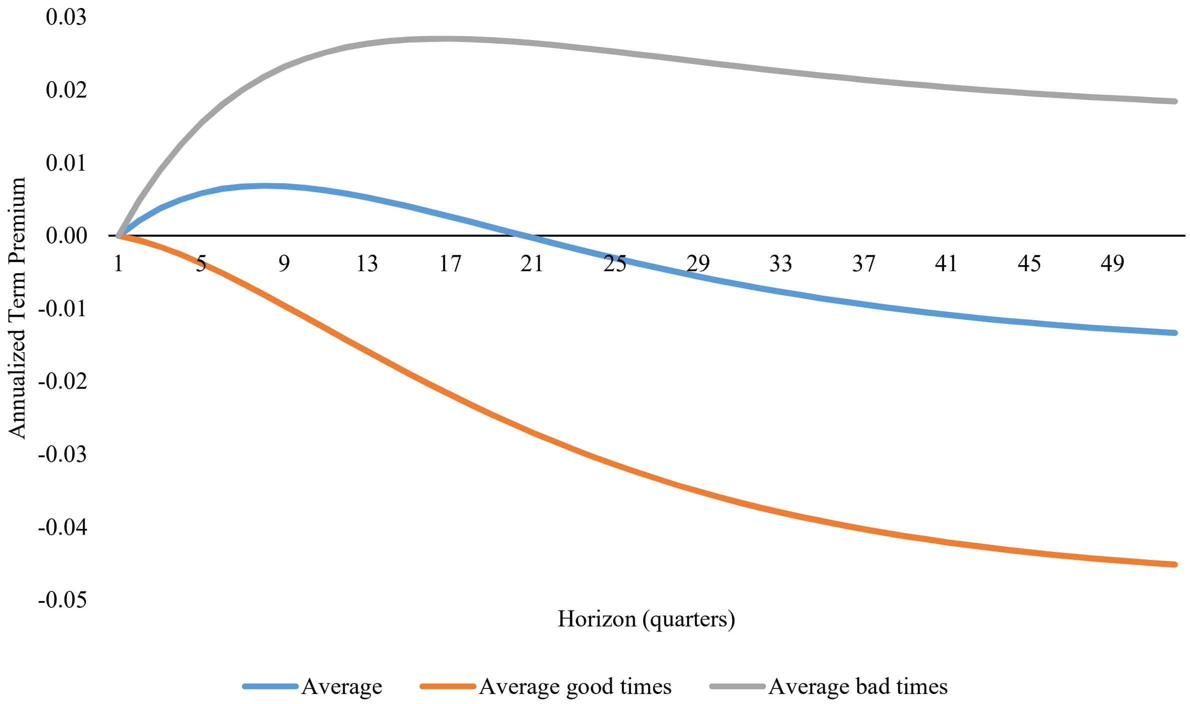


Table A1
Summary Statistics on Dividend Futures

This table provides summary statistics for dividend futures. Returns and standard deviations are for annualized claims. The loading on the dividend price ratio refers to the regression coefficient in a regression of realized excess returns on the ex ante log dividend price ratio of the market portfolio. Good and bad times are based on the median dividend price ratio.

	Maturity of dividend claim (years)							
	1	2	3	4	5	6	7	Mkt
Panel A: S&P 500								
Average futures returns	0.015	0.012	0.021	0.021	0.024	0.028	0.037	-0.024
Variance annual returns	0.002	0.017	0.027	0.031	0.038	0.044	0.048	0.077
Variance quarterly returns	0.006	0.023	0.025	0.030	0.037	0.041	0.046	0.080
Loading on $d_t - p_t$	0.059	0.275	0.328	0.404	0.489	0.548	0.575	0.677
Average good times	0.017	-0.006	0.010	0.002	0.000	0.000	0.012	-0.080
Average bad times	0.013	0.029	0.034	0.045	0.053	0.062	0.067	0.041
Average yields	-0.038	-0.044	-0.044	-0.042	-0.041	-0.038	-0.035	
Standard dev. of yield	0.115	0.077	0.052	0.042	0.036	0.033	0.029	
Panel B: Nikkei 225								
Average futures returns	0.109	0.071	0.048	0.077	0.081	0.084	0.089	-0.040
Variance annual returns	0.006	0.071	0.117	0.135	0.150	0.161	0.170	0.121
Variance quarterly returns	0.018	0.084	0.107	0.113	0.119	0.121	0.123	0.117
Loading on $d_t - p_t$	0.088	0.611	0.855	0.953	1.015	1.055	1.086	1.002
Average good times	0.055	-0.051	-0.083	-0.011	-0.004	0.004	0.017	-0.097
Average bad times	0.13	0.15	0.16	0.16	0.17	0.16	0.16	0.02
Average yields	0.020	0.004	-0.013	-0.017	-0.016	-0.014	-0.012	
Standard dev. of yield	0.160	0.131	0.097	0.077	0.065	0.056	0.048	
Panel C: Euro Stoxx 50								
Average futures returns	0.033	0.044	0.019	0.004	-0.003	-0.007	-0.007	-0.062
Variance annual returns	0.005	0.044	0.091	0.100	0.100	0.099	0.099	0.099
Variance quarterly returns	0.010	0.063	0.080	0.083	0.084	0.082	0.084	0.090
Loading on $d_t - p_t$	0.096	0.500	0.605	0.604	0.587	0.570	0.549	0.560
Average good times	-0.004	-0.015	-0.035	-0.047	-0.050	-0.050	-0.045	-0.120
Average bad times	0.033	0.126	0.110	0.089	0.075	0.064	0.056	0.035
Average yields	0.056	0.046	0.031	0.025	0.020	0.015	0.012	
Standard dev. of yield	0.128	0.124	0.086	0.066	0.053	0.045	0.038	
Panel D: FTSE 100								
Average futures returns	0.018	0.038	0.027	0.020	0.017	0.017	0.020	-0.035
Variance annual returns	0.005	0.030	0.064	0.072	0.073	0.071	0.070	0.063
Variance quarterly returns	0.009	0.043	0.054	0.058	0.059	0.060	0.061	0.062
Loading on $d_t - p_t$	0.151	0.763	0.853	0.876	0.854	0.823	0.787	0.917
Average good times	-0.012	-0.018	-0.013	-0.023	-0.026	-0.023	-0.018	-0.089
Average bad times	0.069	0.089	0.071	0.069	0.065	0.063	0.064	0.025
Average yields	0.000	0.005	0.001	0.000	-0.002	-0.002	-0.002	
Standard dev. of yield	0.098	0.099	0.069	0.053	0.042	0.035	0.030	

Table A2
Counter-Cyclical Equity Term Premia: Quarterly Returns

This table shows the relation between term premia and the dividend price ratio of the market portfolio. The table reports the parameter estimate from the following regression:

$$r^{n}_{t;t+3} - r^{m}_{t;t+3} = \beta^{n,m}_{0} + \beta^{n,m}_{1}(d_t - p_t) + \epsilon_{t,t+3}$$

where $d_t - p_t$ is the dividend price ratio of the market portfolio and $r^{n}_{t,t+3}$ is the three-month forward return to the dividend claim with *n* year maturity. The regression is based on monthly rolling regressions. The *t*-statistics are based on Newey and West (1987) standard errors corrected for 8 lags. The maturities n and m are both measured in years. The row *m=mean(1-7)* refers to the average return to the one- through seven-year maturity dividend claim. The sample is from 2005 to 2016.

	Maturity of long-maturity claim (n)						
	2	3	4	5	6	7	Mkt
Panel A: S&P 500							
m=1	0.03	0.06	0.09	0.12	**0.13**	**0.15**	**0.23**
	(0.50)	(1.07)	(1.63)	(1.91)	(2.00)	(2.09)	(3.23)
m=2		0.01	**0.04**	**0.06**	**0.07**	**0.07**	0.08
		(1.33)	(2.66)	(2.57)	(2.29)	(2.06)	(1.03)
m=3			0.02	0.02	0.03	0.04	0.08
			(1.13)	(0.84)	(1.15)	(1.03)	(1.22)
m=mean(1-7)							0.08
							(1.18)
Panel B: Nikkei 225							
m=1	**0.13**	**0.17**	**0.16**	**0.18**	**0.19**	**0.20**	0.23
	(2.33)	(2.27)	(2.07)	(2.17)	(2.15)	(2.30)	(1.31)
m=2		0.01	0.02	0.04	0.04	0.05	0.16
		(0.49)	(0.72)	(0.96)	(0.95)	(0.97)	(1.39)
m=3			0.00	0.01	0.01	0.00	0.06
			(0.53)	(0.56)	(0.30)	(-0.05)	(0.68)
m=mean(1-7)							1.20
							(0.19)
Panel C: EuroStoxx 50							
m=1	0.09	0.07	0.06	0.04	0.03	0.03	0.04
	(1.08)	(0.75)	(0.65)	(0.49)	(0.41)	(0.31)	(0.37)
m=2		-0.03	-0.04	-0.05	**-0.06**	**-0.06**	-0.02
		(-1.33)	(-1.50)	(-1.65)	(-2.18)	(-2.36)	(-0.59)
m=3			-0.01	-0.02	-0.03	-0.03	0.02
			(-1.69)	(-1.38)	(-1.55)	(-1.63)	(0.38)
m=mean(1-7)							0.03
							(0.90)

continued...

Panel D: FTSE 100							
m=1	0.18 (1.62)	0.16 (1.29)	0.17 (1.48)	0.17 (1.51)	0.17 (1.65)	0.16 (1.59)	**0.19** (2.02)
m=2		-0.06 (-1.48)	-0.07 (-1.42)	-0.08 (-1.50)	-0.08 (-1.31)	-0.08 (-1.33)	0.00 (-0.04)
m=3			-0.01 (-0.84)	-0.02 (-0.99)	-0.02 (-0.63)	-0.03 (-0.66)	0.06 (0.66)
m=mean(1-7)							0.08 (1.17)

Table A3
Counter-Cyclical Difference in Sharpe Ratios

This table shows the relation between the difference in Sharpe ratios for equity claims with different maturity and the dividend price ratio of the market portfolio. The table reports the parameter estimate from the following regression:

$$SR_{t,t+12}^{n} - SR_{t,t+12}^{m} = \beta_0^{n,m} + \beta_1^{n,m}(d_t - p_t) + \epsilon_{t,t+12}$$

where $d_t - p_t$ is the dividend price ratio of the market portfolio and $SR_{t,t+12}^{n}$ is the one-year log-Sharpe ratio of the log-return to the n maturity claim. The regression is based on monthly rolling regressions. The t-statistics are based on Newey and West (1987) standard errors corrected for 18 lags. The maturities n and m are both measured in years. The sample is from 2005 to 2016.

	Maturity of long-maturity claim (n)						
	2	3	4	5	6	7	Mkt
Panel A: S&P 500							
m=1	**1.47**	**2.07**	**2.64**	**3.31**	**3.64**	**3.04**	**3.51**
	(2.63)	(4.11)	(5.56)	(5.85)	(5.65)	(6.15)	(12.89)
m=2		**0.42**	**0.98**	**1.55**	**1.69**	**1.18**	1.18
		(2.24)	(2.83)	(2.97)	(2.45)	(2.70)	(1.29)
m=3			**0.63**	**0.95**	0.87	0.51	1.08
			(3.68)	(2.85)	(1.54)	(1.26)	(1.43)
m=mean(1-7)							0.93
							(1.47)
Panel B: Nikkei 225							
m=1	0.63	1.24	1.59	1.74	1.47	1.23	2.27
	(0.64)	(1.11)	(1.22)	(1.20)	(0.90)	(0.69)	(1.48)
m=2		**0.49**	**0.94**	**1.19**	1.15	1.02	0.99
		(3.64)	(2.57)	(2.24)	(1.80)	(1.43)	(1.09)
m=3			0.35	0.47	0.35	0.03	0.12
			(1.79)	(1.39)	(0.83)	(0.07)	(0.19)
m=mean(1-7)							0.25
							(0.51)
Panel C: EuroStoxx 50							
m=1	**1.45**	**1.83**	**2.01**	**2.12**	**2.29**	**2.22**	**2.00**
	(5.73)	(3.85)	(3.71)	(4.04)	(4.75)	(4.42)	(2.43)
m=2		0.19	0.44	0.49	**0.65**	**0.59**	0.72
		(0.77)	(1.53)	(1.75)	(2.66)	(2.52)	(1.17)
m=3			**0.17**	**0.31**	**0.44**	**0.44**	0.69
			(2.04)	(4.56)	(5.40)	(3.77)	(1.42)
m=mean(1-7)							0.61
							(1.23)

Continued…

Panel D: FTSE 100

m=1	**2.76**	**3.52**	**4.00**	**4.17**	**4.10**	**3.87**	**3.62**
	(4.32)	(3.94)	(3.64)	(3.60)	(3.58)	(3.25)	(3.31)
m=2		0.23	0.65	0.71	0.77	0.63	0.70
		(0.56)	(1.17)	(1.12)	(1.39)	(1.14)	(1.09)
m=3			**0.49**	0.42	**0.45**	0.24	0.29
			(2.52)	(1.79)	(2.13)	(0.90)	(0.62)
m=mean(1-7)							0.47
							(1.19)

Table A4
Counter-Cyclical Equity Term Premia: Stambaugh Correction

This table shows the relation between term premia and the dividend price ratio of the market portfolio. The table reports the parameter estimate from the following regression:

$$r_{t;t+12}^{n} - r_{t;t+12}^{m} = \beta_0^{n,m} + \beta_1^{n,m}(d_t - p_t) + \epsilon_{t,t+12}$$

where $d_t - p_t$ is the dividend price ratio of the market portfolio and $r_{t,t+12}^{n}$ is the twelve-month forward return to the dividend claim with *n* year maturity. The regression is based on monthly rolling regressions. The parameter estimate is corrected for the Stambaugh (1999) bias. The *t*-statistics are based on Newey and West (1987) standard errors corrected for 18 lags. The maturities *n* and *m* are both measured in years. The row *m=mean(1-7)* refers to the average return to the one- through seven-year maturity dividend claim. The sample is from 2005 to 2016.

	Maturity of long-maturity claim (*n*)						
	2	3	4	5	6	7	Mkt
Panel A: S&P 500							
m=1	0.10	**0.13**	**0.20**	**0.28**	**0.35**	**0.38**	**0.49**
	(1.59)	(1.97)	(2.75)	(3.41)	(3.71)	(3.94)	(3.63)
m=2		0.02	**0.10**	**0.18**	**0.23**	**0.24**	0.27
		(1.26)	(2.94)	(3.67)	(3.66)	(3.44)	(1.83)
m=3			0.05	0.07	0.09	0.10	0.21
			(1.84)	(1.15)	(1.00)	(1.02)	(1.54)
m=mean(1-7)							0.20
							(1.46)
Panel B: S&P 500 (using cay)							
m=1	1.30	2.26	**3.51**	**4.72**	**5.66**	**5.63**	**6.54**
	(1.10)	(1.61)	(2.44)	(3.23)	(3.80)	(4.07)	(3.47)
m=2		0.77	**2.09**	**3.32**	**4.01**	**3.95**	3.64
		(1.74)	(4.05)	(4.82)	(4.81)	(3.45)	(1.94)
m=3			**1.22**	**2.31**	**2.90**	**2.82**	2.93
			(4.72)	(3.56)	(3.31)	(2.41)	(1.65)
m=mean(1-7)							1.93
							(1.01)
Panel C: Nikkei 225							
m=1	**0.39**	**0.63**	**0.69**	**0.73**	**0.74**	**0.77**	**0.65**
	(4.91)	(3.23)	(2.89)	(2.64)	(2.42)	(2.31)	(2.29)
m=2		**0.17**	**0.25**	**0.30**	0.33	0.35	0.32
		(2.42)	(2.17)	(2.05)	(1.91)	(1.80)	(1.52)
m=3			0.05	0.06	0.06	0.03	0.00
			(1.08)	(0.86)	(0.57)	(0.21)	(-0.02)
m=mean(1-7)							0.05
							(0.38)

continued...

Panel D: EuroStoxx 50							
m=1	0.20	**0.31**	**0.31**	**0.31**	**0.29**	0.27	0.26
	(1.70)	(2.02)	(2.05)	(2.09)	(2.02)	(1.75)	(1.65)
m=2		0.01	0.00	-0.02	-0.04	-0.06	-0.05
		(0.19)	(-0.03)	(-0.23)	(-0.41)	(-0.60)	(-0.31)
m=3			-0.05	-0.08	**-0.10**	**-0.13**	-0.07
			(-1.52)	(-1.83)	(-2.17)	(-2.61)	(-0.67)
m=mean(1-7)							0.02
							(0.23)
Panel E: FTSE 100							
m=1	**0.26**	**0.32**	**0.34**	**0.33**	**0.30**	0.27	0.43
	(2.29)	(2.52)	(2.81)	(2.53)	(2.14)	(1.75)	(1.89)
m=2		-0.01	0.00	-0.02	-0.05	-0.08	0.06
		(-0.14)	(-0.02)	(-0.20)	(-0.40)	(-0.59)	(0.23)
m=3			-0.01	-0.04	-0.07	-0.11	0.01
			(-0.16)	(-0.55)	(-0.80)	(-0.99)	(0.07)
m=mean(1-7)							0.09
							(0.56)

Table A5
Predictability of Term Premia: R^2

This table shows the adjusted R^2 from the following regression of realized term premia on the dividend price ratio:

$$r^n_{t;t+12} - r^m_{t;t+12} = \beta_0^{n,m} + \beta_1^{n,m}(d_t - p_t) + \epsilon_{t,t+12}$$

where $d_t - p_t$ is the dividend price ratio of the market portfolio and $r^n_{t,t+12}$ is the twelve-month forward return to the dividend claim with n year maturity. The regression is based on monthly rolling regressions. The maturities n and m are both measured in years. The row *m=mean(1-7)* refers to the average return to the one- through seven-year maturity dividend claim. The sample is from 2005 to 2016.

	Maturity of long-maturity claim (n)						
	2	3	4	5	6	7	Mkt
Panel A: S&P 500							
m=1	0.12	0.10	0.14	0.17	0.20	0.20	0.17
m=2		0.02	0.11	0.19	0.21	0.20	0.07
m=3			0.10	0.06	0.05	0.06	0.06
m=mean(1-7)							0.05
Panel B: Nikkei 225							
m=1	0.25	0.23	0.23	0.23	0.22	0.23	0.21
m=2		0.14	0.18	0.19	0.19	0.19	0.09
m=3			0.12	0.09	0.06	0.02	-0.01
m=mean(1-7)							0.01
Panel C: Euro Stoxx 50							
m=1	0.40	0.21	0.20	0.19	0.18	0.17	0.25
m=2		0.00	0.00	0.00	-0.01	-0.01	0.00
m=3			-0.01	0.00	0.01	0.03	-0.01
m=mean(1-7)							0.02
Panel D: FTSE 100							
m=1	0.41	0.27	0.26	0.26	0.26	0.25	0.21
m=2		0.01	0.00	0.00	-0.01	-0.01	-0.01
m=3			0.04	0.06	0.09	0.12	0.00
m=mean(1-7)							0.01

Chapter 2

Conditional Risk

with Christian Skov Jensen

Abstract:
We present a new direct methodology to study conditional risk, that is, the extra return compensation for time-variation in risk. We show theoretically that the conditional part of the CAPM can be captured by augmenting the standard market model with a conditional-risk factor, which is a specific market timing strategy. Both in the U.S. and global sample covering 23 countries, all major equity risk factors load on our conditional-risk factor, implying that each factor has a higher conditional market beta when the market risk premium is high or the market variance is low. Accordingly, these factor returns can be partly explained by conditional risk. Studying the economic drivers of these results, we find evidence that conditional risk arises from variation in discount rate betas (not cash flow betas) due to the endogenous effects of arbitrage trading.

Keywords: asset pricing, conditional CAPM, factor models, time-varying discount rates.

JEL classification: G10, G12.

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According to the conditional CAPM, assets should have higher average returns if they have high market betas during times where the market risk premium is high or the variance is low. It is well known that such conditional risk cannot fully explain the return to the major cross-sectional risk factors (Lewellen and Nagel, 2006), but exactly how much of the cross-section of stock returns can be explained by conditional risk? Which is to say, how many of the major risk factors load on conditional risk and exactly how much of the factor returns does conditional risk explain? These questions have important implications for the economic magnitude of equity risk factors and for market efficiency more generally. In addition, such conditional risk is important for understanding the cost of capital of different firms and investment projects and for evaluating the performance of professional asset managers. In this paper, we therefore estimate and analyze the global impact of conditional risk on stock returns.

We find that conditional risk is a pervasive feature of the data. In a global sample covering 23 developed countries, all the major equity risk factors load on conditional risk. This conditional risk explains a non-negligible part of these factors' alpha: in the global sample, conditional risk explains around 20% of the CAPM alpha of the average cross-sectional risk factor. In addition, conditional risk explains all the alpha to time-series strategies such as volatility-managed portfolios (Moreira and Muir, 2017) or time series momentum (Moskowitz, Ooi, and Pedersen, 2012). In testing for the economics behind this pervasive influence of conditional risk, we find evidence that the conditional risk arises from trading activities of constrained arbitrageurs.

Before we explain our method and results in detail, recall that the basic concern in the conditional CAPM is that assets may have higher betas when the expected return is high or variance is low, meaning that these assets derive alpha from market timing. Previous tests of the conditional CAPM have accounted for such market timing by estimating time-varying betas either using instruments (Jagannathan and Wang, 1996) or rolling short-horizon regressions (Lewellen and Nagel, 2006) or both (Boguth, Carlson, Fisher, and Simutin, 2011; Cederburg and O'Doherty, 2016). But these approaches leave some uncertainty about the exact impact of conditional risk: instruments are unlikely to pick up all variation in betas (Hansen and Richard, 1987), and rolling short-horizon betas are backward looking and may miss some short-horizon variation.

Instead of using time-varying betas, we estimate the effect of conditional risk by using a new conditional-risk factor. We show theoretically that if we know the conditional market risk premium and variance, we can easily capture conditional risk in a factor regression by using a conditional-risk factor. This factor is a dynamic investment strategy that invests more in the market when the conditional market risk premium is high relative to the variance. If an asset loads positively on this conditional-risk factor in factor regressions, it means that the asset has a higher conditional market beta when either the market risk premium is high or the variance is low, and that the asset therefore should have a higher return than its unconditional market beta suggests.

The first step of our analysis is to construct this conditional-risk factor. To do so, we need to estimate the conditional market risk premium and variance. Recent research offers a series of estimators of the conditional market risk premium,[1] some of which are limited to the U.S. or the recent sample. In our main analysis, we rely on the three-stage estimator of Kelly and Pruitt (2013) because this estimator can be implemented in all the countries in our sample and over the full sample length, and because it is proven to forecast returns well both in- and out-of-sample. As to variance, we estimate this based on the assumption that it follows an AR(1) process. Our results are not sensitive to these choices: we document in the Appendix that our results are qualitatively the same when using other estimators of the conditional market risk premium and variance.

We next use our conditional-risk factor to study conditional risk in the cross-section of U.S. and global equities. As an example of this analysis, consider first the global value factor. To estimate the conditional risk in the value factor, we regress the time series of its excess return onto the market portfolio and our conditional-risk factor. Doing so, we find that the value factor has an unconditional market beta of -0.09 and a conditional risk beta of 0.03. The positive conditional risk beta implies that the conditional market beta for the value factor increases when the market risk premium is high or the variance is low, meaning that the factor is more risky than its unconditional market beta suggests. According to our conditional-risk factor, this conditional risk justifies a 1.56 percentage points annual return. These 1.56 percentage points represent 36% of the unconditional CAPM alpha for the value strategy, suggesting that conditional risk cannot explain the full alpha to the value strategy, but nonetheless explains a meaningful part.

More generally, we find in our long U.S. sample that the risk factors value, profitability,

[1](e.g. Lettau and Ludvigson, 2001a; Campbell and Thompson, 2008; Binsbergen and Koijen, 2010; Kelly and Pruitt, 2013; Martin, 2016)

investment, momentum, and betting against beta all load positively on conditional risk. Among these factors, conditional risk explains on average 11% of the unconditional alpha. In our broad global sample from 1986-2016, we find qualitatively similar but quantitatively stronger results: the risk factors value, profitability, investment, momentum, and betting against beta all load on conditional risk, and this positive loading explains on average 20% of the alpha to these strategies. We obtain similar results in the individual countries in our sample: in 22 out of the 23 countries we study, the average cross-sectional equity risk factor loads positively on conditional risk.

Another class of risk factors that we suspect load on conditional risk is time series strategies. These are dynamic trading strategies that vary their position in the market portfolio based on certain signals, meaning that they have time-varying betas and potentially load on conditional risk. One such time series strategy is the volatility-managed portfolios by Moreira and Muir (2017), which is a strategy that increases its position in the market portfolio when the variance of the market is low. We study the strategy empirically and find that conditional-risk explains all of its unconditional alpha, both in the U.S. and global sample. Similarly, we find that conditional-risk helps explain the time-series momentum strategy by Moskowitz, Ooi, and Pedersen (2012).

As the next part of the analysis, we ask why all the major risk factors load on conditional risk. Which is to say, why do the cross-sectional risk factors all have higher conditional betas when when the price of risk is high? As a first step in understanding the conditional risk in the cross-sectional risk factors, we analyze whether the conditional-risk loadings come from conditional cash flow- or discount rate risk. Similarly to how the return to the market portfolio can be decomposed into discount rate news and cash flow news, we show theoretically that one can decompose the conditional risk factor into a conditional cash-flow-risk factor and a conditional discount-rate-risk factor. Using these two factors, we find that the cross-sectional risk factors load primarily on conditional discount rate risk. This result implies that the conditional risk in these factors comes from time-variation in conditional discount rate betas, not conditional cash flow betas.

Motivated in part by this conditional discount rate risk, we next propose and test the hypothesis that the conditional risk comes from arbitrage trading. The arbitrage trading hypothesis, put forth by Cho (2017), argues that arbitrage trading creates betas because funding shocks to arbitrageurs cause the assets in their portfolios to correlate. Indeed, these funding shocks force arbitrageurs to trade large proportions of their different assets simultaneously. If the arbitrageurs are sufficiently large, this trading has a price impact and pushes the price of these assets in the same direction. If such a price impact occurs period after period, the assets thus become correlated. To the extent that arbitrageurs trade both the cross-sectional risk factors and the conditional-risk factor, these factors may thus be correlated because of such arbitrage trading. We test the hypothesis and find consistent empirical evidence. Indeed, we find that there is more conditional risk when there is more arbitrage capital invested in the strategies.

In summary, we introduce a new factor to study conditional risk, and, using this factor, we document that conditional risk is a pervasive feature in the data: all the major risk factors load on conditional risk. These conditional risk loadings imply that the conditional market betas of these strategies are higher when the conditional market risk premium is high or variance low. Going beyond regular betas, we find that this variation in market betas is driven by conditional discount rate betas, not conditional cash flow betas. Finally, we find evidence that the time-variation in betas, and thus the conditional risk, comes from arbitrage trading activities.

The paper proceeds as follows. Section 1 covers the theory behind conditional risk in factor models and shows how it relates to the concepts of discount rate and cash flow risk. Section 2 covers data and identification of expected return and variance. Section 3 studies conditional risk in stock returns. Section 4 studies the effect of arbitrage trading on conditional risk. Section 5 studies the robustness of the results. Section 6 discusses the results in relation to previous implementations of conditional factor models. Section 7 concludes.

1 Conditional Risk Theory

1.1 A Simple Example: The CAPM

The CAPM is the following statement:

$$E_t[r^i_{t+1}] = \frac{\mathrm{cov}_t(r^i_{t+1}; r^m_{t+1})}{\mathrm{var}_t(r^m_{t+1})} E_t[r^m_{t+1}] = \beta_t E_t[r^m_{t+1}] \tag{2.1}$$

where r^i_{t+1} is the excess return to asset i between period t and $t+1$, with m indexing the market, and E_t is the conditional expectation at time t.

To quantify the conditional risk in the CAPM, note first that taking unconditional expectations of (2.1) gives

$$E[r^i_{t+1}] = E[\beta_t]E[r^m_{t+1}] + \text{cov}\left(\beta_t; E_t[r^m_{t+1}]\right) \tag{2.2}$$

We show in the Appendix that the average beta can be written as

$$E[\beta_t] = \tilde{\beta} - \text{cov}\left(\beta_t; \frac{\text{var}_t(\tilde{r}^m_{t+1})}{\text{var}(\tilde{r}^m_{t+1})}\right) \tag{2.3}$$

where $\tilde{r}^m_{t+1} = r^m_{t+1} - E_t[r^m_{t+1}]$ is the shock to the market portfolio and

$$\tilde{\beta} = \frac{\text{cov}(r^i_{t+1}; \tilde{r}^m_{t+1})}{\text{var}(\tilde{r}^m_{t+1})} \tag{2.4}$$

is the asset's unconditional shock-beta. Inserting (2.3) into (2.2) gives

$$E[r^i_{t+1}] = \tilde{\beta}E[r^m_{t+1}] + \underbrace{\text{cov}\left(\beta_t; E_t[r^m_{t+1}] - b\,\text{var}_t(\tilde{r}^m_{t+1})\right)}_{\text{Conditional Risk}} \tag{2.5}$$

where the covariance term summarizes the conditional risk and

$$b = \frac{E[r^m_{t+1}]}{\text{var}(\tilde{r}^m_{t+1})} \tag{2.6}$$

is the unconditional price of risk. The above definition of conditional risk is almost identical to the one reported in equation (3) in Lewellen and Nagel (2006); the only difference is that conditional risk holds with equality in the above definition whereas it holds only as an approximation in Lewellen and Nagel. This difference comes from the fact that we are working with shock-betas whereas Lewellen and Nagel are working with traditional betas. The expression (2.5) intuitively conveys what conditional risk is: conditional risk is the tendency for an asset to have higher conditional beta when either the conditional market risk premium is high or the conditional market variance is low. Lewellen and Nagel (2006), and the literature in general, refers to these terms as *market* and *volatility* timing.

The expression for conditional risk in (2.5) features conditional betas, but we do not need to observe these conditional betas to calculate conditional risk: we only need the part of conditional betas that is spanned by the conditional market risk premium and variance. In fact, there is an intuitive factor representation that captures the effect of time-varying betas. We first define the conditional risk factor as

$$c_{t+1} = \tilde{r}_{r+1}(b_t - b) \tag{2.7}$$

where

$$b_t = \frac{E_t r^m_{t+1}}{\mathrm{var}_t(\tilde{r}_{r+1})}$$

is the conditional price of risk. We can then rewrite the expression in (2.5) as

$$E[r^i_{t+1}] = \tilde{\beta} E[r^m_{t+1}] + \underbrace{\mathrm{cov}(r^i_{t+1}; c_{t+1})}_{\text{Conditional Risk}} \tag{2.8}$$

The covariance term in (2.8) captures conditional risk in another simple and intuitive way. The conditional risk is positive if the asset in question tends to covary more with the market when the price of risk is high, and the conditional risk is negative if the asset tends to covary more with the market when the price of risk is low.

The shock to the market is part of the conditional risk factor but the market portfolio is actually orthogonal to the conditional risk factor. To see why, note that the sign with which the shock to the market influences the conditional risk factor is determined by the conditional price of risk: when the price of risk is high, a positive shock to the market increases the value of the conditional risk factor, and when the conditional price of risk is low, a positive shock to the market decreases the value of the conditional risk fact. This time-varying effect of the shock to the market is what causes the market to be orthogonal to the conditional risk factor: sometimes the market portfolio correlates positively with the conditional risk factor and sometimes it correlates negatively with the conditional risk factor; on average, the two effects cancel out and the unconditional covariance with the conditional risk factor is therefore zero. We formally summarize all the properties of the conditional risk factor in Proposition 2.

Example continued: The SDF Approach

We can arrive at the results above easily if we use the stochastic discount factor language instead of the beta language. The stochastic discount factor approach is also useful when generalizing the results to a multi-factor model.

The stochastic discount factor of the CAPM[2] is

$$m_{t+1} = \frac{1}{R_t^f} - \frac{1}{R_t^f} b_t \tilde{r}_{t+1}^m \tag{2.9}$$

which can be written as

$$m_{t+1} = \frac{1}{R_t^f} - \frac{1}{R_t^f} b\tilde{r}_{t+1}^m - \frac{1}{R_t^f}(b_t - b)\tilde{r}_{t+1}^m \tag{2.10}$$

The law of one prices implies that

$$0 = E_t[m_{t+1} r_{t+1}^i] = E_t[R_t^f m_{t+1} r_{t+1}^i] \tag{2.11}$$

By the law of iterated expectations we have

$$0 = E[R_t^f m_{t+1} r_{t+1}^i)] \tag{2.12}$$

$$= E[r_{t+1}^i] + \text{cov}(r_{t+1}^i; R_t^f m_{t+1}) \tag{2.13}$$

meaning that

$$E[r_{t+1}^i] = -\text{cov}(r_{t+1}^i; R_t^f m_{t+1}) \tag{2.14}$$

$$= \tilde{\beta} E[r_{t+1}^m] + \underbrace{\text{cov}(r_{t+1}^i; c_{t+1})}_{\text{Conditional Risk}} \tag{2.15}$$

which is the same expression as in (2.8). In the following section we use the stochastic

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[2]The notation for the stochastic discount factor for the CAPM in expression (2.9) differs slightly from the one usually used. Cochrane (2001) uses

$$m_{t+1} = A_t + B_t R_{t+1}^M$$

where $A_t = 1/R_t^f - B_t E_t R_{t+1}^M$ and $B_t = -b_t/R_t^f$. But this expression is of course the same as ours:

$$m_{t+1} = A_t + B_t R_{t+1}^M = \frac{1}{R_t^f} + B_t(R_{t+1}^M - E_t[R_{t+1}^M]) = \frac{1}{R_t^f} - \frac{1}{R_t^f} b_t \tilde{r}_{t+1}^m$$

discount factor language to more formally derive a multi factor model with conditional risk.

1.2 Conditional Risk in Factor Models

We now derive a general statement for conditional risk in factor models. Consider the class of factor models captured by the following stochastic discount factor for $k = 1, \ldots, K$ traded risk factors:

$$m_{t+1} = \frac{1}{R_t^f} - \frac{1}{R_t^f} \sum_{k=1}^{K} b_t^k \tilde{r}_{t+1}^k \tag{2.16}$$

where

$$\tilde{r}_{t+1}^k = r_{t+1}^k - E_t[r_{t+1}^k] \tag{2.17}$$

and

$$b_t^k = \frac{E_t[r_{t+1}^k]}{\mathrm{var}_t(\tilde{r}_{r+1}^k)}$$

is the time t shock and price of risk for factor k. The expression in (2.16) can be rewritten as

$$m_{t+1} = \frac{1}{R_t^f} - \frac{1}{R_t^f} \sum_{k=1}^{K} b^k \tilde{r}_{t+1}^k - \frac{1}{R_t^f} \sum_{k=1}^{K} (b_t^k - b^k) \tilde{r}_{t+1}^k \tag{2.18}$$

where b^k is the unconditional price of risk for factor k

$$b^k = \frac{E[r_{t+1}^k]}{\mathrm{var}(\tilde{r}_{r+1}^k)}$$

By applying the law of one price and taking unconditional expectations, we can state an unconditional model that incorporates conditional risk. Before doing so, we define the conditional risk factors $c_{t+1}^k = \tilde{r}_{r+1}^k (b_t^k - b^k)$.

Proposition 1 (conditional risk in factor models)

The unconditional expected excess return on an asset i is given by

$$E[r_{t+1}^i] = \sum_{k=1}^{K} \tilde{\beta}^k \lambda^k + \sum_{k=1}^{K} \beta_c^k \lambda_c^k \tag{2.19}$$

where

$$\tilde{\beta}^k = \frac{\operatorname{cov}(r^i_{t+1}; \tilde{r}^k_{t+1})}{\operatorname{var}(\tilde{r}^k_{t+1})}, \qquad \lambda^k = E[r^k_{t+1}], \tag{2.20}$$

$$\beta^k_c = \frac{\operatorname{cov}(r^i_{t+1}; c^k_{t+1})}{\operatorname{var}(c^k_{t+1})}, \qquad \lambda^k_c = \operatorname{var}(c^k_{t+1}) \tag{2.21}$$

In the factor model above, each factor k is represented by two betas: one for its unconditional risk and the other for its conditional risk. These two orthogonal factors capture all of the unconditional implications of the stochastic discount factor in (2.16). The following proposition summarizes the properties of the two factors and their betas.

Proposition 2 (properties of conditional risk factors and betas)

2.a (zero mean factors): The means of all factors are zero:

$$E[\tilde{r}^k_{t+1}] = E[c^k_{t+1}] = 0 \tag{2.22}$$

2.b (uncorrelated factors): For each factor k, the return and shock to the risk factor is uncorrelated with the conditional risk factor:

$$\operatorname{cov}(r^k_{t+1}; c^k_{t+1}) = \operatorname{cov}(\tilde{r}^k_{t+1}; c^k_{t+1}) = 0 \tag{2.23}$$

2.c (shock betas for the factors): The factor k has a loading of one on its own shock:

$$\frac{\operatorname{cov}(r^k_{t+1}; \tilde{r}^k_{t+1})}{\operatorname{var}(\tilde{r}^k_{t+1})} = 1 \tag{2.24}$$

2.d (constant-beta equivalence): If an asset j has a constant conditional beta, the expected return is given by the usual unconditional beta. That is, if

$$\beta^k_t = \frac{\operatorname{cov}_t(r^j_{t+1}; r^k_{t+1})}{\operatorname{var}_t(r^k_{t+1})} = c \tag{2.25}$$

then

$$\tilde{\beta}^k = \beta^k \qquad \text{and} \qquad \beta^k_c = 0 \tag{2.26}$$

While Proposition 1 allows for the estimation of a k factor model, we will focus on the one factor CAPM model in the empirical section. We do so because conditional risk with respect to the market portfolio has the most tangible interpretation and because the market factor is the most widely used factor.

1.3 Conditional Cash Flow and Discount Rate Risk

Conditional market risk arises because conditional market betas are higher when the price of risk is higher. As shown by Campbell and Vuolteenaho (2004), conditional market betas are the sum of the given asset's conditional cash flow and discount rate betas. Accordingly, the conditional risk must come from either conditional cash flow or discount rate betas being high when the price of risk is high. In this section, we show how to estimate these two sources of conditional risk by decomposing the conditional risk factor into two.

First note that shocks to the market portfolio, $\tilde{r}_{t+1}$, are given by cash flow news and discount rate news (Campbell and Shiller, 1988):

$$\tilde{r}^m_{t+1} = N_{CF,t+1} + N_{DR,t+1} \tag{2.27}$$

The beta of an individual stock can then be expressed as:

$$\beta_t = \frac{\text{cov}_t(r^i_{t+1}; N_{CF,t+1})}{\text{var}_t(\tilde{r}_{t+1})} + \frac{\text{cov}_t(r^i_{t+1}; N_{DR,t+1})}{\text{var}_t(\tilde{r}_{t+1})} \tag{2.28}$$

$$\beta_t \equiv \beta^{CF}_t + \beta^{DR}_t \tag{2.29}$$

Similarly, the market's conditional risk factor can be decomposed into two parts:

$$c^m_{t+1} = \tilde{r}^m_{r+1}(b^m_t - b^m) \tag{2.30}$$

$$= N_{CF,t+1}(b^m_t - b^m) + N_{DR,t+1}(b^m_t - b^m) \tag{2.31}$$

$$\equiv c^{CF}_{t+1} + c^{DR}_{t+1} \tag{2.32}$$

where c^{CF}_{t+1} is the conditional cash-flow-risk factor and c^{DR}_{t+1} is the conditional discount-rate-risk factor. Loading on conditional cash flow risk and conditional discount rate risk has a tangible economic interpretation. The unconditional covariance with the two risk factors summarizes the covariance of cash flow- and discount rate betas with the expected return and variance:

$$\operatorname{cov}(r^i_{t+1}, c^{CF}_{t+1}) = \operatorname{cov}\left(\beta^{CF}_t; E_t[r^m_{t+1}] - b\,\operatorname{var}_t(\tilde{r}^m_{t+1})\right) \tag{2.33}$$

and

$$\operatorname{cov}(r^i_{t+1}, c^{DR}_{t+1}) = \operatorname{cov}\left(\beta^{DR}_t; E_t[r^m_{t+1}] - b\,\operatorname{var}_t(\tilde{r}^m_{t+1})\right) \tag{2.34}$$

2 Methodology

2.1 Identifying Conditional Moments

In order to estimate our factor model, we must estimate the conditional mean and variance of the factors. In this section, we outline the identifying assumptions we rely on in doing so.

To estimate the conditional market risk premium, we use the three pass estimator suggested by Kelly and Pruitt (2013). The estimator uses the cross-section of valuation ratios to estimate the expected return. By using the cross-section of valuation ratios rather than just the valuation ratio for the market, it is possible to separate the effect of expected growth rates and expected discount rates. Accordingly, the methodology consistently recovers the conditional market risk premium based on two simple identifying assumptions: (1) the expected log return and log growth rates are linear in a set of latent factors, and (2) these factors evolve according to a first-order vector autoregression.

We rely on the Kelly and Pruitt estimator for multiple reasons. Most importantly, the method is proven to predict the one-month expected market return well both in- and out-of-sample, and it is proven to work in both the U.S. and internationally. Indeed, Kelly and Pruitt (2013) show that the estimator predicts the one-month expected return on the U.S. market portfolio with an R^2 of 2.38 in-sample and 0.93 out-of-sample; and it predicts the global market portfolio with an R^2 of 1.5 out-of-sample. In addition, the estimator consistently recovers the market risk premium under assumptions that are consistent with the null-hypothesis we test against when we are testing for conditional risk.

With respect to the variance, we similarly assume that the market variance evolves according to a first-order autoregression. We rely on this assumption because it is transparent and in line with recently published papers revolving around time-varying variance, such as

Campbell, Giglio, Polk, and Turley (2017).

Our results in the empirical section are highly robust to other measures of expected return and variance. We verify in the Appendix that the results are robust to estimating expected returns based on the measures of Campbell and Thompson (2008). We also verify that the results are robust to using the variance estimated in Bollerslev, Tauchen, and Zhou (2009) or calculating variance based on SVIX.

In order to estimate conditional cash flow and discount rate risk, we need to decompose returns into cash flow news and discount rate news. For simplicity, we rely on the quarterly time series estimated by Campbell, Giglio, Polk, and Turley (2017). The authors make the time series available online.

2.2 Data

Our sample consists of equities from 23 different countries between August 1963 and December 2016. The 23 markets in our sample correspond to the countries belonging to the MSCI World Developed Index as of December 31, 2016. Stock returns are from the union of the CRSP tape and the XpressFeed Global Database. All returns are in USD and do not include any currency hedging. All excess returns are measured as excess returns above the U.S. Treasury bill rate. We report summary statistics in Table 1.

We study conditional risk in each country in our sample and in a broad global sample. Our broad sample of global equities contains all available common stocks on the union of the CRSP tape and the XpressFeed Global database. For companies traded in multiple markets we use the primary trading vehicle identified by XpressFeed. Our global sample runs from January 1986 to December 2016 because XpressFeed's Global coverage starts in 1986 for most countries (see Table 1).

The Kelly and Pruitt (2013) estimator takes as input portfolios sorted on size and book-to-market. In the U.S., we use 100 portfolios sorted unconditionally on size and book-to-market from Ken French's website. In the global sample, we similarly create 100 portfolios sorted unconditionally on size and book-to-market. In the individual international countries, we create 25 portfolio sorted first on size and then conditionally on book-to-market. We use only 25 portfolios and conditional sorts because some of the countries have few firms in the beginning of the sample and the conditional sorts into 25 portfolios helps ensure an adequate number of firms in each portfolio.

We calculate monthly variance as the sum of squared daily residuals over the month with a degree of freedom adjustment for the estimation of the mean.

$$\widehat{\mathrm{var}}_t(\tilde{r}^m_{t+1}) = \frac{n}{n-1}\sum_{i=1}^{n}(r^m_i - \bar{r}^m)^2 \tag{2.35}$$

where n is the number of trading days in the month. The estimation assumes that the expected return is constant during each month.

The expected time t variance is then calculated as:

$$\mathrm{var}_t(\tilde{r}^m_{t+1}) = \hat{\theta}_0 + \hat{\theta}_1\widehat{\mathrm{var}}_{t-1}(\tilde{r}^m_t) \tag{2.36}$$

where $\hat{\theta}_0$ and $\hat{\theta}_1$ are parameter estimates from the following regression:

$$\widehat{\mathrm{var}}_t(\tilde{r}^m_{t+1}) = \theta_0 + \theta_1\widehat{\mathrm{var}}_{t-1}(\tilde{r}^m_t) \tag{2.37}$$

We rely on in-sample estimations for the expected variance, but the results are robust to using out-of-sample estimates of the variance as in Bollerslev, Tauchen, and Zhou (2009).

3 Conditional Risk in Stock Returns

Table 1 offers summary statistics of the 24 exchanges in our sample. The first three columns show the time-series median market capitalization of the firms listed in a given country, the time-series median number of firms, and the time-series average weight of the given country in the global portfolio. The U.S. has a high average weight in the global portfolio, but this is largely driven by the early years 1986-1990 where the U.S. constitutes the most of the sample. The weight of the U.S. market is downward trending throughout the sample and towards the end of the sample the weight of the U.S. is around .2. The fifth and the sixth columns in Table 1 show the average standard deviation and market risk premium in annualized terms.

The last three columns of Table 1 shows the R^2 of the expected variance and return to the market portfolio. Regarding the variance, the R^2 is generally around 30% to 50%, with the U.S. and the global portfolio being in the low end. This high R^2 corresponds to previous studies on predicting variance (Bollerslev, Tauchen, and Zhou, 2009; Bollerslev, Hood, Huss, and Pedersen, 2016), suggesting that our simple method for predicting variance works well.

The two last columns of Table 1 summarize the R^2 of the expected return on the market portfolio. The first column shows the R^2 of the expected log return to the market portfolio, which is what the Kelly Pruitt estimator extracts. The last column shows the expected excess returns, which is calculated under the assumption of log-normally distributed returns by adding one-half the conditional log-variance to the log-return, taking the exponential, and subtracting the risk-free rate.

The table shows that the R^2 for the log-returns in the U.S. and the global sample is 1.6% and 2.4%, which is around the same as reported by Kelly and Pruitt (2013). Internationally, the R^2 vary between 0.5% to 3.3%, with the median being 2.2%. The results reported by Kelly and Pruitt for the U.S. and global sample thus appear to extend to most individual exchanges. The R^2 for the expected excess return are similar to those for the log-return.

The expected variance and market return is used to calculate the relative price of risk $b_t - b$, which is an important input for the conditional-risk factor. Figure 1 visually inspects this relative price of risk in the U.S. (Panel A) and the global sample (Panel B). The price of risk varies substantially on both the short and long horizon. The substantial short horizon variation in the price of risk underlines the importance of using a forward looking measure of the price of risk. Indeed, an alternative to our approach is to implement the conditional CAPM over short horizons for which the price of risk is assumed to be constant. If daily data are available, the horizon is often around three to six months, and if daily data are not available, the horizon is substantially longer. The price of risk in Figure 1 exhibits substantial variation over these horizons, which, if statistically significant and not driven by forecast errors, invalidates this unparemetric approach.

The price of risk in Figure 1 also shows substantial long-run variation that appears closely linked to economic conditions. In the U.S. in particular, the price of risk tends to increase in the years following economic recessions: the price of risk increases in the years following the recessions in 1973-1975, 1981-1982, 1990-1991, 2001, and 2007-2009. On the other hand, the price of risk is lowest during the tech bubble. The price of risk is also low during the onset of the financial crisis. This result is similar to the findings in Moreira and Muir (2017). Moreira and Muir argue that in the beginning of the financial crisis, and crises more generally, the variance increases by more than the market risk premium which causes the price of risk to go down.

Another way to visualize conditional risk is by looking at the realizations of the conditional-risk factor. Doing so gives us a rough idea of which kinds of assets that have positive conditional risk: an assets with a return that net of the market mimics the conditional-risk factor would has a high level of conditional risk. Panel A in Figure 2 plots the two-year cumulative realization of the conditional-risk factor in the U.S.. The two-year realization shows distinct patterns. In particular, the cumulative value decreases during the tech bubble, indicating that an asset that performed poorly during the tech bubble has a high level of conditional risk. The value factor (HML) is a prominent example of such an asset: value stocks lost heavily to growth stocks during the tech bubble. Accordingly, we would expected HML to be an asset with high conditional risk. Consistent with this logic, and previous research[3], we find empirically that HML has substantial conditional risk.

More generally, Panel B in Figure 2 plots, along with the two-year realization of the conditional-risk factor, the two-year realization to an average cross-sectional risk factor which we call the composite risk factor. The composite risk factor is the average return to the factors value (HML), profitability (RMW), investment (CMA), momentum (UMD), and betting against beta (BAB). The figure shows that the two-year realizations of the composite risk factor and the conditional-risk factor are correlated. For instance, both factors earn high return during the 1980s, lose substantially during the tech bubble, earn high returns again during the 2001-2003 stock market contraction, and lose substantially during the market rebound after the financial crisis. This visual evidence suggests that the composite risk factor might load on conditional risk. We next address formally whether the risk factors load on conditional risk through factor analysis.

3.1 Conditional Risk in the Cross-Section of Stock Returns

In this section, we analyze conditional risk in the cross-sectional of equities by implementing the conditional CAPM as an unconditional two-factor model following Proposition 1. Table 2 summarizes the results for seven cross-sectional risk factors: size (SMB), value (HML), profitability (RMW), investment (CMA), momentum (UMD), and betting against beta (BAB), and a composite factor (COMP) which is the average return to the last five major risk factors. Panel A shows the results in the U.S. The first row shows the monthly alpha in percent. The alpha is statistically significant for all the strategies except the size factor.

[3]For previous research on conditional risk in HML, see Lettau and Ludvigson (2001b); Lewellen and Nagel (2006).

The positive two-factor alphas mean that the well-documented unconditional CAPM alphas of these factors cannot be explained by conditional risk. For HML and UMD, this result is similar to those found by Lewellen and Nagel (2006) and Boguth, Carlson, Fisher, and Simutin (2011), but for betting against beta our results differ from previous findings in Cederburg and O'Doherty (2016). We compare our results more closely to the literature later in the paper.

The third row of Panel A, which shows the loading on the conditional risk factor, reveals a striking relationship between alpha and loading on conditional risk: all the risk factors that have positive alpha are positively exposed to conditional risk. Indeed, value, profitability, investment, momentum, and betting against beta all have positive loadings on conditional risk. The only factor that does not have a positive loading is size, for which the loading is statistically insignificant.

The fourth row summarizes how large a compensation the conditional risk loadings warrant. As mentioned, conditional risk cannot explain the full alpha of the strategies, but it does explain a meaningful amount. Indeed, conditional risk explains between between .03 and .12 percentage point of monthly return, equivalent to 0.39 to 1.41 percentage point of annual return. This is a large amount in absolute terms, considering it arises simply from a failure to implement the CAPM correctly in the first place. It is also a large amount relative to the unconditional CAPM alpha, as can be seen in the sixth row. Indeed, conditional risk explains 8% to 15% of the unconditional CAPM alpha for these strategies; for the average factor COMP, conditional risk explains 11% of CAPM alpha.

Panel B reports the results from the global sample. Qualitatively, the results are similar: value, profit, investment, momentum, betting against beta, and the composite factor are all positively exposed to conditional risk; but the effect of conditional risk is not large enough to render the two-factor alphas insignificant. Furthermore, the size factor is negatively exposed to conditional risk but the exposure is close to zero and statistically insignificant, as in the U.S.

The economic magnitude of conditional risk is larger in the global sample than in the U.S.. Indeed, conditional risk explains as much as 0.17 percentage points of monthly return, equivalent to 2.03 percentage point of annual return. This larger absolute effect of conditional risk, combined with the fact that the average risk factor has lower alpha in the global sample, means that conditional risk explains a larger fraction of the unconditional CAPM alpha. Indeed, conditional risk explains betwen 10% and 36% of the unconditional CAPM alpha to the different strategies; for the average factor COMP, conditional risk explains 20% of CAPM alpha, which is twice as much as in the U.S..

In absolute magnitude, the largest effect of conditional risk is found in betting against beta, both in the U.S. and the global sample. This large effect of conditional risk on betting against beta may, however, partly come from differences in the methodology underlying the factors, as the betting against beta factor uses the more aggressive rank-weighted methodology whereas the other factors use the traditional Fama and French approach. Measured in percent of unconditional CAPM alpha, the effect of conditional risk is more nuanced. In the U.S., the factor for which conditional risk explains the largest fraction of unconditional CAPM alpha is the profitability factor. In the global sample, the factor for which conditional risk explains the largest fraction of unconditional CAPM alpha is the value factor, as conditional risk explain 36% of the conditional CAPM alpha to value.

Table 3 shows ten portfolios sorted on aggregate characteristics. We rank all stocks based on size, book-to-market, profitability, investment, momentum, and beta, and assign a standardized z-score for each of the characteristics to each stock. We then take the average of these z-scores and form portfolios based on this average. This method is similar to that used by Asness, Frazzini, and Pedersen (2013) when measuring the quality of stocks. We set up all characteristics such that they are positively related to expected return, meaning that a higher average z-score leads to a higher expected return.

Panel A shows the results for the portfolios sorted on average characteristics in the U.S.. The first row shows the monthly alpha which, as expected, increases monotonically in the average characteristic. The long-short portfolio in the rightmost column has a large monthly alpha of 1.06% which is highly significant, again underlying that conditional risk cannot fully explain the characteristics.

More importantly, the conditional risk loading also increases almost monotonically in the aggregate characteristic, meaning that the long-short portfolio has a large and statistically significant loading on conditional risk. The conditional risk loading explains 0.13 percentage points of monthly return for the long-short portfolio. The 0.13 monthly percentage points correspond to 11% of the unconditional CAPM alpha.

The results in the global sample are similar to the U.S. results, but again the economic magnitude is larger in the global sample. As seen in Panel B, the alpha and conditional risk loading both increase monotonically in the average characteristic. As to the economic size, conditional risk explains 0.19 percentage points of monthly return to the long-short portfolio, which corresponds to 18% of the unconditional CAPM alpha.

We next analyze the conditional risk in the average COMP factor in all the individual exchanges in our sample. Figure 3 summarizes the results. In 22 out of the 23 countries, the COMP factor loads positively on the conditional risk factor. The conditional risk factor explains the largest absolute amount of return in Germany and Finland where it explains 0.16 percentage point of monthly return (1.92 annually). In general, the effect appears stronger on the larger exchanges: the five largest exchanges in our sample are the U.S., Japan, Germany, Great Britain, and France, for which the loading on conditional risk is positive.

We next address whether the conditional risk in the equity risk factors comes from conditional cash flow risk or conditional discount rate risk. We do so by splitting the conditional risk factor into a cash flow and a discount rate part, as shown in the theory. Table 5 reports the results. Except for SMB, all factors load positively on the factor for conditional discount rate risk. The loadings on the factor for cash flow risk are more varied and do not have as pervasive a pattern. These results suggest that conditional risk comes from time-variation in conditional discount rate betas.

All in all, we find a strong relationship between expected returns and conditional risk loadings in the cross-section of stocks, both in the U.S. and internationally. The pervasive relationship between conditional risk and expected returns suggests that a fundamental economic mechanism might be driving the results. We look closer into such an economic mechanism in the next section, but before doing so we study conditional risk in time-series strategies.

3.2 Conditional Risk in Time-Series Strategies

In this section, we use our two-factor model to evaluate time-series strategies that try to time the market by increasing the position in the market portfolio when the price of risk is high. In doing so, the strategies may load on conditional risk, and it is therefore natural to test if our two-factor model can explain the return to the two strategies.

The two strategies we consider are "volatility-managed portfolios" (Moreira and Muir, 2017) and "time-series momentum" (Moskowitz, Ooi, and Pedersen, 2012). The volatility-managed portfolio by Moreira and Muir increases the position in the market portfolio when the volatility is lower. The authors argue that, because volatility and expected return is far from perfectly correlated, volatility timing also causes price-of-risk timing. Consistent with this, Moreira and Muir show that the volatility-managed portfolios indeed are associated with positive CAPM alphas.

The time-series momentum strategy goes long or short the market portfolio dependent on the momentum of the market portfolio. If the average return over the last year (skipping the most recent month) is positive, the strategy goes long the market portfolio, and vice versa. In addition, the position in the market portfolio is scaled to have a constant volatility. Therefore, to the extent that the momentum captures the expected return, the strategy is timing both expected return and variance, or equivalently, the price of risk. Moskowitz, Ooi, and Pedersen (2012) verify that the strategy delivers a highly significant alpha across 60 different indices.[4]

Table 6 reports the results from evaluating the time-series strategies in our two-factor model. The two leftmost columns show the results for the volatility-managed portfolios. Conditional risk explains the alpha associated with volatility-managed portfolios: the volatility-managed portfolio has a monthly alpha of 0.02% (t-stat of 0.22) in the U.S. and 0.00% (t-stat of 0.06) in the global sample, meaning that conditional risk explains 89% and 100% of the unconditional CAPM alpha. Regarding time-series momentum in the two rightmost columns, the alpha is insignificant in the global sample but remains significant in the U.S., which is surprising. The positive alpha in the U.S. ultimately comes from the fact that the time-series momentum strategy picks up a signal about expected return that is not captured by our measure of expected return.

Tables 7 and 8 report the global pervasiveness of this pattern. Across 23 of the 24 exchanges, the volatility-managed portfolio loads on conditional risk. Similarly, the time series momentum portfolio loads on conditional risk in 23 of the 24 exchanges.

[4]Month by month, both of these strategies are only taking a position in the market portfolio, meaning that by definition they cannot have any conditional alpha. It is clear, however, that if they successfully time the market portfolio and thus load on the conditional risk factor, the strategies will have unconditional alpha when measured only against the market portfolio.

4 Arbitrage Trading as the Source of Conditional Risk

Section 3 documents that the five largest cross-sectional risk factors all load on conditional risk. In this section, we investigate the driver behind this pervasive pattern. In our framework, understanding the driver of conditional risk amounts to understanding why the cross-sectional risk factors are correlated with the conditional-risk factor. One way this correlation can arise is through arbitrage trading. Indeed, when arbitrageurs trade they create correlation between the assets that they trade (Barberis and Shleifer, 2003; Cho, 2017). In particular, Cho (2017) argues that the funding shocks to arbitrageurs cause the assets in their portfolios to correlate because these funding shocks force arbitrageurs to trade large fractions of their assets. If the arbitrageurs are sufficiently large, this trading has a price impact and pushes the price on these assets in the same direction. If such price impact occurs period after period, the assets thus become correlated. To the extent that arbitrageurs trade both the cross-sectional risk factors and the conditional-risk factor, these factors may thus be correlated because of such arbitrage trading.

This arbitrage trading hypothesis offers clear, testable implications. First, the arbitrageurs must trade both the cross-sectional risk factors and the conditional-risk factor. Second, the loading of the cross-sectional risk factors on the conditional-risk factor should be larger when the arbitrageurs are more sensitive to funding shocks. Finally, the loadings on the conditional-risk factor should also be larger when the arbitrageurs trade the factors more intensively.

We first verify that arbitrageurs indeed trade the conditional-risk factor. Trading the conditional risk factor amounts to following a market timing strategy where one enters and exists the market based on the conditional price of risk. One can interpret this literally as some arbitrageurs following such market timing strategies, which they indeed do (Pedersen, 2015). But one can also interpret their market timing as simply being changes in the market tilt in their portfolio. For instance, a discretionary money manager might be inclined to be long more stocks when the price of risk is high, and fewer when the price of risk is low. One way to address if arbitrageurs are more long the market when the price of risk high is by studying their net position in S&P 500 futures. Following Bessembinder (1992); De Roon, Nijman, and Veld (2000); Moskowitz, Ooi, and Pedersen (2012), we estimate the net speculative demand in S&P 500 futures. The Commodity Futures Trading Commission (CFTC) requires large traders to identify themselves as commercial or non-commercial traders. We interpret the position of commercial traders as the arbitrageurs and, following the above literature, estimate their net demand as

$$NSD_t = \frac{\text{Speculator long positions} - \text{Speculator short positions}}{\text{Open interest}} \tag{2.38}$$

In Panel A of Table 9, we regress the price of risk, b_t, on the NSD_t. NSD_t is positively correlated with the price of risk, b_t, in both the U.S. and global sample. The correlation between NSD_t and the U.S. price of risk is 0.21 and the correlation with the global price of risk is 0.28 (in both samples we use the position in S&P 500 futures as our measure of NSD_t). These results suggest that the arbitrageurs indeed trade the conditional-risk factor.

We next consider how leverage influences the amount of conditional risk in the cross-sectional risk factors. There are two reasons to believe that leverage should increase the amount of conditional risk. First, arbitrageurs are likely to be more sensitive to funding shocks when they are more levered. Second, when arbitrageurs are more levered they hold a larger fraction of the available assets and therefore have a larger price impact, meaning that their trading has larger impact on betas. We therefore test if the cross-sectional risk factors load more on the conditional-risk factor when leverage is higher by running the following regression:

$$COMP_{t+1} = \theta_0 + \theta_1 c_{t+1} + \theta_2 \left(c_{t+1} \times LEV_t\right) + \epsilon_{t+1} \tag{2.39}$$

where LEV_t is the amount of intermediary leverage at time t as estimated by He, Kelly, and Manela (2016). A positive θ_2 in the regression means that the loading on the conditional risk factor is higher when leverage is larger.

Panel C of Table 9 reports the results on how leverage influences conditional risk. As can be seen in the table, the composite factor loads positively on the interaction term in (2.39), which means that the composite factor loads more on the conditional-risk factor when financial intermediaries are more levered.

We next test how the exposure of the arbitrageurs to the composite risk factor influences the factor's loading on conditional risk. One of the main drivers of how much arbitrageurs hold of a risk factor is the factor's expected return. We therefore test if the composite factor loads more on conditional risk when its expected return is higher. As the measure of expected return, we use the average value spread of the five factors in the composite risk factor. We measure the value spread of an individual factor as the difference in log-book-to-market in the long- and the short leg of the factor.

Accordingly, Table 10 reports the results of the following regression of the composite risk factor on the conditional-risk factor and the conditional-risk factor interacted with the ex-ante value spread:

$$COMP_{t+1}^{m} = \gamma_0^m + \gamma_1^m c_{t+1}^m + \gamma_2^m \left(c_{t+1}^m \times VS_t^m \right) + \epsilon_{t+1}^m \tag{2.40}$$

where m denotes country and VS_t^m is the value spread for the composite risk factor in country m at time t. A positive γ_2^k in the regression means that the loading on the conditional risk factor is larger when the value spread is larger.

As can be seen in column 6 in Table 10, the composite risk factor loads more on conditional risk when the value spread is larger. This result holds in 22 out of the 24 samples. The effect is statistically significant in the U.S. and global sample. These results are consistent with the conditional risk being driven by arbitrageurs who are more exposed to the risk factors when the expected return on the factors is high.

Finally, Cho (2017) argues that the arbitrage capital in the cross-sectional risk factors is substantially larger in the post-1994 period. If conditional risk is a result of arbitrage trading, we should thus expect to mainly find it in this late sample. Accordingly, Table 11 splits the U.S. sample into pre- and post-1994. As can be seen in the table, conditional risk is almost exclusively a feature of the late sample. In the post-1994 sample, the effect of conditional risk is substantially larger than in the full U.S. sample reported in Table 2 Panel A. In contrast, conditional risk is hardly present in the pre-1994 sample. The results are thus consistent with our arbitrage trading hypothesis: without any arbitrage capital, there is no conditional risk.[5]

Cho (2017) also shows that the factors that have larger alphas in the early sample attract more arbitrage capital. Accordingly, we should expect the factors that have larger alphas (or information ratios) in the pre-1994 sample to have more conditional risk in the post-1994 sample. Consistent with this prior, we see that the factor with the largest pre-1994 alphas, namely betting against beta, also has the most conditional risk in the late sample. Similarly, momentum and value are the second and third most profitable pre-1994 factors, and these

[5]The results reported in Table 11 are not sensitive to the choice of 1994 as the cut-off year.

have the second and third most conditional risk in the late sample.

Finally, it is worth providing a simple example of how the arbitrage trading actually creates time-variation in the conditional betas. Consider an economy with two states: a high and a low price-of-risk state. In the high price-of-risk state, the arbitrageurs are long the market and in the low price-of-risk state they are short the market. In both states, they hold the composite risk factor. In the good state, funding shocks to the arbitrageurs create a positive correlation between the composite risk factor and the market factor because they are long both factors, which means that the conditional beta of the composite factor is high in this high state. Similarly, funding shocks create negative correlation between the composite risk factor and the market when the price of risk is low because the arbitrageur is short the market. Accordingly, the arbitrage trading creates low conditional betas for the composite risk factor in this low state. Taken together, the funding shocks and the resulting arbitrage trading thus create high conditional betas when the price of risk is high and low conditional betas when the price of risk is low, which is to say that it creates conditional risk.

In conclusion, we find strong evidence that conditional risk is driven in part by arbitrage activity. If arbitrageurs trade both the cross-sectional risk factors and the conditional-risk factor, these become correlated and the cross-sectional risk factors therefore load on conditional risk. This effect is stronger the more the arbitrageurs are present in the factors. Consistent with this, we find that the conditional risk in the cross sectional risk factors is stronger when: (1) the factors have higher expected return and arbitrageurs therefore are trading them more; (2) there is more leverage in the economy and arbitrageurs therefore are likely to hold larger positions; and (3) there is more arbitrage capital. In addition, using the net speculative position in S&P 500 futures, we find evidence that arbitrageurs trade the conditional-risk factor.

5 Robustness

In this section we consider how robust our results are to using other measures of the conditional market risk premium and variance. Tables A1 to A10 report a range of robustness checks where we redo our analysis using different measures of these conditional estimates.

Tables A1 through A4 show the results of using the measures of expected return reported in Campbell and Thompson (2008). Campbell and Thompson show how the dividend price ratio, earnings price ratio, and book-to-market are linked to the expected market return through accounting identities. Using these identities, we calculate the expected market risk premium and estimate the conditional risk factor and the market shock factor. The results are robust to using these measures of expected returns. The composite risk factors load on the conditional risk factor in both the U.S. and global sample for all three measures of expected return. In addition, the composite risk factor loads on conditional risk in at least 18 of the 22 other samples. The economic effect of conditional risk is, however, smaller than when using the Kelly-Pruitt measure of expected return.

Tables A5 and A6 report results where the market risk premium is assumed to be constant, such that only the expected variance varies. The results are also robust to this specification: the composite risk factor loads on conditional risk in all samples. However, the economic effect is smaller, with conditional risk only explaining about 4% of the alpha.

Tables A7 and A8 report results where the variance is assumed constant, such that only the expected market risk premium varies. We again extract the conditional market risk premium using the Kelly-Pruitt method. The results are robust, with all risk factors loading on conditional risk in the U.S. sample (except SMB), and with the composite risk factor loading on conditional risk in all but two of the 24 samples. In addition, the economic effect is close to as large as when using time-varying variance.

Finally, Table A9 reports results in the U.S. sample when using more sophisticated methods for estimating expected variance. Panel A reports results of using the expected variance in Bollerslev, Tauchen, and Zhou (2009). The results are robust. Similarly to our baseline case, all the major risk factors load on conditional risk. The economic effect is slightly larger than in the baseline case. Panel B reports the results of using the risk neutral variance SVIX. These results are also robust, with all risk factors loading on conditional risk.

Finally, in Table A10 we report results based on using an index of multiple estimators for the conditional market risk premium. We calculate the index of expected returns as the average of the expected return in Campbell and Thompson (2008); Kelly and Pruitt (2013); Lettau and Ludvigson (2001a) and Martin (2016). The results are robust to using this index of expected returns: both in the U.S. and globally, the factors have the same conditional-risk loadings as when using just the Kelly and Pruitt (2013) estimate for the conditional market risk premium.

In conclusion, we find that our results are robust to various different methods for identifying and estimating the conditional market risk premium and variance. The results are stronger than the baseline results if we use more sophisticated measures of conditional variance, but weaker if we assume constant variance. The results are robust to, but weaker, when using simpler measures of the conditional market risk premium.

6 Relation to the Literature

Our results relate to and extend a long strand of literature on the conditional CAPM. Jagannathan and Wang (1996) show that the conditional CAPM helps explain asset returns when using instruments to measure betas. Lettau and Ludvigson (2001b) show that using the cay variable variable as instrument explains the returns to size and value sorted portfolio, but Lewellen and Nagel (2006) argue that the effect is overestimated and that the conditional CAPM cannot explain the cross-section of stocks. Lewellen and Nagel further advocate the use of short-horizon regressions as an instrument-free way of testing the conditional CAPM. However, Boguth, Carlson, Fisher, and Simutin (2011) argue that the short-horizon regressions has certain small-sample issues, and instead advocate the use of an instrumental approach that uses past betas and state variables as instruments. Using this approach, they show that momentum portfolios load on conditional risk. More recently, Cederburg and O'Doherty (2016) argue that the conditional CAPM explains the low risk anomaly documented by Black, Jensen, and Scholes (1972) and Frazzini and Pedersen (2014). Going beyond unconditional expected returns, Nagel and Singleton (2011) test the additional implication that conditional expected returns must be consistent with the conditional factor models. In the following, we address more closely the two papers most closely related to ours.

Lettau and Ludvigson (2001b): Our approach is most closely related to the study by Lettau and Ludvigson. Similarly to Lettau and Ludgivson, we estimate the price of risk rather than time-variation in betas and use this estimate of the price of risk to implement the conditional CAPM. The difference in our approaches is that we explicitly estimate the price of risk by estimating the expected return and variance, whereas Lettau and Ludvigson assume that it is a function of the cay variable. To estimate the risk premium on their conditional risk factor, they must estimate the variance of the price of risk, which they do in a second-stage regression in the cross-section of stocks. However, this second-stage regression may estimate unrealistically high variance of the price of risk, leading to an overestimation of the ability of the conditional CAPM to explain the cross-section of stock. Indeed, Lewellen and Nagel (2006) argue that the results do not hold under reasonable estimates of the variance of expected return and variance.

We avoid this problem by instead estimating the price of risk in first-stage regressions. This approach ensures that we rely on reasonable estimates of the variance of expected return and variance. Indeed, as can be seen in Table 1, the R^2 of the expected return is a few percent, which is generally believed to be a meaningful variability in expected returns on short horizons (see e.g. Ross (2015)).

Cederburg and O'Doherty (2016): Our results on the low-risk effect differ substantially from those by Cederburg and O'Doherty, as they find that the low-risk effect is statistically insignificant once controlling for conditional risk. There are two potential reasons for this discrepancy.

First, Cederburg and O'Doherty use instruments to pick up variation in betas. These instruments are unlikely to pick up all the variation in betas. The instruments may therefore miss variation in betas that is either negatively correlated with the expected return or positively correlated with volatility. If this is the case, the estimate of conditional risk in Cederburg and O'Doherty (2016) too high. Alternatively, the instruments may have picked up variation in expected return or variance that was not expected ex ante, in which case the estimate of conditional risk may also be too high.

Second, we study the returns to the monthly betting against beta factor and not quarterly beta sorted portfolios as Cederburg and O'Doherty do. The advantage of studying the betting against beta factor is that the factor is hedged ex ante to have a conditional beta of zero, mitigating the risk of missing variation in conditional betas. In addition, the fact that the factor is hedged conditionally to have a beta of zero, and has an alpha of 10 percentage points per year, means that it is unlikely that the conditional CAPM can explain its average return in the first place: it would require the estimated conditional betas to be far from the true betas.

7 Conclusion

We document a global pattern of conditional risk in stock returns: across 23 developed countries, the five largest risk factors are exposed to conditional risk. The conditional risk explains around 20% of the alpha to these strategies. In addition, conditional risk explains all of the alpha of time-series strategies such as volatility-managed portfolios.

This conditional risk has broad economic implications. For instance, a CFO of a value firm who discounts cash flows using the unconditional CAPM would use the company's beta of, say, 1 times the global market risk premium, which gives an annual discount rate of around 5 percent. However, given the conditional risk in global value firms, the CFO should in fact use an annual discount rate of 6.5 percent to also reflect the conditional-risk premium. In addition to NPV analysis, the conditional risk is also important for judging the economic importance of different anomalies, understanding market efficiency, evaluating the performance of asset managers, and in financial analysis more generally.

We document the global pattern in conditional risk by using a new, simple method for estimating conditional risk. The method augments the unconditional CAPM with a conditional-risk factor, which is a precisely defined market timing factor. This conditional-risk factor is sufficient to capture all of the implications of the conditional CAPM and can easily be applied in future factor analysis, performance analysis of money managers, or by CFOs to determine their company cost of capital.

We also address the economic source of the conditional risk. Previous explanations of why conditional risk arises are often unique to a single factor. However, the fact that all the major risk factors load on conditional risk hints at a common explanation for all the factors. We find evidence of such a common explanation, namely that the conditional risk in all the factors arises from arbitrage trading. Consistent with this arbitrage trading hypothesis, we find that there is more conditional risk in the the cross-sectional risk factors when arbitrageurs trade these more intensely and when the abitrageurs are more levered.

8 Appendix

Proof of (2.3). Note that we can write the conditional beta as $\beta_t = E[\beta] + \eta_t$. We can then write the unconditional covariance between the excess return to asset i and the shock to the market portfolio as

$$\begin{aligned}\operatorname{cov}(r^i_{t+1}; \tilde{r}_{t+1}) &= \operatorname{cov}(E[\beta]\tilde{r}_{t+1} + \eta_t \tilde{r}_{t+1}; \tilde{r}_{t+1}) \\ &= E[\beta] \operatorname{var}(\tilde{r}_{t+1}) + \operatorname{cov}(\eta_t; \operatorname{var}(\tilde{r}_{t+1}))\end{aligned}$$

given that $\operatorname{cov}(\eta_t \tilde{r}_{t+1}; \tilde{r}_{t+1}) = E[\eta_t \tilde{r}^2_{t+1}] = \operatorname{cov}(\eta_t; \tilde{r}^2_{t+1})$ and using that $\tilde{r}^2_{t+1} = E_t[\tilde{r}^2_{t+1}] + \epsilon_{t+1} = \operatorname{var}_t(\tilde{r}^2_{t+1}) + \epsilon_{t+1}$ where $\operatorname{cov}(\eta_t; \epsilon_{t+1}) = 0$. By dividing both sides by the unconditional variance of $\tilde{r}_{t+1}$ we obtain the expression in (3).

Proof of (2.8). Note that the covariance term in (2.5) can be written as

$$\begin{aligned}\operatorname{cov}\left(\beta_t; E_t[r^m_{t+1}] - b \operatorname{var}_t(\tilde{r}^m_{t+1})\right) =& E\left[\beta_t(E_t[r^m_{t+1}] - b \operatorname{var}_t(\tilde{r}_{t+1}))\right] \\ & - \left(E\left[\beta_t\right] E\left[(E_t[r^m_{t+1}] - b \operatorname{var}_t(\tilde{r}_{t+1}))\right]\right)\end{aligned}$$

where the first term is equal to

$$\begin{aligned}E\left[\frac{r^i_{t+1}\tilde{r}_{t+1}}{\operatorname{var}_t(\tilde{r}_{t+1})}(E_t[r^m_{t+1}] - b \operatorname{var}_t \tilde{r}_{t+1})\right] =& E\left[r^i_{t+1}\right] E\left[\tilde{r}_{t+1}(b_t - b)\right] + \operatorname{cov}(r^i_{t+1}; \tilde{r}_{t+1}(b_t - b)) \\ =& \operatorname{cov}(r^i_{t+1}; c_{t+1}),\end{aligned}$$

given that $E[c_{t+1}] = 0$ (shown later), and the second term is equal to zero:

$$E\left[\beta_t\right] E\left[(E_t[r^m_{t+1}] - b \operatorname{var}_t \tilde{r}_{t+1})\right] = E\left[\beta_t\right]\left(E[r^m_{t+1}] - b \operatorname{var}(\tilde{r}_{t+1})\right) = 0$$

Finally, to see that $E[c_{t+1}] = 0$, note that

$$E[c_{t+1}] = E\left[\tilde{r}_{t+1}\right] E[b_t - b] + \operatorname{cov}(\tilde{r}; b_t - b)$$

which is equal to zero because the shock to the market portfolio has a zero mean and is uncorrelated with (unpredictable by) the ex ante price of risk, b_t.

Proof of Proposition 2.b. The covariance between the conditional-risk factor and the shock to the market is

$$\mathrm{cov}(\tilde{r}_{t+1}; c_{t+1}) = E[\tilde{r}_{t+1} c_{t+1}] = E\left[\tilde{r}^2_{t+1}(b_t - b)\right] = E\left[r^m_{t+1}\right] - E\left[r^m_{t+1}\right] = 0$$

Table 1

Summary Statistics

This table reports summary statistics for the 24 exchanges in our sample. Our sample consist of the union of all U.S. common stocks on CRSP tape ("shrcd" equal to 10 or 11) and all global stocks in the Xpressfeed global databse ("tcpi" equal to 0). The expected market risk premium is calculated using the Kelly and Pruitt (2013) method. Expected variance is calculated using an AR(1) regression. All returns are in USD. The standard deviation of the market risk premium is annualized. The market risk premium is in annual percent. The R^2 is based on monthly regressions. Returns are total log returns. Excess returns are simple returns in excess of the risk-free rate.

				Market risk premium		R^2 in predictive regressions		
Exchange	Starting year	Median number of firms	Mean weight in global portfolio	St. dev	Average	Variance	Returns	Excess returns
AUS	1990	1178.5	0.020	0.195	7.9%	0.487	0.005	0.005
AUT	1992	88	0.002	0.199	2.3%	0.510	0.029	0.029
BEL	1991	164	0.009	0.181	7.7%	0.444	0.015	0.019
CAN	1986	574.5	0.025	0.160	6.3%	0.571	0.019	0.019
CHE	1991	267	0.027	0.171	7.5%	0.337	0.031	0.030
DEU	1991	1002.5	0.080	0.181	3.0%	0.379	0.036	0.034
DNK	1991	175	0.005	0.183	8.8%	0.426	0.021	0.022
ESP	1991	151	0.017	0.208	3.9%	0.391	0.019	0.018
FIN	1991	135.5	0.005	0.254	9.2%	0.540	0.041	0.038
FRA	1991	739.5	0.050	0.194	5.0%	0.460	0.014	0.014
GBR	1987	2045.5	0.113	0.170	5.8%	0.454	0.019	0.019
HKG	1991	932	0.035	0.217	10.9%	0.429	0.022	0.021
IRL	1995	52	0.003	0.237	5.7%	0.344	0.032	0.025
ISR	1996	246	0.003	0.217	6.8%	0.350	0.026	0.023
ITA	1992	273	0.019	0.218	2.9%	0.422	0.020	0.022
JPN	1989	3578	0.169	0.204	1.9%	0.214	0.014	0.021
NLD	1991	181.5	0.022	0.176	6.3%	0.452	0.034	0.028
NOR	1991	179.5	0.004	0.233	7.0%	0.496	0.037	0.037
NZL	1991	126	0.003	0.204	7.6%	0.466	0.014	0.018
PRT	1997	57	0.003	0.216	4.1%	0.472	0.042	0.039
SGP	1991	480.5	0.012	0.184	7.9%	0.367	0.035	0.038
SWE	1991	328	0.014	0.223	9.0%	0.444	0.015	0.015
USA	1964	4789	0.450	0.173	5.8%	0.305	0.016	0.018
WOR	1986	18366	NA	0.147	5.0%	0.259	0.024	0.023

Table 2

Conditional Risk in Equity Factors

This table reports results from evaluation of different equity strategies in the conditional CAPM. We regress the monthly excess returns of different factors on the shock to the market factor and the conditional risk factor and evaluate returns in the following two-factor model from Proposition 1:

$$E\left[r_{t+1}^{i}\right] = \alpha^{i} + \beta^{m}\lambda^{m} + \beta_{c}^{m}\lambda_{c}^{m}$$

where r_{t+1}^{i} is the excess return to the risk factor i, β^{m} and β_{c}^{m} are the beta for the market- and conditional-risk factor, and λ^{m} and λ_{c}^{m} are their risk premia. The composite factor COMP is the average return to HML, RMW, CMA, UMD, and BAB. "Compensation for conditional risk" is the product $\beta_{c}^{m}\lambda_{c}^{m}$. All alphas are in monthly percent. t-statistics are reported below the parameter estimates and statistical significance at the 5% level is indicated in bold. Standard errors are bootstrapped to account for generated regressors. The U.S. and global samples run from 1964-2015 and 1986-2015.

	SMB	HML	RMW	CMA	UMD	BAB	COMP
Panel A: U.S. Sample							
Alpha	0.13	**0.36**	**0.26**	**0.29**	**0.71**	**0.90**	**0.50**
	(1.00)	(3.24)	(2.45)	(3.63)	(3.19)	(4.71)	(5.12)
Market beta	**0.21**	**-0.17**	**-0.12**	**-0.15**	**-0.13**	-0.05	**-0.12**
	(6.36)	(-5.05)	(-4.88)	(-7.86)	(-2.15)	(-0.97)	(-5.37)
Conditional risk beta	0.00	**0.02**	0.03	**0.02**	0.05	**0.07**	**0.04**
	(-0.23)	(2.08)	(1.94)	(2.66)	(1.46)	(2.36)	(2.23)
Compensation for conditional risk	0.00	0.03	0.05	0.03	0.09	0.12	0.06
Fraction of alpha explained by conditional risk	-0.03	0.08	0.15	0.09	0.11	0.12	0.11
Observations	623	623	623	623	623	623	623
Adjusted R^2	0.09	0.08	0.09	0.13	0.04	0.08	0.19
Panel B: Global Sample							
Alpha	0.08	0.24	**0.27**	**0.21**	**0.66**	**0.65**	**0.39**
	(0.64)	(1.81)	(2.88)	(2.58)	(2.80)	(3.82)	(4.32)
Market beta	**0.06**	**-0.09**	**-0.18**	**-0.08**	**-0.22**	**-0.13**	**-0.14**
	(2.01)	(-3.17)	(-9.53)	(-4.50)	(-3.27)	(-2.34)	(-6.51)
Conditional risk beta	0.00	**0.03**	0.01	**0.02**	0.02	**0.04**	**0.02**
	(-0.25)	(2.29)	(1.43)	(3.36)	(1.19)	(2.40)	(3.01)
Compensation for conditional risk	-0.01	0.13	0.03	0.08	0.09	0.17	0.10
Fraction of alpha explained by conditional risk	-0.09	0.36	0.10	0.28	0.12	0.21	0.20
Observations	354	354	354	354	354	306	354
Adjusted R^2	0.01	0.12	0.21	0.13	0.07	0.12	0.25

Table 3

Conditional Risk in Portfolios Sorted on Aggregate Characteristics

This table reports results from evaluation of characteristics sorted portfolios in the conditional CAPM. We regress the monthly excess returns of different portfolios on the shock to the market factor and the conditional risk factor and evaluate returns in the following two-factor model from Proposition 1:

$$E\left[r_{t+1}^{i}\right] = \alpha^{i} + \beta^{m}\lambda^{m} + \beta_{c}^{m}\lambda_{c}^{m}$$

where r_{t+1}^{i} is the excess return to the portfolio i, β^{m} and β_{c}^{m} are the beta for the market- and conditional-risk factor, and λ^{m} and λ_{c}^{m} are their risk premia. Each month, we sort stocks into ten portfolios based on the aggregate size, book-to-market, profitability, investment, momentum, and beta characteristic. We measure characteristics in cross-sectional percentiles and chose signs such that higher characteristics are associated with higher returns. In the U.S., we use NYSE breakpoints for the portfolios sorts. In the international sample, we use calculate breakpoints based on the 20% largest firms. Portfolios are value-weighted, refreshed, and rebalanced monthly. "Compensation for conditional risk" is the product $\beta_{c}^{m}\lambda_{c}^{m}$. All alphas are in monthly percent. *t*-statistics are reported below the parameter estimates and statistical significance at the 5% level is indicated in bold. Standard errors are bootstrapped to account for generated regressors. The U.S. and global samples run from 1964-2015 and 1986-2015.

	Portfolios sorted on aggregate characteristics										
	1 (low)	2	3	4	5	6	7	8	9	10 (high)	11 (10-1)
Panel A: U.S. Sample											
Alpha	**-0.56**	-0.04	0.00	0.10	0.20	0.20	0.22	0.22	**0.38**	**0.50**	**1.06**
	(-2.13)	(-0.18)	(-0.01)	(0.58)	(1.25)	(1.33)	(1.38)	(1.47)	(2.36)	(2.87)	(4.02)
Market beta	**1.36**	**1.13**	**1.01**	**0.98**	**0.90**	**0.85**	**0.84**	**0.79**	**0.75**	**0.77**	**-0.59**
	(32.10)	(39.81)	(41.88)	(37.33)	(37.99)	(35.18)	(31.65)	(27.83)	(24.39)	(21.56)	(-9.38)
Conditional risk beta	-0.03	-0.01	0.01	**0.02**	**0.03**	**0.03**	**0.03**	**0.05**	**0.04**	**0.05**	**0.08**
	(-1.83)	(-1.02)	(1.76)	(2.33)	(2.35)	(2.27)	(2.36)	(2.72)	(2.24)	(2.23)	(2.15)
Compensation for conditional risk	-0.06	-0.01	0.02	0.04	0.04	0.04	0.05	0.07	0.07	0.08	0.13
Fraction of alpha explained by conditional risk	0.09	0.26	1.15	0.27	0.18	0.18	0.20	0.25	0.16	0.14	0.11
Observations	623	623	623	623	623	623	623	623	623	623	623
Adjusted R^2	0.86	0.89	0.90	0.88	0.86	0.85	0.82	0.79	0.71	0.70	0.33

Table 3

Conditional Risk in Portfolios Sorted on Aggregate Characteristics (continued)

	Portfolios sorted on aggregate characteristics									
	1 (low)	2	3	4	5	6	7	8	9	10 (high)	11 (10-1)
Panel B: Global Sample											
Alpha	-0.33	-0.03	0.09	0.15	0.19	0.21	0.26	0.31	0.36	**0.55**	**0.89**
	(-0.90)	(-0.09)	(0.33)	(0.59)	(0.76)	(0.96)	(1.18)	(1.48)	(1.71)	(2.59)	(3.18)
Market beta	**1.28**	**1.13**	**1.02**	**0.97**	**0.91**	**0.82**	**0.81**	**0.76**	**0.73**	**0.72**	**-0.56**
	(31.21)	(37.04)	(35.82)	(36.74)	(36.50)	(29.37)	(28.24)	(24.04)	(22.43)	(20.09)	(-8.70)
Conditional risk beta	**-0.03**	-0.01	0.00	0.01	0.01	0.02	0.02	**0.02**	**0.02**	**0.02**	**0.05**
	(-2.46)	(-1.23)	(-0.01)	(1.18)	(1.58)	(1.81)	(1.93)	(2.38)	(2.48)	(2.46)	(2.88)
Compensation for conditional risk	-0.11	-0.04	0.00	0.03	0.04	0.06	0.07	0.08	0.08	0.08	0.19
Fraction of alpha explained by conditional risk	0.26	0.59	0.00	0.18	0.17	0.23	0.21	0.21	0.19	0.13	0.18
Observations	282	282	282	282	282	282	282	282	282	282	282
Adjusted R^2	0.88	0.93	0.93	0.93	0.91	0.88	0.87	0.84	0.79	0.74	0.40

Table 4

Conditional Risk around the World

This table reports results from evaluation of the composite risk factor (COMP) in the conditional CAPM across different exchanges. For each exchange, we regress the monthly excess returns COMP on the shock to the market factor and the conditional risk factor for the given exchange. For each exchange, we evaluate returns in the following two-factor model from Proposition 1:

$$E[r_{t+1}^{COMP}] = \alpha^i + \beta^m \lambda^m + \beta_c^m \lambda_c^m$$

where r_{t+1}^{COMP} is the excess return to COMP, β^m and β_c^m are the beta for the market- and conditional-risk factor, and λ^m and λ_c^m are their risk premia. The composite factor COMP is the average return to HML, RMW, CMA, UMD, and BAB. "Compensation for conditional risk" is the product $\beta_c^m \lambda_c^m$. All alphas are in monthly percent. *t*-statistics are reported below the parameter estimates and statistical significance at the 5% level is indicated in bold. Standard errors are bootstrapped to account for generated regressors. The U.S. and global samples runs from 1964-2015 and 1986-2015.

Exchange	Alpha		Market Beta		Conditional Risk Beta		Compensation for conditional risk	Fraction of alpha explained by conditional risk
AUS	**0.73**	(6.04)	**-0.06**	(-3.24)	0.03	(1.77)	0.04	0.05
AUT	**0.36**	(2.43)	**-0.08**	(-2.07)	0.01	(0.72)	0.03	0.07
BEL	**0.43**	(3.45)	**-0.11**	(-3.84)	0.02	(0.57)	0.03	0.06
CAN	**0.88**	(6.06)	**-0.13**	(-4.43)	0.01	(0.84)	0.04	0.04
CHE	**0.48**	(3.85)	**-0.11**	(-3.69)	0.00	(0.40)	0.01	0.03
DEU	**0.64**	(3.63)	**-0.18**	(-5.19)	0.03	(1.44)	0.16	0.20
DNK	**0.49**	(3.57)	**-0.11**	(-2.99)	**0.02**	(2.87)	0.09	0.15
ESP	**0.41**	(3.07)	**-0.11**	(-4.82)	0.01	(0.59)	0.07	0.14
FIN	0.45	(1.77)	**-0.23**	(-5.49)	0.03	(0.82)	0.16	0.26
FRA	**0.53**	(3.66)	**-0.12**	(-3.74)	0.02	(0.92)	0.04	0.07
GBR	**0.49**	(5.36)	**-0.05**	(-2.28)	**0.02**	(1.98)	0.04	0.08
HKG	**0.50**	(3.24)	**-0.10**	(-3.52)	0.00	(-0.33)	-0.02	-0.04
IRL	**0.83**	(2.73)	**-0.14**	(-2.76)	0.02	(1.18)	0.06	0.06
ISR	**0.62**	(3.61)	-0.05	(-1.78)	0.01	(0.29)	0.02	0.03
ITA	0.18	(1.41)	-0.02	(-0.73)	0.02	(1.27)	0.05	0.22
JPN	**0.21**	(2.43)	**-0.05**	(-2.73)	0.02	(0.91)	0.01	0.03
NLD	**0.51**	(3.87)	**-0.10**	(-3.69)	0.01	(1.41)	0.06	0.10
NOR	**0.51**	(3.00)	**-0.05**	(-2.63)	0.01	(1.46)	0.09	0.15
NZL	**0.43**	(3.24)	-0.02	(-0.74)	0.01	(1.80)	0.04	0.09
PRT	0.18	(1.03)	**-0.10**	(-3.61)	0.01	(0.43)	0.05	0.22
SGP	**0.38**	(2.23)	**-0.14**	(-4.34)	0.00	(0.06)	0.01	0.02
SWE	**0.51**	(2.93)	**-0.08**	(-2.28)	0.06	(1.21)	0.02	0.05
USA	**0.50**	(5.12)	**-0.12**	(-5.37)	**0.04**	(2.23)	0.06	0.11
WOR	**0.39**	(4.32)	**-0.14**	(-6.51)	**0.02**	(3.01)	0.10	0.20

Table 5

Conditional Cash Flow- and Discount Rate Risk

This table reports results from evaluation of different equity strategies in the conditional CAPM. We regress quarterly excess returns of different factors on the shock to the market portfolio, the conditional discount-rate-risk factor and the conditional cash-flow-risk factor. The composite factor COMP is the average return to HML, RMW, CMA, UMD, and BAB. "Compensation for conditional risk" is the conditional risk beta multiplied by the risk premium on the conditional risk factor. All alphas are in monthly percent. *t*-statistics are reported below the parameter estimates and statistical significance at the 5% level is indicated in bold. The U.S. sample runs from 1964-2015. The global sample runs from 1986-2015.

	SMB	HML	RMW	CMA	UMD	BAB	COMP
Panel A: U.S. Sample							
Alpha	0.77	1.00	0.68	**0.78**	**2.15**	**2.59**	**1.43**
	(1.38)	(1.85)	(1.78)	(2.29)	(3.05)	(3.44)	(4.37)
Market beta	0.28	**-0.31**	-0.17	**-0.21**	-0.16	0.04	-0.15
	(1.83)	(-1.98)	(-1.45)	(-2.06)	(-0.69)	(0.17)	(-1.63)
Conditional cash flow beta	0.00	-0.04	-0.03	**-0.05**	0.01	0.00	-0.02
	(-0.06)	(-1.12)	(-1.20)	(-2.15)	(0.24)	(-0.10)	(-1.04)
Conditional discount rate beta	-0.03	0.04	**0.06**	0.03	0.03	**0.09**	**0.05**
	(-1.32)	(1.34)	(2.41)	(1.95)	(0.76)	(1.98)	(2.12)
Observations	192	192	192	192	192	192	192
Adjusted R^2	0.05	0.06	0.16	0.11	0.00	0.08	0.18
Panel B: Global Sample							
Alpha	0.35	1.02	0.43	0.64	1.73	**1.75**	**1.07**
	(0.66)	(1.54)	(1.03)	(1.67)	(1.75)	(2.05)	(2.73)
Market beta	0.03	-0.27	-0.19	-0.11	-0.07	-0.06	-0.14
	(0.29)	(-1.46)	(-1.95)	(-0.99)	(-0.30)	(-0.23)	(-1.25)
Conditional cash flow beta	0.00	0.00	-0.02	-0.03	-0.04	0.03	-0.02
	(-0.12)	(0.02)	(-0.82)	(-0.93)	(-0.87)	(0.57)	(-0.71)
Conditional discount rate beta	-0.01	0.05	**0.03**	0.03	0.00	0.06	0.03
	(-0.58)	(1.37)	(2.07)	(1.65)	(0.12)	(1.55)	(1.86)
Observations	102	102	102	102	102	86	102
Adjusted R^2	-0.02	0.17	0.21	0.17	-0.01	0.15	0.20

Table 6

Conditional Risk in Time-Series Strategies

This table reports results from evaluation of different time-series strategies in the conditional CAPM. We regress the monthly excess returns of different factors on the shock to the market factor and the conditional risk factor and evaluate returns in the following two-factor model from Proposition 1:

$$E[r_{t+1}^i] = \alpha^i + \beta^m \lambda^m + \beta_c^m \lambda_c^m$$

where r_{t+1}^i is the excess return to the strategy i, β^m and β_c^m are the beta for the market- and conditional-risk factor, and λ^m and λ_c^m are their risk premia. We consider two strategies: Volatility Managed Portfolios (Morreira and Muir, 2017) and Time-Series Momentum (Moskowitz, Ooi, and Pedersen, 2012). "Compensation for conditional risk" is the product $\beta_c^m \lambda_c^m$. All alphas are in monthly percent. *t*-statistics are reported below the parameter estimates and statistical significance at the 5% level is indicated in bold. Standard errors are bootstrapped to account for generated regressors. The U.S. and global samples run from 1964-2015 and 1986-2015.

	Volatility Managed Portfolios				Time Series Momentum			
	USA	USA	WOR	WOR	USA	USA	WOR	WOR
Alpha	0.13	-0.03	0.19	-0.01	**0.41**	**0.34**	0.13	-0.07
	(0.95)	(-0.22)	(0.99)	(-0.06)	(2.81)	(2.12)	(0.56)	(-0.25)
Market beta	**0.57**	**0.57**	**0.63**	**0.63**	-0.01	-0.01	0.13	0.13
	(16.83)	(16.80)	(11.31)	(11.11)	(-0.22)	(-0.21)	(1.70)	(1.69)
Conditional risk beta		**0.10**		**0.05**		**0.04**		**0.04**
		(3.30)		(1.98)		(2.86)		(2.40)
Compensation for conditional risk		0.17		0.22		0.07		0.20
Fraction of alpha explained by conditional risk		0.89		1.00		0.16		1.52
Observations	623	623	354	354	623	623	348	348
Adjusted R^2	0.43	0.55	0.45	0.51	0.00	0.02	0.02	0.06

Table 7

Conditional Risk in Volatility Managed Portfolios around the World

This table reports results from evaluation of volatility managed portfolios (VMP) in the conditional CAPM across different exchanges. For each exchange, we regress the monthly excess returns of VMP on the shock to the market factor and the conditional risk factor for the given exchange. For each exchange, we evaluate returns in the following two-factor model from Proposition 1:

$$E[r_{t+1}^{VMP}] = \alpha^i + \beta^m \lambda^m + \beta_c^m \lambda_c^m$$

where r_{t+1}^{VMP} is the excess return to VMP, β^m and β_c^m are the beta for the market- and conditional-risk factor, and λ^m and λ_c^m are their risk premia. All alphas are in monthly percent. *t*-statistics are reported below the parameter estimates and statistical significance at the 5% level is indicated in bold. Standard errors are bootstrapped to account for generated regressors. The U.S. and global samples runs from 1964-2015 and 1986-2015.

Exchange	Alpha		Market Beta		Conditional Risk Beta		Compensation for conditional risk	Fraction of alpha explained by conditional risk
AUS	-0.11	(-0.34)	**0.75**	(10.13)	**0.22**	(2.01)	0.28	1.61
AUT	0.31	(0.84)	**0.71**	(8.03)	0.06	(1.80)	0.23	0.43
BEL	0.10	(0.40)	**0.71**	(7.71)	0.07	(0.56)	0.11	0.52
CAN	-0.11	(-0.38)	**0.75**	(8.24)	0.03	(0.51)	0.17	2.90
CHE	0.13	(0.55)	**0.72**	(12.00)	0.04	(0.69)	0.14	0.52
DEU	0.11	(0.44)	**0.70**	(12.15)	0.04	(0.88)	0.21	0.66
DNK	0.32	(1.39)	**0.64**	(9.34)	**0.07**	(2.74)	0.29	0.48
ESP	0.65	(0.71)	**1.14**	(3.35)	-0.10	(-0.55)	-0.86	4.02
FIN	0.31	(1.14)	**0.54**	(10.78)	0.07	(0.87)	0.44	0.58
FRA	0.16	(0.66)	**0.63**	(12.00)	0.10	(0.94)	0.16	0.50
GBR	0.20	(1.07)	**0.68**	(13.09)	0.07	(1.75)	0.15	0.43
HKG	0.45	(1.22)	**0.61**	(8.76)	**0.10**	(2.84)	0.44	0.49
IRL	0.54	(1.48)	**0.55**	(6.57)	0.06	(1.66)	0.15	0.22
ISR	-0.25	(-0.66)	**0.70**	(10.69)	0.09	(1.54)	0.30	6.07
ITA	0.49	(1.35)	**0.74**	(11.27)	0.05	(0.43)	0.11	0.19
JPN	-0.21	(-0.72)	**0.76**	(11.31)	0.13	(1.01)	0.04	-0.25
NLD	0.07	(0.32)	**0.64**	(11.60)	**0.07**	(2.17)	0.33	0.81
NOR	0.30	(0.91)	**0.71**	(9.04)	0.01	(0.37)	0.08	0.22
NZL	0.05	(0.15)	**0.86**	(12.46)	**0.09**	(2.59)	0.29	0.86
PRT	0.51	(1.43)	**0.55**	(9.35)	0.02	(0.20)	0.17	0.25
SGP	-0.34	(-0.85)	**0.60**	(8.38)	0.02	(0.56)	0.50	3.05
SWE	0.32	(1.09)	**0.69**	(12.77)	0.18	(0.99)	0.07	0.18
USA	-0.03	(-0.22)	**0.57**	(16.80)	**0.10**	(3.30)	0.16	1.26
WOR	-0.01	(-0.06)	**0.63**	(11.11)	**0.05**	(1.98)	0.21	1.07

Table 8

Conditional Risk in Time Series Momentum Portfolios around the World

This table reports results from evaluation of time series momentum (TSMOM) in the conditional CAPM across different exchanges. For each exchange, we regress the monthly excess returns of TSMOM on the shock to the market factor and the conditional risk factor for the given exchange. For each exchange, we evaluate returns in the following two-factor model from Proposition 1:

$$E[r_{t+1}^{TSMOM}] = \alpha^i + \beta^m \lambda^m + \beta_c^m \lambda_c^m$$

where r_{t+1}^{TSMOM} is the excess return to TSMOM, β^m and β_c^m are the beta for the market- and conditional-risk factor, and λ^m and λ_c^m are their risk premia. All alphas are in monthly percent. *t*-statistics are reported below the parameter estimates and statistical significance at the 5% level is indicated in bold. Standard errors are bootstrapped to account for generated regressors. The U.S. and global samples runs from 1964-2015 and 1986-2015.

Exchange	Alpha		Market Beta		Conditional Risk Beta		Compensation for conditional risk	Fraction of alpha explained by conditional risk
AUS	0.09	(0.27)	0.13	(1.53)	0.17	(1.92)	0.21	0.69
AUT	-0.03	(-0.07)	0.12	(1.35)	**0.09**	(2.82)	0.36	1.08
BEL	0.48	(1.35)	0.07	(0.54)	-0.01	(-0.06)	-0.01	-0.02
CAN	0.60	(1.65)	0.09	(0.68)	0.03	(1.05)	0.21	0.26
CHE	0.08	(0.29)	0.12	(1.57)	0.06	(1.56)	0.22	0.73
DEU	0.06	(0.19)	0.13	(1.57)	0.03	(0.62)	0.13	0.68
DNK	0.14	(0.52)	0.13	(1.74)	**0.07**	(2.93)	0.31	0.69
ESP	-0.06	(-0.05)	-0.52	(-1.17)	0.16	(0.93)	1.45	1.04
FIN	0.25	(0.67)	**0.13**	(2.11)	0.09	(1.54)	0.51	0.67
FRA	0.34	(1.16)	0.06	(0.91)	0.06	(0.83)	0.09	0.21
GBR	-0.08	(-0.32)	-0.01	(-0.14)	0.06	(1.76)	0.14	2.41
HKG	**1.01**	(2.39)	**0.15**	(2.01)	0.05	(1.75)	0.22	0.18
IRL	**0.84**	(2.01)	0.05	(0.63)	**0.11**	(3.22)	0.27	0.24
ISR	-0.06	(-0.12)	0.15	(1.73)	0.06	(1.18)	0.22	1.36
ITA	0.04	(0.09)	0.08	(0.84)	0.16	(1.90)	0.35	0.89
JPN	0.54	(1.57)	0.06	(0.65)	0.06	(0.59)	0.02	0.03
NLD	0.13	(0.47)	0.11	(1.42)	0.04	(1.34)	0.18	0.58
NOR	-0.02	(-0.04)	0.00	(-0.02)	**0.11**	(3.56)	0.93	1.02
NZL	-0.36	(-0.94)	**0.33**	(3.70)	**0.07**	(2.03)	0.22	-1.59
PRT	**1.57**	(3.70)	0.09	(1.43)	0.02	(0.32)	0.16	0.09
SGP	0.27	(0.46)	0.09	(1.09)	0.03	(1.09)	0.69	0.71
SWE	0.20	(0.58)	0.04	(0.56)	0.03	(0.20)	0.01	0.05
USA	**0.34**	(2.12)	-0.01	(-0.21)	**0.04**	(2.86)	0.06	0.16
WOR	-0.07	(-0.25)	0.13	(1.69)	**0.04**	(2.40)	0.19	1.51

Table 9

Arbitrage Trading and Conditional Risk

Panel A reports the results of a regression of the price of risk (b_t) on the net speculative demand (NSD_t). Net speculative demand is calculated as the difference in commercial long and short positions in S&P 500 futures dividend by open interest at time *t*. Panel B reports the results of a regression of the returns to the composite risk factor on the shock to the market portfolio and the product of the shock and the ex ante NSD. Panel C reports the results of a regression of the composite risk factor on the conditional risk factor and the product of the conditional risk factor and the ex ante intermediary leverage as defined by He, Kelly, and Manela (2017). *t*-statistics are reported below the parameter estimates and statistical significance at the 5% level is indicated in bold. The *t*-statistics in Panel A are based on Newey and West (1987) standard errors. The table considers both the U.S. and global (WOR) sample.

Panel A: Correlation between the price of risk (b_t) and net speculative demand (NSD)

	Dependent variable	Intercept	NSD_t	Obs	R^2	Correlation
U.S.	b_t	**2.80**	**6.42**	358	0.04	0.21
		(8.27)	(1.96)			
WOR	b_t	**3.06**	**13.46**	354	0.07	0.26
		(5.49)	(2.06)			

Panel B: The composite factor has higher market beta when NSD is higher

	Dependent variable	Intercept	$\tilde{r}^m_{t+1}$	$\tilde{r}^m_{t+1} \times NSP_t$	Obs	R^2
U.S.	$COMP_{t+1}$	**0.46**	**-0.16**	**1.05**	358	0.20
		(4.98)	(-7.80)	(5.04)		
WOR	$COMP_{t+1}$	**0.42**	**-0.14**	**0.71**	354	0.21
		(5.72)	(-8.88)	(4.79)		

Panel C: The composite factor has higher beta to the conditional risk factor when leverage is higher

	Dependent variable	Intercept	c_{t+1}	$c_{t+1} \times LEV_t$	Obs	R^2
U.S.	$COMP_{t+1}$	**0.48**	**-0.04**	**1.17**	550	0.17
		(6.94)	(-3.32)	(7.33)		
WOR	$COMP_{t+1}$	**0.36**	**-0.03**	**0.56**	354	0.13
		(4.56)	(-2.37)	(4.60)		

Table 10

Expected Factor Return and Conditional Risk Loading

This table reports results from the following regression of the composite risk factor on the conditional risk factor and the conditional risk factor interacted with the value spread of the composite risk factor:

$$COMP_{t+1} = \gamma_0 + \gamma_1 c_{t+1} + \gamma_2 \left(c_{t+1} \times VS_t\right) + \epsilon_{t+1}$$

where VS_t is the average value spread at time *t* of the five factors in $COMP$. The composite factor $COMP$ is the average return to HML, RMW, CMA, UMD, and BAB. *t*-statistics are reported below the parameter estimates and statistical significance at the 5% level is indicated in bold. Standard errors are bootstrapped to account for generated regressors. The U.S. and global samples runs from 1964-2015 and 1986-2015.

Exchange	γ_0^k		γ_1^k		γ_2^k		Observations	Adjusted R^2
AUS	**0.70**	(5.74)	-0.04	(-1.23)	0.19	(1.95)	306	0.05
AUT	**0.34**	(2.22)	-0.01	(-0.83)	0.11	(1.65)	282	0.00
BEL	**0.34**	(2.59)	0.01	(0.43)	0.00	(0.04)	294	0.00
CAN	**0.78**	(5.23)	-0.03	(-0.80)	0.09	(0.99)	354	0.01
CHE	**0.40**	(3.21)	0.00	(0.25)	0.00	(0.04)	294	-0.01
DEU	**0.62**	(3.44)	-0.01	(-0.28)	0.15	(0.74)	294	0.09
DNK	**0.35**	(2.26)	**0.02**	(2.58)	**0.07**	(2.00)	294	0.06
ESP	**0.31**	(2.18)	0.00	(0.05)	0.07	(0.63)	294	0.02
FIN	0.07	(0.24)	-0.01	(-0.21)	0.10	(0.82)	294	0.10
FRA	**0.44**	(3.10)	-0.06	(-1.19)	0.24	(1.19)	294	0.04
GBR	**0.48**	(5.22)	-0.01	(-0.63)	0.12	(1.29)	342	0.09
HKG	**0.40**	(2.38)	0.00	(-0.00)	-0.01	(-0.36)	294	0.00
IRL	**0.76**	(2.61)	0.00	(-0.15)	0.13	(1.45)	246	0.01
ISR	**0.61**	(3.51)	-0.01	(-0.42)	0.07	(0.71)	234	0.00
ITA	0.17	(1.29)	-0.01	(-0.62)	0.12	(1.06)	282	0.05
JPN	**0.21**	(2.42)	-0.01	(-0.31)	0.13	(0.82)	318	0.00
NLD	**0.43**	(3.08)	0.00	(0.38)	0.06	(0.82)	294	0.02
NOR	**0.54**	(3.07)	-0.01	(-0.72)	0.05	(1.15)	294	0.01
NZL	**0.39**	(2.88)	0.00	(-0.23)	0.12	(1.87)	294	0.03
PRT	0.16	(0.88)	0.01	(0.30)	-0.02	(-0.14)	222	0.00
SGP	0.26	(1.37)	0.00	(0.00)	0.01	(0.06)	294	-0.01
SWE	**0.41**	(2.41)	-0.16	(-1.31)	0.49	(1.85)	294	0.09
USA	**0.45**	(4.78)	-0.01	(-0.88)	**0.16**	(2.05)	623	0.13
WOR	**0.37**	(4.08)	-0.03	(-1.50)	0.14	(1.78)	354	0.15

Table 11

Conditional Risk in Equity Factors Pre and Post 1994

This table reports results from evaluation of different equity strategies in the conditional CAPM. We regress the monthly excess returns of different factors on the shock to the market factor and the conditional risk factor and evaluate returns in the following two-factor model from Proposition 1:

$$E\left[r_{t+1}^{i}\right] = \alpha^{i} + \beta^{m}\lambda^{m} + \beta_{c}^{m}\lambda_{c}^{m}$$

where r_{t+1}^{i} is the excess return to the risk factor i, β^{m} and β_{c}^{m} are the beta for the market- and conditional-risk factor, and λ^{m} and λ_{c}^{m} are their risk premia. The composite factor COMP is the average return to HML, RMW, CMA, UMD, and BAB. "Compensation for conditional risk" is the product $\beta_{c}^{m}\lambda_{c}^{m}$. All alphas are in monthly percent. *t*-statistics are reported below the parameter estimates and statistical significance at the 5% level is indicated in bold. Standard errors are bootstrapped to account for generated regressors. Panel A shows the U.S. sample from 1994-2015 and Panel B shows the U.S. sample from 1964-1993.

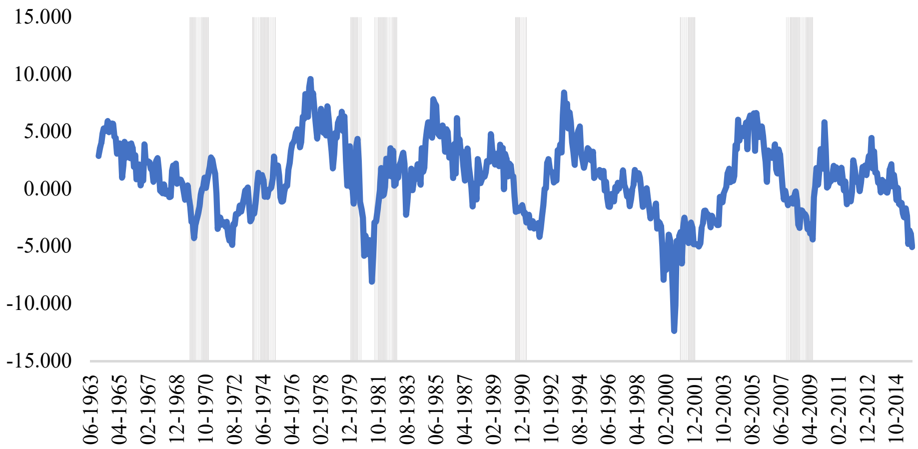
	SMB	HML	RMW	CMA	UMD	BAB	COMP
Panel A: U.S. Sample Post 1994							
Alpha	0.00	0.13	**0.55**	**0.25**	**0.73**	**0.97**	**0.53**
	(-0.02)	(0.86)	(3.03)	(2.45)	(2.43)	(4.02)	(3.83)
Market beta	**0.19**	**-0.12**	**-0.28**	**-0.11**	**-0.34**	**-0.29**	**-0.23**
	(4.74)	(-2.79)	(-8.74)	(-4.51)	(-4.32)	(-4.13)	(-7.60)
Conditional risk beta	0.01	**0.05**	**0.04**	**0.03**	0.07	**0.11**	**0.06**
	(0.47)	(1.99)	(2.07)	(2.05)	(1.60)	(2.57)	(2.52)
Compensation for conditional risk	0.01	0.07	0.06	0.05	0.10	0.15	0.09
Fraction of alpha explained by conditional risk	1.53	0.36	0.09	0.16	0.12	0.14	0.14
Observations	262	262	262	262	262	262	262
Adjusted R^2	0.05	0.08	0.22	0.11	0.11	0.18	0.32
Panel B: U.S. Sample Pre 1994							
Alpha	0.25	**0.50**	**0.18**	**0.30**	**0.84**	**1.03**	**0.57**
	(1.71)	(3.82)	(2.50)	(2.88)	(4.34)	(8.19)	(8.82)
Market beta	**0.22**	**-0.19**	0.00	**-0.17**	0.02	**0.13**	**-0.04**
	(6.37)	(-6.15)	(-0.25)	(-9.56)	(0.43)	(3.28)	(-2.62)
Conditional risk beta	-0.02	0.01	-0.01	**0.02**	0.01	0.01	0.01
	(-1.57)	(1.36)	(-1.57)	(2.52)	(0.30)	(0.89)	(0.98)
Compensation for conditional risk	-0.02	0.01	-0.01	0.02	0.01	0.01	0.01
Fraction of alpha explained by conditional risk	-0.10	0.03	-0.08	0.08	0.01	0.01	0.02
Observations	361	361	361	361	361	361	361
Adjusted R^2	0.12	0.11	0.00	0.17	0.00	0.04	0.03

Figure 1

The Conditional Price of Risk

This figure plots the time series of the conditional price of risk minus the unconditional price of risk. Panel A plots the price of risk in the U.S. sample and Panel B plots the price of risk in the global sample.

Panel A: U.S. conditional price of risk (b_t-b)



Panel B: Global conditional price of risk (b_t-b)

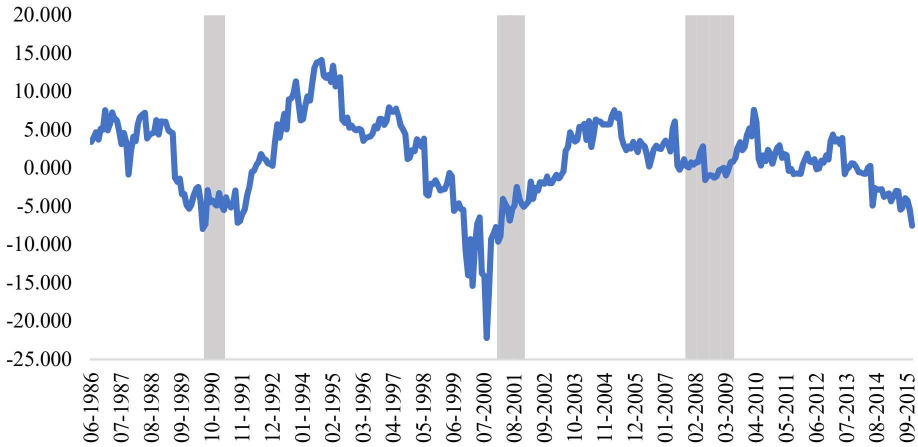


Figure 2

Rolling Realizations of the Conditional-Risk Factor

This figure plots the two-year rolling realizations of the conditional-risk factor together with the two-year rolling CAPM alpha to the composite risk factor (Panel B). Shaded bars indicate NBER recessions. The conditional-risk factor is the unexpected return to the market portfolio multiplied by the difference between the conditional and unconditional price of risk. The composite risk factor is the average return to HML, RMW, CMA, UMD, and BAB. The figure shows the U.S. sample.

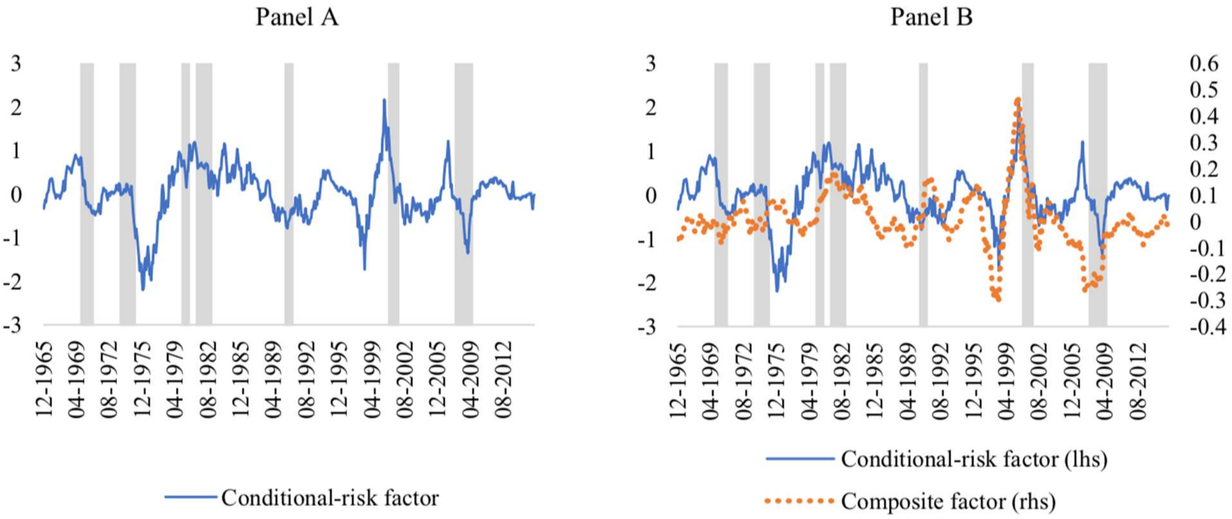


Figure 3

Compensation for Conditional Risk in the Cross-Section of Equity Returns

This figure shows how many percentage point of return conditional risk justifies for portfolios sorted on aggregate characteristics. Each month, we sort stocks into ten portfolios based on the aggregate size, book-to-market, profitability, investment, momentum, and beta characteristic. We measure characteristics in cross-sectional percentiles and chose signs such that higher characteristics are associated with higher returns. In the U.S., we use NYSE breakpoints for the portfolios sorts. In the international sample, we use calculate breakpoints based on the 20% largest firms. Portfolios are value-weighted, refreshed, and rebalanced monthly. The figure shows "compensation for conditional risk", which is the conditional risk beta multiplied by the risk premium on the conditional risk factor. The U.S. sample runs from 1964-2015. The global sample runs from 1986-2015.

Figure 4

Conditional Risk in the Cross-Section of Equity Returns around the World

This figure plots how many percent of the unconditional CAPM alpha to the composite risk factor that can be explained by conditional risk. The composite risk factor is the average return to HML, RMW, CMA, UMD, and BAB.

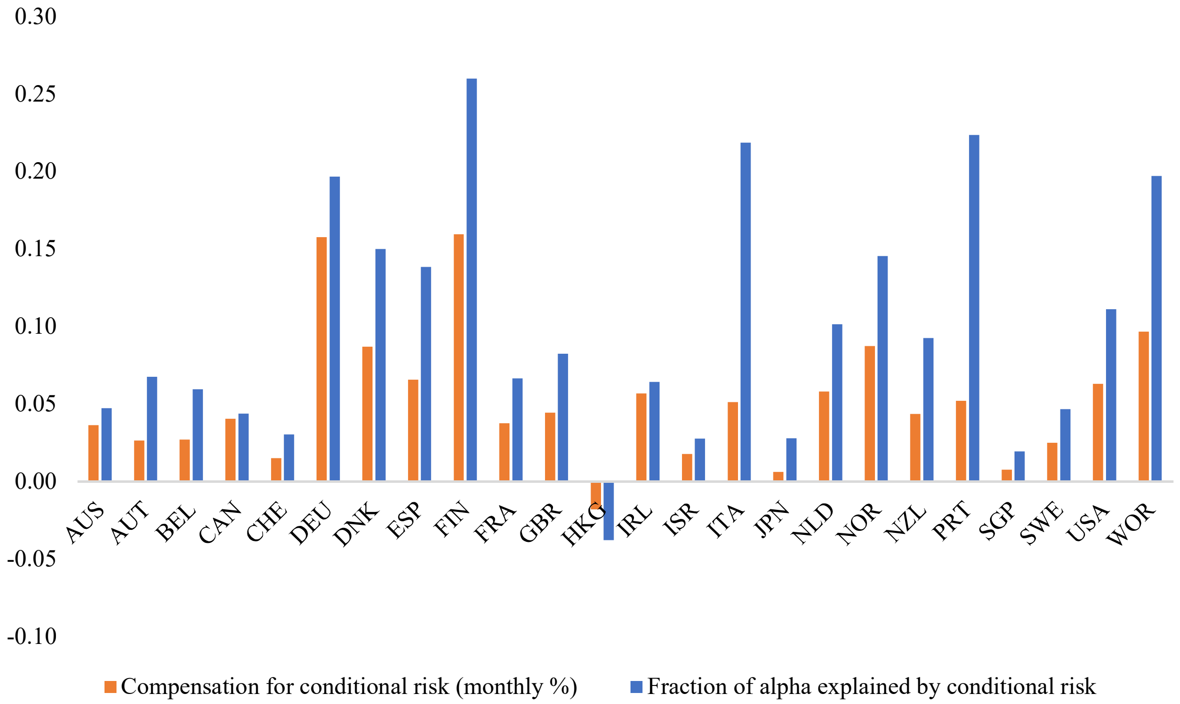


Figure 5

The Composite Factor has Larger Conditional Risk When it has Higher Expected Return

This figure plots γ_2^k from the following regression of the composite risk factor on the conditional risk factor and the conditional risk factor interacted with the value spread of the composite risk factor:

$$COMP_{t+1}^k = \gamma_0^k + \gamma_1^k c_{t+1}^k + \gamma_2^k (c_{t+1}^k \times VS_t^k) + \epsilon_{t+1}^k$$

where k denotes country and VS_t^k is the average value spread in country k at time t of the five factors in $COMP^k$. The composite factor $COMP^k$ is the average return in country k to HML, RMW, CMA, UMD, and BAB.

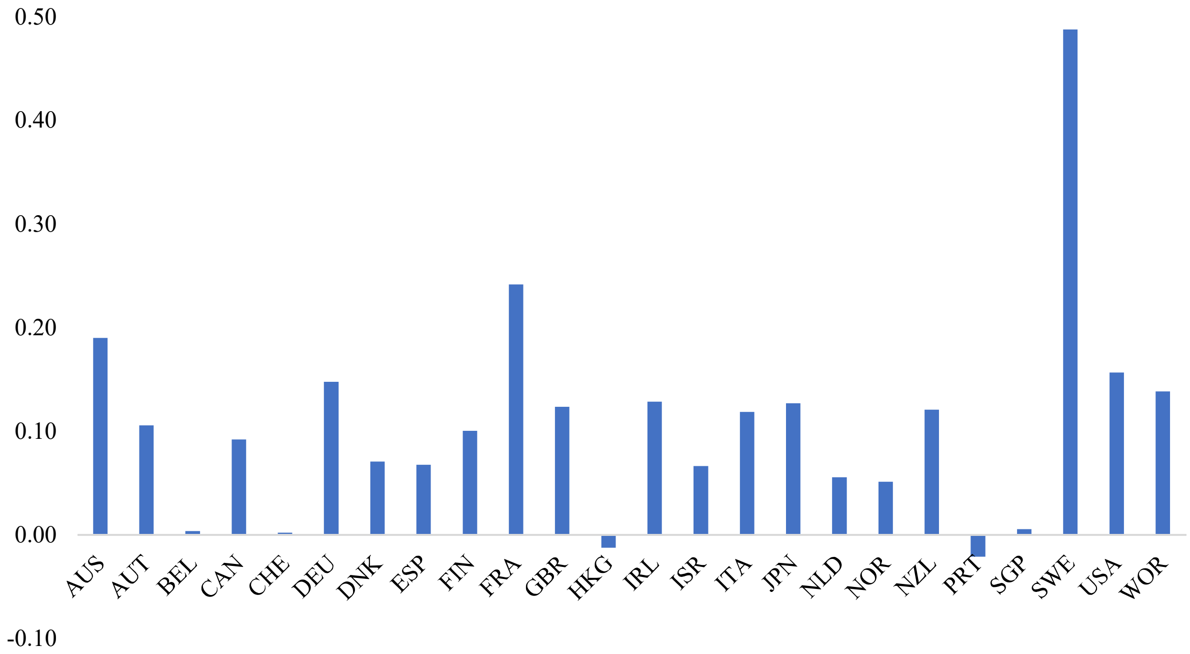


Table A1

Robustness: Conditional Risk Using Campbell and Thompson (2008)

This reports robustness analysis where the market risk premium used in the conditional-risk factor is measured using the dividend to price ratio of the market portfolio as in Campbell and Thompson (2008). We regress the monthly excess returns of different factors on the shock to the market factor and the conditional risk factor and evaluate returns in the following two-factor model from Proposition 1:

$$E\left[r_{t+1}^{i}\right] = \alpha^{i} + \beta^{m}\lambda^{m} + \beta_{c}^{m}\lambda_{c}^{m}$$

where r_{t+1}^{i} is the excess return to the risk factor i, β^{m} and β_{c}^{m} are the beta for the market- and conditional-risk factor, and λ^{m} and λ_{c}^{m} are their risk premia. The composite factor COMP is the average return to HML, RMW, CMA, UMD, and BAB. "Compensation for conditional risk" is the product $\beta_{c}^{m}\lambda_{c}^{m}$. All alphas are in monthly percent. t-statistics are reported below the parameter estimates and statistical significance at the 5% level is indicated in bold. The U.S. and global samples run from 1964-2015 and 1986-2015.

	SMB	HML	RMW	CMA	UMD	BAB	COMP
Panel A: U.S. Sample							
Alpha	0.13	**0.35**	**0.31**	**0.30**	**0.79**	**1.01**	**0.55**
	(1.08)	(3.39)	(3.66)	(4.31)	(4.76)	(7.46)	(8.69)
Market beta	**0.21**	**-0.17**	**-0.12**	**-0.15**	**-0.13**	-0.05	**-0.12**
	(7.80)	(-7.35)	(-6.47)	(-9.71)	(-3.38)	(-1.67)	(-8.71)
Conditional risk beta	0.00	**0.05**	0.00	**0.04**	0.00	0.02	**0.02**
	(0.30)	(4.43)	(0.19)	(4.39)	(0.18)	(1.34)	(3.11)
Compensation for conditional risk	0.00	0.04	0.00	0.03	0.00	0.02	0.02
Fraction of alpha explained by conditional risk	0.02	0.10	0.00	0.08	0.00	0.01	0.03
Observations	624	624	624	624	624	624	624
Adjusted R^2	0.09	0.10	0.06	0.15	0.01	0.00	0.12
Panel B: Global Sample							
Alpha	0.08	**0.31**	**0.32**	**0.28**	**0.79**	**0.77**	**0.48**
	(0.73)	(2.85)	(3.86)	(3.82)	(4.04)	(4.85)	(6.50)
Market beta	**0.05**	**-0.10**	**-0.18**	**-0.08**	**-0.21**	**-0.15**	**-0.14**
	(2.12)	(-4.10)	(-9.99)	(-5.31)	(-4.98)	(-4.27)	(-8.68)
Conditional risk beta	-0.01	**0.07**	0.01	**0.03**	-0.03	**0.04**	**0.02**
	(-1.07)	(6.01)	(1.29)	(3.70)	(-1.27)	(2.14)	(2.78)
Compensation for conditional risk	-0.01	0.06	0.01	0.02	-0.02	0.03	0.02
Fraction of alpha explained by conditional risk	-0.16	0.16	0.03	0.08	-0.03	0.04	0.04
Observations	359	359	359	359	359	306	359
Adjusted R^2	0.01	0.12	0.22	0.10	0.06	0.06	0.18

Table A2

Robustness: Conditional Risk Using Dividend to Price Ratio from Campbell and Thompson (2008)

This table reports robustness analysis where the market risk premium used in the conditional-risk factor is measured using the dividend to price ratio of the market portfolio as in Campbell and Thompson (2008). For each exchange, we regress the monthly excess returns COMP on the shock to the market factor and the conditional risk factor for the given exchange. For each exchange, we evaluate returns in the following two-factor model from Proposition 1:

$$E[r_{t+1}^{COMP}] = \alpha^i + \beta^m \lambda^m + \beta_c^m \lambda_c^m$$

where r_{t+1}^{COMP} is the excess return to COMP, β^m and β_c^m are the beta for the market- and conditional-risk factor, and λ^m and λ_c^m are their risk premia. The composite factor COMP is the average return to HML, RMW, CMA, UMD, and BAB. "Compensation for conditional risk" is the product $\beta_c^m \lambda_c^m$. All alphas are in monthly percent. *t*-statistics are reported below the parameter estimates and statistical significance at the 5% level is indicated in bold. The U.S. and global samples runs from 1964-2015 and 1986-2015.

Exchange	Alpha		Market Beta		Conditional Risk Beta		Compensation for conditional risk	Fraction of alpha explained by conditional risk
AUS	**0.74**	(6.32)	**-0.06**	(-3.16)	0.01	(0.97)	0.01	0.02
AUT	**0.39**	(2.74)	**-0.07**	(-2.88)	0.06	(1.18)	0.01	0.01
BEL	**0.43**	(3.74)	**-0.11**	(-5.26)	**0.10**	(4.57)	0.03	0.06
CAN	**0.86**	(6.82)	**-0.13**	(-5.50)	0.01	(1.39)	0.03	0.04
CHE	**0.49**	(4.23)	**-0.10**	(-4.19)	0.01	(0.74)	0.01	0.01
DEU	**0.76**	(5.46)	**-0.20**	(-7.58)	**0.11**	(4.03)	0.03	0.04
DNK	**0.52**	(3.91)	**-0.11**	(-4.50)	**0.05**	(3.24)	0.04	0.07
ESP	**0.44**	(3.78)	**-0.10**	(-6.07)	0.04	(1.80)	0.01	0.03
FIN	**0.47**	(2.16)	**-0.21**	(-8.18)	**0.03**	(2.88)	0.13	0.22
FRA	**0.52**	(4.03)	**-0.13**	(-5.64)	**0.07**	(3.80)	0.03	0.06
GBR	**0.52**	(5.80)	**-0.05**	(-2.88)	0.02	(1.67)	0.01	0.02
HKG	**0.46**	(3.82)	**-0.10**	(-6.02)	0.01	(0.74)	0.01	0.02
IRL	**0.84**	(3.15)	**-0.14**	(-4.05)	0.03	(0.64)	0.01	0.01
ISR	**0.65**	(3.92)	-0.05	(-1.81)	0.00	(-0.18)	0.00	0.00
ITA	0.24	(1.90)	-0.02	(-0.87)	-0.03	(-0.54)	0.00	-0.01
JPN	**0.21**	(2.57)	**-0.05**	(-3.54)	-0.01	(-0.78)	0.00	-0.02
NLD	**0.53**	(4.48)	**-0.09**	(-3.98)	**0.03**	(2.08)	0.02	0.03
NOR	**0.59**	(3.75)	**-0.05**	(-2.17)	-0.01	(-0.66)	-0.01	-0.02
NZL	**0.47**	(4.05)	-0.02	(-0.78)	0.01	(0.41)	0.00	0.01
PRT	0.25	(1.62)	**-0.09**	(-4.33)	0.05	(0.95)	0.00	0.02
SGP	**0.40**	(3.10)	**-0.14**	(-7.93)	-0.01	(-0.76)	-0.01	-0.03
SWE	**0.52**	(3.23)	**-0.08**	(-3.27)	0.03	(1.15)	0.01	0.02
USA	**0.55**	(8.69)	**-0.12**	(-8.71)	**0.02**	(3.11)	0.02	0.03
WOR	**0.48**	(6.50)	**-0.14**	(-8.68)	**0.02**	(2.78)	0.02	0.04

Table A3

Robustness: Conditional Risk Using Earnings to Price Ratio from Campbell and Thompson (2008)

This reports robustness analysis where the market risk premium used in the conditional-risk factor is measured using the earnings to price ratio of the market portfolio as in Campbell and Thompson (2008). For each exchange, we regress the monthly excess returns COMP on the shock to the market factor and the conditional risk factor for the given exchange. For each exchange, we evaluate returns in the following two-factor model from Proposition 1:

$$E[r_{t+1}^{COMP}] = \alpha^i + \beta^m \lambda^m + \beta_c^m \lambda_c^m$$

where r_{t+1}^{COMP} is the excess return to COMP, β^m and β_c^m are the beta for the market- and conditional-risk factor, and λ^m and λ_c^m are their risk premia. The composite factor COMP is the average return to HML, RMW, CMA, UMD, and BAB. "Compensation for conditional risk" is the product $\beta_c^m \lambda_c^m$. All alphas are in monthly percent. *t*-statistics are reported below the parameter estimates and statistical significance at the 5% level is indicated in bold. The U.S. and global samples runs from 1964-2015 and 1986-2015.

Exchange	Alpha		Market Beta		Conditional Risk Beta		Compensation for conditional risk	Fraction of alpha explained by conditional risk
AUS	**0.73**	(6.21)	**-0.06**	(-3.21)	0.01	(1.63)	0.03	0.03
AUT	**0.39**	(2.73)	**-0.07**	(-2.91)	**0.10**	(1.97)	0.01	0.02
BEL	**0.43**	(3.71)	**-0.11**	(-5.22)	**0.09**	(4.14)	0.03	0.06
CAN	**0.86**	(6.81)	**-0.12**	(-5.46)	0.01	(1.88)	0.04	0.04
CHE	**0.48**	(4.16)	**-0.10**	(-4.17)	0.01	(1.02)	0.01	0.02
DEU	**0.76**	(5.45)	**-0.20**	(-7.61)	**0.12**	(4.43)	0.03	0.04
DNK	**0.51**	(3.87)	**-0.11**	(-4.54)	**0.04**	(3.10)	0.04	0.07
ESP	**0.44**	(3.76)	**-0.10**	(-6.08)	0.04	(1.86)	0.01	0.03
FIN	**0.63**	(2.68)	**-0.20**	(-8.01)	0.00	(-1.04)	-0.10	-0.19
FRA	**0.51**	(3.96)	**-0.13**	(-5.58)	**0.04**	(2.65)	0.03	0.05
GBR	**0.52**	(5.77)	**-0.05**	(-2.89)	0.02	(1.47)	0.01	0.02
HKG	**0.46**	(3.79)	**-0.10**	(-6.04)	0.01	(1.06)	0.01	0.03
IRL	**0.83**	(3.15)	**-0.14**	(-4.06)	**0.16**	(2.57)	0.03	0.03
ISR	**0.64**	(3.91)	-0.05	(-1.82)	0.00	(0.08)	0.00	0.00
ITA	0.24	(1.91)	-0.02	(-0.88)	-0.02	(-0.71)	0.00	-0.01
JPN	**0.21**	(2.56)	**-0.05**	(-3.54)	-0.01	(-0.58)	0.00	-0.01
NLD	**0.53**	(4.47)	**-0.09**	(-4.05)	**0.03**	(2.15)	0.02	0.03
NOR	**0.55**	(3.30)	**-0.04**	(-2.00)	0.00	(0.36)	0.02	0.04
NZL	**0.47**	(4.06)	-0.01	(-0.75)	0.00	(0.22)	0.00	0.00
PRT	0.25	(1.59)	**-0.09**	(-4.36)	0.08	(1.71)	0.01	0.03
SGP	**0.40**	(3.10)	**-0.14**	(-7.96)	-0.01	(-0.73)	-0.01	-0.03
SWE	**0.48**	(3.06)	**-0.08**	(-3.28)	**0.07**	(3.03)	0.03	0.06
USA	**0.55**	(8.73)	**-0.12**	(-8.68)	**0.02**	(2.75)	0.02	0.03
WOR	**0.48**	(6.50)	**-0.14**	(-8.69)	**0.02**	(2.66)	0.02	0.04

Table A4

Robustness: Conditional Risk Using Book to Market Ratio from Campbell and Thompson (2008)

This reports robustness analysis where the market risk premium used in the conditional-risk factor is measured using the book-to-market ratio of the market portfolio as in Campbell and Thompson (2008). For each exchange, we regress the monthly excess returns COMP on the shock to the market factor and the conditional risk factor for the given exchange. For each exchange, we evaluate returns in the following two-factor model from Proposition 1:

$$E[r_{t+1}^{COMP}] = \alpha^i + \beta^m \lambda^m + \beta_c^m \lambda_c^m$$

where r_{t+1}^{COMP} is the excess return to COMP, β^m and β_c^m are the beta for the market- and conditional-risk factor, and λ^m and λ_c^m are their risk premia. The composite factor COMP is the average return to HML, RMW, CMA, UMD, and BAB. "Compensation for conditional risk" is the product $\beta_c^m \lambda_c^m$. All alphas are in monthly percent. *t*-statistics are reported below the parameter estimates and statistical significance at the 5% level is indicated in bold. The U.S. and global samples runs from 1964-2015 and 1986-2015.

Exchange	Alpha		Market Beta		Conditional Risk Beta		Compensation for conditional risk	Fraction of alpha explained by conditional risk
AUS	**0.74**	(6.30)	**-0.06**	(-3.21)	0.01	(0.86)	0.02	0.02
AUT	**0.39**	(2.72)	**-0.07**	(-2.91)	**0.10**	(2.22)	0.01	0.02
BEL	**0.43**	(3.72)	**-0.12**	(-5.32)	**0.11**	(5.13)	0.03	0.07
CAN	**0.87**	(6.95)	**-0.13**	(-5.58)	0.01	(1.08)	0.02	0.02
CHE	**0.49**	(4.24)	**-0.10**	(-4.26)	0.00	(0.30)	0.00	0.01
DEU	**0.76**	(5.43)	**-0.20**	(-7.56)	**0.09**	(3.85)	0.03	0.04
DNK	**0.51**	(3.89)	**-0.11**	(-4.50)	**0.04**	(3.32)	0.04	0.08
ESP	**0.44**	(3.78)	**-0.10**	(-6.08)	0.04	(1.77)	0.01	0.03
FIN	0.43	(1.45)	**-0.13**	(-5.63)	0.00	(0.90)	0.17	0.28
FRA	**0.49**	(3.89)	**-0.13**	(-5.73)	**0.07**	(5.50)	0.07	0.12
GBR	**0.53**	(5.87)	**-0.05**	(-2.88)	0.00	(0.09)	0.00	0.00
HKG	**0.47**	(3.87)	**-0.10**	(-6.06)	0.00	(0.35)	0.00	0.01
IRL	**0.89**	(3.33)	**-0.15**	(-4.24)	-0.02	(-1.12)	-0.05	-0.06
ISR	**0.63**	(3.84)	-0.04	(-1.70)	0.00	(0.31)	0.01	0.01
ITA	0.23	(1.86)	-0.02	(-0.84)	0.05	(0.98)	0.00	0.01
JPN	**0.21**	(2.61)	**-0.05**	(-3.54)	-0.01	(-1.09)	-0.01	-0.04
NLD	**0.55**	(4.54)	**-0.09**	(-3.94)	0.01	(0.65)	0.01	0.01
NOR	**0.57**	(3.51)	**-0.05**	(-2.28)	0.00	(0.41)	0.02	0.03
NZL	**0.46**	(4.00)	-0.02	(-0.79)	0.02	(1.18)	0.01	0.02
PRT	0.25	(1.63)	**-0.09**	(-4.35)	0.07	(1.30)	0.01	0.02
SGP	**0.40**	(3.11)	**-0.14**	(-7.90)	-0.01	(-0.92)	-0.01	-0.03
SWE	**0.47**	(2.91)	**-0.07**	(-3.09)	0.01	(1.58)	0.05	0.09
USA	**0.55**	(8.73)	**-0.12**	(-8.65)	0.01	(1.38)	0.01	0.01
WOR	**0.49**	(6.51)	**-0.14**	(-8.71)	**0.02**	(2.53)	0.02	0.04

Table A5

Robustness: Conditional Risk Using Constant Expected Returns

This reports robustness analysis where the market risk premium is assumed to be constant. We regress the monthly excess returns of different factors on the shock to the market factor and the conditional risk factor and evaluate returns in the following two-factor model from Proposition 1:

$$E[r_{t+1}^i] = \alpha^i + \beta^m\lambda^m + \beta_c^m\lambda_c^m$$

where r_{t+1}^i is the excess return to the risk factor i, β^m and β_c^m are the beta for the market- and conditional-risk factor, and λ^m and λ_c^m are their risk premia. The composite factor COMP is the average return to HML, RMW, CMA, UMD, and BAB. "Compensation for conditional risk" is the product $\beta_c^m\lambda_c^m$. All alphas are in monthly percent. *t*-statistics are reported below the parameter estimates and statistical significance at the 5% level is indicated in bold. The U.S. and global samples run from 1964-2015 and 1986-2015.

	SMB	HML	RMW	CMA	UMD	BAB	COMP
Panel A: U.S. Sample							
Alpha	0.12	**0.39**	**0.30**	**0.32**	**0.74**	**0.99**	**0.55**
	(1.04)	(3.76)	(3.56)	(4.65)	(4.65)	(7.49)	(8.96)
Market beta	**0.21**	**-0.17**	**-0.12**	**-0.15**	**-0.13**	-0.05	**-0.12**
	(7.91)	(-7.43)	(-6.57)	(-9.67)	(-3.57)	(-1.69)	(-9.09)
Conditional risk beta	0.02	0.00	**0.07**	0.00	**0.20**	**0.14**	**0.08**
	(0.73)	(-0.04)	(4.00)	(0.33)	(6.33)	(5.36)	(6.77)
Compensation for conditional risk	0.00	0.00	0.02	0.00	0.05	0.03	0.02
Fraction of alpha explained by conditional risk	0.03	0.00	0.05	0.00	0.06	0.03	0.04
Observations	624	624	624	624	624	624	624
Adjusted R^2	0.09	0.08	0.08	0.13	0.08	0.05	0.17
Panel B: Global Sample							
Alpha	0.08	**0.37**	**0.33**	**0.30**	**0.71**	**0.80**	**0.49**
	(0.70)	(3.33)	(3.93)	(4.06)	(3.81)	(4.97)	(6.64)
Market beta	**0.05**	**-0.10**	**-0.18**	**-0.08**	**-0.22**	**-0.13**	**-0.14**
	(2.19)	(-4.00)	(-9.85)	(-5.25)	(-5.35)	(-3.72)	(-8.81)
Conditional risk beta	-0.03	-0.02	0.01	0.01	**0.21**	0.04	**0.05**
	(-1.30)	(-1.09)	(0.70)	(0.94)	(6.20)	(1.47)	(3.88)
Compensation for conditional risk	-0.01	-0.01	0.00	0.00	0.06	0.01	0.02
Fraction of alpha explained by conditional risk	-0.11	-0.02	0.01	0.01	0.08	0.02	0.03
Observations	359	359	359	359	359	306	359
Adjusted R^2	0.01	0.04	0.21	0.07	0.15	0.05	0.20

Table A6

Robustness: Conditional Risk Using Constant Expected Returns

This reports robustness analysis where the market risk premium is assumed to be constant. For each exchange, we regress the monthly excess returns COMP on the shock to the market factor and the conditional risk factor for the given exchange. For each exchange, we evaluate returns in the following two-factor model from Proposition 1:

$$E[r_{t+1}^{COMP}] = \alpha^i + \beta^m \lambda^m + \beta_c^m \lambda_c^m$$

where r_{t+1}^{COMP} is the excess return to COMP, β^m and β_c^m are the beta for the market- and conditional-risk factor, and λ^m and λ_c^m are their risk premia. The composite factor COMP is the average return to HML, RMW, CMA, UMD, and BAB. "Compensation for conditional risk" is the product $\beta_c^m \lambda_c^m$. All alphas are in monthly percent. *t*-statistics are reported below the parameter estimates and statistical significance at the 5% level is indicated in bold. The U.S. and global samples runs from 1964-2015 and 1986-2015.

Exchange	Alpha		Market Beta		Conditional Risk Beta		Compensation for conditional risk	Fraction of alpha explained by conditional risk
AUS	**0.73**	(6.32)	**-0.06**	(-3.26)	**0.04**	(2.56)	0.02	0.03
AUT	**0.36**	(2.52)	**-0.07**	(-2.94)	**0.07**	(2.89)	0.02	0.06
BEL	**0.40**	(3.46)	**-0.12**	(-5.30)	**0.06**	(4.25)	0.04	0.09
CAN	**0.87**	(7.03)	**-0.13**	(-5.57)	**0.04**	(2.79)	0.03	0.04
CHE	**0.48**	(4.16)	**-0.10**	(-4.28)	**0.05**	(2.32)	0.01	0.03
DEU	**0.78**	(5.63)	**-0.20**	(-7.59)	**0.20**	(4.15)	0.02	0.02
DNK	**0.53**	(4.00)	**-0.11**	(-4.50)	**0.05**	(3.15)	0.03	0.06
ESP	**0.44**	(3.69)	**-0.10**	(-6.07)	0.01	(0.69)	0.01	0.01
FIN	**0.55**	(2.67)	**-0.22**	(-8.81)	**0.12**	(4.55)	0.07	0.11
FRA	**0.53**	(4.11)	**-0.13**	(-5.66)	**0.08**	(3.22)	0.02	0.04
GBR	**0.52**	(5.78)	**-0.05**	(-2.93)	**0.05**	(3.05)	0.02	0.03
HKG	**0.45**	(3.71)	**-0.10**	(-6.01)	0.02	(1.83)	0.02	0.05
IRL	**0.79**	(3.00)	**-0.14**	(-4.05)	**0.11**	(2.56)	0.04	0.05
ISR	**0.66**	(3.96)	-0.04	(-1.80)	0.08	(0.98)	0.00	0.00
ITA	0.22	(1.81)	-0.02	(-0.90)	**0.09**	(2.48)	0.01	0.04
JPN	**0.20**	(2.49)	**-0.05**	(-3.49)	0.09	(1.65)	0.00	0.01
NLD	**0.54**	(4.54)	**-0.09**	(-4.14)	**0.05**	(2.40)	0.02	0.03
NOR	**0.58**	(3.71)	**-0.05**	(-2.13)	0.02	(0.68)	0.01	0.01
NZL	**0.46**	(3.99)	-0.01	(-0.74)	**0.05**	(2.28)	0.01	0.03
PRT	0.25	(1.64)	**-0.09**	(-4.35)	0.08	(1.23)	0.00	0.02
SGP	**0.36**	(2.83)	**-0.14**	(-7.89)	0.00	(-0.33)	0.00	-0.01
SWE	**0.48**	(3.07)	**-0.08**	(-3.41)	**0.08**	(3.22)	0.03	0.06
USA	**0.55**	(8.96)	**-0.12**	(-9.09)	**0.08**	(6.77)	0.02	0.04
WOR	**0.49**	(6.64)	**-0.14**	(-8.81)	**0.05**	(3.88)	0.02	0.03

Table A7

Robustness: Conditional Risk Using Constant Variance

This reports robustness analysis where the market variance is assumed to be constant. We regress the monthly excess returns of different factors on the shock to the market factor and the conditional risk factor and evaluate returns in the following two-factor model from Proposition 1:

$$E\left[r_{t+1}^{i}\right] = \alpha^{i} + \beta^{m}\lambda^{m} + \beta_{c}^{m}\lambda_{c}^{m}$$

where r_{t+1}^{i} is the excess return to the risk factor i, β^{m} and β_{c}^{m} are the beta for the market- and conditional-risk factor, and λ^{m} and λ_{c}^{m} are their risk premia. The composite factor COMP is the average return to HML, RMW, CMA, UMD, and BAB. "Compensation for conditional risk" is the product $\beta_{c}^{m}\lambda_{c}^{m}$. All alphas are in monthly percent. *t*-statistics are reported below the parameter estimates and statistical significance at the 5% level is indicated in bold. The U.S. and global samples run from 1964-2015 and 1986-2015.

	SMB	HML	RMW	CMA	UMD	BAB	COMP
Panel A: U.S. Sample							
Alpha	0.15	**0.35**	**0.25**	**0.29**	**0.72**	**0.90**	**0.50**
	(1.25)	(3.36)	(3.05)	(4.17)	(4.39)	(6.93)	(8.32)
Market beta	**0.21**	**-0.17**	**-0.12**	**-0.15**	**-0.13**	-0.05	**-0.12**
	(7.78)	(-7.17)	(-6.53)	(-9.36)	(-3.59)	(-1.71)	(-9.10)
Conditional risk beta	-0.01	**0.03**	**0.04**	**0.02**	**0.05**	**0.08**	**0.04**
	(-1.16)	(3.44)	(6.00)	(3.82)	(3.48)	(7.44)	(8.81)
Compensation for conditional risk	-0.02	0.04	0.06	0.03	0.07	0.12	0.06
Fraction of alpha explained by conditional risk	-0.13	0.11	0.19	0.10	0.09	0.12	0.11
Observations	623	623	623	623	623	623	623
Adjusted R^2	0.09	0.09	0.11	0.14	0.04	0.08	0.20
Panel B: Global Sample							
Alpha	0.09	**0.24**	**0.26**	**0.24**	**0.75**	**0.70**	**0.42**
	(0.76)	(2.28)	(3.14)	(3.29)	(3.77)	(4.50)	(5.82)
Market beta	**0.06**	**-0.09**	**-0.18**	**-0.08**	**-0.22**	**-0.13**	**-0.14**
	(2.31)	(-4.16)	(-9.88)	(-5.19)	(-5.05)	(-3.88)	(-8.93)
Conditional risk beta	-0.01	**0.06**	**0.02**	**0.02**	0.00	**0.05**	**0.03**
	(-0.90)	(8.20)	(3.21)	(4.88)	(-0.25)	(5.20)	(5.95)
Compensation for conditional risk	-0.02	0.13	0.04	0.05	-0.01	0.12	0.07
Fraction of alpha explained by conditional risk	-0.22	0.35	0.13	0.18	-0.01	0.15	0.13
Observations	354	354	354	354	354	306	354
Adjusted R^2	0.01	0.19	0.23	0.12	0.06	0.12	0.24

Table A8

Robustness: Conditional Risk Using Constant Variance

This reports robustness analysis where the market variance is assumed to be constant. For each exchange, we regress the monthly excess returns COMP on the shock to the market factor and the conditional risk factor for the given exchange. For each exchange, we evaluate returns in the following two-factor model from Proposition 1:

$$E[r_{t+1}^{COMP}] = \alpha^i + \beta^m \lambda^m + \beta_c^m \lambda_c^m$$

where r_{t+1}^{COMP} is the excess return to COMP, β^m and β_c^m are the beta for the market- and conditional-risk factor, and λ^m and λ_c^m are their risk premia. The composite factor COMP is the average return to HML, RMW, CMA, UMD, and BAB. "Compensation for conditional risk" is the product $\beta_c^m \lambda_c^m$. All alphas are in monthly percent. *t*-statistics are reported below the parameter estimates and statistical significance at the 5% level is indicated in bold. The U.S. and global samples runs from 1964-2015 and 1986-2015.

Exchange	Alpha		Market Beta		Conditional Risk Beta		Compensation for conditional risk	Fraction of alpha explained by conditional risk
AUS	**0.76**	(6.49)	**-0.06**	(-3.23)	0.05	(1.94)	0.01	0.01
AUT	**0.39**	(2.69)	**-0.08**	(-3.24)	0.00	(0.11)	0.00	0.00
BEL	**0.46**	(3.80)	**-0.11**	(-4.84)	-0.01	(-0.59)	-0.01	-0.01
CAN	**0.91**	(6.86)	**-0.13**	(-5.28)	0.01	(0.71)	0.01	0.01
CHE	**0.50**	(4.25)	**-0.11**	(-4.49)	0.00	(-0.10)	0.00	0.00
DEU	**0.67**	(4.78)	**-0.18**	(-7.02)	**0.04**	(5.27)	0.13	0.16
DNK	**0.53**	(3.97)	**-0.11**	(-4.66)	**0.02**	(2.35)	0.05	0.08
ESP	**0.45**	(3.80)	**-0.11**	(-6.24)	0.01	(1.53)	0.02	0.05
FIN	**0.55**	(2.56)	**-0.23**	(-8.82)	0.02	(1.65)	0.06	0.11
FRA	**0.55**	(4.16)	**-0.12**	(-5.25)	0.02	(1.37)	0.02	0.03
GBR	**0.52**	(5.69)	**-0.05**	(-2.68)	**0.02**	(2.21)	0.02	0.04
HKG	**0.51**	(4.24)	**-0.10**	(-5.85)	**-0.03**	(-2.83)	-0.03	-0.07
IRL	**0.86**	(3.21)	**-0.14**	(-3.92)	0.02	(0.74)	0.02	0.03
ISR	**0.64**	(3.91)	-0.05	(-1.96)	0.00	(-0.13)	0.00	0.00
ITA	0.22	(1.72)	-0.02	(-0.97)	0.01	(1.31)	0.02	0.08
JPN	**0.21**	(2.60)	**-0.05**	(-3.40)	0.02	(1.31)	0.01	0.03
NLD	**0.50**	(4.06)	**-0.10**	(-4.34)	**0.01**	(2.49)	0.07	0.13
NOR	**0.55**	(3.48)	**-0.05**	(-2.35)	0.02	(1.93)	0.05	0.08
NZL	**0.45**	(3.92)	-0.02	(-0.77)	0.02	(1.94)	0.02	0.04
PRT	0.23	(1.46)	**-0.10**	(-4.53)	0.00	(0.03)	0.00	0.00
SGP	**0.37**	(2.82)	**-0.14**	(-7.73)	0.00	(0.65)	0.02	0.04
SWE	**0.53**	(3.31)	**-0.08**	(-3.15)	0.01	(0.33)	0.00	0.01
USA	**0.50**	(8.32)	**-0.12**	(-9.10)	**0.04**	(8.81)	0.06	0.11
WOR	**0.42**	(5.82)	**-0.14**	(-8.93)	**0.03**	(5.95)	0.07	0.13

Table A9

Robustness: Conditional Risk Using Bollerslev et al (2009) and SVIX

This reports robustness analysis where the market variance used in the conditional-risk factor is measured using either Bollerslev, Tauchen, Zhou (2009) or the SVIX measure of risk neutral variance (Martin, 2017). For each exchange, we regress the monthly excess returns COMP on the shock to the market factor and the conditional risk factor for the given exchange. We evaluate returns in the following two-factor model from Proposition 1:

$$E[r_{t+1}^{COMP}] = \alpha^i + \beta^m \lambda^m + \beta_c^m \lambda_c^m$$

where r_{t+1}^{COMP} is the excess return to COMP, β^m and β_c^m are the beta for the market- and conditional-risk factor, and λ^m and λ_c^m are their risk premia. The composite factor COMP is the average return to HML, RMW, CMA, UMD, and BAB. "Compensation for conditional risk" is the product $\beta_c^m \lambda_c^m$. All alphas are in monthly percent. *t*-statistics are reported below the parameter estimates and statistical significance at the 5% level is indicated in bold. The sample is the U.S. sample from 1990-2015 (Panel A) and 1996-2015 (Panel B).

	SMB	HML	RMW	CMA	UMD	BAB	COMP
Panel A: Bollerslev et. al (2009)							
Alpha	0.00	0.16	**0.48**	**0.25**	**0.79**	**0.99**	**0.53**
	(-0.01)	(1.05)	(3.47)	(2.42)	(2.95)	(4.58)	(5.17)
Market beta	**0.18**	**-0.13**	**-0.25**	**-0.13**	**-0.30**	**-0.26**	**-0.21**
	(4.43)	(-3.72)	(-8.22)	(-5.77)	(-4.91)	(-5.44)	(-9.28)
Conditional risk beta	0.00	**0.02**	**0.02**	**0.02**	**0.04**	**0.05**	**0.03**
	(0.44)	(2.86)	(2.88)	(3.55)	(2.48)	(4.64)	(5.55)
Compensation for conditional risk	0.01	0.08	0.07	0.06	0.11	0.17	0.10
Fraction of alpha explained by conditional risk	1.17	0.32	0.13	0.20	0.13	0.15	0.16
Observations	311	311	311	311	311	311	311
Adjusted R^2	0.05	0.06	0.19	0.12	0.08	0.14	0.27
Panel B: SVIX							
Alpha	0.05	0.15	**0.56**	**0.25**	**0.76**	**1.04**	**0.55**
	(0.21)	(0.80)	(3.33)	(2.12)	(2.27)	(4.00)	(4.42)
Market beta	**0.20**	**-0.12**	**-0.29**	**-0.12**	**-0.35**	**-0.31**	**-0.24**
	(4.05)	(-3.19)	(-7.94)	(-4.55)	(-4.92)	(-5.50)	(-8.87)
Conditional risk beta	0.02	**0.07**	**0.05**	**0.04**	0.06	**0.11**	**0.07**
	(0.95)	(3.68)	(3.00)	(3.77)	(1.71)	(4.28)	(5.31)
Compensation for conditional risk	0.02	0.06	0.05	0.04	0.05	0.11	0.06
Fraction of alpha explained by conditional risk	0.30	0.31	0.08	0.15	0.07	0.09	0.10
Observations	238	238	238	238	238	238	238
Adjusted R^2	0.06	0.08	0.23	0.12	0.10	0.17	0.31

Table A10

Robustness: Index of Expected Return

This reports robustness analysis where the market risk premium used in the conditional-risk factor is measured as the average of estimators by: the Campbell and Thompson (2008), Kelly and Pruitt (2013), Lettau and Ludvigson (2001), and Martin (2017). We regress the monthly excess returns of different factors on the shock to the market factor and the conditional risk factor and evaluate returns in the following two-factor model from Proposition 1:

$$E\left[r_{t+1}^{i}\right] = \alpha^{i} + \beta^{m}\lambda^{m} + \beta_{c}^{m}\lambda_{c}^{m}$$

where r_{t+1}^{i} is the excess return to the risk factor i, β^{m} and β_{c}^{m} are the beta for the market- and conditional-risk factor, and λ^{m} and λ_{c}^{m} are their risk premia. The composite factor COMP is the average return to HML, RMW, CMA, UMD, and BAB. "Compensation for conditional risk" is the product $\beta_{c}^{m}\lambda_{c}^{m}$. All alphas are in monthly percent. *t*-statistics are reported below the parameter estimates and statistical significance at the 5% level is indicated in bold. The U.S. and global samples run from 1964-2015 and 1986-2015.

	SMB	HML	RMW	CMA	UMD	BAB	COMP
Panel A: Bollerslev et. al (2009)							
Alpha	0.17	**0.36**	**0.26**	**0.29**	**0.69**	**0.93**	**0.51**
	(1.46)	(3.50)	(3.17)	(4.20)	(4.25)	(7.13)	(8.32)
Market beta	**0.21**	**-0.17**	**-0.12**	**-0.15**	**-0.13**	-0.05	**-0.12**
	(7.87)	(-7.32)	(-6.60)	(-9.57)	(-3.53)	(-1.68)	(-9.07)
Conditional risk beta	-0.01	0.00	**0.03**	0.01	**0.10**	**0.09**	**0.05**
	(-0.89)	(0.44)	(3.91)	(1.36)	(5.67)	(6.69)	(7.40)
Compensation for conditional risk	-0.01	0.00	0.03	0.01	0.08	0.08	0.04
Fraction of alpha explained by conditional risk	-0.06	0.01	0.10	0.03	0.11	0.08	0.08
Observations	623	623	623	623	623	623	623
Adjusted R^2	0.09	0.08	0.08	0.13	0.06	0.07	0.18
Panel B: SVIX							
Alpha	0.08	**0.29**	**0.27**	**0.25**	**0.64**	**0.68**	**0.42**
	(0.72)	(2.66)	(3.23)	(3.39)	(3.31)	(4.48)	(5.90)
Market beta	**0.06**	**-0.10**	**-0.18**	**-0.08**	**-0.22**	**-0.12**	**-0.14**
	(2.26)	(-4.06)	(-10.05)	(-5.37)	(-5.26)	(-3.47)	(-9.36)
Conditional risk beta	0.00	**0.05**	**0.01**	**0.03**	**0.06**	**0.08**	**0.04**
	(-0.43)	(5.44)	(2.04)	(4.97)	(3.59)	(6.04)	(7.48)
Compensation for conditional risk	-0.01	0.07	0.02	0.04	0.08	0.12	0.06
Fraction of alpha explained by conditional risk	-0.08	0.20	0.07	0.15	0.12	0.14	0.13
Observations	354	354	354	354	354	306	354
Adjusted R^2	0.01	0.11	0.23	0.13	0.10	0.15	0.28

Figure A1

Conditional Risk in Volatility Managed Portfolios around the World

This figure the loading of volatility managed portfolios on the conditional risk factor around the world.

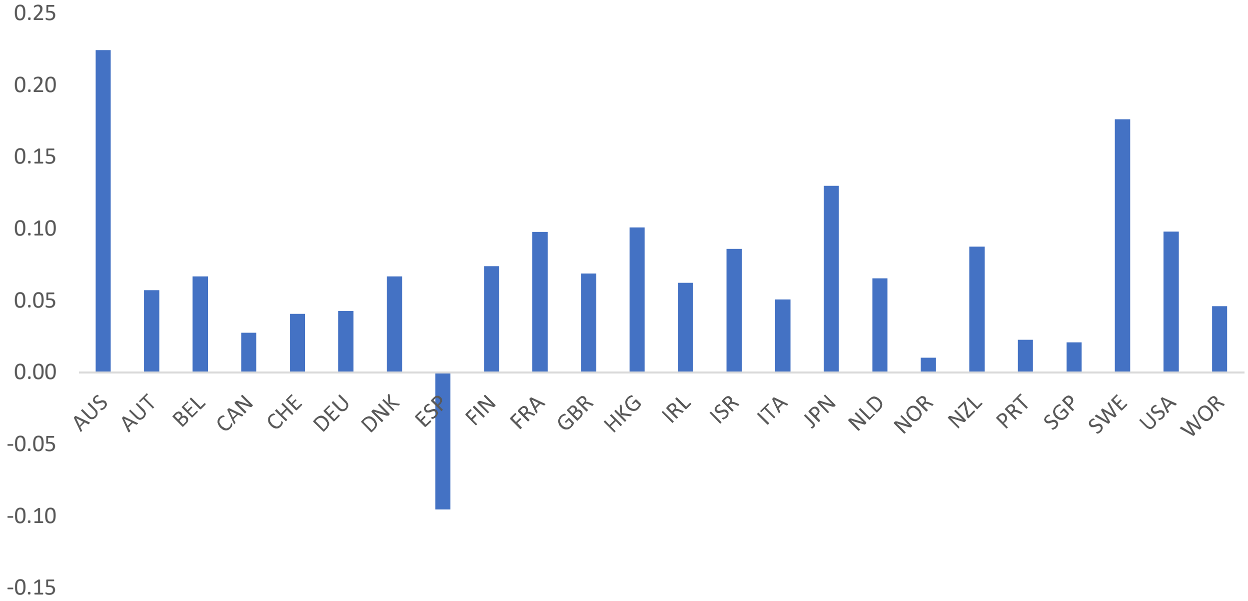


Figure A2

Conditional Risk in Time Series Momentum around the World

This figure the loading of time-series momentum portfolios on the conditional risk factor around the world.

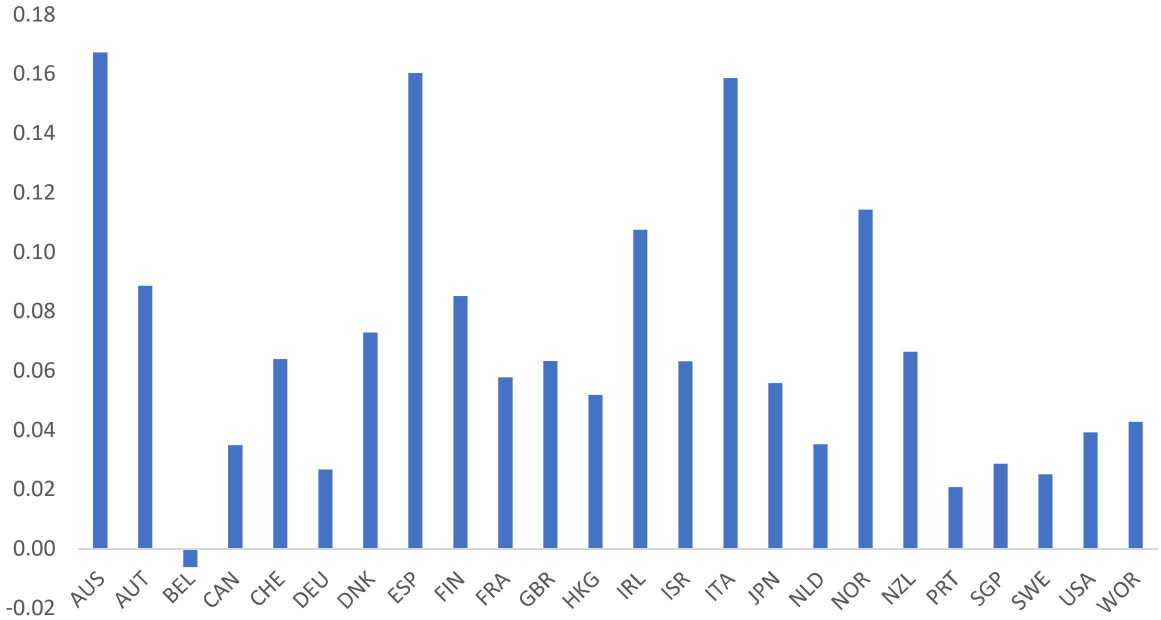
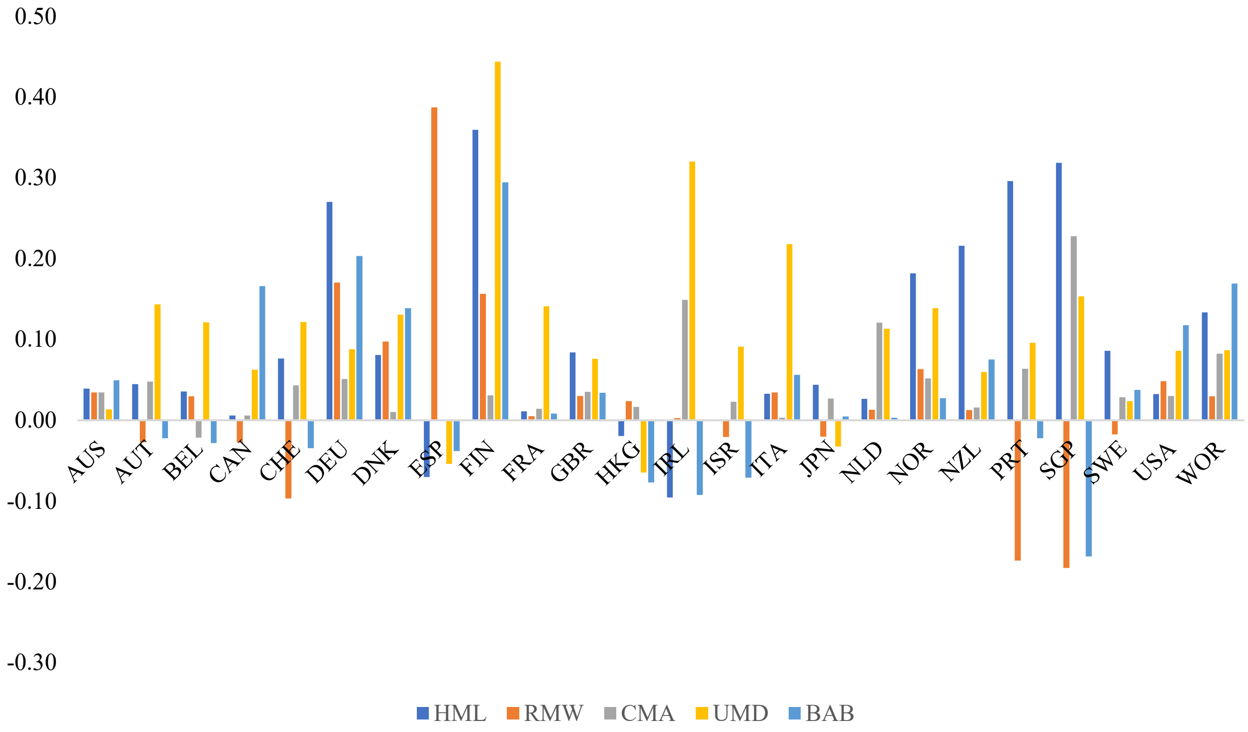


Figure A3

Conditional Risk in Cross-Sectional Risk Factors around the World

This figure shows the compensation for conditional risk is in different cross-sectional strategies in different countries. The composite risk factor is the average return to HML, RMW, CMA, UMD, and BAB.



Chapter 3

Bettin Against Correlation: Testing Theories of the Low-Risk Effect

with Cliff Asness, Andrea Frazzini, and Lasse Heje Pedersen

Abstract:

We test whether the low-risk effect is driven by (a) leverage constraints and thus risk should be measured using beta vs. (b) behavioral effects and thus risk should be measured by idiosyncratic risk. Beta depends on volatility and correlation, where only volatility is related to idiosyncratic risk. Hence, the new factor betting against correlation (BAC) is particularly suited to differentiating between leverage constraints vs. lottery explanations. BAC produces strong performance in the US and internationally, supporting leverage constraint theories. Similarly, we construct the new factor SMAX to isolate lottery demand, which also produces positive returns. Consistent with both leverage and lottery theories contributing to the low-risk effect, we find that BAC is related to margin debt while idiosyncratic risk factors are related to sentiment and casino profits.

Keywords: asset pricing, leverage constraints, lottery demand, margin, sentiment.

JEL classification: G02, G12, G14, G15.

Asness and Frazzini are at AQR Capital Management, Two Greenwich Plaza, Greenwich, CT 06830, e-mail: andrea.frazzini@aqr.com; web: www.econ.yale.edu/ af227/. Pedersen is at AQR Capital Management, Copenhagen Business School, NYU, and CEPR; e-mail: lhp001@gmail.com; web: www.lhpedersen.com. Gormsen is at Copenhagen Business School; e-mail ng.fi@cbs.dk. We are grateful for helpful comments from Robin Greenwood, Toby Moskowitz, and Tatyana Marchuk (discussant) as well as from seminar participants at AQR, BI-SHoF conference on Asset Pricing and Financial Econometrics 2017, the Q-group spring seminar 2017, Instinet Annual Global Quant Research Conference, Bernstein Research conference on Controversies in Quantitative Finance, and Copenhagen Business School. Gormsen and Pedersen gratefully acknowledge support from FRIC Center for Financial Frictions (grant no. DNRF102).

1 Introduction

The relation between risk and expected return is a central issue in finance with broad implications for investment behavior, corporate finance, and market efficiency. One of the major stylized facts on the risk-return relation, indeed in empirical asset pricing more broadly, is the observation that assets with low risk have high alpha, the so-called "low-risk effect" (Black, Jensen, and Scholes, 1972).[1] However, the literature offers different views on the underlying economic drivers of the low-risk effect and the best empirical measures. In short, the debate is whether (a) the low-risk effect is driven by leverage constraints and risk should be measured using systematic risk vs. (b) the low-risk effect is driven by behavioral effects and risk should be measured using idiosyncratic risk.[2] This paper seeks to test these theories using broad global data, controlling for more existing factors, using measures of the economic drivers, and using new factors that we call betting against correlation (BAC) and scaled MAX (SMAX) that help solve the problem that the existing low-risk factors are highly correlated.

The theory of leverage constraints for the low-risk effect was proposed by Black (1972) and extended by Frazzini and Pedersen (2011, 2014) who study an extensive set of global stocks, bonds, credits, and derivatives based on their betting against beta (BAB) factor. Hence, the systematic low-risk effect is based on a rigorous economic theory and has survived more than 40 years of out of sample evidence. Further, a number of papers document evidence consistent with the underlying economic mechanism of leverage constraints: Jylhä (2018) finds that exogenous changes in margin requirements influence the slope of the security market line, Boguth and Simutin (2017) show that funding constraints as proxied by mutual fund beta predict BAB, Malkhozov, Mueller, Vedolin, and Venter (2016) show that international illiquidity predict BAB, and Adrian, Etula, and Muir (2014) document a strong link between the return to BAB and financial intermediary leverage.[3]

The alternative view is that the low-risk effect stems from behavioral biases leading to

[1]We use the standard term "low-risk effect" to refer to the (risk-adjusted) return spread between low- and high-risk stocks (i.e., it does not just refer to low-risk stocks).

[2]A related but distinct debate is whether other factors subsume low-risk factors or vice versa (see, for instance, Novy-Marx, 2014 and Fama and French, 2016) and we also address this debate herein as discussed below. We note however, that BAB and BAC are based on equilibrium theories of asset pricing while the other factors are ad hoc empirical specifications.

[3]See also the related evidence on corporate finance and banking (Baker and Wurgler, 2015, 2016), benchmark constraints (Brennan, 1993; Baker, Bradley, and Wurgler, 2011) and leverage constraints and differences of opinion (Hong and Sraer, 2015).

a preference for lottery-like returns (Barberis and Huang, 2008; Brunnermeier, Gollier, and Parker, 2007) and therefore the focus should be on idiosyncratic risk. Indeed, Ang, Hodrick, Xing, and Zhang (2006, 2009) find that stocks with low idiosyncratic volatility (IVOL) have high risk-adjusted returns in the U.S. and internationally. In a similar vein, Bali, Cakici, and Whitelaw (2011) consider stocks sorted on the maximum return (MAX) over the past month, finding that low MAX is associated with high risk-adjusted returns,[4] and Bali, Brown, Murray, and Tang (2017) argue that the low-risk effect is driven by idiosyncratic risk rather than systematic risk. Also, Liu, Stambaugh, and Yuan (2017) argue that the low-risk effect is driven by idiosyncratic risk and only appears among over-priced stocks.

The challenge with the existing literature is that it seeks to run a horse race between factors that are, by construction, highly correlated since risky stocks are usually risky in many ways. Indeed, the reason that all these factors are known under the umbrella term "the low-risk effect" is that they are so closely related. Hence, the most powerful way to credibly distinguish these theories is to construct a new factor that captures one theory while at the same being relatively unrelated to factors capturing the alternative theory. To accomplish this, we decompose BAB into two factors: betting against correlation (BAC) and betting against volatility (BAV). BAC goes long stocks that have low correlation to the market and shorts those with high correlation, while seeking to match the volatility of the stocks that are bought and sold. Likewise, BAV goes long and short based on volatility, while seeking to match correlation. This decomposition of BAB creates a component that is relatively unrelated to the behavioral factors (BAC) and a closely related component (BAV). To see that BAC is relatively unrelated to the behavioral-based factors, we note that the long and short sides of BAC have similar average volatility, skewness, and MAX.[5] At the same time, sorting on ex ante market correlation successfully creates a BAC factor that is long stocks with low ex post market correlations (and short stocks with high ones).

Since stocks with low market correlation have low market betas, the theory of leverage constraints implies that BAC has positive risk-adjusted returns, just like BAB. Empirically, we find that BAC is about as profitable as the BAB factor and BAC has a highly significant CAPM alpha as predicted by the theory of leverage constraints. This evidence thus supports the theory of leverage constraints and is clearly separate from the behavioral factors. To address the findings of Liu, Stambaugh, and Yuan (2017), we double-sort on their measure

[4]See also the measure related to idiosyncratic skewness studied by Boyer, Mitton, and Vorkink (2009).
[5]See also the measure related to idiosyncratic skewness studied by Boyer, Mitton, and Vorkink (2009).

of each stock's "mispricing" and our measure of each stock's correlation with the market, finding that low-correlation stocks deliver higher risk-adjusted returns in each quintile of mispricing, providing further evidence that the low-risk effect is not just about idiosyncratic risk or its interaction with mispricing.

Another challenge to the low-risk effect, both with systematic and idiosyncratic risk, is posed by Fama and French (2016) who argue that that a five-factor model of the market (MKT), size (SMB), value (HML), profitability (RMW), and investment (CMA) explains the low-risk effect (and the majority of the cross-section of returns more broadly, except for momentum). While they don't test BAB explicitly, they suggest that there is no relationship between alpha and systematic risk once controlling for the five factors. We study this question explicitly and, further, we also control for short-term reversal (REV), which is particularly relevant for the idiosyncratic risk factors (due to their high turnover as discussed below). We find significant alpha for BAB and BAC for a variety of combinations of control factors in the US and globally. For example, BAC has a five-factor alpha of 0.62

Turning to the behavioral theory, we next consider the factors that go long stocks with low MAX return (LMAX) or low idiosyncratic volatility (IVOL). We sign all factors such that they are long low-risk stocks (even though the literature is not always consistent in this regard).[6] Since IVOL is already based on decomposing volatility into its systematic and idiosyncratic parts, we do not further decompose IVOL. For LMAX, however, we can again create a new factor that helps differentiate alternative hypotheses by removing the common component (namely, volatility). Just like we created BAC to remove the effect of volatility from beta (which left us with correlation), we can remove the effect of volatility from MAX: We construct a scaled-MAX (SMAX) factor that goes long stocks with low MAX return divided by ex ante volatility and shorts stocks with the opposite characteristic. This factor captures lottery demand in a way that is not as mechanically related to volatility as it is more purely about the shape of the return distribution.

Behavioral theories imply that these idiosyncratic risk factors should have positive alphas, which we confirm in the data. In the U.S., SMAX, LMAX, and IVOL all produce significant alphas with respect to the Fama-French five-factor model, but SMAX performs stronger than both LMAX and IVOL. In the global sample, however, none of the factors are robust to controlling for the five Fama-French factors and short-term reversal.

[6]For example, LMAX is the negative of the FMAX factor considered by Bali, Cakici, and Whitelaw (2011).

To go beyond studying the risk-adjusted returns, we study additional predictions arising from the different economic theories for the low-risk effect. To capture the idea underlying the theory of leverage constraints, we consider the margin debt held by customers at NYSE member organizations (broker-dealers). To capture the behavioral effects, we consider investor sentiment as suggested by Liu, Stambaugh, and Yuan (2017). We find that BAB and BAC are predicted by measures of leverage constraints, while these factors are not predicted by investor sentiment. In contrast, MAX and IVOL are related to sentiment, but not measures of leverage constraints. This evidence is consistent with both of the alternative theories playing a role and that the alternative factors may, to some extent, capture different effects.[7]

The result that sentiment predicts the idiosyncratic- risk factors supports the role of behavioral biases, but it does not tell exactly which behavioral bias is at play. To study behavioral lottery demand more specifically, we consider two new measures of lottery demand: profits earned by casinos in the U.S. and sales of lottery tickets in the UK. We find that casino profits predict the returns to LMAX and IVOL, consistent with theories of lottery demand. We find no evidence, however, that higher sales of lottery tickets predict higher return to any of the lottery factors. Finally, we find that neither BAB nor BAC load on any of the lottery demand measures, consistent with these factors being driven by leverage constraints and not lottery demand.

Having tested the specific predictions arising from the competing theories of the leverage effect, we next run "horseraces" between the different low-risk factors to judge their relative importance. We regress each type of low-risk factor (systematic/idiosyncratic) on the alternate type of low-risk factor as well as several controls (the Fama-French factors and short-term reversal). We find that BAB and BAC are robust to controlling for LMAX in the US and globally. Turning things around, we find that SMAX is robust to controlling for BAB in the US, but LMAX and IVOL both have insignificant alphas when we control for BAB (recall that the behavioral factors were insignificant globally even before we control for BAB).

These insignificant alphas of the idiosyncratic risk factors arise because their returns are

[7]We also consider other alternative theories of the low-risk effect. In particular, the literature also includes so-called Money Illusion as suggested by Modigliani and Cohn (1979) and studied by Cohen, Polk, and Vuolteenaho (2005). However, we find no evidence that inflation predicts either BAB or BAC. This result holds despite the fact that we include the 70's and 80's, time periods that included large shocks to inflation.

captured by BAB and our control variables. Indeed, controlling for profitability lowers the alpha as documented by Novy-Marx (2014) and so does controlling for short-term reversal (REV), which is natural since both the IVOL and MAX characteristics are computed over the last month like REV and, hence, may be partly driven by microstructure effects. Controlling for BAB further lowers their alphas, making them insignificant. These insignificant alphas may not, however, rule out that lottery demand matters since we are controlling for many factors, some of which could themselves capture similar effects.

Finally, we address that the different factors we have considered are based on different construction methods. BAB, BAC, and BAV are rank-weighted while the other factors are constructed using the Fama and French (1993) methodology. Further, the LMAX, SMAX, and IVOL characteristics are calculated over only a single month and the factors thus have much higher turnover than typical factors that capture a more stable stock characteristic (e.g., BAB, BAC, or the Fama-French factors). To address these differences, we run apples-to-apples regressions where we construct all factors using the same method and, in some cases, we also slow down the turnover of the MAX characteristic by calculating it over a longer period. We find that the systematic-risk factors are relatively robust across apples-to-apples regressions, while the idiosyncratic-risk factors appear less robust, especially with respect to formation periods as the alphas of LMAX and SMAX are almost exclusively associated with the month after the characteristics is calculated.

In summary, we find that BAB and BAC are robust to controlling for a host of other factors, have survived significant out-of-sample evidence – both through time and across asset classes and geographies – have lower turnover than many of the well-known idiosyncratic-risk measures, making them more implementable and realistic, and are supported by rigorous theory of leverage constraints with consistent evidence based on margin debt. Turning to the factors based on idiosyncratic risk, we note that these are more often defined based on a relatively short time period (high turnover) making them susceptible to microstructure noise and making it harder to believe that they capture the idea underlying the behavioral theory,[8] they are less robust to controlling for other factors and to using a lower turnover, and they are weaker globally. The strongest version appears to be our new SMAX factor, which is related to measures of sentiment. The low-risk effect can be driven by more than

[8]If behavioral investors naively look for lottery stocks, then perhaps the simplest way to do so would be to buy stocks from industries with high skewness. However, the MAX factor does not work for industry selection (see appendix). In contrast, Asness, Frazzini, and Pedersen (2014) find that BAB works both within and across industries.

one economic effect and the evidence is not inconsistent with both leverage constraints and lottery demand playing a role.

2 Data and Methodology

Our sample consists of 58,415 stocks covering 24 countries between January 1926 and December 2015. The 24 markets in our sample correspond to the countries belonging to the MSCI World Developed Index as of December 31, 2012. We report summary statistics in Table I. Stock returns are from the union of the CRSP tape and the XpressFeed Global Database. All returns are in USD and do not include any currency hedging. All excess returns are measured as excess returns above the U.S. Treasury bill rate.

We divide stocks into a long U.S. sample and a broad global sample. The U.S. sample consists of all available common stocks on the CRSP tape from January 1926 to December 2015. For each regression, we use the longest available sample depending on the availability of relevant factors, where some factors are only available from 1964 and onwards.

Our broad global sample contains all available common stocks on the union of the CRSP tape and the XpressFeed Global database. Table I contains the start date of the data in each country, but all regressions are from July 1990, the starting data of the global Fama-French factors, to December 2015. For companies traded in multiple markets, we use the primary trading vehicle identified by XpressFeed.

2.1 Constructing BAC and BAV factors

We construct betting against correlation portfolios in each country in the following way. At the beginning of each month, stocks are ranked in ascending order based on the estimate of volatility at the end of the previous month. The ranked stocks are assigned to one of five quintiles. U.S. sorts are based on NYSE breakpoints. Within each quintile, stocks are ranked based on the estimate of correlation at the end of the previous month and assigned to one of two portfolios: low correlation and high correlation. In these portfolios, stocks are weighted by ranked correlation (lower correlation stocks have larger weights in the low-correlation portfolios and larger correlation stocks have larger weights in the high-correlation portfolios), and the portfolios are rebalanced every calendar month. Both portfolios are (de)levered to have a beta of one at formation. Within each volatility quintile, a self-financing BAC portfolio is constructed to go long the low-correlation portfolio and short the high-correlation portfolio. Our overall BAC factor is then the equal-weighted average of the five betting against correlation factors.

More formally, let z^q be the $n(q) \times 1$ vector of correlation ranks within each volatility quintile $q = 1, 2, 3, 4, 5$ and $\bar{z^q} = 1'_{n(q)} z^q / n(q)$ be the average rank, where $n(q)$ is the number of securities in volatility quintile q and $1_{n(q)}$is an $n(q) \times 1$ vector of ones. The portfolio weights of the high-correlation and the low-correlation portfolios in each volatility quintile are then given by

$$w_H^q = k^q (z^q - \bar{z^q})^+$$

and

$$w_L^q = k^q (z^q - \bar{z^q})^-$$

where k^q is a normalizing constant $k^q = 2/1'_{n(q)} |z^q - \bar{z^q}|$ and $x^+$and x^- indicate the positive and negative elements of a vector x. By construction, we have $1'_{n(q)} w_H^q = 1$ and $1'_{n(q)} w_L^q = 1$. The excess return to BAC in each volatility quintile is then

$$r_{t+1}^{BAC(q)} = \frac{1}{\beta_t^{L,q}} (r_{t+1}^{L,q} - r^f) - \frac{1}{\beta_t^{H,q}} (r_{t+1}^{H,q} - r^f)$$

Here, r^f is the risk-free return, $r_{t+1}^{L,q} = r_{t+1}^{q'} w_L^qandr_{t+1}^{H,q} = r_{t+1}^{q'} w_H^q$are the returns of the low- and high-correlation portfolios, and $\beta_t^{L,q} = \beta_t^{q'} w_L^q$,and $\beta_t^{H,q} = \beta_t^{q'} w_H^q$are the corresponding betas. The return to the final BAC factor is given by

$$r_{t+1}^{BAC} = 1/5 \sum_{q=1}^{5} r_{t+1}^{BAC(q)}$$

Betting against volatility is constructed similarly to BAC, only stocks are first sorted into quintiles based on correlation instead of volatility:

$$r_{t+1}^{BAV} = 1/5 \sum_{q=1}^{5} r_{t+1}^{BAV(q)}$$

The global BAC factors are the average of the national portfolios in the sample weighted by their ex-ante market capitalization.

$$r_{t+1}^{BAC,global} = \sum_{k=1}^{K} \frac{\pi_t^k}{\sum_j \pi_t^j} r_{t+1}^{BAC,k}$$

and

$$r_{t+1}^{BAC,global} = \sum_{k=1}^{K} \frac{\pi_t^k}{\sum_j \pi_t^j} r_{t+1}^{BAC,k}$$

where π_t^k is the market capitalization of country k at time t.

To construct BAC and BAV portfolios, we need to estimate beta, correlation, and volatility for all stocks. We estimate of beta as in Frazzini and Pedersen (2014):

$$\hat{\beta}_i^{TS} = \hat{\rho}_{i,m} \frac{\hat{\sigma}_i}{s\hat{igma}_m}$$

where $\hat{\sigma}_i$ and $s\hat{igma}_m$ are the estimated volatilities of stock i and the market m and $\hat{\rho_{i,m}}$ is the estimated correlation. To estimate correlation, we use a five-year rolling windows of overlapping three-day[9] log-returns, $r_{i,t}^{3d} = \sum_{k=0}^{2} \ln(1 + r_{t+k}^i)$. Volatilities are estimated using one-year rolling windows of one-day log-returns. We require at least 750 trading days of non-missing return data to estimate correlation and 120 trading days of non-missing return data to estimate volatility. Finally, we shrink the time-series estimate of betas towards their cross-sectional mean, $\hat{\beta}_i = w_i \hat{\beta}_i^{TS} + w_i \beta^{XS}$, with shrinkage factor $w_i = 0.6$ and cross-sectional mean $\beta^{XS} = 1$. The choice of shrinkage factor does not affect the sorting of the portfolios, only the amount of leverage applied.

2.2 Constructing LMAX, SMAX, and IVOL factors

To capture the behavioral explanations of the low-risk effect, we construct LMAX, SMAX, and IVOL factors. First, we consider the LMAX factor. The LMAX factor is the negative of the FMAX factor introduced by Bali, Brown, Murray, and Tang (2017) to ensure that all factors are long low-risk stocks. Specifically, LMAX is long stocks with low MAX and short stocks with high MAX, where MAX is the average of the five highest daily returns over the last month.

We construct an LMAX factor in each country and a global LMAX factor, which is the average of the country-specific LMAX factors weighted by each country's market capitalization π_t^k:

$$r_{t+1}^{LMAX,global} = \sum_{k=1}^{K} \frac{\pi_t^k}{\sum_j \pi_t^j} r_{t+1}^{LMAX,k}$$

The country-specific LMAX portfolios are constructed as the intersection of six value-

[9]We use 3-day overlapping returns to estimate correlations to account for non-synchronous trading.

weighted portfolios formed on size and MAX. For U.S. securities, the size breakpoint is the median NYSE market equity. For international securities, the size breakpoint is the 80th percentile by country. The MAX breakpoints are the 30th and 70th percentile. We use unconditional sorts in the U.S. and conditional sorts in the international sample as many countries do not have a sample size that makes unconditional sorts useful (first we sort on size and then MAX). Portfolios are value-weighted, refreshed every calendar month, and rebalanced every calendar month to maintain value weights. LMAX is the average of the low-MAX/large-cap and low-MAX/small-cap portfolio returns minus the average of the high-MAX/large-cap and high-MAX/small-cap portfolio returns.

Just as beta is the product of correlation and volatility, a stock can have a high MAX because of high volatility or high positive skewness. To decompose these effects, we construct a scaled MAX (SMAX) as follows. For each stock, we compute the average of the five highest daily returns over the last month, divided by the stock's volatility (estimated as described in Section 2.1). We then compute the SMAX factor exactly as above just based on this scaled MAX characteristic rather than the standard MAX.

Lastly, we construct IVOL factors based on the characteristic used in Ang, Hodrick, Xing, Zhang (2006). To estimate idiosyncratic volatility, we regress each firm's daily stock returns over the given month on the daily returns to the market, size, and value factors. The residual volatility in this estimation is our measure of idiosyncratic volatility for the given firm in the given month. In the U.S., we follow Ang, Hodrick, Xing, and Zhang (2006) and use the market, size, and value portfolios of Fama and French (1993) as right-hand-side variables and, outside the U.S., we use the factor portfolios of Asness and Frazzini (2013). Based on these estimated characteristics, the IVOL factor is constructed in the same way as the LMAX and SMAX factors. The IVOL factor is long low-IVOL stocks and short high-IVOL stocks.

2.3 Explanatory variables in factor regressions

We use the Fama and French factors (1993, 2015) whenever available. In particular, we use their 5-factor model based on the value-weighted market factor (MKT), size factor small-minus-big (SMB), value factor high-minus-low (HML), profitability factor robust-minus-weak (RMW), and investment factor conservative-minus-aggressive (CMA). We also use their short-term reversal factor (REV).

2.4 Economic variables

We construct our leverage measure based on the amount of margin debt held by customers at NYSE member organizations (broker-dealers). The data is available from 1959-2015 and it is published on the NYSE website.[10] At the end of each month, we calculate the ratio of margin debt to the market capitalization of NYSE stocks which constitute our margin debt (MD) measure:

$$\mathrm{MD}_t = \frac{\text{Margin debt}_t}{\text{Market capitalization of NYSE firms}_t}$$

To capture investor sentiment, we use the sentiment index by Baker and Wurgler (2006). As inflation measure, we use the yearly change in the consumer price index from the FRED database.

We introduce two new measures of lottery demand. The first measure is a measure of casino profits in the U.S. The measure is the quarterly time-series of profits for the Casino industry scaled by nominal GDP. The casino industry has the North American Industry Classification Code (NAICS) 713210. We measure profits as revenue (REVTQ in Compustat) minus cost of goods sold (COGSQ in Compustat). We correct for seasonality using the X11 procedure.

The second measure of lottery demand is based on sales in the UK state lottery. Each month, we aggregate the total sales in the UK state lottery, which takes place every Wednesday and Saturday starting in 1993. These total monthly sales divided by UK nominal GDP constitute our UK lottery factor.[11]

We again correct for seasonality using the X11 procedure. Throughout the analysis, we use UK factors on the right-hand side whenever we have the UK lottery measure on the right hand side.

[10]The data can be found on http://www.nyxdata.com/nysedata/asp/factbook/viewer_edition.asp?mode=table&key=3153&category=8.

[11]The data can be found on http://lottery.merseyworld.com/Sales_index.html.

3 Systematic Risk: Betting Against Correlation, Volatility, and Beta

In this section, we dissect the betting against beta factor into a betting against correlation factor and a betting against volatility factor. The idea is to decompose BAB into two components: one component, BAV, that is more closely linked to idiosyncratic volatility and MAX and another component, BAC, with little relation to these alternative factors. BAV is a pure volatility bet and BAC is a pure bet against systematic risk.

3.1 Double-sorting on correlation and volatility

Before we consider the actual factors, we consider a simple double sort of volatility and correlation. Table II shows risk-adjusted returns for 25 portfolios sorted first on volatility and then conditionally on correlation. In each row, all portfolios have approximately the same volatility, but increase in correlation from the left column to the right column.

Panel A considers whether sorting on ex ante volatility and correlation successfully sorts on ex post market beta. Indeed, as correlation is often considered more difficult to estimate than volatility, it is important to consider whether the ex ante estimate predicts future systematic risk. As seen in the table, ex post CAPM beta does increase with both ex ante correlation and ex ante volatility. In fact, sorting on correlation and volatility produce similar magnitudes of spreads in ex post betas.

Table II Panel B and C next consider the risk-adjusted returns for these portfolios. We see that both the CAPM alpha (Panel B) and the three-factor alpha (Panel C) decrease as correlation or volatility increase. To examine the economic and statistical significance of these results, we consider the long/short portfolios in, respectively, the rightmost column and the bottom row. We see that the separate effects of volatility and correlation on risk-adjusted returns are significant for many of the cases, with the effect of correlation appearing especially strong.

3.2 Decomposing BAB into BAC and BAV

We next turn to the study of the long-short factors constructed as described in Section 2. Given that market betas can be decomposed into market correlation and volatility, we first show how BAB can be decomposed into BAC and BAV:

$$\text{BAB}_t = a_0 + a_1\text{BAC}_t + a_2\text{BAV}_t + \epsilon_t$$

Table III reports the result, showing that both BAC and BAV contribute to the return of the original BAB factor. In the U.S., BAB has a loading of 0.71 on BAC and 0.51 on BAV, while the loadings in the global sample are 0.84 and 0.49. The R-squared of the regressions are 85

3.3 The performance and factor loadings of BAC

We next focus on the performance of the key new factor, BAC. Table IV reports the return and factor loadings of the BAC factor and its building blocks. Recall that we construct betting against correlation factors within each volatility quintile and then the overall BAC factor is the equal-weighted average of these five factors. Panel A shows the results in the U.S., and we see that BAC has a statistically significant alpha with respect to the Fama-French 5-factor model within each volatility quintile as well as for the overall BAC factor.

Panel B in Table IV reports the analogous results in the global sample. We see that the overall BAC factor has a positive and statistically significant alpha. Also, the BAC factors within each volatility quintile have positive alphas, but they are not all statistically significant.

Turning to the factor loadings, we see that the overall BAC factor has a beta close to zero, suggesting that the ex-ante market hedge works as intended. Further, the overall BAC factor loads substantially on the small-minus-big factor as firms with, for the same volatility, low correlation often are small, undiversified firms. The BAC factor has a positive loading on the value factor (HML), consistent with the theory of leverage constraints. Indeed, the theory of leverage constraints predicts that safe stocks, those with low correlation and volatility, become cheap because they are "abandoned" by leverage constrained investors, giving rise to a positive HML loading. Lastly, we see that the loadings on RMW and CMA also tend to be positive, especially those of RMW. This is also expected since, as noted by Asness, Frazzini, and Pedersen (2013), all these are measures of quality and safety. Said differently, a stock's safety can be measured based on price data or accounting data and it is not surprising that these measures are related.

Given that the Fama-French factors (other than the MKT) have little theoretical foundation and given that the return of these factors is consistent with the theory of leverage constraints, controlling for these factors is arguably too stringent of a test.[12] Indeed, the theory of leverage constraints predicts that BAB and BAC produce positive CAPM alphas, but this theory does not predict that these factors produces positive alphas relative to right-hand-side variables that capture the same idea. All that said, it is all the more impressive that the alpha of BAC remains significant when controlling for the 5 factors, which reflects that these factors are sufficiently different in their content and construction.

Given the positive factor loadings, we could also turn the regression around and conclude that BAC and, more broadly, the theory of leverage constraints, could partly explain these Fama-French factors.

The performance of BAV is less interesting for our purposes since it is close to the factors in the literature by construction. However, for completeness, we present similar factor regressions for the BAV factor in appendix Tables A1 and A2 (see also Table VI below). In the U.S., BAV produces positive and statistically significant CAPM- and three-factor alphas, but its five-factor alpha is insignificant as are the alphas in the global sample. One striking difference in factor loadings between BAC and BAV is on small-minus-big. Where low correlation stocks, holding volatility constant, tend to be small stocks, low volatility stocks, holding correlation constant, tend to be big stocks.

In summary, BAB – and especially its purely systematic component BAC – appears robust across a variety specifications and control variables. In section 5, we test if the economic drivers of this systematic part, but, before doing so, we analyze the robustness of the idiosyncratic part of the low-risk effect.

4 Idiosyncratic Risk: LMAX, SMAX, and IVOL

In this section, we analyze the robustness of the empirical observations that stocks with high idiosyncratic volatility and lottery-like returns have low alpha. By idiosyncratic volatility, we refer to the idiosyncratic volatility characteristic defined by Ang, Hodrick, Xing, Zhang (2006), which is the monthly residual volatility in the Fama-French three-factor model as

[12] In principle if book-to-price was a perfect measure of "value" then the BAB factor would be fully explained by HML. One interpretation based on the theory of leverage constraints, is that low beta stocks tend to be cheaper due to leverage constraints, and because we do not have near a perfect measure of cheapness, the beta itself helps measure it. Said another way, both low book-to-price and low beta are noisy measures of "value."

explained in our methodology section. By lottery-like we again refer to the MAX characteristic (Bali, Cakici, and Whitelaw 2011), which is the mean of the five highest daily returns over the last month as explained in our methodology section, and our new factor SMAX.

4.1 Double-sorting on MAX and volatility

A stock can have a high MAX return either because it is volatile or because its return distribution is right-skewed. To draw this distinction, we consider each stock's scaled maximum return, that is, its MAX return divided by its ex ante volatility. This measure captures a stock's realized return distribution. An investor who does not face leverage constraints but seeks lottery-like returns can apply leverage to a stock with low volatility and high scaled MAX. Hence, scaled MAX isolates what's different about the lottery demand.

Table V shows CAPM and three factor alphas of 25 portfolios sorted first on volatility and then conditionally on scaled MAX. We see that scaled MAX is associated with significant alpha, even when keeping volatility constant.

4.2 Decomposing LMAX into SMAX and BAV

We next turn to the LMAX factor that goes long stocks with low MAX returns while shorting those with high MAX. The results in Section 4.1 suggest that LMAX gets its alpha both from betting against high volatility and from betting against stocks with high scaled max. Table VI formally decomposes LMAX into the factor that goes long stocks with low scaled max (SMAX) and the factor that goes long stocks with low total volatility over the past month (TV). Both in the U.S. and globally, the two factors combine to explain most of the variation in LMAX; the R-squared is 90 percent in the U.S. and 97 percent globally with insignificant intercepts.

4.3 The performance of idiosyncratic risk factors: LMAX, SMAX, and IVOL

Table VII reports the performance and factor exposures of the three idiosyncratic risk factors. The three factors have almost identical three-factor alpha and three-factor information ratios. All three factors remain significant when we also control for RMW, CMA, and REV, but the alpha of SMAX is statistically more robust than LMAX and IVOL in the sense that the six-factor t-statistic is more significant for SMAX.

Turning to the factor loadings, we see that the idiosyncratic risk factors tend to load on the quality variables RMW and CMA. Also, LMAX and SMAX load strongly on the short-term reversal factor REV. This reversal loading is intuitive since LMAX and SMAX go long stocks with high returns on their best days. IVOL has little loading on REV (so excluding REV from the right-hand side hardly changes the results; not shown).

Panel B of Table VII considers the three idiosyncratic factors in the global sample. In the global sample, the idiosyncratic risk factors have positive and significant three-factor alphas, but their alphas become insignificant once controlling for RMW, CMA, and REV.

In summary, the idiosyncratic risk factors LMAX, SMAX, and IVOL produce positive alphas in the U.S., but their alphas are weak outside the U.S. In addition, our new scaled factor SMAX appears more robust, especially in the U.S.

5 Testing the Underlying Economic Drivers

Having decomposed the low-risk effect into a systematic and an idiosyncratic part, we next analyze the economic drivers of these two parts of the low-risk effect. To test the theory of leverage constraints, we include a measure of margin debt. Similarly, to test the behavioral theories, we consider measures of investor sentiment, casino profits, and lottery ticket sales. Lastly, to test the Modigliani-Cohn hypothesis of Money Illusion, we include inflation. For each of these, we consider both the ex ante value and the contemporaneous change. Further, we control for the five Fama-French factors and short-term reversal factor such that we effectively predicts each factors alpha in excess of these factors, i.e., the parts of the return more unique to each factor.

The data sources of the economic variables are discussed in Section 2, but a brief comment on the measure of leverage constraints is in order. We construct a new measure of leverage constraints based on the amount of margin debt (MD) held against NYSE stocks as a fraction of the total market equity of NYSE stocks. When margin debt is low, we interpret this as tight leverage constraints, that is, we implicitly assume that the variation in the amount of margin debt is primarily driven by changes in the supply of leverage. This is a simplification, but, consistent with this idea, changes in margin debt are negatively correlated with the TED spread, VIX, noise in the term structure of U.S. government bonds as defined by Hu, Pan, and Wang (2013), and the leverage applied by financial intermediaries as seen Table A6 in the appendix.

Panel A of Table VIII tests the extent to which the different low-risk factors are predicted by margin debt, sentiment, and inflation. As seen in the first four columns, both BAC and BAB have higher future return when ex ante margin debt is low, i.e.., when leverage constraints are high. Contemporaneous increases in margin debt are associated with positive returns to BAB and BAC, consistent with the theory that investors shifting their portfolios towards low-risk stocks when leverage constraints decrease. This contemporaneous effect is statistically significant. In other words, since prices should go in the opposite direction of expected returns, both of these findings are consistent with the theory of leverage constraints.

Investor sentiment does not seem to have an influence on the return to BAB and BAC consistent with the idea that these factors capture leverage constraints rather than sentiment. Further, the sign of inflation is wrong relative to the Modigliani-Cohn hypothesis of money illusion tested by Cohen, Polk, and Vuelteenaho (2005) so it seems unlikely that money illusion drives the low-risk effect.

We next consider the determinants of the idiosyncratic risk factors, also reported in Panel A of Table VIII. We see that LMAX, IVOL and SMAX all have higher return when ex ante investor sentiment is high, consistent with the factors being driven, at least partly, by behavioral demand as suggested by Liu, Stambaugh, and Yuan (2017). The effect is statistically significant for IVOL and LMAX. The effect of the contemporaneous change in sentiment is insignificant for IVOL and LMAX while it appears to go in the wrong direction for SMAX. Finally, neither of the idiosyncratic factors LMAX, SMAX, and IVOL appear related to margin debt, which is consistent with leverage constraints influencing the price of systematic risk, but not the price of idiosyncratic risk.

In Panel B we test if the predictive power of sentiment comes directly from lottery demand. We find that when casino profits are larger, the returns to the idiosyncratic low-risk factors are higher. We also find that an increase in casino profits causes contemporaneously lower returns to the idiosyncratic low-risk factors. These results are consistent with lottery demand partly driving the idiosyncratic part of the low-risk effect. However, we find no statistically significant effect of lottery tickets on the idiosyncratic low-risk factors. We note that the idiosyncratic low-risk factors are not very profitable in the first place in UK, which is the sample for our lottery ticket regressions.

To further address the hypothesis that BAB and BAC might be driven by demand for lottery, we also test if the lottery measures predicts these factors. We find no evidence for this hypothesis. Neither BAB nor BAC load on either of the two lottery measures. This result is again consistent with the notion that lottery demand might influence the idiosyncratic low-risk factors, but not the systematic low-risk factors.

The last test on the economic drivers addresses whether the low-risk effect is present among all stocks or only among the overpriced stocks. Liu, Stambaugh, and Yuan (2017) argue that the betting-against-beta phenomenon is only present among overpriced stocks based on the idea that the low-risk effect is a symptom of limited arbitrage. One of their main pieces of evidence is a double sort on beta and the mispricing measure of Stambaugh, Yu, and Yuan (2015). Liu, Stambaugh, and Yuan (2017) report that, when keeping mispricing constant, the relationship between beta and alpha only exist among overpriced stocks. The result echoes the finding in Stambaugh, Yu, and Yuan (2015), who find that among overpriced stocks, higher IVOL leads to lower alpha, but among underpriced stocks, higher IVOL leads to higher alpha.

There are two potential issues with the analysis of Liu, Stambaugh, and Yuan (2017) as a test of the theory of leverage constraints. First, the theory of leverage constraints predicts that high-beta stocks endogenously become over-priced (relative to the standard CAPM) so the theory does not make clear predictions for the alpha-beta relation when controlling for over-pricing (i.e., controlling for over-pricing could "throw the baby out with the bathwater"). Second, their finding related to idiosyncratic volatility could confound the alpha-beta relation to the extent that there are multiple drivers of the low-risk effect.

To get a cleaner test of the alpha-beta relation when controlling for overpricing (and address at least the second issue mentioned above), we proceed as follows. We sort stocks first by mispricing and then by correlation. By sorting on correlation instead of beta, we pick up the effect of systematic risk without also picking up the effect of idiosyncratic volatility. Panel C in Table VIII reports the results. Consistent with the leverage constraints explanation, higher correlation leads to lower alpha irrespective of the degree of over- or underpricing. Indeed, in all five mispricing quintiles, higher correlation leads to a lower alpha. The size of the alpha is also similar across mispricing quintiles. This provides further evidence of the theory of leverage constraints.

6 Horserace

The analysis so far suggests that the low-risk effect is driven by both systematic and idiosyncratic risk due to, respectively, leverage constraints and lottery demand. Our analysis suggests that the competing explanations share an element related to volatility, but also have separate elements related to, respectively, correlation and the shape of the return distribution. To further judge whether both explanations have separate power and their relative importance in the low-risk effect, we now run a "horserace."

6.1 Horserace based on published factors

We first consider a horserace between the various factors constructed as in the papers where they were first considered (as we have also done in the previous analysis). Table IX shows the results of regressing each systematic/idiosyncratic risk factor on a competing factor (BAB or LMAX) as well as several controls, namely the five Fama-French factors and the reversal factor REV.

Panel A of Table IX reports our findings for US factors. The BAB factor in the U.S. has a positive and significant alpha (t-statistic of 3.0) when controlling for LMAX, the five Fama-French factors, and REV. Further, we see that BAC has an even more significant alpha when controlling for these factors: BAC has an alpha of 0.6 percent per month with a t-statistic of 4.8. The higher alpha of BAC is likely due to the fact that it is constructed to be less correlated to other factors. Indeed, BAC has a much smaller factor loading on LMAX than BAB, although both are significantly positive. Collectively, these findings are evidence that the low-risk effect is not simply explained by a combination of idiosyncratic risk and the five Fama-French factors.

Finally, we see in Panel A of Table IX that BAV is not robust to controlling for LMAX, the five Fama-French factors, and REV. This finding is not surprising since BAV captures the part of BAB that is most closely connected to the idiosyncratic risk factors such as LMAX. When we have similar variables on the left-hand side and right-hand side, the intercept is naturally insignificant. Indeed, recall that BAV has significant excess returns, 1-factor, and 3-factor alpha, so its alpha only turns insignificant when we control for all other factors, which could simply reflect that the collection of right-hand-side variables already capture effects of leverage constraints (as discussed above).

We next turn our attention to the idiosyncratic factors in Table IX. We see that LMAX and IVOL have insignificant alphas in these regressions where we control for BAB, the five Fama-French factors, and REV. Given our earlier results, this finding reflects that BAB drives the alpha of these factors to zero. However, SMAX has a positive and significant alpha. The fact that SMAX is the only idiosyncratic risk factor that retains its alpha may be because it is constructed to be more exclusively focused on idiosyncratic skewness, making it less correlated to BAB (and perhaps the other factors).

Panel B of Table VI shows the same factor regressions in the global sample. Again, we see that BAB and BAC have significant alphas, highlighting the importance of systematic risk in the global low-risk effect. None of the idiosyncratic factors has significant alpha in the global sample.

6.2 Turnover and alpha decay

So far, we have followed the literature and considered factors constructed as in the papers that first developed these factors, but these methodologies differ across factors. In particular, BAB (and, likewise, BAC and BAV) are rank-weighted while the others are based on the Fama-French methodology. Further, the factors have different turnover: LMAX, SMAX, and IVOL are based on monthly characteristics that change quickly, and thus have high turnover relative to BAB and the Fama-French factors that are more stable. We address both of these issues in order to make apples-to-apples comparisons.

We first consider turnover. Table X shows that LMAX and IVOL have much faster turnover than BAB, BAC, and BAV. Indeed, LMAX and IVOL have a monthly turnover of about 2 dollars. Said differently, an idiosyncratic volatility factor that goes long \$1 and shorts \$1 has an annual turnover of about $12 \times \$2 = \$24$. In contrast, the FF and BAB-type factors have about six times lower turnover (e.g., BAC has a monthly turnover of \$0.35). This large difference in turnover is partly explained by the length of the time periods over which the characteristics are estimated: MAX and IVOL are both estimated over the previous month, whereas the characteristics used for the BAB-type factors are estimated over one to five years. Further, the characteristics of correlation and volatility may simply be more stable economic characteristics than variables such as MAX. The high turnover of the MAX and IVOL factors makes them more difficult to interpret, for instance because it may be more difficult for behavioral investors to keep track of such transient properties.

Further, the high turnover means that these factors are more sensitive to microstructure issues, noise, and trading cost. To capture one element of these issues, we have included the factor REV, but constructing more stable characteristics is a much more direct way to address the turnover issue.

We introduce a new one-year MAX characteristic that calculates max returns over the last year rather than the last month and a corresponding factor that we denote LMAX(1Y). The characteristic is simply the average return on the 20 highest return days. Similarly, we construct the factor SMAX(1Y) based on volatility-scaled MAX returns over the 1-year look-back period.

As can be seen in Table X, the idiosyncratic risk factors with 1-year lookback period, namely LMAX(1Y) and SMAX(1Y), have substantially lower turnover than their monthly counterparts. Nevertheless, these factors still have higher turnover than the BAB and Fama-French factors.

Table XI shows the return to LMAX(1Y) and SMAX(1Y). We see that LMAX(1Y) has significant three-factor alpha, but the alpha is driven out when controlling for RMW, CMA, and REV. For SMAX(1Y), the situation is worse. The factor has insignificant three-factor alpha, and significantly negative alpha once controlling for RMW, CMA, and REV. These results suggest that the factors get much of their alphas from the high turnover.

Another way to illustrate the importance of turnover is to consider how quickly the alpha decays after portfolio formation. To illustrate the alpha decay of the various factors, Figure 1 plots the cumulative alpha in event time, relative to the portfolio formation period. Panel A of Figure 1 plots the 3-factor alphas while Panel B plots 5-factor alphas.

As can be seen in Panel A, the cumulative alphas of the BAB and BAC factors grow continually over the year after the portfolio formation period. To understand what happens, note that low-beta stocks typically remain low-beta stocks over the following 12 months and, therefore, they continue to earn positive alphas. Likewise, the cumulative 3-factor alphas of LMAX and LMAX-1-year gradually rise over the next 12 months, although these curves flatten out. The cumulative alpha of SMAX is striking: It flattens out after 1 month, meaning that all of the three-factor alpha associated with the monthly SMAX characteristic is earned in the first month – holding SMAX for longer does not give any additional alpha.

Panel B of figure 5 shows cumulative five-factor alpha in event time, that is, the same as Panel A except that we now also control for the quality factors RMW and CMA. For

BAB and BAC, the results are similar to those of Panel A, reflecting that the BAB and BAC factors continue to earn alpha, whether the 3-factor or 5-factor model is used, over the 12 months following portfolio formation. However, now all of the idiosyncratic risk factors have flat cumulative alpha curves, looking similar to the flat alpha curve for SMAX in Panel A. In other words, as for SMAX, LMAX and even the version with 1-year-lookback now only earn alpha in the month following portfolio formation and holding it for longer hardly contributes with additional alpha. This difference in the persistence of three-factor and five-factor alpha for LMAX is due to the loading of LMAX on the quality factors (profitability and investment). Indeed, it seems that LMAX picks up a slow-moving return pattern captured by RMW and CMA, but, once we control for RMW and CMA, the effect disappears and only a transient return component remains.

6.3 All factors constructed based on Fama-French methodology

We next run a horserace where all factors are constructed based on the Fama-French methodology. In particular, all factors are constructed by double sorting on size and the characteristic in question, creating value-weighted portfolios, and going long a small and a big one and shorting a small and a big one (as described in Section 2). For BAC and BAV, we continue to create volatility (correlation) neutral editions of the factors. That is, within each volatility (correlation) quintile, we create a Fama-French-type factor based on stocks' correlation (volatility) characteristic, and then finally take an equal-weighted average of these five factors.

The results are reported in Table XII. As is seen in the table, BAB, BAC, and BAV have positive and significant alphas when controlling for the five Fama-French factors and REV. These results thus reject the claim by Fama and French (2016) that the low-risk effect is explained by the five-factor model. The alpha for BAB and BAC, however, become insignificant once also controlling for LMAX, but the alpha of BAV is robust to controlling for LMAX. Looking at idiosyncratic risk factors, SMAX is the only factor with significant alpha. In the global sample, only BAV produce significant alpha.

6.4 All factors constructed based on rank-weighting-BAB methodology

We next run a horserace where all factors are rank-weighted. Since some of the Fama and French characteristics, such as book-to-price, are highly correlated with size, we make all the rank-weighted factors size neutral. For each factor we, similarly to Fama and French (1993), first assign stocks into two groups based on the median NYSE size and then create a rank-weighted factor within each size group. Each factor is then the average return to the two rank-weighted factors. That is, for HML for instance, the return is given by

$$\mathrm{HML}_{t+1}^{Rank} = 0.5\mathrm{HML}_{t+1}^{Rank,small} + 0.5\mathrm{HML}_{t+1}^{Rank,large}$$

where the rank-weighted returns are calculated using the method of Frazzini and Pedersen (2014) such that the portfolios are hedged ex-ante to have a beta of zero. We also construct new editions of BAB, BAC, and BAV using the above method.

Table XIII shows the results for the rank-weighted portfolios. As we already knew, BAB and BAC work well with rank weights and the factors thus have large Sharpe ratios. What is new in Table XIII, however, is that their alphas are robust to using rank-weighted factors on the right hand side. Indeed, the alpha for BAB is essentially the same as when we use the traditional Fama-French factors on the right hand side in Table IX. The alpha for BAC is a little lower than in Table IX but it remains highly significant.

The alphas for the idiosyncratic risk factors are generally not robust to using rank weights. Only the six-factor alpha of SMAX is statistically significant, but this alpha becomes insignificant once controlling for BAB. It is worth noting that using rank weights actually also "works" for the idiosyncratic in the sense that these rank-weighted factors have larger Sharpe ratios than their Fama-French-type counterparts. The reason that the rank-weighted idiosyncratic risk factors nevertheless have negative alphas is that the rank-weighted right-hand-side factors are even more effective in explaining them.

7 Conclusion

The low-risk effect has profound implications for investors, firms, and capital markets. Can investors benefit from low-risk stocks if they learn to overcome their biases? Or, are their hands tied by leverage constraints? These questions are not just academic as most assets are controlled by institutional investors where leverage constraints are in principle directly observable – and changeable! – e.g., for many pension funds and mutual funds. Likewise, if professional asset managers really suffer from sentiment-based lottery demand such that they change their preference for stocks based on the returns over the past month then perhaps this bias can be alleviated by education.

Further, the low-risk effect impacts firms' cost of capital and, hence, possibly their investment decisions and other corporate behavior. Should firms try to undertake lottery-like real investments to lower their cost of capital? Or should they simply add some debt to their balance sheet (relative to what they would do in the absence of the low-risk effect)?

We contribute to the literature that seeks to address these questions in four ways. First, we present new evidence consistent specifically with the theory of leverage constraints by showing that low-correlation stocks have high risk-adjusted returns that cannot be explained by other low-risk factors. Both in the U.S. and internationally, our BAC factor produces statistically significant six-factor alpha that is close to orthogonal to other low-risk factors.

Second, we present a new factor SMAX that captures the returns to betting against stocks with lottery-like return distributions. SMAX has positive risk-adjusted returns in the US, but not globally – as is the case for other idiosyncratic risk factors.

Third, we show that the tightness of margin constraints predicts the return to systematic low-risk factors, but not that of the idiosyncratic low-risk factors. On the other hand, investor sentiment and casino profits predict the return to some of the idiosyncratic low-risk factors, but not that of the systematic factors BAB and BAC.

Fourth, in horseraces between the low-risk factors, we find that systematic low-risk factors tend to outperform idiosyncratic low-risk factors. The outperformance of the systematic low-risk factors becomes even more pronounced once all the low-risk factors are put on a level playing field in terms of turnover since the idiosyncratic risk factors derive much of their alphas from a short-term effect.

In conclusion, our results suggest that both leverage constraints and lottery demand play a role for the low-risk effect. The results are stronger for leverage constraints, especially outside the US, consistent with the underlying equilibrium theory and the fact that these constraints are observable for many investors.

Table I
Summary Statistics

This table shows summary statistics as of June of each year. The sample includes all U.S. common stocks (CRSP "shrcd" equal to 10 or 11) and all global stocks ("tcpi" equal to 0) in the merged CRSP/Xpressfeed global databases.

Country	Total number of stocks	Average number of stocks	Firm size (Billion-USD)	Weight in global portfolio	Start Year	End Year
Australia	3,286	1,027	0.61	0.018	1985	2015
Austria	217	84	0.82	0.002	1986	2015
Belgium	445	147	1.90	0.009	1986	2015
Canada	2,106	576	1.20	0.022	1982	2015
Switzerland	596	226	3.72	0.024	1986	2015
Germany	2,414	850	3.09	0.071	1986	2015
Denmark	411	156	1.01	0.004	1986	2015
Spain	415	147	3.65	0.015	1986	2015
Finland	307	117	1.32	0.004	1986	2015
France	1,932	641	2.35	0.044	1986	2015
United Kingdom	6,371	2,013	1.63	0.102	1986	2015
Greece	425	186	0.40	0.002	1988	2015
Hong Kong	2,510	816	1.50	0.030	1986	2015
Ireland	157	53	1.52	0.002	1986	2015
Israel	724	282	0.39	0.003	1994	2015
Italy	686	245	2.34	0.018	1986	2015
Japan	5,309	3,053	1.21	0.188	1986	2015
Netherlands	423	173	3.58	0.020	1986	2015
Norway	719	185	0.85	0.004	1986	2015
New Zealand	349	112	1.04	0.003	1986	2015
Portugal	157	63	1.56	0.002	1988	2015
Singapore	1,259	474	0.71	0.011	1986	2015
Sweden	1,201	309	1.44	0.012	1986	2015
United States	24,218	3,328	1.21	0.389	1926	2015

Table II
Correlation vs. Volatility: Beta and Risk-Adjusted Returns

This table shows properties of 25 portfolios of U.S. stocks from 1926 to 2015. At the beginning of each calendar month, stocks are sorted first on ex ante volatility and then conditionally on ex ante correlation. Specifically, the stocks are assigned to one of five volatility quintiles based on NYSE breakpoints. Within each quintile, stocks are assigned to one of five correlation quintile portfolios based on NYSE breakpoints. Portfolios are value-weighted, refreshed every calendar month, and rebalanced every calendar month to maintain value weights. The long-short portfolios are self-financing portfolios that are long \$1 in the portfolio with highest correlation (volatility) within each volatility (correlation) quintile and short \$1 in the portfolio with lowest correlation (volatility) within the same volatility (correlation) quintiles. Panel A reports CAPM betas and Panel B reports CAPM alphas, i.e., respectively the slope and intercept in a regression of monthly excess return on excess returns to the CRSP value-weighted market portfolio (MKT). Panel B reports three-factor alphas, i.e., the intercept in a regression of monthly excess return on MKT, size (SMB), and value (HML) factors of Fama and French (1993). Returns and alphas are in monthly percent, *t*-statistics are shown in parenthesis below the coefficient estimates and 5% statistical significance is indicated in bold.

US 1930-2015

Panel A: CAPM beta

Sort on volatility	Conditional sort on correlation	P1 (low)	P2	P3	P4	P5 (high)	LS
	P1 (low)	**0.5**	**0.6**	**0.7**	**0.8**	**0.9**	**0.4**
							(24.9)
	P2	**0.7**	**0.9**	**1.0**	**1.1**	**1.2**	**0.5**
							(26.2)
	P3	**0.7**	**1.0**	**1.2**	**1.3**	**1.4**	**0.7**
							(27.1)
	P4	**0.8**	**1.0**	**1.2**	**1.3**	**1.6**	**0.8**
							(24.3)
	P5 (high)	**0.8**	**1.0**	**1.1**	**1.3**	**1.6**	**0.8**
							(15.3)
	LS	**0.4**	**0.5**	**0.5**	**0.5**	**0.7**	
		(8.3)	(12.6)	(15.3)	(17.0)	(21.1)	

US 1930-2015

Panel B: CAPM alpha

Sort on volatility	Conditional sort on correlation	P1 (low)	P2	P3	P4	P5 (high)	LS
	P1 (low)	**0.4**	**0.3**	**0.2**	**0.1**	**0.1**	**-0.3**
		(5.6)	(3.9)	(3.2)	(2.1)	(2.3)	(-3.6)
	P2	**0.3**	**0.2**	0.1	0.1	-0.1	**-0.3**
		(3.3)	(2.1)	(1.6)	(0.7)	(-0.7)	(-3.0)
	P3	**0.4**	**0.3**	0.1	0.0	**-0.2**	**-0.6**
		(4.1)	(2.8)	(0.6)	(-0.2)	(-2.3)	(-4.4)
	P4	**0.4**	**0.3**	0.0	-0.1	**-0.3**	**-0.7**
		(3.3)	(2.3)	(0.3)	(-1.0)	(-2.2)	(-4.2)
	P5 (high)	0.3	0.1	0.1	-0.3	**-0.5**	**-0.8**
		(1.4)	(0.2)	(0.4)	(-1.7)	(-2.7)	(-3.3)
	LS	-0.1	-0.2	-0.2	**-0.4**	**-0.6**	
		(-0.5)	(-1.0)	(-0.8)	(-2.2)	(-3.0)	

Table II
Correlation vs. Volatility: Beta and Risk-Adjusted Returns (Continued)

US 1930-2015

Panel C: Three-factor al|

		Conditional sort on correlation					
		P1 (low)	P2	P3	P4	P5 (high)	LS
Sort on volatility	P1 (low)	**0.4**	**0.2**	**0.2**	0.1	**0.1**	**-0.3**
		(5.2)	(3.3)	(2.6)	(1.8)	(2.9)	(-3.3)
	P2	**0.2**	0.1	0.1	0.0	-0.1	**-0.3**
		(2.6)	(1.1)	(0.8)	(-0.6)	(-1.6)	(-3.0)
	P3	**0.3**	0.1	-0.1	**-0.2**	**-0.4**	**-0.6**
		(3.4)	(1.5)	(-1.4)	(-2.4)	(-4.2)	(-4.9)
	P4	**0.3**	0.1	-0.2	**-0.3**	**-0.5**	**-0.8**
		(2.4)	(1.1)	(-1.5)	(-2.9)	(-4.4)	(-4.5)
	P5 (high)	0.1	-0.2	-0.1	**-0.5**	**-0.7**	**-0.8**
		(0.4)	(-0.9)	(-1.1)	(-3.9)	(-4.5)	(-3.2)
	LS	-0.3	**-0.4**	**-0.3**	**-0.6**	**-0.9**	
		(-1.4)	(-2.1)	(-2.0)	(-4.0)	(-4.9)	

Table III
Betting Against Beta as Betting Against Correlation and Volatility

This table shows the results of regressions of the monthly return to betting against beta (BAB) on the monthly return to betting against correlation (BAC) and betting against volatility (BAV). Panel A reports results in the U.S. sample and panel B reports the results in the global sample. *t*-statistics are shown in parenthesis below the coefficient estimates and 5% statistical significance is indicated in bold.

Panel A: Long U.S. Sample (1930-2015)		Panel B: Global sample (1990-2015)	
	BAB		BAB
Intercept	0.00	Intercept	0.00
	(-1.56)		(-0.02)
BAC	**0.71**	BAC	**0.84**
	(63.00)		(66.77)
BAV	**0.51**	BAV	**0.49**
	(60.33)		(58.52)
R2	0.85	R2	0.96
Num	1020		306

Table IV
Betting Against Correlation

This table shows returns to the betting against correlation (BAC) factor in each volatility quintile, along with the equal-weighted average of these factors, which constitute our overall BAC factor. Panel A reports the BAC performance in the U.S. sample and panel B reports the performance in the global sample. At the beginning of each month stocks are ranked in ascending order based on the estimated of volatility at the end of the previous month. The ranked stocks are assigned to one of five quintiles. U.S. sorts are based on NYSE breakpoints. Within each quintile, stocks are assigned to one of two portfolios: low correlation and high correlation. In these portfolios, stocks are rank-weighted by correlation (lower correlation stocks have larger weights in the low-correlation portfolios and larger correlation stocks have larger weights in the high-correlation portfolios), and the portfolios are rebalanced every calendar month. The portfolios are (de)levered to have a beta of one at formation. Within each volatility quintile, a self-financing BAC portfolio is made that is long the low-correlation portfolio and short the high-correlation portfolio. We form one set of portfolios in each country and compute global portfolios by weighting each country's portfolio by the country's total (lagged) market capitalization. Alpha is the intercept in a regression of monthly excess return. The explanatory variables are the monthly excess return to the CRSP value-weighted market portfolio and the monthly returns to the SMB, HML, RMW, and CMA factors of Fama and French (2015). Returns and alphas are in monthly percent, *t*-statistics are shown in parenthesis below the coefficient estimates, and 5% statistical significance is indicated in bold. '$ long' and '$ short' measures how many dollars the betting against correlation portfolio is long and short. Sharpe ratios and information ratios are annualized.

	Panel A: U.S. Sample (1963-2015)					
Volatility quintile	1	2	3	4	5	BAC
Excess return	**0.55**	**0.86**	**0.92**	**1.03**	**1.48**	**0.97**
	(4.32)	(6.52)	(6.31)	(5.88)	(5.78)	(6.74)
Alpha	**0.39**	**0.63**	**0.57**	**0.68**	**1.25**	**0.70**
	(3.56)	(5.50)	(4.26)	(4.08)	(4.96)	(5.45)
MKT	**-0.14**	-0.05	0.05	**0.09**	**0.13**	0.02
	(-5.1)	(-1.9)	(1.5)	(2.2)	(2.14)	(0.5)
SMB	**0.62**	**0.61**	**0.58**	**0.58**	**0.61**	**0.60**
	(16.6)	(15.7)	(12.7)	(10.1)	(7.1)	(13.6)
HML	**0.12**	**0.17**	**0.26**	**0.31**	0.23	**0.22**
	(2.3)	(3.2)	(4.0)	(3.9)	(1.9)	(3.5)
RMW	0.02	0.05	**0.17**	0.16	**-0.28**	0.02
	(0.4)	(0.9)	(2.5)	(1.9)	(-2.2)	(0.3)
CMA	0.08	0.08	0.18	0.04	0.01	0.08
	(1.0)	(0.9)	(1.9)	(0.4)	(0.0)	(0.8)
SR	0.60	0.90	0.87	0.81	0.80	0.93
IR	0.52	0.80	0.62	0.59	0.72	0.79
R2	0.34	0.31	0.25	0.18	0.13	0.27
# obs	630	630	630	630	630	630

Table IV
Betting Against Correlation (continued)

	Panel B: Global Sample (1990-2015)					
Volatility quintile	1	2	3	4	5	BAC
Excess return	**0.27**	**0.64**	**0.64**	**0.70**	**1.15**	**0.68**
	(2.08)	(4.57)	(3.98)	(3.95)	(4.55)	(4.48)
Alpha	0.11	**0.41**	0.27	0.24	**0.81**	**0.37**
	(0.99)	(3.19)	(1.84)	(1.48)	(3.39)	(2.77)
MKT	0.01	**0.07**	**0.15**	**0.18**	**0.21**	**0.12**
	(0.4)	(2.0)	(3.7)	(4.1)	(3.27)	(3.5)
SMB	**0.65**	**0.71**	**0.75**	**0.85**	**1.11**	**0.81**
	(11.9)	(11.5)	(10.6)	(10.8)	(9.6)	(12.6)
HML	0.10	0.14	**0.26**	**0.23**	0.05	0.16
	(1.4)	(1.9)	(2.9)	(2.4)	(0.4)	(1.9)
RMW	**0.18**	**0.31**	**0.49**	**0.71**	**0.41**	**0.42**
	(2.2)	(3.3)	(4.6)	(6.0)	(2.3)	(4.3)
CMA	0.10	0.09	0.08	0.11	0.15	0.10
	(1.2)	(0.9)	(0.7)	(0.8)	(0.8)	(1.0)
SR	0.41	0.90	0.79	0.78	0.90	0.89
IR	0.21	0.69	0.40	0.32	0.73	0.60
R2	0.33	0.31	0.29	0.30	0.23	0.35
# obs	306	306	306	306	306	306

Table V
SMAX vs. Volatility: Risk-Adjusted Returns

This table shows the risk adjusted returns to 25 portfolios sorted first on volatility and then conditionally on SMAX in the U.S. from 1926 to 2015. At the beginning of each calendar month, stocks are ranked in ascending order based on the estimate of volatility at the end of the previous month. The ranked stocks are assigned to one of five quintiles based on NYSE breakpoints. Within each quintile, stocks are ranked in ascending order based on the estimate of SMAX at the end of the previous month and assigned to one of five quintile portfolios based on NYSE breakpoints. Portfolios are value-weighted, refreshed every calendar month, and rebalanced every calendar month to maintain value weights. The long-short portfolios are self-financing portfolios that are long $1 in the portfolio with highest SMAX (volatility) within each volatility (SMAX) quintile and short $1 in the portfolio with lowest SMAX (volatility) within the same volatility (SMAX) quintiles. SMAX is the average of the five highest daily returns for a stock over the previous month dividend by its volatility. Volatility is estimated as daily volatility over the previous month. Panel A reports CAPM alphas, Panel B reports three-factor alphas (Mkt, SMB, HML), and Panel C reports five-factor alpha (MKT, SMB, HML, RMW, CMA). Alphas are in monthly percent, *t*-statistics are shown in parenthesis below the coefficient estimates and 5% statistical significance is indicated in bold.

US 1930-2015

Panel A: CAPM alpha		Conditional sort on SMAX					
		P1 (low)	P2	P3	P4	P5 (high)	LS
Sort on volatility	P1 (low)	**0.3**	**0.2**	0.1	**0.1**	0.1	**-0.3**
		(5.4)	(3.2)	(1.4)	(2.0)	(1.1)	(-3.4)
	P2	**0.3**	**0.2**	0.1	0.0	**-0.2**	**-0.5**
		(3.8)	(2.5)	(1.6)	(0.1)	(-2.7)	(-5.0)
	P3	**0.3**	0.2	-0.1	-0.1	**-0.4**	**-0.7**
		(3.6)	(1.7)	(-1.3)	(-1.3)	(-3.8)	(-5.5)
	P4	**0.4**	0.1	-0.1	**-0.3**	**-0.5**	**-0.9**
		(3.5)	(1.1)	(-0.9)	(-2.1)	(-3.7)	(-6.2)
	P5 (high)	**0.4**	0.0	-0.2	**-0.5**	**-0.8**	**-1.2**
		(2.0)	(-0.0)	(-0.8)	(-2.6)	(-3.8)	(-5.5)
	LS	0.0	-0.2	-0.2	**-0.7**	**-0.9**	
		(0.2)	(-1.0)	(-1.0)	(-2.8)	(-3.7)	

US 1930-2015

Panel B: Three-factor alpha		Conditional sort on SMAX					
		P1 (low)	P2	P3	P4	P5 (high)	LS
Sort on volatility	P1 (low)	**0.3**	**0.2**	0.1	0.1	0.1	**-0.3**
		(5.4)	(3.3)	(1.1)	(1.9)	(1.0)	(-3.4)
	P2	**0.2**	0.1	0.1	-0.1	**-0.3**	**-0.5**
		(3.1)	(1.8)	(0.9)	(-0.9)	(-3.9)	(-5.1)
	P3	**0.2**	0.0	**-0.3**	**-0.2**	**-0.5**	**-0.7**
		(2.8)	(0.3)	(-3.1)	(-2.9)	(-5.4)	(-5.7)
	P4	**0.3**	0.0	**-0.2**	**-0.4**	**-0.6**	**-0.9**
		(3.0)	(-0.3)	(-2.4)	(-3.9)	(-5.6)	(-6.3)
	P5 (high)	**0.4**	-0.2	-0.3	**-0.8**	**-1.0**	**-1.3**
		(2.3)	(-0.9)	(-1.9)	(-4.3)	(-5.2)	(-6.2)
	LS	0.0	**-0.4**	**-0.4**	**-0.9**	**-1.0**	
		(0.3)	(-2.0)	(-2.0)	(-4.4)	(-5.1)	

Table VI
LMAX as SMAX and BAV

This table shows the results of regressions of the monthly return to the factor going long stocks with low maximum return over the past month (LMAX) on the monthly returns to the factor going long stocks with low maximum return scaled by volatility (SMAX) and the monthly return to the factor going long stocks with low total volatility (TV). Total volatility is total daily volatility measured over the previous month. *t*-statistics are shown in parenthesis below the coefficient estimates and 5% statistical significance is indicated in bold.

Panel A: Long U.S. Sample (1930-2015)		Panel B: Global sample (1990-2015)	
	LMAX		LMAX
Intercept	0.00	Intercept	0.00
	(1.33)		(1.24)
SMAX	**0.34**	SMAX	**0.23**
	(16.16)		(9.09)
TV	**0.75**	TV	**0.80**
	(83.92)		(81.26)
R2	0.90	R2	0.97
Num	1020	Num	306

Table VII
The Idiosyncratic Factors: LMAX, SMAX, and IVOL

This table shows regression results for monthly returns to the factor going long stocks with low maximum return over the past month (LMAX), the factor going long stocks with low maximum return scaled by volatility (SMAX), and the factor going long stocks with low idiosyncratic volatility (IVOL). Panel A reports the results from the U.S. sample and Panel B reports the results from the global sample. Total volatility is total daily volatility measured over the previous month. The intercept alpha is in monthly percent. The control variables are the monthly excess return to the market portfolio (MKT), size (SMB), value (HML), profitability (RMW), investment (CMA), and short-term reversal (REV). *t*-statistics are shown in parenthesis below the coefficient estimates, and 5% statistical significance is indicated in bold. The Sharpe ratio (SR) and information ratio (IR) are annualized.

	Panel A: U.S. FMAX Sample (1963-2015)							
	SMAX	SMAX	SMAX	LMAX	LMAX	LMAX	IVOL	IVOL
Alpha	**0.44**	**0.38**	**0.25**	**0.58**	**0.31**	**0.24**	**0.53**	**0.22**
	(5.60)	(4.78)	(3.69)	(5.81)	(3.34)	(2.64)	(5.27)	(2.46)
MKT	**-0.04**	-0.02	**-0.09**	**-0.42**	**-0.35**	**-0.39**	**-0.44**	**-0.35**
	(-2.0)	(-1.2)	(-5.4)	(-17.8)	(-15.8)	(-17.40)	(-18.2)	(-16.2)
SMB	-0.02	0.01	-0.03	**-0.48**	**-0.35**	**-0.37**	**-0.65**	**-0.50**
	(-0.7)	(0.3)	(-1.1)	(-14.3)	(-11.2)	(-12.0)	(-19.7)	(-16.8)
HML	**0.08**	0.04	-0.03	**0.45**	**0.24**	**0.20**	**0.41**	**0.18**
	(2.8)	(1.1)	(-0.9)	(12.6)	(5.5)	(4.8)	(11.4)	(4.4)
RMW		**0.12**	**0.12**		**0.57**	**0.57**		**0.68**
		(3.0)	(3.6)		(12.3)	(12.7)		(15.5)
CMA		0.08	**0.16**		**0.46**	**0.50**		**0.49**
		(1.4)	(3.4)		(6.9)	(7.8)		(7.8)
REV			**0.36**			**0.19**		-0.01
			(16.9)			(6.6)		(-0.5)
SR	0.78	0.78	0.78	0.34	0.34	0.34	0.22	0.22
IR	0.79	0.70	0.54	0.82	0.49	0.39	0.74	0.36
R2	0.03	0.04	0.34	0.64	0.71	0.73	0.69	0.78
# obs	630	630	630	630	630	630	630	630

Table VII
The Idiosyncratic Factors: LMAX, SMAX, and IVOL (continued)

	Panel B: Global Sample (1990-2015)							
	SMAX	SMAX	SMAX	LMAX	LMAX	LMAX	IVOL	IVOL
Alpha	**0.19**	0.10	0.05	**0.45**	0.02	-0.01	**0.46**	-0.01
	(1.97)	(1.01)	(0.63)	(3.71)	(0.16)	(-0.12)	(3.76)	(-0.09)
MKT	**-0.07**	-0.03	**-0.10**	**-0.56**	**-0.35**	**-0.39**	**-0.51**	**-0.30**
	(-3.1)	(-1.1)	(-4.5)	(-20.2)	(-11.9)	(-13.60)	(-18.4)	(-10.3)
SMB	-0.02	0.02	0.04	**-0.49**	**-0.26**	**-0.25**	**-0.68**	**-0.43**
	(-0.5)	(0.5)	(1.0)	(-8.4)	(-5.0)	(-5.1)	(-11.6)	(-8.5)
HML	**0.18**	**0.14**	0.06	**0.57**	**0.18**	**0.14**	**0.56**	0.11
	(4.2)	(2.2)	(1.2)	(10.7)	(2.8)	(2.3)	(10.5)	(1.7)
RMW		**0.19**	**0.22**		**0.83**	**0.85**		**0.86**
		(2.5)	(3.9)		(10.4)	(11.2)		(11.2)
CMA		0.05	**0.14**		**0.61**	**0.66**		**0.72**
		(0.7)	(2.3)		(7.2)	(8.2)		(8.7)
REV			**0.39**			**0.21**		**0.07**
			(14.6)			(6.0)		(2.0)
SR	0.43	0.43	0.43	0.34	0.34	0.34	0.35	0.35
IR	0.40	0.22	0.14	0.75	0.03	-0.03	0.76	-0.02
R2	0.09	0.10	0.48	0.69	0.78	0.81	0.68	0.80
# obs	306	306	306	306	306	306	306	306

Table VIII
Economic Drivers of the Low-Risk Effect

This table reports results on the economic drivers of the low-risk effect. The dependent variables are the excess returns to betting against beta (BAB), betting against correlation (BAC), betting against volatility (BAV), the factor going long stocks with low maximum return over the past month (LMAX), the factor going long stocks with low maximum return scaled by volatility (SMAX), and the factor going long stocks with low idiosyncratic volatility (IVOL). The independent are MD, SENT, INF, Casino, and Lottery. MD is the amount of margin debt on NYSE firms held at dealer-brokers divided by the market capitalization of NYSE firms. SENT is the sentiment index of Baker and Wurgler (2006) multiplied by 100 for ease of interpretation. INF is the average change in the consumer price index over the last year. Casino is the profits in the casino industry in the previous quarter dividend by GDP. Lottery is the total sale of lottery tickets in UK over the previous month divided by GDP. We include as control variables the monthly excess return to the CRSP value-weighted market portfolio and the monthly returns to the SMB, HML, RMW, and CMA factors of Fama and French (2015) and the short-term reversal factor from Ken French's data library. We use UK factors in all regressions where the Lottery measure is on the right-hand side. Returns and alphas are in monthly percent, *t*-statistics are shown in parenthesis below the coefficient estimates, and 5% statistical significance is indicated in bold.

Panel A: Margin Debt and Sentiment

	$BAB_{t;t+1}$	$BAB_{t;t+1}$	$BAC_{t;t+1}$	$BAC_{t;t+1}$	$LMAX_{t;t+1}$	$LMAX_{t;t+1}$	$SMAX_{t;t+1}$	$SMAX_{t;t+1}$	$IVOL_{t;t+1}$	$IVOL_{t;t+1}$
MD_t	-0,31	**-0,60**	-0,36	**-0,76**		0,18		-0,03		0,14
	(-1,69)	(-2,78)	(-1,87)	(-3,30)		(1,14)		(-0,22)		(0,91)
MD_{t+1}-MD_t	**6,18**	**5,74**	**10,45**	**9,30**		-2,03		0,88		-1,96
	(3,55)	(3,17)	(5,63)	(4,83)		(-1,51)		(0,86)		(-1,49)
$SENT_t$		0,13		-0,06	**0,21**	0,17	0,09	0,07	**0,24**	**0,24**
		(1,09)		(-0,46)	(2,35)	(1,85)	(1,35)	(1,03)	(2,79)	(2,69)
$SENT_{t+1}$-$SENT_t$		1,07		1,24	0,55	0,69	**1,03**	**1,03**	0,00	0,11
		(1,33)		(1,44)	(0,91)	(1,14)	(2,27)	(2,24)	(0,01)	(0,19)
INF_t		**-0,10**		**-0,16**		-0,03		-0,03		0,03
		(-2,03)		(-3,14)		(-0,75)		(-1,18)		(0,77)
INF_{t+1}-INF_t		-0,30		-0,19		**-0,65**		-0,17		-0,42
		(-1,00)		(-0,58)		(-2,90)		(-0,98)		(-1,89)
Controls										
Mkt	**0,16**	**0,16**	**0,12**	**0,11**	**-0,38**	**-0,41**	**-0,09**	**-0,08**	**-0,35**	**-0,37**
	(4,6)	(4,4)	(3,3)	(2,9)	(-16,8)	(-15,5)	(-5,0)	(-4,0)	(-15,8)	(-14,4)
SMB	0,08	0,07	**0,55**	**0,55**	**-0,36**	**-0,36**	-0,03	-0,03	**-0,50**	**-0,50**
	(1,8)	(1,7)	(12,4)	(12,0)	(-11,6)	(-11,4)	(-1,2)	(-1,4)	(-16,3)	(-15,9)
HML	**0,28**	**0,29**	**0,24**	**0,23**	**0,21**	**0,22**	-0,04	-0,03	**0,19**	**0,20**
	(4,9)	(4,9)	(3,9)	(3,7)	(4,8)	(4,9)	(-1,1)	(-1,0)	(4,5)	(4,6)
RMW	**0,50**	**0,48**	0,09	0,09	**0,56**	**0,52**	**0,12**	**0,12**	**0,67**	**0,64**
	(8,2)	(7,6)	(1,4)	(1,3)	(12,2)	(11,1)	(3,4)	(3,3)	(15,0)	(13,9)
CMA	**0,40**	**0,38**	0,12	0,11	**0,49**	**0,47**	**0,16**	**0,16**	**0,47**	**0,45**
	(4,6)	(4,3)	(1,3)	(1,2)	(7,4)	(7,1)	(3,3)	(3,3)	(7,4)	(7,1)
REV	-0,06	-0,06	0,02	0,02	**0,18**	**0,19**	**0,36**	**0,36**	-0,02	-0,02
	(-1,5)	(-1,6)	(0,6)	(0,6)	(6,3)	(6,6)	(16,4)	(16,5)	(-0,6)	(-0,6)
Adjusted R2	0,24	0,25	0,31	0,32	0,74	0,74	0,34	0,34	0,78	0,78
# obs	684	684	684	684	684	684	684	684	684	684

Table VIII
Economic Drivers of the Low-Risk Effect (continued)

Panel B: Lottery Sales and Casino Profits

	$BAB_{t;t+1}$	$BAB_{t;t+1}$	$BAC_{t;t+1}$	$BAC_{t;t+1}$	$LMAX_{t;t+1}$	$LMAX_{t;t+1}$	$SMAX_{t;t+1}$	$SMAX_{t;t+1}$	$IVOL_{t;t+1}$	$IVOL_{t;t+1}$
$Casino_t$	-0,47		-0,43		0,49		-0,05		0,04	
	(-0,83)		(-0,65)		(1,74)		(-0,28)		(0,11)	
$Casino_{t+1}$ - $Casino_t$	-1,84		-0,79		**-2,68**		-0,59		**-2,42**	
	(-1,28)		(-0,48)		(-3,75)		(-1,37)		(-2,86)	
$Lottery_t$		0,00		0,00		0,00		0,00		0,00
		(0,50)		(0,48)		(0,91)		(1,02)		(-0,31)
$Lottery_{t+1}$ - $Lottery_t$		0,00		0,00		0,00		0,00		0,00
		(1,29)		(1,52)		(0,62)		(0,42)		(1,94)
Controls										
Mkt	**0,27**	**0,21**	0,14	**0,19**	**-0,32**	**0,50**	-0,02	**0,18**	**-0,29**	**0,48**
	(3,4)	(4,1)	(1,6)	(4,1)	(-8,1)	(12,9)	(-0,8)	(6,2)	(-6,2)	(11,9)
SMB	0,25	**0,67**	**0,80**	**0,88**	**-0,26**	**0,21**	0,03	-0,03	**-0,40**	**0,49**
	(2,0)	(9,8)	(5,4)	(14,3)	(-4,2)	(4,1)	(0,9)	(-0,7)	(-5,3)	(9,0)
HML	**0,47**	**0,16**	0,19	0,10	**0,22**	**-0,23**	0,01	**-0,17**	**0,22**	**-0,28**
	(3,3)	(2,0)	(1,2)	(1,4)	(3,1)	(-3,9)	(0,3)	(-3,8)	(2,7)	(-4,6)
RMW	**0,51**	**0,46**	-0,12	0,16	**0,79**	**-0,46**	**0,09**	**-0,16**	**0,91**	**-0,46**
	(3,8)	(4,6)	(-0,8)	(1,7)	(11,9)	(-6,2)	(2,3)	(-2,7)	(11,6)	(-5,8)
CMA	0,19	0,06	0,21	0,05	**0,41**	-0,03	0,04	0,03	**0,46**	-0,08
	(0,9)	(0,5)	(0,9)	(0,5)	(4,0)	(-0,3)	(0,7)	(0,5)	(3,7)	(-0,9)
REV	-0,15	0,06	-0,01	0,03	**0,11**	**0,34**	**0,25**	**0,40**	-0,03	**0,19**
	(-1,4)	(0,9)	(-0,1)	(0,5)	(2,2)	(6,5)	(7,9)	(9,9)	(-0,4)	(3,3)
Adjusted R2	0,29	0,29	0,25	0,48	0,83	0,61	0,34	0,38	0,82	0,65
# obs	142	254	142	254	142	254	142	254	142	254

Panel C: CAPM alpha for portfolios sorted on mispricing and correlation

		Conditional sort on correlation					
		P1 (low)	P2	P3	P4	P5 (high)	LS
Sort on mispricing	P1 (low)	**0,6**	**0,5**	**0,4**	**0,3**	0,1	**-0,5**
		(5,5)	(5,2)	(4,6)	(3,8)	(1,8)	(-3,2)
	P2	**0,4**	**0,5**	**0,3**	0,2	0,0	**-0,4**
		(3,8)	(5,0)	(3,2)	(2,0)	(-0,4)	(-2,9)
	P3	**0,4**	**0,3**	0,1	0,1	-0,1	**-0,4**
		(3,4)	(2,7)	(1,1)	(1,7)	(-0,8)	(-2,8)
	P4	**0,3**	**0,2**	**0,2**	0,0	**-0,3**	**-0,6**
		(2,8)	(2,1)	(2,1)	(0,3)	(-3,6)	(-4,2)
	P5 (high)	-0,1	**-0,3**	**-0,3**	**-0,4**	**-0,7**	**-0,6**
		(-1,1)	(-2,1)	(-3,1)	(-2,9)	(-5,8)	(-3,1)
	LS	**-0,8**	**-0,8**	**-0,8**	**-0,7**	**-0,9**	
		(-6,3)	(-5,6)	(-5,6)	(-4,6)	(-5,3)	

Table IX
Horserace: Factors as Published

This table reports the result of regressing one low-risk factor on another, as well as control variables. Panel A reports the results for the U.S. sample and panel B reports the results for the global sample. The dependent variables are the monthly excess returns to betting against beta (BAB), betting against correlation (BAC), betting against volatility (BAV), the factor going long stocks with low maximum return over the past month (LMAX), the factor going long stocks with low maximum return scaled by volatility (SMAX), and the factor going long stocks with low idiosyncratic volatility (IVOL). The intercept alpha is in monthly percent. The control variables are the monthly excess return to the market portfolio (MKT), size (SMB), value (HML), profitability (RMW), investment (CMA), and short-term reversal (REV). *t*-statistics are shown in parenthesis below the coefficient estimates, and 5% statistical significance is indicated in bold. The Sharpe ratio (SR) and information ratio (IR) are annualized.

	Panel A: U.S. Sample (1963 - 2015)					
	BAB	BAC	BAV	LMAX	SMAX	IVOL
Alpha	**0.31**	**0.60**	-0.20	0.05	**0.18**	0.08
	(3.00)	(4.76)	(-1.54)	(0.64)	(2.69)	(1.02)
MKT	**0.37**	**0.17**	**0.43**	**-0.42**	**-0.10**	**-0.38**
	(11.8)	(4.5)	(10.8)	(-22.2)	(-6.4)	(-18.6)
SMB	**0.37**	**0.75**	**-0.17**	**-0.41**	-0.04	**-0.53**
	(9.5)	(15.9)	(-3.3)	(-15.7)	(-1.9)	(-19.2)
HML	**0.13**	**0.13**	**0.17**	**0.10**	**-0.07**	**0.11**
	(2.5)	(2.1)	(2.6)	(2.7)	(-2.2)	(2.7)
RMW	0.05	**-0.21**	**0.64**	**0.39**	0.05	**0.55**
	(0.9)	(-3.0)	(8.6)	(9.9)	(1.6)	(13.1)
CMA	0.02	-0.12	0.05	**0.35**	**0.11**	**0.38**
	(0.3)	(-1.3)	(0.5)	(6.4)	(2.2)	(6.5)
REV	**-0.19**	-0.05	**-0.26**	**0.21**	**0.37**	0.00
	(-5.6)	(-1.3)	(-6.0)	(8.6)	(18.0)	(0.1)
BAB				**0.39**	**0.15**	**0.28**
				(15.4)	(7.0)	(10.3)
LMAX	**0.71**	**0.41**	**0.82**			
	(15.4)	(7.4)	(13.9)			
SR	0.90	0.93	0.27	0.34	0.78	0.22
IR	0.44	0.70	-0.23	0.10	0.40	0.15
R2	0.43	0.33	0.62	0.81	0.39	0.81
# obs	630	630	630	630	630	630

Table IX
Horserace: Factors as Published (continued)

	Panel B: Global Sample (1990 - 2015)					
	BAB	BAC	BAV	LMAX	SMAX	IVOL
Alpha	**0.21**	**0.37**	-0.16	-0.11	0.02	-0.09
	(1.98)	(2.89)	(-1.27)	(-1.33)	(0.24)	(-1.02)
MKT	**0.43**	**0.27**	**0.40**	**-0.44**	**-0.11**	**-0.34**
	(11.3)	(5.9)	(8.7)	(-19.4)	(-5.4)	(-13.6)
SMB	**0.73**	**0.91**	**-0.14**	**-0.50**	-0.04	**-0.64**
	(13.5)	(14.2)	(-2.1)	(-11.7)	(-1.1)	(-13.6)
HML	**0.16**	0.10	**0.23**	0.01	0.02	-0.01
	(2.5)	(1.2)	(2.9)	(0.2)	(0.3)	(-0.1)
RMW	**0.20**	0.10	0.09	**0.42**	0.08	**0.49**
	(2.1)	(0.9)	(0.8)	(6.3)	(1.3)	(6.7)
CMA	**-0.20**	-0.14	-0.20	**0.49**	0.09	**0.57**
	(-2.1)	(-1.2)	(-1.8)	(7.7)	(1.5)	(8.1)
REV	**-0.23**	-0.05	**-0.31**	**0.24**	**0.40**	**0.10**
	(-6.1)	(-1.0)	(-6.6)	(8.7)	(15.5)	(3.2)
BAB				**0.47**	**0.15**	**0.41**
				(14.0)	(4.9)	(10.8)
LMAX	**0.84**	**0.38**	**1.06**			
	(14.0)	(5.3)	(14.6)			
SR	0.92	0.89	0.33	0.34	0.43	0.35
IR	0.43	0.63	-0.28	-0.29	0.05	-0.22
R2	0.64	0.40	0.73	0.88	0.51	0.85
# obs	306	306	306	306	306	306

Table X
Turnover

This table reports the turnover of the different trading strategies considered in the paper. We measure turnover as the amount of dollars that has to be traded in each trading strategy on a monthly basis. BAC and BAV: At the beginning of each month stocks are ranked in ascending order based on the estimate of volatility (correlation) at the end of the previous month. The ranked stocks are assigned to one of five quintiles. U.S. sorts are based on NYSE breakpoints. Within each quintile, stocks are assigned to one of two portfolios: low correlation (volatility) and high correlation (volatility). In these portfolios, stocks are weighted by ranked correlation (volatility) (lower correlation (volatility) stocks have larger weights in the low-correlation (volatility) portfolios and larger correlation (volatility) stocks have larger weights in the high-correlation (volatility) portfolios), and the portfolios are rebalanced every calendar month. The portfolios are (de)levered to have a beta of one at formation. Within each volatility (correlation) quintile, a self-financing portfolio is made that is long the low-correlation (volatility) portfolio and short the high-correlation (volatility) portfolio. Betting against correlation (volatility) is the equal-weighted average of these five portfolios. This table shows regression results for monthly returns to LMAX, SMAX, and IVOL. Panel A reports the results from the U.S. sample and Panel B reports the results from the global sample. LMAX (SMAX, IVOL) is constructed as the intersection of six value-weighted portfolios formed on size and MAX (SMAX, IVOL). For U.S. securities, the size breakpoint is the median NYSE market equity. For International securities, the size breakpoint is the 80th percentile by country. The MAX (SMAX, IVOL) breakpoints are the 30th and 70th percentile. We use unconditional sorts in the U.S. and conditional sorts in the international sample (first we sort on size and then MAX (SMAX, IVOL)). Firms are assigned to one of six portfolios based on these breakpoints. Portfolios are value-weighted, refreshed every calendar month, and rebalanced every calendar month to maintain value weights. LMAX (SMAX, IVOL) is then the average return to the two low-MAX (SMAX, IVOL) portfolios minus the average return to the two high-MAX (SMAX, IVOL) portfolios. We form one set of portfolios in each country and compute global portfolios by weighting each country's portfolio by the country's lagged total market capitalization. MAX is the sum of the five highest returns over the previous month. SMAX is the MAX characteristic divided by one-year daily volatility. The IVOL factor is based on the characteristics defined by Ang, Hodrick, Xing, and Zhang (2006). The U.S. sample is form 1926-2015.

	Portfolio										
	HML	BAB	BAB	BAB	BAC	BAV	LMAX	SMAX	IVOL	LMAX(1Y)	SMAX(1Y)
Method	FF: june update	FF: june update	FF: monthly	Rank weights	Rank weights	Rank weights	FF: monthly	FF: monthly	FF: monthly	FF: monthly	FF: monthly
Turnover	0.24	0.21	0.41	0.34	0.35	0.36	2.06	2.77	1.76	0.46	1.14
Period over which the characteristics are calculated	NA	1 to 5 years	1 to 5 years	1 to 5 years	1 to 5 years	1 to 5 years	1 month	1 to 12 months	1 month	1 year	1 year

Table XI
MAX Factors Based on Yearly Look-Back Periods

This table shows regression results for monthly returns to LMAX and SMAX factors that are produced based on yearly estimates of MAX. Panel A reports the results from the long U.S. sample and Panel B reports the results from the global sample. LMAX 1-year (SMAX 1-year) is constructed as the intersection of six value-weighted portfolios formed on size and MAX 1-year (SMAX 1-year). For U.S. securities, the size breakpoint is the median NYSE market equity. For International securities, the size breakpoint is the 80th percentile by country. The MAX 1-year (SMAX 1-year) breakpoints are the 30th and 70th percentile. We use unconditional sorts in the U.S. and conditional sorts in the international sample (first we sort on size and then MAX 1-year (SMAX 1-year)). Firms are assigned to one of six portfolios based on these breakpoints. Portfolios are value-weighted, refreshed every calendar month, and rebalanced every calendar month to maintain value weights. LMAX 1-year (SMAX 1-year) is then the average return to the two low- MAX 1-year (SMAX 1-year) portfolios minus the average return to the two high-MAX (SMAX 1-year) portfolios. We form one set of portfolios in each country and compute global portfolios by weighting each country's portfolio by the country's lagged total market capitalization. MAX 1-year is the sum of the 20 highest returns over the previous year. SMAX 1-year is the MAX 1-year characteristic divided by one-year daily volatility. The explanatory variables are monthly excess to the value-weighted market portfolio and the monthly returns for the SMB, HML, RMW, CMA, REV, and BAB factor. SMB, HML, RMW, and CMA are from Fama and French (2015). BAB is from Frazzini and Pedersen (2014). Returns and alphas are in monthly percent, *t*-statistics are shown in parenthesis below the coefficient estimates, and 5% statistical significance is indicated in bold. Sharpe ratios and information ratios are annualized.

	Panel A: U.S. Sample (1963 - 2015)					
	LMAX(1Y)	LMAX(1Y)	LMAX(1Y)	SMAX(1Y)	SMAX(1Y)	SMAX(1Y)
Alpha	**0.40**	0.09	-0.11	-0.13	**-0.25**	**-0.23**
	(3.73)	(0.89)	(-1.26)	(-1.67)	(-3.57)	(-3.25)
MKT	**-0.50**	**-0.43**	**-0.47**	0.00	**-0.05**	**-0.04**
	(-19.6)	(-17.5)	(-21.9)	(0.0)	(-2.6)	(-2.4)
SMB	**-0.67**	**-0.54**	**-0.59**	**-0.23**	**-0.21**	**-0.21**
	(-18.8)	(-16.0)	(-19.9)	(-9.1)	(-8.8)	(-8.6)
HML	**0.36**	**0.11**	0.00	**0.16**	**0.17**	**0.18**
	(9.2)	(2.3)	(-0.1)	(5.8)	(4.8)	(5.1)
RMW		**0.61**	**0.42**		**0.17**	**0.19**
		(12.3)	(9.4)		(4.8)	(5.2)
CMA		**0.52**	**0.37**		-0.07	-0.05
		(7.4)	(5.9)		(-1.3)	(-1.0)
REV		0.04	**0.06**		**0.25**	**0.25**
		(1.2)	(2.3)		(10.9)	(10.8)
BAB			**0.41**			-0.04
			(14.5)			(-1.8)
SR	0.07	0.07	0.07	-0.22	-0.22	-0.22
IR	0.53	0.13	-0.19	-0.24	-0.52	-0.48
R2	0.68	0.75	0.81	0.18	0.34	0.34
# obs	630	630	630	630	630	630

Table XI
MAX Factors Based on Yearly Look-Back Periods (continued)

	Panel B: Global Sample (1990 - 2015)					
	LMAX(1Y)	LMAX(1Y)	LMAX(1Y)	SMAX(1Y)	SMAX(1Y)	SMAX(1Y)
Alpha	**0.34**	-0.15	**-0.26**	**-0.19**	**-0.29**	**-0.27**
	(2.57)	(-1.32)	(-2.93)	(-2.08)	(-3.40)	(-3.26)
MKT	**-0.63**	**-0.40**	**-0.45**	-0.01	-0.04	-0.04
	(-20.9)	(-12.5)	(-18.3)	(-0.4)	(-1.9)	(-1.6)
SMB	**-0.57**	**-0.31**	**-0.59**	**-0.28**	**-0.24**	**-0.21**
	(-9.1)	(-5.7)	(-12.6)	(-6.5)	(-6.0)	(-4.8)
HML	**0.49**	0.05	-0.10	**0.22**	**0.23**	**0.24**
	(8.6)	(0.7)	(-1.9)	(5.5)	(4.4)	(4.7)
RMW		**0.92**	**0.44**		**0.20**	**0.26**
		(10.9)	(6.0)		(3.3)	(3.7)
CMA		**0.69**	**0.50**		-0.07	-0.04
		(7.7)	(7.1)		(-1.0)	(-0.7)
REV		0.04	**0.07**		**0.28**	**0.27**
		(1.0)	(2.4)		(9.7)	(9.6)
BAB			**0.54**			-0.06
			(14.4)			(-1.7)
SR	0.17	0.17	0.17	-0.27	-0.27	-0.27
IR	0.52	-0.29	-0.64	-0.42	-0.74	-0.71
R2	0.68	0.79	0.87	0.21	0.42	0.42
# obs	306	306	306	306	306	306

Table XII
Horserace: Factors based on Fama-French Methodology

This table reports regression results of horseraces where factors are constructed following the Fama and French (1993) methodology. Panel A reports the results for the U.S. sample and panel B reports the results for the global sample. The dependent variables are the monthly returns BAB, BAC, BAV, LMAX, SMAX, SMAX 1-year, and IVOL. All factors are constructed following the same methodology. BAB, for example, is constructed as the intersection of six value-weighted portfolios formed on size and beta. For U.S. securities, the size breakpoint is the median NYSE market equity. For International securities, the size breakpoint is the 80th percentile by country. The beta breakpoints are the 30th and 70th percentile. We use unconditional sorts in the U.S. and conditional sorts in the international sample (first we sort on size and then beta). Firms are assigned to one of six portfolios based on these breakpoints. Portfolios are value-weighted, refreshed every calendar month, and rebalanced every calendar month to maintain value weights. BAB is then the average return to the two low-BAB portfolios minus the average return to the two high-BAB portfolios. We form one set of portfolios in each country and compute global portfolios by weighting each country's portfolio by the country's lagged total market capitalization. All factors are set up such they have positive CAPM alpha. For BAC and BAV, we create a factor within each volatility (correlation) quintile, and the BAC (BAV) factor is then the averages of these five. MAX is the sum of the five highest returns over the previous month. SMAX is the MAX characteristic divided by one-year daily volatility. IVOL is the characteristics defined by Ang, Hodrick, Xing, and Zhang (2006). Returns and alphas are in monthly percent, *t*-statistics are shown in parenthesis below the coefficient estimates, and 5% statistical significance is indicated in bold. Sharpe ratios and information ratios are annualized.

Panel A: U.S. Sample (1963 - 2015)										
	BAB	BAB	BAC	BAC	BAV	BAV	LMAX	SMAX	SMAX(1Y)	IVOL
Alpha	**0.20**	0.06	**0.19**	0.09	**0.36**	**0.26**	0.06	**0.21**	**-0.25**	0.06
	(3.23)	(0.87)	(2.01)	(1.01)	(4.67)	(3.01)	(1.05)	(3.18)	(-3.43)	(0.99)
MKT	**-0.18**	**-0.22**	**-0.15**	**-0.15**	**-0.14**	**-0.19**	-0.03	-0.01	**-0.06**	**-0.04**
	(-9.7)	(-10.0)	(-5.3)	(-5.4)	(-6.0)	(-7.2)	(-1.6)	(-0.5)	(-2.7)	(-2.1)
SMB	**0.12**	-0.03	**0.39**	**0.31**	**-0.28**	**-0.43**	**-0.14**	0.03	**-0.22**	**-0.31**
	(4.8)	(-1.1)	(10.2)	(8.8)	(-9.2)	(-13.2)	(-6.5)	(1.0)	(-8.6)	(-12.8)
HML	**0.09**	0.00	0.03	-0.04	0.03	-0.03	**0.09**	-0.05	**0.17**	**0.08**
	(2.9)	(-0.1)	(0.6)	(-0.8)	(0.8)	(-0.8)	(3.2)	(-1.7)	(5.0)	(2.7)
RMW	**-0.15**	**-0.13**	**-0.15**	**-0.16**	**0.09**	**0.13**	**0.32**	0.07	**0.18**	**0.46**
	(-4.3)	(-3.1)	(-2.9)	(-3.1)	(2.0)	(2.8)	(10.5)	(1.9)	(5.0)	(13.7)
CMA	-0.07	-0.05	-0.11	-0.12	-0.05	-0.01	**0.25**	**0.11**	-0.06	**0.27**
	(-1.4)	(-1.0)	(-1.5)	(-1.7)	(-0.9)	(-0.2)	(5.8)	(2.2)	(-1.1)	(5.6)
REV	**-0.09**	**-0.23**	**-0.17**	**-0.26**	-0.01	**-0.11**	**0.22**	**0.37**	**0.25**	0.01
	(-4.5)	(-9.6)	(-5.7)	(-8.4)	(-0.3)	(-3.9)	(11.8)	(17.7)	(10.8)	(0.7)
BAB							**0.62**	**0.14**	-0.03	**0.54**
							(28.9)	(5.7)	(-1.1)	(22.5)
LMAX(1Y)	**0.91**		**0.54**		**0.73**					
	(36.0)		(14.4)		(23.7)					
LMAX		**0.92**		**0.60**		**0.70**				
		(28.9)		(14.3)		(18.2)				
SR	0.11	0.11	0.13	0.13	0.21	0.21	0.34	0.78	-0.22	0.22
IR	0.47	0.13	0.30	0.15	0.69	0.45	0.16	0.47	-0.51	0.15
R2	0.91	0.88	0.56	0.56	0.86	0.83	0.89	0.37	0.34	0.88
# obs	630	630	630	630	630	630	630	630	630	630

Table XII
Horserace: Factors based on Fama-French Methodology (continued)

	Panel B: Global Sample (1990 - 2015)									
	BAB	BAB	BAC	BAC	BAV	BAV	LMAX	SMAX	SMAX(1Y)	IVOL
Alpha	0.09	-0.03	0.01	-0.06	**0.29**	**0.19**	0.02	0.06	0.06	**-0.29**
	(1.29)	(-0.40)	(0.16)	(-0.66)	(3.86)	(2.33)	(0.25)	(0.76)	(0.76)	(-3.44)
MKT	**-0.14**	**-0.12**	-0.03	-0.03	**-0.16**	**-0.16**	**-0.06**	-0.01	-0.01	**-0.07**
	(-5.7)	(-4.4)	(-1.0)	(-0.9)	(-6.4)	(-5.6)	(-2.9)	(-0.3)	(-0.3)	(-2.5)
SMB	**0.19**	**0.16**	**0.45**	**0.42**	**-0.38**	**-0.41**	**-0.20**	0.05	0.05	**-0.25**
	(5.3)	(4.2)	(9.7)	(8.9)	(-9.9)	(-10.1)	(-6.6)	(1.4)	(1.4)	(-6.1)
HML	**-0.11**	**-0.21**	**-0.14**	**-0.19**	0.00	-0.07	**0.19**	0.07	0.07	**0.22**
	(-2.6)	(-4.5)	(-2.4)	(-3.3)	(0.0)	(-1.4)	(5.0)	(1.6)	(1.6)	(4.3)
RMW	0.04	0.04	0.03	0.06	0.00	0.03	**0.29**	0.07	0.07	**0.26**
	(0.6)	(0.6)	(0.4)	(0.7)	(-0.1)	(0.4)	(5.5)	(1.1)	(1.1)	(3.7)
CMA	0.02	0.00	0.04	0.05	-0.04	-0.04	**0.24**	0.03	0.03	-0.03
	(0.4)	(-0.0)	(0.5)	(0.6)	(-0.7)	(-0.5)	(4.6)	(0.4)	(0.4)	(-0.4)
REV	**-0.10**	**-0.26**	**-0.19**	**-0.28**	-0.01	**-0.14**	**0.25**	**0.40**	**0.40**	**0.27**
	(-4.0)	(-9.7)	(-5.9)	(-8.3)	(-0.5)	(-4.8)	(11.8)	(15.7)	(15.7)	(9.5)
BAB							**0.66**	**0.18**	**0.18**	-0.06
							(22.8)	(5.2)	(5.2)	(-1.6)
LMAX(1Y)	**0.89**		**0.55**		**0.73**					
	(24.6)		(12.0)		(19.3)					
LMAX		**0.96**		**0.57**		**0.75**				
		(22.8)		(10.8)		(16.5)				
SR	0.15	0.15	0.09	0.09	0.30	0.30	0.34	0.43	0.43	-0.27
IR	0.28	-0.09	0.03	-0.14	0.84	0.51	0.05	0.16	0.16	-0.75
R2	0.92	0.91	0.72	0.71	0.90	0.89	0.93	0.52	0.52	0.42
# obs	306	306	306	306	306	306	306	306	306	306

Table XIII
Horserace: Rank-Weighted Factors

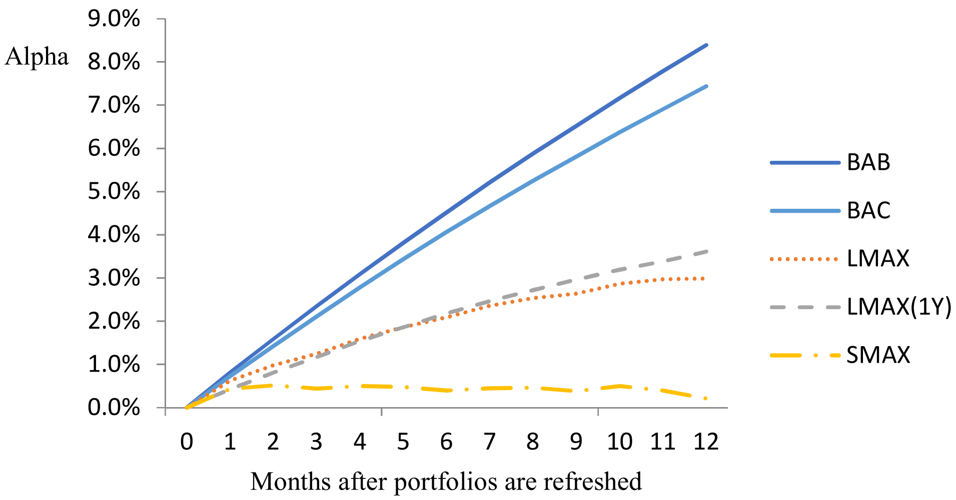
This table reports regression results of horseraces where all factors are rank-weighted. The dependent variables are the monthly returns BAB, BAC, BAV, LMAX, SMAX, and IVOL. All factors are constructed following the same methodology. BAB, for example, is constructed as follows: All stocks are sorted into two groups based on size. The size breakpoint is the median NYSE market equity. Within each size group, stocks are assigned to one of two portfolios: low beta and high beta. In these portfolios, stocks are weighted by rank (lower beta stocks have larger weights in the low-beta portfolios and larger beta stocks have larger weights in the high-beta portfolios), and the portfolios are rebalanced every calendar month. The portfolios are (de)levered to have a beta of one at formation. A self-financing portfolio is made that is long the low-beta portfolio and short the high-beta portfolio. All factors are set up such they have positive CAPM alpha. MAX is the sum of the five highest returns over the previous month. SMAX is the MAX characteristic divided by one-year daily volatility. IVOL is the characteristics defined by Ang, Hodrick, Xing, and Zhang (2006). Returns and alphas are in monthly percent, *t*-statistics are shown in parenthesis below the coefficient estimates, and 5% statistical significance is indicated in bold. Sharpe ratios and information ratios are annualized.

	Panel A: U.S. Sample (1952 - 2015)											
	BAB	BAB	BAC	BAC	BAV	BAV	LMAX	LMAX	SMAX	SMAX	IVOL	IVOL
Alpha	**0.32**	**0.24**	**0.27**	**0.24**	0.02	**-0.10**	0.14	-0.10	**0.22**	0.14	0.14	-0.05
	(3.34)	(3.29)	(3.56)	(3.33)	(0.16)	(-2.25)	(1.26)	(-1.12)	(2.84)	(1.90)	(1.56)	(-0.80)
MKT	0.02	**0.06**	-0.01	0.01	**-0.05**	0.01	**-0.08**	**-0.09**	**-0.04**	**-0.05**	**-0.06**	**-0.07**
	(1.0)	(3.7)	(-0.4)	(0.6)	(-2.1)	(1.1)	(-2.8)	(-4.5)	(-2.4)	(-2.8)	(-2.8)	(-4.6)
SMB	**0.14**	**0.15**	**0.36**	**0.37**	**-0.17**	**-0.16**	-0.02	**-0.12**	**0.09**	**0.06**	**-0.15**	**-0.24**
	(8.1)	(11.2)	(25.8)	(27.4)	(-9.5)	(-20.3)	(-0.8)	(-7.4)	(6.4)	(4.0)	(-9.5)	(-18.7)
HML	**0.33**	**0.31**	**0.20**	**0.19**	**0.24**	**0.22**	0.03	**-0.21**	**-0.12**	**-0.20**	**0.17**	-0.03
	(7.7)	(9.4)	(5.8)	(5.9)	(5.6)	(11.4)	(0.7)	(-5.2)	(-3.6)	(-5.9)	(4.3)	(-0.8)
RMW	**0.49**	**-0.12**	**0.12**	**-0.12**	**1.05**	**0.16**	**1.12**	**0.75**	**0.43**	**0.31**	**0.96**	**0.67**
	(14.7)	(-3.1)	(4.7)	(-3.3)	(30.5)	(7.7)	(28.5)	(21.9)	(16.3)	(11.0)	(31.1)	(25.2)
CMA	0.02	**-0.18**	-0.10	**-0.18**	**0.34**	0.05	**0.36**	**0.35**	0.11	0.10	**0.31**	**0.30**
	(0.2)	(-2.9)	(-1.6)	(-3.0)	(4.1)	(1.4)	(3.9)	(4.9)	(1.7)	(1.7)	(4.3)	(5.4)
REV	-0.01	**-0.15**	**-0.05**	**-0.10**	**0.05**	**-0.15**	**0.25**	**0.27**	**0.37**	**0.37**	-0.02	-0.01
	(-0.6)	(-7.7)	(-2.5)	(-5.3)	(2.2)	(-12.8)	(8.9)	(12.0)	(18.9)	(20.0)	(-0.7)	(-0.4)
BAB								**0.75**		**0.24**		**0.59**
								(22.7)		(8.7)		(23.8)
LMAX		**0.54**		**0.22**		**0.79**						
		(22.7)		(9.3)		(57.4)						
SR	0.83	0.83	0.78	0.78	0.33	0.33	0.68	0.68	1.17	1.17	0.36	0.36
IR	0.48	0.48	0.52	0.48	0.02	-0.33	0.18	-0.16	0.41	0.28	0.23	-0.12
R2	0.44	0.67	0.51	0.56	0.79	0.96	0.65	0.79	0.45	0.50	0.79	0.88
# obs	762	762	762	762	762	762	762	762	762	762	761	761

Figure I
Cumulative Alpha for Longer Holding Periods

This figure shows cumulative alpha for trading strategies in event time. The event time is months after the characteristics were last refreshed.

Panel A: Cumulative Three Factor Alpha



Panel B: Cumulative Five Factor Alpha

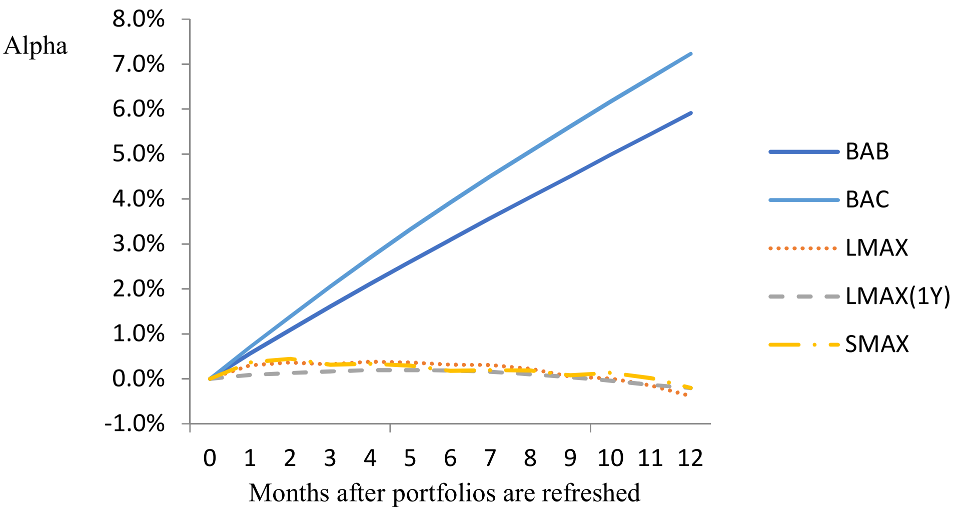


Table A1
Betting Against Volatility – Three Factor Alphas

This table shows returns to the betting against volatility factor in each correlation quintile, along with the equal-weighted average of these factors, which constitute our overall BAV factor. Panel A reports the BAV performance in the U.S. sample and panel B reports the performance in the global sample. At the beginning of each month stocks are ranked in ascending order based on the estimate of correlation at the end of the previous month. The ranked stocks are assigned to one of five quintiles. U.S. sorts are based on NYSE breakpoints. Within each quintile, stocks are assigned to one of two portfolios: low volatility and high volatility. In these portfolios, stocks are weighted by ranked volatility (lower volatility stocks have larger weights in the low- volatility portfolios and larger volatility stocks have larger weights in the high- volatility portfolios), and the portfolios are rebalanced every calendar month. The portfolios are (de)levered to have a beta of one at formation. Within each correlation quintile, a self-financing BAC portfolio is made that is long the low-correlation portfolio and short the high-correlation portfolio. We form one set of portfolios in each country and compute global portfolios by weighting each country's portfolio by the country's total (lagged) market capitalization. Alpha is the intercept in a regression of monthly excess return. The explanatory variables are the monthly excess return to the CRSP value-weighted market portfolio and the monthly returns to the SMB and HML factors of Fama and French (2015). Returns and alphas are in monthly percent, *t*-statistics are shown in parenthesis below the coefficient estimates, and 5% statistical significance is indicated in bold. '$ long' and '$ short' measures how many dollars the betting against correlation portfolio is long and short. Sharpe ratios and information ratios are annualized.

	Panel A: U.S. Sample (1963-2015)					
Correlation quintile	1	2	3	4	5	BAV
Excess return	-0.10	**0.63**	**0.59**	**0.57**	0.30	**0.40**
	(-0.31)	(2.68)	(2.76)	(3.20)	(1.93)	(1.99)
Alpha	0.07	**0.57**	**0.54**	**0.55**	**0.30**	**0.40**
	(0.23)	(2.65)	(2.90)	(3.74)	(2.51)	(2.40)
MKT	**-0.16**	0.07	0.04	0.01	0.00	-0.01
	(-2.3)	(1.3)	(1.0)	(0.4)	(0.03)	(-0.2)
SMB	**-0.97**	**-0.67**	**-0.69**	**-0.65**	**-0.65**	**-0.73**
	(-10.2)	(-9.3)	(-11.1)	(-13.3)	(-16.5)	(-12.9)
HML	**0.49**	**0.60**	**0.61**	**0.53**	**0.50**	**0.55**
	(4.8)	(7.8)	(9.1)	(9.9)	(11.9)	(9.0)
SR	-0.04	0.37	0.38	0.44	0.27	0.27
IR	0.03	0.37	0.41	0.53	0.35	0.34
R2	0.22	0.21	0.27	0.34	0.44	0.32
# obs	630	630	630	630	630	630

	Panel B: Global Sample (1990-2015)					
Correlation quintile	1	2	3	4	5	BAV
Excess return	-0.06	**0.53**	**0.58**	**0.52**	**0.35**	0.38
	(-0.18)	(2.08)	(2.44)	(2.51)	(1.98)	(1.68)
Alpha	-0.16	**0.41**	**0.48**	**0.48**	**0.31**	0.31
	(-0.57)	(1.98)	(2.62)	(2.97)	(2.30)	(1.73)
MKT	**-0.27**	**-0.21**	**-0.26**	**-0.29**	**-0.25**	**-0.26**
	(-4.2)	(-4.4)	(-6.3)	(-7.8)	(-8.21)	(-6.4)
SMB	**-1.04**	**-0.68**	**-0.62**	**-0.54**	**-0.45**	**-0.67**
	(-7.8)	(-6.8)	(-7.0)	(-7.0)	(-7.1)	(-7.9)
HML	**0.85**	**0.79**	**0.77**	**0.62**	**0.56**	**0.72**
	(6.9)	(8.6)	(9.5)	(8.8)	(9.5)	(9.3)
SR	-0.04	0.41	0.48	0.50	0.39	0.33
IR	-0.12	0.40	0.53	0.60	0.46	0.35
R2	0.33	0.35	0.41	0.42	0.45	0.42
# obs	306	306	306	306	306	306

Table A2
Betting Against Volatility – Five Factor Alphas

This table shows returns to the betting against volatility factor in each correlation quintile, along with the equal-weighted average of these factors, which constitute our overall BAV factor. Panel A reports the BAV performance in the U.S. sample and panel B reports the performance in the global sample. At the beginning of each month stocks are ranked in ascending order based on the estimate of correlation at the end of the previous month. The ranked stocks are assigned to one of five quintiles. U.S. sorts are based on NYSE breakpoints. Within each quintile, stocks are assigned to one of two portfolios: low volatility and high volatility. In these portfolios, stocks are weighted by ranked volatility (lower volatility stocks have larger weights in the low- volatility portfolios and larger volatility stocks have larger weights in the high- volatility portfolios), and the portfolios are rebalanced every calendar month. The portfolios are (de)levered to have a beta of one at formation. Within each correlation quintile, a self-financing BAC portfolio is made that is long the low-correlation portfolio and short the high-correlation portfolio. We form one set of portfolios in each country and compute global portfolios by weighting each country's portfolio by the country's total (lagged) market capitalization. Alpha is the intercept in a regression of monthly excess return. The explanatory variables are the monthly excess return to the CRSP value-weighted market portfolio and the monthly returns to the SMB, HML, RMW, and CMA factors of Fama and French (2015). Returns and alphas are in monthly percent, *t*-statistics are shown in parenthesis below the coefficient estimates, and 5% statistical significance is indicated in bold. '$ long' and '$ short' measures how many dollars the betting against correlation portfolio is long and short. Sharpe ratios and information ratios are annualized.

	Panel A: U.S. Sample (1963-2015)					
Correlation quintile	1	2	3	4	5	BAV
Excess return	-0.10	**0.63**	**0.59**	**0.57**	0.30	**0.40**
	(-0.31)	(2.68)	(2.76)	(3.20)	(1.93)	(1.99)
Alpha	-0.48	0.04	0.06	0.17	-0.03	-0.05
	(-1.77)	(0.18)	(0.35)	(1.26)	(-0.32)	(-0.34)
MKT	-0.05	**0.19**	**0.15**	**0.10**	**0.08**	**0.09**
	(-0.7)	(3.9)	(3.6)	(3.0)	(3.02)	(2.6)
SMB	**-0.65**	**-0.39**	**-0.43**	**-0.44**	**-0.48**	**-0.48**
	(-7.0)	(-5.8)	(-7.4)	(-9.7)	(-13.3)	(-9.3)
HML	**0.29**	**0.28**	**0.37**	**0.34**	**0.30**	**0.31**
	(2.2)	(3.0)	(4.5)	(5.3)	(6.0)	(4.4)
RMW	**1.43**	**1.23**	**1.17**	**0.94**	**0.76**	**1.11**
	(10.5)	(12.3)	(13.8)	(14.0)	(14.2)	(14.6)
CMA	**0.41**	**0.67**	**0.51**	**0.40**	**0.42**	**0.48**
	(2.1)	(4.7)	(4.3)	(4.2)	(5.6)	(4.5)
SR	-0.04	0.37	0.38	0.44	0.27	0.27
IR	-0.26	0.03	0.05	0.18	-0.05	-0.05
R2	0.33	0.36	0.44	0.50	0.58	0.49
# obs	630	630	630	630	630	630

Table A2 (continued)
Betting Against Volatility – Five Factor Alphas

	Panel B: Global Sample (1990-2015)					
Correlation quintile	1	2	3	4	5	BAV
Excess return	-0.06	**0.53**	**0.58**	**0.52**	**0.35**	0.38
	(-0.18)	(2.08)	(2.44)	(2.51)	(1.98)	(1.68)
Alpha	**-0.62**	-0.05	-0.01	-0.07	-0.19	-0.19
	(-2.16)	(-0.23)	(-0.07)	(-0.46)	(-1.67)	(-1.12)
MKT	-0.06	0.00	-0.03	-0.03	-0.02	-0.03
	(-0.8)	(-0.0)	(-0.7)	(-0.8)	(-0.63)	(-0.6)
SMB	**-0.80**	**-0.44**	**-0.35**	**-0.25**	**-0.18**	**-0.40**
	(-5.7)	(-4.3)	(-4.1)	(-3.5)	(-3.3)	(-4.9)
HML	**0.56**	**0.46**	**0.39**	**0.21**	**0.20**	**0.37**
	(3.2)	(3.6)	(3.6)	(2.4)	(2.9)	(3.6)
RMW	**0.97**	**0.93**	**0.99**	**1.09**	**1.01**	**1.00**
	(4.6)	(6.0)	(7.4)	(10.1)	(11.8)	(8.0)
CMA	0.41	**0.49**	**0.58**	**0.61**	**0.53**	**0.52**
	(1.8)	(3.0)	(4.1)	(5.3)	(5.8)	(4.0)
SR	-0.04	0.41	0.48	0.50	0.39	0.33
IR	-0.47	-0.05	-0.01	-0.10	-0.36	-0.24
R2	0.37	0.42	0.51	0.58	0.63	0.53
# obs	306	306	306	306	306	306

Table A3

Inter-Industry Sort: Industries Sorted on Maximum Returns of Industries

This table shows the returns to industries sorted on the industries' maximum return over the previous month. At the beginning of each calendar month, all industries are ranked in ascending order based on their maximum return over the previous month and decile breakpoints are calculated. Based on these breakpoints, stocks are sorted into portfolios based on the maximum return of their industry. Portfolios are value-weighted, refreshed, and rebalanced every calendar month. The long short portfolio, LS, is short one dollar in the portfolio of stocks with lowest industry maximum return and long one dollar in the portfolio of stocks with highest industry maximum return. Industry maximum return is calculated as the sum of the five highest daily returns for industry portfolios. Industry portfolios are value-weighted and based on the 49 Fama and French portfolios. CAPM alpha is the intercept in a regression of monthly excess return where the explanatory variable is the monthly excess return to the CRSP value-weighted market. Three factor alpha is the intercept in a regression of monthly excess return where the explanatory variables are the monthly excess return to the CRSP value-weighted market portfolio and the monthly returns to the SMB and HML factors of Fama and French (1993). Five factor alpha is the intercept in a regression of monthly excess return where the explanatory variables are the monthly excess return to the CRSP value-weighted market portfolio and the monthly returns to the SMB, HML, RMW, and CMA factors of Fama and French (2015). Returns and alphas are in monthly percent, *t*-statistics are shown in parenthesis below the coefficient estimates, and 5% statistical significance is indicated in bold. Sharpe ratios and information ratios are annualized.

U.S. 1963-2013	1 (low-MAX)	2	3	4	5	6	7	8	9	10 (high MAX)	LS
Excess return	0.32	**0.44**	**0.44**	**0.50**	**0.51**	**0.44**	**0.65**	**0.48**	**0.79**	**0.69**	**0.36**
	(1.40)	(2.04)	(2.08)	(2.42)	(2.59)	(2.30)	(3.14)	(2.35)	(3.80)	(3.14)	(2.07)
CAPM alpha	-0.20	-0.08	-0.07	0.00	0.03	-0.03	0.16	-0.02	**0.30**	0.18	**0.38**
	(-1.60)	(-0.77)	(-0.64)	(-0.01)	(0.30)	(-0.36)	(1.53)	(-0.17)	(2.87)	(1.54)	(2.14)
Three-factor alpha	-0.24	-0.10	-0.13	0.01	-0.01	-0.09	0.16	-0.05	**0.25**	0.13	**0.36**
	(-1.84)	(-0.93)	(-1.25)	(0.08)	(-0.11)	(-1.09)	(1.53)	(-0.56)	(2.36)	(1.10)	(2.02)
Five-factor alpha	**-0.34**	-0.07	-0.16	-0.06	-0.05	-0.14	**0.25**	-0.10	0.20	0.05	**0.40**
	(-2.63)	(-0.68)	(-1.53)	(-0.56)	(-0.52)	(-1.62)	(2.31)	(-1.03)	(1.82)	(0.46)	(2.14)
MKT	**1.06**	**1.01**	**1.05**	**1.02**	**1.01**	**0.98**	**0.94**	**1.01**	**0.99**	**1.03**	-0.03
	(33.6)	(39.1)	(40.8)	(42.2)	(46.24)	(45.7)	(35.4)	(41.9)	(38.4)	(35.45)	(-0.7)
SMB	**0.17**	**0.10**	0.01	0.00	-0.01	**0.09**	0.05	**0.10**	**0.13**	**0.16**	0.00
	(3.8)	(2.7)	(0.4)	(0.0)	(-0.4)	(2.8)	(1.4)	(3.0)	(3.7)	(4.0)	(-0.1)
HML	0.04	0.07	**0.18**	-0.04	**0.11**	0.06	-0.02	0.02	0.05	0.01	-0.03
	(0.7)	(1.4)	(3.5)	(-1.0)	(2.7)	(1.5)	(-0.3)	(0.4)	(0.9)	(0.2)	(-0.4)
RMW	**0.33**	0.02	**0.15**	**0.14**	**0.14**	**0.09**	**-0.22**	**0.10**	**0.12**	**0.16**	-0.17
	(5.1)	(0.4)	(2.7)	(2.8)	(3.0)	(2.1)	(-4.1)	(2.1)	(2.3)	(2.7)	(-1.8)
CMA	-0.03	**-0.15**	-0.08	0.08	-0.04	0.09	-0.06	0.07	0.04	0.09	0.12
	(-0.3)	(-2.0)	(-1.0)	(1.1)	(-0.7)	(1.5)	(-0.7)	(0.9)	(0.5)	(1.1)	(0.9)
SR	0.20	0.29	0.29	0.34	0.37	0.32	0.44	0.33	0.54	0.44	0.29
IR	-0.39	-0.10	-0.23	-0.08	-0.08	-0.24	0.34	-0.15	0.27	0.07	0.32
R2	0.71	0.78	0.77	0.79	0.82	0.81	0.75	0.79	0.76	0.73	0.00
# obs	606	606	606	606	606	606	606	606	606	606	606

Table A4
Inter-Industry Sort: Industries Sorted on Average Maximum Returns within Industries

This table shows the returns to industries sorted on the average maximum return over the previous month among stocks in a given industry. At the beginning of each calendar month, the value-weighted average maximum return over the previous month in each industry is calculated. All industries are ranked in ascending order based on their average maximum return over the previous month and decile breakpoints are calculated. Based on these breakpoints, stocks are sorted into portfolios based on the average maximum return of their industry. Portfolios are value-weighted, refreshed, and rebalanced every calendar month. The long short portfolio, LS, is short one dollar in the portfolio of stocks with lowest average maximum return and long one dollar in the portfolio of stocks with highest average maximum return. CAPM alpha is the intercept in a regression of monthly excess return where the explanatory variable is the monthly excess return to the CRSP value-weighted market. Three factor alpha is the intercept in a regression of monthly excess return where the explanatory variables are the monthly excess return to the CRSP value-weighted market portfolio and the monthly returns to the SMB and HML factors of Fama and French (1993). Five factor alpha is the intercept in a regression of monthly excess return where the explanatory variables are the monthly excess return to the CRSP value-weighted market portfolio and the monthly returns to the SMB, HML, RMW, and CMA factors of Fama and French (2015). Returns and alphas are in monthly percent, *t*-statistics are shown in parenthesis below the coefficient estimates, and 5% statistical significance is indicated in bold. Sharpe ratios and information ratios are annualized.

U.S. 1963-2013	1 (low-MAX)	2	3	4	5	6	7	8	9	10 (high MAX)	LS
Excess return	**0.36**	**0.57**	**0.59**	**0.58**	**0.67**	**0.65**	**0.59**	**0.69**	**0.61**	**0.74**	0.38
	(2.37)	(3.21)	(3.21)	(3.00)	(3.26)	(2.98)	(2.57)	(2.84)	(2.26)	(2.38)	(1.40)
CAPM alpha	0.04	0.16	0.16	0.11	0.17	0.11	0.02	0.10	-0.04	0.03	-0.01
	(0.45)	(1.70)	(1.72)	(1.28)	(1.87)	(1.23)	(0.21)	(0.93)	(-0.29)	(0.19)	(-0.05)
Three-factor alpha	-0.07	0.07	0.06	0.02	0.10	0.03	-0.07	0.04	-0.07	0.18	0.25
	(-0.77)	(0.76)	(0.71)	(0.28)	(1.09)	(0.31)	(-0.81)	(0.34)	(-0.61)	(1.15)	(1.21)
Five-factor alpha	**-0.19**	-0.12	-0.09	-0.14	0.01	-0.04	**-0.20**	0.06	0.06	**0.41**	**0.60**
	(-2.05)	(-1.46)	(-1.04)	(-1.66)	(0.16)	(-0.39)	(-2.20)	(0.59)	(0.51)	(2.72)	(3.00)
MKT	**0.76**	**0.96**	**0.97**	**1.03**	**1.05**	**1.07**	**1.17**	**1.10**	**1.17**	**1.18**	**0.42**
	(33.6)	(47.2)	(47.5)	(51.1)	(47.32)	(47.6)	(53.6)	(42.3)	(39.7)	(32.15)	(8.7)
SMB	**-0.11**	**-0.07**	-0.03	0.01	**0.12**	**0.22**	**0.24**	**0.36**	**0.38**	**0.39**	**0.51**
	(-3.6)	(-2.4)	(-1.1)	(0.5)	(3.8)	(6.8)	(7.7)	(9.8)	(9.3)	(7.6)	(7.4)
HML	**0.18**	**0.15**	**0.19**	**0.13**	**0.10**	**0.13**	**0.12**	**0.12**	0.09	**-0.31**	**-0.50**
	(4.1)	(3.8)	(4.8)	(3.3)	(2.4)	(3.0)	(2.8)	(2.4)	(1.6)	(-4.4)	(-5.2)
RMW	**0.20**	**0.42**	**0.38**	**0.37**	**0.22**	**0.21**	**0.35**	0.07	**-0.16**	**-0.47**	**-0.67**
	(4.2)	(10.1)	(9.0)	(9.0)	(4.9)	(4.6)	(7.7)	(1.3)	(-2.7)	(-6.2)	(-6.6)
CMA	**0.26**	**0.22**	0.10	**0.17**	0.03	-0.04	0.03	**-0.25**	**-0.38**	**-0.37**	**-0.63**
	(3.9)	(3.7)	(1.7)	(2.9)	(0.5)	(-0.6)	(0.4)	(-3.3)	(-4.5)	(-3.4)	(-4.4)
SR	0.33	0.45	0.45	0.42	0.46	0.42	0.36	0.40	0.32	0.34	0.20
IR	-0.31	-0.22	-0.16	-0.25	0.02	-0.06	-0.33	0.09	0.08	0.41	0.45
R2	0.66	0.80	0.81	0.83	0.82	0.84	0.86	0.82	0.82	0.79	0.51
# obs	605	605	605	605	605	605	605	605	605	605	605

Table A5
Intra-Industry Sort: Stocks Sorted on Industry-Neutral Maximum Returns

This table shows the returns to stocks sorted on the maximum return over the previous month minus the value-weighted average maximum return within the stocks industry over the previous month. At the beginning of each calendar month, the value-weighted average maximum return over the previous month in each industry is calculated. NYSE stocks are ranked in ascending order based on their maximum return in excess of the industry average over the previous month and decile breakpoints are calculated. Based on these breakpoints, stocks are assigned into portfolios based on their maximum return in excess of the industry average. Portfolios are value-weighted, refreshed, and rebalanced every calendar month. The long short portfolio, LS, is short one dollar in the portfolio of stocks with lowest maximum return in excess of the industry average and long one dollar in the portfolio of stocks with highest maximum return in excess of the industry average. CAPM alpha is the intercept in a regression of monthly excess return where the explanatory variable is the monthly excess return to the CRSP value-weighted market. Three factor alpha is the intercept in a regression of monthly excess return where the explanatory variables are the monthly excess return to the CRSP value-weighted market portfolio and the monthly returns to the SMB and HML factors of Fama and French (1993). Five factor alpha is the intercept in a regression of monthly excess return where the explanatory variables are the monthly excess return to the CRSP value-weighted market portfolio and the monthly returns to the SMB, HML, RMW, and CMA factors of Fama and French (2015). Returns and alphas are in monthly percent, *t*-statistics are shown in parenthesis below the coefficient estimates, and 5% statistical significance is indicated in bold. Sharpe ratios and information ratios are annualized.

U.S. 1963-2013	1 (low-MAX)	2	3	4	5	6	7	8	9	10 (high MAX)	LS
Excess return	**0.83**	**0.68**	**0.64**	**0.48**	**0.40**	**0.61**	**0.50**	0.19	-0.02	-0.53	**-1.36**
	(4.69)	(3.85)	(3.69)	(2.75)	(2.08)	(2.73)	(1.97)	(0.65)	(-0.07)	(-1.37)	(-4.62)
CAPM alpha	**0.41**	**0.23**	**0.19**	0.03	-0.10	0.03	-0.14	**-0.52**	**-0.80**	**-1.30**	**-1.71**
	(4.88)	(3.75)	(3.71)	(0.52)	(-1.88)	(0.48)	(-1.41)	(-4.07)	(-4.49)	(-5.01)	(-6.40)
Three-factor alpha	**0.32**	**0.17**	**0.16**	0.01	**-0.14**	0.04	-0.12	**-0.52**	**-0.82**	**-1.41**	**-1.73**
	(3.93)	(2.74)	(3.19)	(0.19)	(-2.58)	(0.54)	(-1.44)	(-4.95)	(-6.02)	(-6.60)	(-7.38)
Five-factor alpha	**0.33**	**0.14**	0.08	-0.04	**-0.14**	0.12	0.09	**-0.23**	**-0.47**	**-0.81**	**-1.14**
	(3.93)	(2.26)	(1.67)	(-0.85)	(-2.45)	(1.77)	(1.11)	(-2.35)	(-3.75)	(-4.25)	(-5.37)
MKT	**0.83**	**0.93**	**0.96**	**0.96**	**1.03**	**1.10**	**1.12**	**1.21**	**1.26**	**1.14**	**0.31**
	(41.7)	(61.1)	(80.7)	(84.9)	(76.66)	(64.7)	(57.7)	(51.6)	(41.6)	(24.72)	(6.0)
SMB	**0.20**	**0.05**	**-0.05**	**-0.09**	-0.01	**0.11**	**0.28**	**0.46**	**0.76**	**0.94**	**0.74**
	(7.2)	(2.3)	(-3.1)	(-5.6)	(-0.5)	(4.7)	(10.2)	(13.9)	(17.9)	(14.6)	(10.3)
HML	**0.19**	**0.11**	**0.07**	**0.05**	**0.12**	-0.01	-0.02	-0.02	**-0.14**	0.05	-0.14
	(4.8)	(3.6)	(2.8)	(2.1)	(4.7)	(-0.3)	(-0.7)	(-0.4)	(-2.4)	(0.6)	(-1.4)
RMW	**0.08**	0.06	**0.18**	**0.10**	0.04	**-0.18**	**-0.43**	**-0.59**	**-0.79**	**-1.35**	**-1.44**
	(2.0)	(1.9)	(7.3)	(4.4)	(1.5)	(-5.2)	(-10.7)	(-12.2)	(-12.7)	(-14.3)	(-13.6)
CMA	**-0.17**	0.02	**0.07**	0.06	**-0.08**	**-0.12**	**-0.32**	**-0.45**	**-0.38**	**-0.64**	**-0.47**
	(-2.8)	(0.5)	(2.1)	(1.9)	(-2.2)	(-2.4)	(-5.6)	(-6.5)	(-4.3)	(-4.7)	(-3.2)
SR	0.66	0.54	0.52	0.39	0.29	0.38	0.28	0.09	-0.01	-0.19	-0.65
IR	0.59	0.34	0.25	-0.13	-0.37	0.27	0.17	-0.35	-0.56	-0.64	-0.80
R2	0.81	0.89	0.93	0.93	0.93	0.91	0.91	0.90	0.88	0.78	0.54
# obs	605	605	605	605	605	605	605	605	605	605	605

Table A6
Correlation Between MD and Other Measures of Liquidity

US. 1963-2013 (quarterly)

	dMD	TED	VIX	NOISE	LEV
dMD	1	-0.02	-0.01	-0.21	0.08
TED	-0.02	1	0.29	0.54	0.73
VIX	-0.01	0.29	1	0.56	0.30
NOISE	-0.21	0.54	0.56	1	0.14
LEV	0.08	0.73	0.30	0.14	1
MEAN	0.00	0.58	20.26	3.56	30.61
N obs	182	78	94	106	182

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