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Speculative Betas in Europe

– Based on Evidence from Western European Stocks and Bonds*

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ABSTRACT

We find and present compelling evidence to reject the classic one-regime CAPM Security Market Line based on data from developed European equity markets which we proxy by taking the original 12 members of the euro area combined with the UK. We construct a bottom-up measure for aggregate disagreement which we prove to negatively influence the curvature of the Security Market Line. When disagreement is high the curve is concave, thus, a beta anomaly emerges under which low-beta assets tend to outperform high-beta assets due to speculative mispricing, however, when disagreement is low conventional, positive risk-return trade-off prevails. Our results support Hong and Sraer's (2016) theoretical model and are on par with their empirical results in terms of both economic and statistical significance. We also expand the analysis to bond markets of the same country group, however, we fail to document the spillover effect of the phenomenon.

JEL classification: G10, G12

Keywords: Asset pricing, Heterogeneous beliefs, Disagreement, Speculative betas, Security Market Line

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Contents

1 Introduction

The low (high) abnormal relative returns of stocks with high (low) beta – the high-risk, low-return puzzle – is one of the most persistent puzzles in empirical asset pricing research. Contrary to the conventional view, empirical studies find that portfolios which long low-risk and short high-risk assets consistently yield positive returns in the long-term, often referred to as the beta anomaly in earlier research.[1]

We are interested in examining this puzzle further especially in the light of the recent, influential paper by Hong and Sraer (2016). They establish a theoretical framework with three fundamental elements: common one-factor dividend process for assets, heterogeneous beliefs and short-sale restrictions. If investors disagree (i.e. hold conflicting heterogeneous beliefs), pessimists would optimally short some assets, however, given their short-sale constraints they are sidelined and thus those assets suffer from speculative mispricing. Absent of heterogeneous beliefs or short-sale constraints, mispricing evaporates and performance of assets is consistent with the CAPM: (a) if investors agree then all agents hold the same efficient portfolio or (b) pessimists always drive asset prices back to fundamental values, clearing any speculative mispricing. Calibrating this model, Hong and Sraer (2016) show that for the risk-return trade-off (graphically represented by the Security Market Line or SML) a two-regime pattern is expected to prevail: when disagreement is low the risk-return relationship is strictly positive, however, when disagreement is high this relationship has a "kink" and for risky assets the relationship is actually negative.

Building on the theoretical framework, Hong and Sraer (2016) test how aggregate disagreement affects the empirical Security Market Line for US stocks. We follow their methodology and expand the empirical analysis to a wider range of countries and also to bond markets. We hypothesize firstly that, due to the globalization of financial markets, the impact of investors' aggregate disagreement on the SML and thus on equity excess returns is identical in Western Europe to that in the US. Secondly, we also predict that the impact of investors' aggregate disagreement on Western European fixed income markets mimics that on equities because of tight relationships and overlaps between agents pricing these two asset classes. To our knowledge, we are the first to empirically test the "speculative betas" theory on an exhaustive non-US dataset.

Specifically, we retrieve historical data of stocks and bond indices, starting at the end of 1980's and at the end of the 1990's, respectively. To have a comparable dataset to the US, i.e. a fairly homogeneous, and large economic unit, we focus on the eurozone and the UK combined. We also argue that these countries are

[1] For example Black, Jensen, and Scholes (1972) show that the traditional risk-return trade-off (Sharpe's (1964) CAPM) is not fully supported even by early historical data.

viewed as one economic bloc, thus, investors form views on the outlook of these economies jointly. We sort the pooled assets to CAPM beta-sorted portfolios to fit the one-factor theoretical model to the data. Betas of sorted portfolios along with excess returns on different horizons are also calculated. Further, we build proxies for investors' disagreement about the common factor affecting all assets (referred to as aggregate disagreement) from investor forecast dispersions. Explicitly for stocks, we construct a pre-ranking beta-weighted average standard deviation measure from I/B/E/S equity analyst earnings per share (EPS) long-term growth estimates. For bonds, because of data availability, we construct the proxy as the first principal component of government benchmark bond yield forecast standard deviations from Reuters polls. We then apply a two-stage regression method. First, the 12-month portfolio excess returns are cross-sectionally regressed on a constant, portfolio beta and squared portfolio beta. The time series of the coefficient estimate of squared portfolio beta represents the excess returns of the square portfolio which essentially quantifies the curvature of the Security Market Line. As a second stage, we regress the time series of the curvature coefficient on lagged aggregate disagreement and a number of control asset pricing factors.

Our results suggest strong empirical support for a number of interesting features of the theoretical framework. Firstly, Figure 1 shows that stock-level disagreement empirically increases with beta especially in periods when disagreement is high. This illustrates that beta (i.e. the loading on the common factor) amplifies the disagreement. More importantly, we investigate the shape of the Security Market Line visually during high and low disagreement periods in Figure 3 and Figure 4. Patterns for stocks (Figure 3) are well in line with the predictions of Hong and Sraer's (2016) model. On the one hand, we have a generally positive trend in low disagreement times while on the other hand we have a skewed inverted-U shaped pattern in high disagreement periods on all four horizons (6 to 24 months). However, we do not find similar patterns for bond indices (Figure 4) because even under the high disagreement regime the trend seems to be flat or slightly U-shaped.

The formal regression test is conducted for stocks both using value-weighted, thus weighted by their market capitalization, and equal-weighted portfolio returns in the first stage. In case of bonds we restrict ourselves to equal weights. We find compelling evidence supporting our Hypothesis 1. In Table 4, we show that for both value- and equal-weighted stock portfolios lagged aggregate disagreement has a negative and statistically significant coefficient estimate. This demonstrates that when disagreement increases the Security Market Line becomes significantly more concave: given the point estimates we expect that a 1 standard deviation increase in aggregate disagreement results in a 5.07% – 8.36%[2] more concave SML. Out of

[2]Sample standard deviation of non-standardized aggregate disagreement is 1.1%point. 1.1% ·

other control variables, the size factor is pervasive on a 5% significance level, however, the magnitude of the point estimate suggests that its impact on the curvature is much weaker than that of aggregate disagreement. Our results are in line with the theoretical and empirical findings of Hong and Sraer (2016). However, as presented in Table 5, we do not find strong evidence for our Hypothesis 2. For bonds, the coefficient point estimate on lagged aggregate disagreement is again negative, however, not statistically significant. We conclude that we have unfortunately too few quarters and/or too low number of assets to produce significant results.

To further confirm our main results, several robustness tests are conducted as well. Generally, our results for stocks withstand checks while unfortunately we receive even more inconclusive results for bonds. Results for stocks are robust among others to (a) alternative baseline specifications[3], (b) alternative asset pricing factors[4], (c) an alternative proxy for aggregate disagreement[5] and (d) further controls such as to controlling for idiosyncratic volatility[6]. On the contrary, for bonds we see conflicting results. For example, regression results with the alternative proxy for aggregate disagreement suggest that there is a positive relationship between lagged disagreement and the curvature of the SML.

Overall, we cannot reject our Hypothesis 1 which is equivalent to rejecting the classic one-regime CAPM SML. The *curve* representative to Western European stocks is prone to a two-regime pattern and is concave when disagreement is high. Nonetheless, we reject our Hypothesis 2 given contradicting results. In our view, we fail to document the spillover of the two-regime phenomenon to bonds possibly due to data quality issues.

Our paper is structured as follows. This brief introduction is followed by a review of the most relevant literature in section 2. Section 3 provides a short overview of the related theoretical model and the development of our hypotheses. Data and descriptive statistics are discussed in section 4. We show our main empirical results and further robustness checks in section 5 and section 6, respectively. In section 7, we conclude our paper. The most relevant tables and figures are placed in the main text while additional visuals can be found in appendicies A and B.

$-4.57 = -5.07\%$ and $1.1\% \cdot -7.53 = -8.36\%$ where -4.57 and -7.53 are the point estimates in column (1) and (4) of Table 4 respectively.

[3]This includes alternative subsampling (sampling is driven by our equity analyst coverage threshold that we set to 50% by default), alternative number of portfolios or alternative horizons. We also show results for individual countries and for the euro area alone and conclude that from smaller samples statistically significant results are harder to be produced.

[4]We replace originally used AQR factors with factors from Kenneth French's website.

[5]We substitute our bottom-up measure with one constructed from the European Central Bank's Survey of Professional Forecasters data.

[6]Specifically, we control both for portfolio idiosyncratic volatility and for the time series of stock-level disagreement to differentiate our findings from those in Ang, Hodrick, Xing, and Zhang (2009) and Diether, Malloy, and Scherbina (2002).

2 Literature Review

The relationship between risk and return has always been a core topic in asset pricing theory. Originated from the pivotal works of Sharpe (1964), Lintner (1965), the Capital Asset Pricing Model (CAPM) and its extended versions have been used widely. The centerpiece of Sharpe's (1964) model is non-diversifiable systematic risk, represented by beta with the market, which is a core driver of the expected excess return of assets. Further, the expected returns of securities are an upward sloping linear function of their market beta. Lintner (1965) shows that their is a positive correlation between asset risk and average returns in cross-section regressions.

However, numerous further studies (even as early as in 1972) have argued that empirically the returns of securities are not consistent with their loadings on the systematic factor. Black, Jensen, and Scholes (1972) find, based on stocks listed on NYSE (1926-1966), that the proportional risk-return trade-off is not supported by historical data. The findings that the alphas of high-beta securities are negative while that of low-beta securities are positive are sufficiently strong to warrant the rejection of the traditional form of CAPM.

A variety of theories has been put forward to explain this high-risk low-return puzzle, including both rational and behavioural explanations. In this section we focus mainly on explanations within the rational paradigm. First of all, Black (1972) shows that the expected return of risky asset is, albeit flatter, still a linear function of its beta even if investors cannot short the riskless asset. Miller (1977) argues that the divergence of investors' opinions could be the driving force of the puzzle since optimists price assets while pessimists are set aside due to short-selling constraints. Miller's (1977) theory lacked due empirical testing in the literature for a quarter of a century, however, both Chen, Hong, and Stein (2002) and Diether, Malloy, and Scherbina (2002) independently provide evidence. On the one hand, Chen, Hong, and Stein (2002) document that stocks whose breadth declines (thus more investors' pessimistic views are not registered in the stocks' price) tend to underperform those whose breadth increases. On the other hand, Diether, Malloy, and Scherbina (2002) use one year ahead analysts' earnings estimates to test the impact of differences of opinion and observe that higher dispersion in forecasts lead to lower future returns relative to otherwise similar stocks. Though we can find contradicting examples in the literature as well: Doukas, Kim, and Pantzalis (2006) for example refute the methodology and empirical results of Diether, Malloy, and Scherbina (2002) by arguing that analysts' forecasts cannot be used directly as a proxy for disagreement because they are contaminated by time-varying uncertainty. More recently, Yu (2011) takes Diether, Malloy, and Scherbina's (2002) method one step further and studies the impact of disagreement on portfolios by using long-term EPS growth estimates, avoiding the potential issues with direct earnings estimates.[7] He observes that in line with theory the disagreement on the whole market's prospects is negatively related to ex-post expected return and that growth stocks are more sensitive to variations in disagreement compared with value stocks. Then, Hong and Sraer's (2016) study contributes significantly by providing not only a thorough theoretical model[8] but also compelling empirical evidence on US stocks.

Hong and Sraer's (2016) influential work sparked high interest among researchers, leading to rich contemporaneous literature. These frontier studies build on Hong and Sraer's (2016) model to various degrees. For example, Li (2016) takes the model and decomposes the disagreement on the common factor into macro disagreement and idiosyncratic disagreement. Similarly to Hong and Sraer (2016), he also documents a two-regime pattern by using single variables of the Survey of Professional Forecasters (SPF) database as proxy for macro disagreement.[9] In their similar work, Shen, Yu, and Zhao (2017) claim that the failure to document positive risk-return relationship among high macro beta stocks is due to the fact that these assets are endogenously more speculative and more prone to market sentiment. Using Baker and Wurgler's (2006) sentiment index, they also observe a two-regime phenomenon according to which high-risk portfolios earn significantly lower returns than low-risk portfolios do following high-sentiment periods. Gao, Lu, Song, and Yan (2017) set out to analyse the explanatory power of macro disagreement proxies on US assets. Using the Blue Chip Economic Indicators survey data, they conclude similar results to those in Hong and Sraer (2016) even without short-sale constraints for multiple asset classes: US stocks, corporate bonds as well as mortgage-backed securities. In a closely related paper, Huang, Li, Wang, and Zhou (2017) focus on different ways of aggregating disagreement measures[10] and compete them based on their predictive power. They claim that their index, aggregated by partial least squares, have, unlike single measures, predictive power even on as short horizon as 1 month. However, the forecasting power is asymmetric and stronger in high sentiment times which is in line with the implications of Atmaz and Basak's (2017) recent theoretical model on the subject. Last but not least, Hong, Sraer, and Yu (2017) expand Hong and Sraer's (2016) model and testable implications to US Treasuries using household inflation expectations as a proxy for fixed income aggregate disagreement. Their results show that (a) in case of high disagreement the yield curve is flatter and (b)

[7] See discussion in Diether, Malloy, and Scherbina (2002).

[8] See discussion in subsection 3.1

[9] Hong and Sraer (2016) use the SPF series as well, however, only as a robustness check and aggregately.

[10] They use both macro and micro proxies such as the already mentioned SPF data or for example the Michigan University Survey of Consumers (SCA) as a proxy for household forecast disagreement.

in case of high disagreement *and* low supply of Treasuries the yield curve could be downward sloping.

Alternative rational explanations have been provided for the high-risk low-return puzzle as well. For example, Ang, Hodrick, Xing, and Zhang (2006, 2009) show, based on both US and international data, that stocks with higher idiosyncratic volatility actually yield lower returns, which could not be explained by either CAPM beta or Fama and French (1992) 3 factors. Karceski (2002) proposes a model that illustrates the incentives of fund managers to tilt their portfolios towards high-risk end which pushes the returns lower than the CAPM equilibrium. Baker, Bradley, and Wurgler (2011) find that high-beta and high-volatility stocks have long underperformed low-beta and low-volatility stocks. They attribute their findings to the typical institutional investor's mandate to beat a fixed benchmark which discourages arbitrage activity in both high-alpha, low-beta stocks and low-alpha, high-beta stocks. Hsu, Kudoh, and Yamada (2013) argues that sell-side analysts tend to inflate the growth forecast of equities, in order to please clients, which is hard to be detected. This attitude systematically contributes to the overvaluation of high risk stocks, leading to lower returns of high-beta stocks. Finally, Frazzini and Pedersen (2014) present that funding constraints, such as leverage constraints and margin requirements, are the main factors that explain the puzzle. They form betting against beta (long leveraged low-beta assets and short high-beta assets) factors for several asset classes (and jurisdictions) and show that they deliver positive risk-adjusted returns consistently.

To flash one behavioural explanation, Bali, Brown, Murray, and Tang (2017) analyse the puzzle thoroughly. Building on Kumar (2009), they illustrate that investors' demand for lottery-like stocks is an important driver and that the anomaly is no longer detected when beta-sorted portfolios are neutralized to lottery demand, regression specifications control for lottery demand, or factor models include lottery demand.

3 Hypothesis Development

Our starting point in this paper is Hong and Sraer's (2016) theoretical model and its assumptions which we discuss briefly below. Taking their model given leads us naturally to ask ourselves: is this a phenomenon that solely applies to the highly analysed US stock market? If stocks seem to be affected by investors' disagreement should not other asset classes be affected as well? We set ourselves to try to answer these questions in this paper.

3.1 Overview of the Model and Motivation

The Model Summarized

As mentioned in section 1, Hong and Sraer (2016) propose a model that first of all consists of a continuum of assets that follow a one-factor dividend process and a continuum of investors.

Asset i's dividend process is the following:

$$d_i = d + b_i\tilde{z} + \varepsilon_i \tag{1}$$

where $\tilde{z}$ represents the common factor that investors can disagree on and ε_i is the idiosyncratic component such that $Cov(\tilde{z}, \varepsilon_i) = 0$. From (1) and investors' mean-variance preferences, an equilibrium emerges in which there is a positive relationship between an assets' loading on the common factor and conflicts of opinion about the dividend expectations (thus about the valuations) of that asset: the higher the loading (b_i), the higher the disagreement.

The continuum of investors is assigned to three investor groups: short-sale constrained optimists, short-sale constrained pessimists (both hold heterogeneous beliefs) and non-constrained arbitrageurs (who hold homogeneous and correct beliefs). Above a certain $\bar{b}$ threshold pessimists would optimally short, however, they are unable to: in line with Miller's (1977) model pessimists are sidelined and assets with high loading on the common factor ($b_i > \bar{b}$) in their dividend processes are overpriced by optimists. Finally, high current valuations naturally lead to lower expected returns. Therefore, the relationship between the loading on the common factor (b_i or in CAPM analogy β_i) and expected returns could be significantly lower than what conventional CAPM would imply if disagreement is high and it is amplified by the factor loading.

As the main takeaway of the model, a two-regime pattern of the Security Market Line is expected to emerge: (1) the relationship is strictly positive when disagreement is low; while (2) the relationship is positive for stocks with $b_i \leq \bar{b}$ but negative for those with $b_i > \bar{b}$ when disagreement is high. Regime (2) yields then a Security Market Line that resembles an inverted-U shape where the "kink" is at $\bar{b}$.

Motivation

We believe that these aforementioned main assumptions[11] are well in line with reality. Firstly, there is documented evidence of time-varying dispersion of expectations about state variables of the economy[12] (i.e. the common factor) as well as anecdotal evidence of investors not delving into the true fundamentals but rather focusing on the "bigger picture"[13]. Secondly, one can think of optimists and pessimists as a group of mutual funds and households. On the one hand, there is compelling evidence, for example shown by Almazan, Keith, Carlson, and Chapman (2004), that the vast majority of mutual funds are short-sale constrained either for instance by charter or due to noise trader risk (see De Long, Schleifer, Summers, and Waldmann (1990)). On the other hand, households, though undoubtedly represent a significant investor base (cf. *SIFMA 2017 Fact Book* (2017) and Guiso and Sodini (2013))[14], are usually not capable of exploiting arbitrage opportunities because of market microstructure[15] or behavioural biases as shown by Barber and Odean (2000).

3.2 Hypotheses

Hong and Sraer (2016) provide solid empirical results to back the implications of their model, however, they restrict their analysis to US stocks. We believe that since global equity markets are tightly interconnected, it is likely that this mechanism is not an isolated phenomenon of the US.

Though investors nowadays may think globally, a common factor that affects all stock prices on this planet is rather difficult to motivate, therefore, an empirical extension requires a similar market to the US. Further, the construction of a bottom-up proxy for heterogeneous beliefs requires reliable and rich equity analyst coverage data, thus, only developed markets can come into play. Therefore, we consider the eurozone pooled together with the UK [16] a sufficiently similar market to the US:

[11] Please find a complete discussion of all underlying assumptions in Hong and Sraer (2016).

[12] Examples: Survey of Professional Forecasts (macro) and Michigan University Survey of Consumers (micro).

[13] We refer here to common investor rules of thumb such as "buying the dip" Bloomberg (2018).

[14] As of 2016, households hold 40% of US stocks directly (fairly constantly over time) and their direct and indirect invested wealth combined add up to nearly \$26 trillion. Regarding household finance, its recent emergence in research is a direct evidence of the sector's increased importance.

[15] For example in order to short one needs to borrow the asset which households usually cannot, however, this microstructure issue has been mitigated by the emergence of exchange traded funds/products.

[16] Strictly speaking we take the original 12 members of the eurozone and the United Kingdom.

(a) the currency bloc plus the UK represent a significant market capitalization of all global equities,
(b) the high degree of economic integration suggests that investors form expectations on the common prospects of the group and
(c) the market is sufficiently covered by analysts.

Our first hypothesis follows directly from here:

HYPOTHESIS 1 *Given the similar underlying mechanism, the impact of investors' aggregate disagreement on the Security Market Line and thus on equity excess returns is identical in Western Europe to that in the US.*

Continuing the main line of thought, investors consider allocations not only across jurisdictions but also across asset classes.[17] Therefore, a second-stage extension of the analysis is to look at asset classes beyond stocks. Similar criteria apply here as well: analysis should be carried out on developed markets, on covered assets and last but not least on assets which we can reasonably expect to be affected by the same common factor. A natural candidate here is the combined eurozone-UK fixed income market because of multiple reasons:
(a) similar underlying common factor expectations should affect the market, therefore, the spillover of the mechanism from stocks is likely,
(b) it is a highly developed market and
(c) well covered by analysts.

Furthermore, key element of the underlying theoretical model is the short-sale constrained group of investors. On the one hand, many mutual funds deploy a cross-asset strategy of investing both in equities and fixed income and on the other hand, as Canner, Mankiw, and Weil (1997) show, private bankers often provide a similar two-fund separation advice to retail clients, thus, there should be a high overlap between agents pricing stocks and those pricing bonds. Therefore, our second hypothesis follows:

HYPOTHESIS 2 *Since financial markets are globalised and similar agents price the assets, the impact of investors' aggregate disagreement on Western European fixed income markets mimics that on equities.*

In the following sections we deploy a rigorous yet straightforward method to test our hypotheses on historical data and we hope to contribute to the contemporaneous literature by adding further empirical evidence to the heterogeneous beliefs explanation of the high-risk, low-return puzzle.

[17] For a discussion of the topic see Campbell and Viceira (2002).

4 Data and Descriptive Statistics

4.1 Data Preparation

Stocks

We download historical price data for the 12 original eurozone countries plus the United Kingdom individually from S&P Compustat Xpressfeed. In each stock market, we take only ordinary and primary listed stocks into consideration (TPCI = 0 and IID = PRIROW). We then pool the country level data together to form the country group of main interest. Further, we convert all stock prices in local currencies to USD using FX rates from the Federal Reserve H10 database. Penny stocks, whose price is smaller than 5 dollars, and microcap stocks, whose market cap is in the bottom 2 decile, are excluded from our dataset on that specific date but can be added back before or after. Our dataset covers the fairly long period between 1986 and 2017. In order to exclude potentially distortive data, we winsorize the raw price and market cap data with thresholds of 2.5% and 97.5%. Stock excess returns are calculated over the US risk-free rate from Kenneth French's website. Market excess return at time t is calculated as a value-weighted return of all stocks available at t.

Beyond the obvious geographical differences, our dataset differs from that used in Hong and Sraer (2016) in the following ways:

(i) dual-listed stocks are excluded,

(ii) market cap deciles for identifying microcaps are calculated taking all available stocks into account and

(iii) the raw data is winsorized.

Since Hong and Sraer (2016) take NYSE quantile thresholds to calculate the cutting level of microcaps, they actually take out more than simply the bottom 2 decile of all stocks since on average NYSE stocks are bigger than those listed for example on Nasdaq. This means that our dataset contains more relatively smaller stocks. Nevertheless, given the structure of European funding markets fewer companies tend to finance themselves from the capital markets than out of bank lending which leads to more mature companies going public compared to those in the US.

The stock-level investor disagreement is represented by the standard deviation of unadjusted long-term EPS growth forecast from I/B/E/S. First of all, we filter on the stock level by only taking months with more than one available forecast. Then, as a main difference from Hong and Sraer (2016), we further filter the whole database based on a 50% threshold of equity analyst coverage ratio each month. The monthly coverage ratio refers to the percentage of total market capitalization covered by the stocks that have more than one available analyst forecast. Analyst coverage is an indicator of the development of a country's stock market and there is valid concern that we may not avoid the Dimson (1979) critique if we include all months: if relatively few stocks are liquid and important enough to be covered by analysts then we may underestimate betas even with including 1 to 5 lags of the market return. Furthermore, according to Hong and Sraer's (2016) theoretical model investors disagree on the common factor and we are concerned that we would not capture the disagreement on the common factor but rather idiosyncratic disagreement in case only a relative minority of stocks is taken into account to calculate aggregate disagreement. Thus, a threshold is motivated and we decide to require 50% because then we base our measure on the relative majority of value-weight, however, we avoid restricting ourselves too much in terms of valid months. The coverage criterion heavily affects the number of valid portfolio formation dates (i.e. valid months): we drop most of the 90's and some periods in early 00's in our main analysis, however, as we show in section 6, our main results are robust to alternative thresholds and thus alternative sub-samples.

Bonds

We retrieve historical sovereign and corporate bond total return index series from Datastream. Sovereigns are Thomson Reuters indices and they cover the original 12 member states of the eurozone and the United Kingdom. The target maturity of the underlying bonds range from 2 to 50 years. Corporate bond series are iBoxx indices for eurozone and UK financial and non-financial corporate bonds. The target maturity of the underlying assets range from 1 to 15 years while the credit ratings range from BBB to AAA. The total daily historical data cover the period between 1998 and 2017[18], however some individual series are not available through the whole period.[19] Further, we convert all bond indices from local euro or pound sterling to USD, using FX rates from the Federal Reserve H10 database. Similarly to stocks, excess returns are calculated against the US risk-free rate from Kenneth French's website while market excess return at time t is calculated as an equal-weighted return of all bond indices available at t.

We do not have access to individual bond-level disagreement data, although, we aim to create a bottom-up aggregate disagreement proxy. Therefore, we take investors' yield forecast data from Thomson Reuters. The quarterly fixed income polls are available from 2002Q3 almost continually and we focus on the 1 year ahead yield forecasts for 2 and 10 year benchmark of Germany and the UK. Then

[18]As before for stocks, this period includes the earliest datapoint used for beta estimation until the last one used for portfolio return calculations.

[19]A complete list of bond indices as well as the corresponding series start dates are available in the submitted package of programs and data.

we aggregate the individual dispersion series by taking the first principal component of the standard deviations of the yield forecasts. Contrary to our equity analyst coverage threshold for stocks, additional filters are not applied this measure given the low number of available forecast dates.

4.2 Beta and Beta-Sorted Portfolios

Beta Estimation

To derive our beta-sorted portfolios we follow the methodology in Hong and Sraer (2016) closely. We first estimate the CAPM beta of each asset i with time series OLS regression on 12 months daily excess returns on contemporaneous market excess return and 1 to 5 lags of it:

$$r^e_{i,t} = \alpha + \beta_1 r^e_{m,t} + \beta_2 r^e_{m,t-1} + \beta_3 r^e_{m,t-2} + \beta_4 r^e_{m,t-3} + \beta_5 r^e_{m,t-4} + \beta_6 r^e_{m,t-5} + \varepsilon_{i,t} \quad (2)$$

Then the beta is simply a sum of the coefficient estimates of regression (2) $\left(\sum_{j=1}^{6} \beta_j\right)$, referred to as pre-ranking beta in our paper. We estimate the pre-ranking beta for a valid month t[20] only if a stock/bond index fulfils the following criteria:

(a) it is active,
(b) it has at least 100 trading days before t and
(c) its price is not completely stale over the estimation period.

After estimating the pre-ranking beta, we then sort each stock with available pre-ranking beta to beta-sorted portfolios. Given the average number of assets with available pre-ranking betas, we sort stocks into 20 while bonds only into 5 portfolios. Sorting thresholds for each month are calculated as every fifth/twentieth percentile of pre-ranking betas of all stocks/bonds. Then for stocks, we compute both value- and equal-weighted portfolio returns on different horizons while we only compute equal-weighted returns of the bond index portfolios.

After sorting, we estimate post-ranking betas, following Fama and French (1992), by taking full-sample daily portfolio returns and regressing them on contemporaneous market excess return and 1 to 5 lags of it. Similarly to the pre-ranking betas, the post-ranking beta is then the sum of the coefficient estimates of market returns.

[20] As discussed in subsection 4.1, please note that for stocks month t is valid only if analyst coverage threshold (by default 50%) is met.

Beta-Sorted Portfolios

Stocks

Table 1 Panel A displays the descriptive statistics of our 20 beta-sorted stock portfolios. On average, portfolios consist of 105-106 stocks and their post-ranking betas range nicely from 0.4 to 1.65. Looking at average median pre-ranking volatility of the sorted stocks, we conclude that light but clear pattern of increasing idiosyncratic volatility is apparent from portfolio (2) onwards going from 1.55 to 2.79 while the lowest-beta portfolios (three bottom ones) have a spike in idiosyncratic volatility in line with portfolios in Hong and Sraer (2016). There is, however, no clear pattern for either the average 1-month or 12-month returns. The overall trend of average stock dispersion resembles an asymmetrical U-shape where for the first quarter of the portfolios the trend is decreasing while subsequently that is increasing: going from 4 (sixth portfolio) to as high as 10.3 (last portfolio). Generally, there is an increasing trend for the relative market capitalizations, increasing from 0.4 to around 8. Even though, we have some value-weight tilt towards high beta stocks[21], potentially because we for example do not filter out financial institutions, we are overall satisfied with the descriptive characteristics of the beta-sorted portfolios.

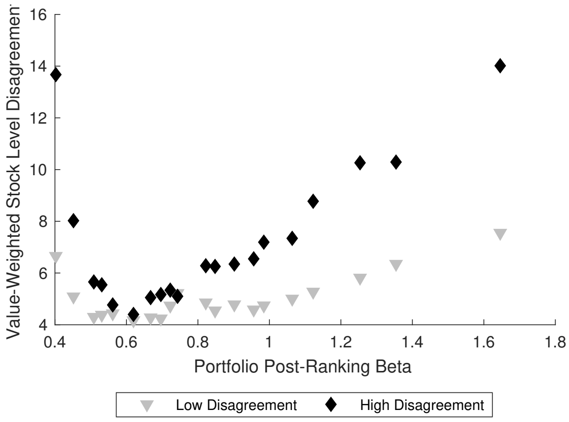

Figure 1: High/Low Stock-Level Disagreement vs. Beta
The 20 value-weighted portfolios consist of stocks from the Global S&P Compustat database and primarily listed in the original 12 members countries of the eurozone plus UK. Daily historical data is retrieved between 1986 and 2017, excluding penny stocks (price < \$5) and microcaps (market capitalization in the bottom 2 deciles). Stocks are sorted every valid month based on pre-ranking beta. *Portfolio Post-Ranking Beta* is a daily full-sample estimate calculated from portfolio returns regressed on contemporaneous and 1 to 5 lags of market returns. *Value-Weighted Stock-Level Disagreement* is the average of value-weighted long-term EPS growth forecast standard deviations from the I/B/E/S unadjusted summary database. An I/B/E/S observation is valid if the number of long-term EPS growth forecasts is greater than 1 and months are excluded in which the analyst coverage, the relative market capitalization that is covered by valid long-term EPS growth forecast dispersion data, is below 50%. High (low) disagreement months are those for which the aggregate disagreement is in the top (bottom) quartile.

[21]Similar tilt is apparent among the beta-sorted portfolios in Hong and Sraer (2016) though lighter probably because they apply NYSE market capitalization breakpoints.

Table 1: Descriptive Statistics of 20 Beta-Sorted Portfolios

Panel A shows the descriptive characteristics of the 20 value-weighted portfolios while Panel B shows those of the 5 equal-weighted bond index portfolios. The stock portfolios consist of stocks from the Global S&P Compustat database and primarily listed in the original 12 members countries of the eurozone plus UK. Daily historical data is retrieved between 1986 and 2017, excluding penny stocks (price $<$ \$5) and microcaps (market capitalization in the bottom 2 deciles). Bond indices within portfolios are Thomson Reuters sovereign bond indices of the original 12 members of the eurozone plus the UK ranging from 2 to 50 years of residual maturity as well as iBoxx eurozone corporate bond indices ranging from 1 to 10+ years of residual maturity and from BBB to AAA of credit ratings. Asset-level pre-ranking betas for each time t are calculated from contemporaneous and 1 to 5 lagged market returns from the preceding 12 months. We exclude assets at t that are not active or do not have at least 100 trading days before t or their prices are completely stale over the estimation period. Assets are sorted every valid month based on pre-ranking beta. First row of the table lists the post-ranking beta of each portfolio that is a daily full-sample estimate calculated from portfolio returns regressed on contemporaneous and 1 to 5 lags of market returns. *Avg. Median Vola.* shows the average median pre-ranking market model implied idiosyncratic volatility of each portfolio. $R^{(1)}$ and $R^{(12)}$ are calculated based on the period of t to $t+1$ and t to $t+11$ respectively. *Avg. Stock Disp.* is the average of value-weighted stock-level disagreement in each portfolio. *Market Cap.* is the average relative market capitalization of each portfolio. N illustrates the number of assets in each portfolio.

Panel A: Stock Beta-Sorted Portfolios

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)
Post-rank β	0.4	0.45	0.53	0.51	0.56	0.62	0.67	0.7	0.72	0.74	0.82	0.85	0.9	0.96	0.98	1.06	1.12	1.25	1.35	1.65
Avg. Median Vola. (%)	2.68	1.77	1.55	1.57	1.64	1.69	1.7	1.68	1.7	1.71	1.72	1.74	1.76	1.8	1.82	1.86	1.94	2.07	2.22	2.79
$R_t^{(1)}$ (%)	0.37	0.37	0.03	0.11	0.13	0.08	0.26	0.3	0.23	0.35	0.39	0.57	0.53	0.18	0.2	0.16	0.33	0.25	0.36	0.46
$R_t^{(12)}$ (%)	5.11	2.96	1.14	2.46	2.76	3.52	4.39	4.15	4.96	6.18	5.73	5.79	3.95	3.88	4.89	3.35	3.77	3.59	4.66	5.97
Avg. Stock Disp. (%)	7.23	5.74	5.14	4.71	4.66	4.01	4.68	4.45	4.49	4.53	4.85	4.72	5.04	5.29	5.39	5.52	6.17	7.25	7.87	10.32
Market Cap. (%)	0.44	0.78	1.36	1.53	1.88	2.33	2.77	3.8	3.99	4.38	5.38	5.67	6.58	7.06	7.67	8.21	8.53	8.5	8.64	7.24
N	106	106	106	105	106	105	106	106	106	106	105	106	106	106	106	105	106	106	105	106

Panel B: Bond Beta-Sorted Portfolios

	(1)	(2)	(3)	(4)	(5)
Post-rank β	0.83	0.93	0.99	1.08	1.17
Median vola.	0.31	0.16	0.13	0.16	0.32
$R_{p,t}^{(1)}$	0.48	0.29	0.40	0.51	0.83
$R_{p,t}^{(12)}$	4.56	3.90	5.00	6.33	8.55
N bonds	24	24	24	24	24

Investigating the relationship between stock-level dispersion and post-ranking betas, Figure 1 shows a scatter plot of the average measure in high disagreement months as well as in low disagreement months. High (low) disagreement months are those for which the aggregate disagreement is in the top (bottom) quartile. We can see that the value-weighted average stock-level dispersion increases with beta more significantly when disagreement is high compared with when that is low. This proves visually that, as Hong and Sraer's (2016) model suggests, beta amplifies the disagreement on the common factor.

Bonds

Table 1 Panel B shows the descriptive statistics of bond portfolios. Due to the limited total number of available bond indices, each portfolio (5 total) on average consists of 24 instruments. From the lowest to the highest, post-ranking betas increase from 0.84 to 1.2. Compared to betas of stock beta-sorted portfolios, bond betas are more condensed which is in line with our predictions. We expect lower idiosyncratic risk because on the one hand these indices are aggregating multiple underlying bonds in the first place and on the other hand they co-move strongly[22], given their common exposure to business cycles (Fama and French (1989), Cochrane and Piazzesi (2005)). There is a pattern of gradually increasing returns with beta on both the 1 and 12 months horizon. Both the lowest and highest beta portfolios seem to be slight outliers. On the one hand, the lowest beta portfolio has an abnormally high return. On the other hand, on both horizons the return increase between the fourth and the fifth portfolio is considerably larger than that between the other portfolios.

4.3 Time Series Variables

Aggregate Disagreement

As in Hong and Sraer (2016), we construct our aggregate disagreement proxy for stocks the following way:

$$\text{Aggr. Disp.}_t^{stock} = \frac{\sum_{i=1}^{n} \beta_{i,t}^{pre-rank} \cdot \sigma_{i,t}^{\text{EPS LTG}}}{\sum_{i=1}^{n} \beta_{i,t}^{pre-rank}} \tag{3}$$

where $\beta_{i,t}^{pre-rank}$ is the pre-ranking beta estimate of stock i at valid month t, $\sigma_{i,t}^{\text{EPS LTG}}$ is stock i's EPS LTG forecast standard deviation from the unadjusted I/B/E/S

[22]The 10th, 50th and 90th percentile of the pairwise correlations of the individual excess return series are 0.53, 0.82 and 0.96 respectively.

summary database and n is the number of stocks with both available pre-ranking beta estimate and I/B/E/S data at valid month t.

To gauge the aggregate disagreement among bond investors, we take the first principal component of the standard deviations of 1-year ahead yield forecasts of 2 and 10 year benchmarks of Germany and the UK. Forecast dispersions are retrieved from Reuters, however, caveats of this dataset are that it is unfortunately only available on a quarterly frequency and that it goes back only until 2002Q3.

As a robustness check, we also construct an alternative measure using the ECB's Survey of Professional Forecasters (SPF) data. We take the SPF data only as a secondary measure because it is only available since 1999 and also only at quarterly frequency. Furthermore, the median of available forecasts is 50 while one can build the aggregate disagreement from hundreds of stocks (as also motivated by Hong and Sraer (2016)). To aggregate the forecast dispersion across the 3 forecasted variables[23], we take the first principal component of the standard deviation series. All 3 measures are standardized to mean 0 and standard deviation of 1 to make them directly comparable.

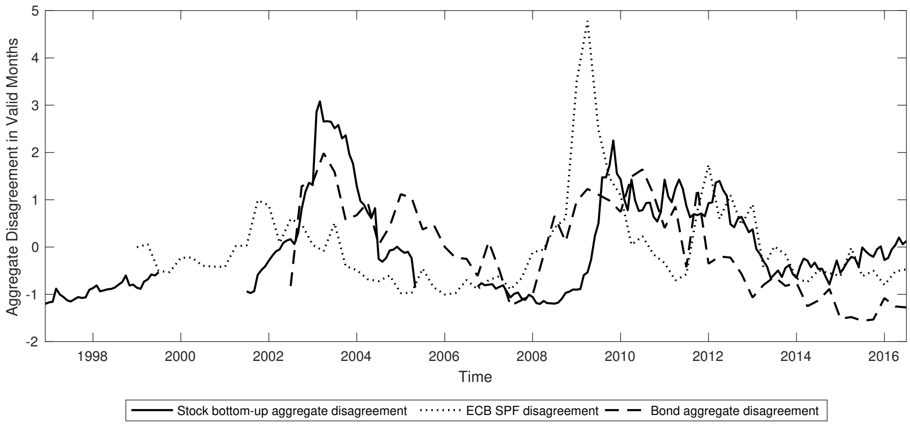

Figure 2: Time Series of Aggregate Disagreement

Stock bottom-up aggregate disagreement is the beta-weighted average long-term EPS growth standard deviation from unadjusted summary I/B/E/S database. Historical price data is from S&P Compustat for stocks primarily listed in the original 12 member countries of the eurozone plus UK. Daily historical data is retrieved between 1986 and 2017, excluding penny stocks (price $<$ \$5) and microcaps (market capitalization in the bottom 2 deciles). Stock-level market betas for each time t are calculated from contemporaneous and 1 to 5 lagged market returns from the preceding 12 months. We exclude stocks at t that are not active or do not have at least 100 trading days before t or their prices are completely stale over the estimation period. I/B/E/S observations are valid if the number of long-term EPS growth forecasts is greater than 1 and the analyst coverage, which is the relative market capitalization covered by valid long-term EPS growth forecast dispersion data, is at least 50%. *ECB SPF disagreement* is the first principal component of the forecast standard deviations from the ECB SPF database. *Bond aggregate disagreement* is the first principal component of the standard deviations of 1-year ahead yield forecasts of 2 and 10 year benchmarks of Germany and the UK obtained from Reuters forecast polls.

[23] These are namely HICP, real GDP growth as well as unemployment in the eurozone on a one year ahead rolling horizon.

Figure 2 plots the time series of the main aggregate disagreement measures and the ECB SPF measure during the valid months. Some months are missing for the stock disagreement measure given that we apply our analyst coverage criterion. Further, the available data for the ECB SPF starts in 1999 while that for bond disagreement proxy starts only in 2002. We can see that generally all series are persistent and have positive pairwise correlations as summarized in Table 2. It is quite intriguing that our bottom-up disagreement measure for stocks seems to capture a different set of information compared with the ECB SPF proxy given that the sample pairwise correlation is lower than 10% (although again we have a low number of observations for the ECB SPF measure).

Looking at Figure 2 closely, there are quite surprising patterns in some periods especially for the bottom-up stock disagreement series: for example the spike around 2003 and the very low value around 2008Q3-2008Q4. Although a full investigation of the underlying process of the analysts' long-term EPS growth dispersion is beyond the scope of this paper, we attempt to provide one potential explanation for the shape for example around the Lehman Brothers crash. According to our understanding, when such a negative tail event occurs analysts mostly agree that the common factor i.e. the overall prospect of the stock market is to decline, yielding a low aggregate disagreement measure. Couple of months in the recession and after measures taken by government or the central bank, analysts start to heavily disagree on the recovery prospects, yielding a very high value.

Table 2: Pairwise Correlations of Aggregate Disagreement Proxies

Aggr. Disp.$_t^{stock}$ is calculated as a market beta-weighted average long-term EPS growth standard deviation from unadjusted summary I/B/E/S database. Historical price data is from S&P Compustat for stocks primarily listed in the original 12 member countries of the eurozone plus UK. Daily historical data is retrieved between 1986 and 2017, excluding penny stocks (price $< \$5$) and microcaps (market capitalization in the bottom 2 deciles). Stock-level market betas for each time t are calculated from contemporaneous and 1 to 5 lagged market returns from the preceding 12 months. We exclude stocks at t that are not active or do not have at least 100 trading days before t or their prices are completely stale over the estimation period. An I/B/E/S observation is valid if the number of long-term EPS growth forecasts is greater than 1 and months are excluded in which the analyst coverage, the relative market capitalization that is covered by valid long-term EPS growth forecast dispersion data, is below 50%. *ECB SPF Disp.* is the first principal component of the forecast standard deviations from the ECB SPF database. Aggr. Disp.^{bond} is the first principal component of the standard deviations of 1-year ahead yield forecasts of 2 and 10 year benchmarks of Germany and the UK obtained from Reuters forecast polls.

	Aggr. Disp.^{stock}	ECB SPF Disp.	Aggr. Disp.^{bond}
Aggr. Disp.^{stock}	1.00		
ECB SPF Disp.	0.09	1.00	
Aggr. Disp.^{bond}	0.55	0.30	1.00

Table 3: Descriptive Statistics of Time-Series Variables
Aggr. Disp. $_t^{stock}$ is the monthly beta-weighted average of stock-level disagreement, which is the standard deviation of analysts' forecasts of long-term EPS growth from the unadjusted summary I/B/E/S database. *ECB SPF Disp.* $_t$ is the first principal component of the forecast standard deviations from the ECB's SPF database. *Aggr. Disp.* $_t^{bond}$ is the first principal component of the standard deviations of 1 year ahead yield forecasts of 2 and 10 year benchmarks of Germany and the UK obtained from Reuters forecast polls. $R_{m,t}$, HML_t, SMB_t and UMD_t are the European market, size, returns and momentum factors taken from AQR Data Library. D/P_t is the monthly European (including UK) dividend yield index downloaded from Kenneth French's website. Inflation represents the 12-month rolling yearly inflation rate. $TED\ Spread_t$ is the US dollar denominated TED spread, which is the difference between the 3-month US dollar LIBOR and the 3-month US government debt (T-bills). $CP\ factor_t^{DEU}$ is Cochrane and Piazzesi's (2005) factor constructed from German zero yields obtained from Thomson Reuters.

	Mean	Std. Dev.	p10	p25	Median	p75	p90	Obs.
Aggr Disp. $_t^{stock}$	0.00	1.00	-1.06	-0.84	-0.26	0.70	1.42	198
ECB SPF Disp. $_t$	0.00	1.00	-0.82	-0.61	-0.34	0.36	1.03	71
Aggr. Disp. ^{bond}	0.00	1.00	-1.26	-0.83	-0.10	0.94	1.30	54
$R_{m,t}$	7.67	21.14	-16.09	-5.81	9.73	22.63	30.00	198
HML_t	3.08	10.01	-11.15	-3.86	4.52	9.01	13.03	198
SMB_t	-0.80	8.05	-13.38	-6.95	0.47	5.09	8.46	198
UMD_t	1.04	4.49	-3.29	-0.12	1.36	2.97	5.18	198
D/P_t	0.65	7.29	-8.56	-3.67	0.75	5.65	9.16	198
Inflation $_t$	1.69	0.89	0.18	1.12	1.82	2.15	2.82	198
TED Spread $_t$	0.46	0.43	0.18	0.21	0.28	0.56	0.96	198
CP factor $_t^{DEU}$	1.53	0.65	0.58	1.07	1.49	2.05	2.36	54

Asset Pricing Factors

To maintain comparability with the results in Hong and Sraer (2016), we take also market, value, size and momentum factors, dividend yield (D/P), inflation, and TED spread as control variables for our main regression analysis. $R_{m,t}$, HML, SMB and UMD returns are monthly European level factors taken from the AQR Data Library[24] and taken into account as 12-month excess returns from t to $t + 11$. We choose to use factors from AQR as opposed to Kenneth French's site because we can retrieve country-level factors[25] and for example for UMD a longer European historical time series. D/P is the monthly European (including the UK) dividend yield index downloaded from Kenneth French's website. Inflation represents the 12-month rolling yearly inflation rate. Given that Eurostat HICP has only been available since the end of the 1990's, we construct a synthetic HICP using OECD inflation data and Eurostat current price household final expenditure weights for the missing years. Finally, TED Spread is the US dollar denominated TED spread,

[24] URL: https://www.aqr.com/Insights/Datasets

[25] We use country level factors for individual country analysis as robustness checks in section 6.

which is the difference between the 3-month US dollar LIBOR and the 3-month US government debt (T-bills). We take the dollar TED spread because all local prices are converted to USD and thus our hypothetical carry currency is always USD, meaning that the corresponding funding conditions (represented by the TED spread based on Frazzini and Pedersen (2014)) should also be in USD. Finally, for bond analysis, in the spirit of Hong, Sraer, and Yu (2017), we use Cochrane and Piazzesi's (2005) factor (referred to as CP factor), however, we construct it from German zero yields that we obtain from Reuters.[26]

The descriptive statistics of the aggregate disagreement measures as well as the asset pricing factors are summarized in Table 3 where the number of observations (column Obs.) corresponds to the number of valid months for our main analysis which differs between stocks and bonds as discussed earlier.

[26]To construct the CP factor we run the programs used for the original paper available on the authors' website.

5 Empirical Analysis

5.1 Empirical Security Market Line

As a first check, we inspect visually the impact of investors' disagreement on the SML.

Stocks

Figure 3 shows the SML derived from the post-ranking betas as well as the calculated average value-weighted forward returns for stocks. We plot the graph for returns on different horizons. The relationship between excess returns and beta are similar for the different horizons: 6, 12, 18 and 24 months. For the high disagreement months, with 20 portfolios, the relationship resembles a positively skewed inverted-U shape, where maximum is at the fifth/sixth portfolio. For the low disagreement periods, the overall trend is upward sloping. The results seem to be stronger on longer horizons. The patterns are aligned with the theoretical and empirical findings presented in Hong and Sraer (2016). When disagreement is low, portfolios show excess returns in line with traditional view while when disagreement is high, high-beta portfolios suffer from mispricing, therefore, the SML appears to be inverted-U shaped. However, there are also some significant elements that differ from what Hong and Sraer (2016) present. First, the high disagreement portfolios have significantly higher returns than the low disagreement ones. This is mainly due to the low disagreement period around the beginning of the 2007-2008 financial crisis in our sample (cf. Figure 2). Second, we have a clearer patterns for the short forward excess return horizon (6 month) as well, while Hong and Sraer's (2016) comparable graph is significantly noisier on this horizon.

Bonds

Figure 4 plots the SML for bond portfolios. The results for different horizons, 6, 12, 18 and 24 months, are very similar and contrary to our expectations. For the high disagreement months, we have a unclear U-shaped pattern and the low point is at the second portfolio, which is the opposite of what we see for the equity portfolios. However, the limitation of our dataset (in terms of number of individual assets) and hence the small number of portfolios may affect the power of our results greatly and also cause the striking differences compared to the graph on equities (cf. Figure 3). When it comes to the low disagreement periods, the graph shows a relatively similar pattern to the one we get for stocks: upward sloping trend since portfolio returns gradually increase with post-ranking betas. Compared with graphs presented in

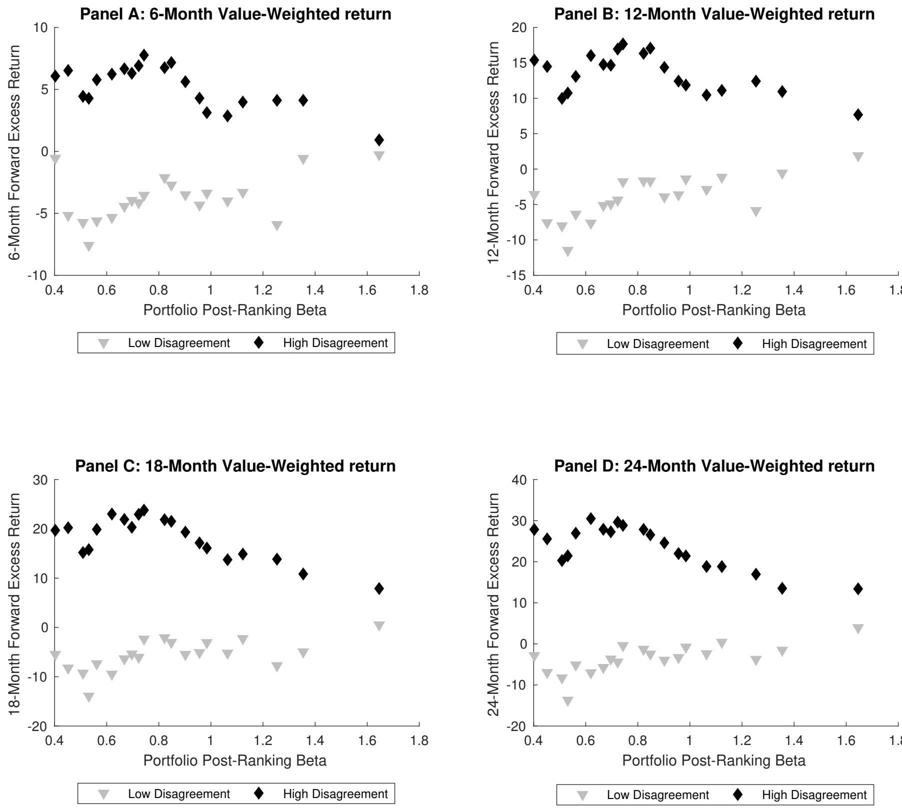

Figure 3: Empirical Security Market Line on Different Horizons for Stocks

The 20 value-weighted portfolios consist of stocks from the Global S&P Compustat database and primarily listed in the original 12 members countries of the eurozone plus UK. Daily historical data is retrieved between 1986 and 2017, excluding penny stocks (price $<$ \$5) and microcaps (market capitalization in the bottom 2 deciles). Stock-level pre-ranking market betas for each t are calculated from contemporaneous and 1 to 5 lagged market returns from the preceding 12 months. We exclude stocks at t that are not active or do not have at least 100 trading days before t or their prices are completely stale over the estimation period. Stocks are sorted every valid month based on pre-ranking beta. *Portfolios Post-Ranking Beta* is a daily full-sample estimate calculated from portfolio returns regressed on contemporaneous and 1 to 5 lags of market returns. We aggregate investor disagreement bottom-up as a beta weighted average of stock-level disagreement, which is the standard deviation of analysts' forecasts of long-term EPS growth from the unadjusted summary I/B/E/S database. An I/B/E/S observation is valid if the number of long-term EPS growth forecasts is greater than 1 and months are excluded in which the analyst coverage, the relative market capitalization that is covered by valid long-term EPS growth forecast dispersion data, is below 50%. High (low) disagreement months are those for which the aggregate disagreement is in the top (bottom) quartile. Panel A plots 6-month ahead average excess returns while Panel B, C, D plot 12-month, 18-month and 24-month ahead average excess returns respectively.

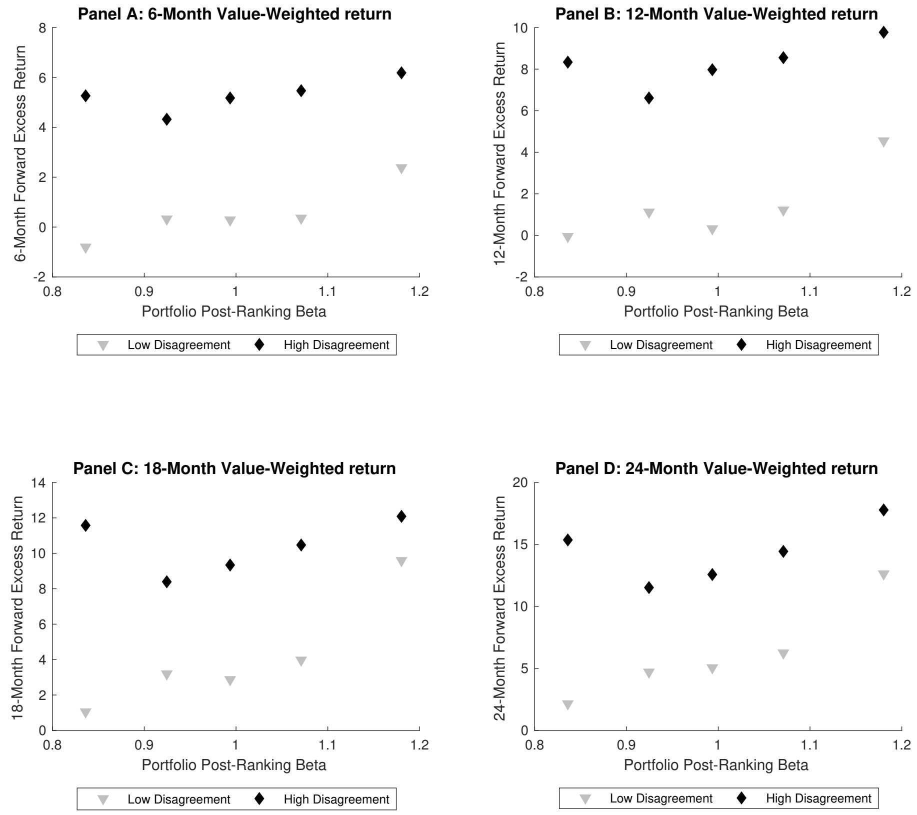

Figure 4: Empirical Security Market Line on Different Horizons for Bonds

The 5 equal-weighted portfolios consist of sovereign and corporate bond indices. Sovereign indices for the original 12 members of the eurozone plus the UK are Thomson Reuters indices with residual maturity ranging from 2 to 50 years while the corporate indices are iBoxx financial and non-financial corporate indices with residual maturity ranging from 1 to 10+ years and credit rating ranging from BBB to AAA. Daily historical data is retrieved between 1999 and 2017. Index-level pre-ranking market betas for each t are calculated from contemporaneous and 1 to 5 lagged market returns (equal-weighted return) from the preceding 12 months. We exclude indices at t that are not active or do not have at least 100 trading days before t or their prices are completely stale over the estimation period. Indices are sorted every quarter based on pre-ranking beta. *Portfolios Post-Ranking Beta* is a daily full-sample estimate calculated from portfolio returns regressed on contemporaneous and 1 to 5 lags of market returns. Aggregate bond market disagreement is the first principal component of the standard deviations of 1-year ahead yield forecasts of 2 and 10 year benchmarks of Germany and the UK Yield forecasts come from Reuters polls conducted on quarterly basis. High (low) disagreement periods are those for which the aggregate disagreement is in the top (bottom) quartile. Panel A plots 6-month ahead average excess returns while Panel B, C, D plot 12-month, 18-month and 24-month ahead average excess returns respectively.

Hong, Sraer, and Yu (2017), a related work on the asset pricing implications of aggregate disagreement on fixed income products, ours are less compelling. This could be accounted for on the one hand that they sort bonds into different maturity groups instead of beta sorting and on the other hand that their dataset is homogeneous and more comprehensive (although solely on US Treasuries).

5.2 Regression Methodology

To test Hypothesis 1 and Hypothesis 2, we carry out a straightforward 2-stage regression method in the spirit of Hong and Sraer (2016). First, we run a cross-sectional regression every valid month t, regressing the kth portfolio's 12-month ahead excess return ($r_{k,t}^{(12)}$) on its full-sample post-ranking beta (β_k) as well as on the squared beta (β_k^2):

$$r_{k,t}^{(12)} = \kappa_t + \eta_t \beta_k + \gamma_t \beta_k^2 + \varepsilon_{k,t} \qquad \begin{cases} \text{k} = 1, 2, 3, \ldots, 20 & \text{for stocks} \\ \text{k} = 1, 2, 3, 4, 5 & \text{for bonds} \end{cases} \tag{4}$$

We base our main analysis on the 12-month ahead returns because our underlying bottom-up aggregate disagreement measure is expected to be very persistent. For example, we use long-term EPS growth forecasts to capture the expectations of equity analysts mainly because this measure is an important component of models, nevertheless, it should be the least affected by day-to-day or quarter-to-quarter idiosyncratic surprise news. A downside of the measure is that it is the least updated figure, therefore, we cannot expect to see significant fluctuations on a stock-level per forecaster. Furthermore, we base our estimation on the monthly unadjusted summary database although absent of major news analysts are anticipated to update their models on earnings reports, thus, on a quarterly basis.

From (4) we obtain a time series of κ_t, η_t, and γ_t estimates. The main variable of interest is γ_t because it represents the time series of the excess returns on a portfolio that goes long in the two bottom portfolios (for example k = 1,2 for stocks) as well as in the two top portfolios (for example k = 19, 20 for stocks) and goes short in the remaining portfolios (Hong and Sraer (2016)). Moreover γ_t, thus, also captures the curvature of the Security Market Line each t. κ_t and η_t correspond to level and slope coefficients respectively.

As a second stage, we run time-series regressions with Newey and West (1987) robust standard errors with 11 lags. The dependent variables are the obtained κ_t, η_t, and γ_t estimates. We estimate the regressions with different specifications.
For stocks we vary the right hand side variables according to the below 4 specifications:

(1) specification: constant and lagged aggregate disagreement,
(2) specification: same as previously but we also control for Fama and French (1992) 3 factors and for Carhart's (1997) momentum,
(3) specification: same as previously but we also control for lagged dividend-price ratio and lagged 12-month rolling inflation and
(4) specification: same as previously but we also control for funding con-

straints by adding the lagged TED Spread.

For bonds we vary the explanatory variables according to only 2 specifications:

(1) specification: constant and lagged aggregate disagreement and
(2) specification: same as previously but we also control for the CP factor from Cochrane and Piazzesi (2005).

The above time-series variables are explained and discussed in subsection 4.3. According to Hypothesis 1, we expect that higher aggregate disagreement induces more negative curvature of the Security Market Line. Our Hypothesis 2 suggests that this effect should be pervasive across asset classes, thus, we expect similar results for the Bond Security Market Line as well.

5.3 Main Results

5.3.1 Stocks

Value-Weighted Portfolios

Panel A of Table 4 shows our main results. Before turning our attention to the main variable of interest, we conclude that the impact of aggregate disagreement is generally not statistically significant on η_t or κ_t. Since the focus of our main analysis is naturally the curvature of the Security Market Line, therefore, the following section will mainly describe the regression results of γ_t. Regression with only the constant and the lagged aggregate disagreement (column (1)) returns a significant negative coefficient estimate of aggregate disagreement: -4.57 with t-statistic of -2.09 meanwhile the negative constant estimate is not significant. This result means that the higher the aggregate disagreement is the more concave the SML becomes. Compared with the result in Hong and Sraer (2016), ours seems to be more powerful given the insignificance of the constant. By adding the market, HML, SMB and UMD factors (specification (2)), the significance does not evaporate. On the contrary, the coefficient estimate of aggregate disagreement increases in absolute terms to -7.28 and the SMB factor is the only significant one among additional factors. The constant continues to be insignificant. This result is quite aligned with what Hong and Sraer (2016) present, except the significance of aggregate disagreement decreases in Hong and Sraer (2016) by adding HML, SMB and UMD factors. The third and fourth regressions control for lagged dividend yield (D/P), inflation and Ted Spread. The UMD factor becomes slightly significant, while the rest of the parameters are unchanged. Interesting, substantial differences from Hong and Sraer's (2016) results arise. In their paper, the estimate for inflation is very significant, UMD is insignificant while HML is positive and persistently significant. They connect the opposing significant sign of HML, compared to aggregate disagreement, to an extension of their model, however, as shown in Table 4 we fail to document empirical evidence for that on developed European equities. The outlined differences between our results and those in Hong and Sraer (2016) can potentially be a consequence of the different sources of factors we use in this paper.[27] The point estimate coming from specification (4) suggests that 1 standard deviation increase in aggregate disagreement (which corresponds to a 1.11%point increase in beta-weighted EPS LTG forecast dispersion) pushes the 12-month excess return on the square portfolio down by 8.36% ($1.11\% \cdot -7.53$) or equivalently leads to a 8.36% more concave Security Market Line. Overall, these results illustrate that aggregate disagreement is proven to have significant effect on the shape of the Security Market Line: the more investors disagree, the more inverted-U shaped the curve is.

Equal-Weighted Portfolios

Panel B of Table 4 shows our results for equal-weighted portfolios. Compared with the value-weighted portfolio results, the aggregate disagreement becomes very significant (on 1% significance level again) through all four regressions. The constant is also highly significant in the second and third regressions, which suggests that we potentially face an omitted-variable bias. However, the SMB factor is no longer significant, instead, UMD comes into play with a high t-statistics (around -2.6). Significant difference from the results of Hong and Sraer (2016): market, HML and inflation are non-significant parameters though all of them are significant in Hong and Sraer (2016) on 1% level. Interestingly, the Ted Spread is not significant in either the value-weighted portfolio regressions or in Hong and Sraer (2016), but it is strongly significant in this panel, with a t-statistic of 2.81. Overall, we confidently conclude based on value- and equal-weighted portfolio results that we cannot reject Hypothesis 1.

[27] Hong and Sraer (2016) use US factors from Kenneth French's site while we use European AQR factors as discussed in subsection 4.3.

Table 4: Two-Stage Regression Results Testing The Shape of SML for Stocks

Two-stage regressions on stocks from the Global S&P Compustat database and primarily listed in the original 12 members countries of the eurozone plus UK. Daily historical data is retrieved between 1986 and 2017, excluding penny stocks (price < \$5) and microcaps (market capitalization in the bottom 2 deciles). Stock-level pre-ranking market betas for each time t are calculated from contemporaneous and 1 to 5 lagged market returns from the preceding 12 months. We exclude stocks at t that are not active or do not have at least 100 trading days before t or their prices are completely stale over the estimation period. Stocks are sorted every valid month based on pre-ranking beta to 20 portfolios both value-weighted (Panel A) and equal-weighted (Panel B). A month is valid if the number of long-term EPS growth forecasts is greater than 1 and in which the analyst coverage, the relative market capitalization that is covered by valid long-term EPS growth forecast dispersion data, is at least 50%. Post-ranking betas are daily full-sample estimates of the market beta resulting from OLS regression of the portfolio returns on contemporaneous and 1 to 5 lags of market returns.

Stage 1: we run a cross-sectional regression where 12-month ahead excess returns are regressed on the corresponding post-ranking beta estimates and squared post-ranking betas:

$r_{k,t}^{(12)} = \kappa_t + \eta_t \beta_k + \gamma_t \beta_k^2 + \varepsilon_{k,t} \qquad$ k = 1, 2, 3,..., 20

Stage 2: we run OLS time series regressions where left-hand side variables are the time-series of coefficient estimates obtained in Stage 1:

$\gamma_t = c_1 + \lambda_1 Agg.Disp_{t-1} + \chi_1 controls + u_{1,t}$

$\eta_t = c_2 + \lambda_2 Agg.Disp_{t-1} + \chi_2 controls + u_{2,t}$

$\kappa_t = c_3 + \lambda_3 Agg.Disp_{t-1} + \chi_3 controls + u_{3,t}$

We have 4 specifications where (2) (3) and (4) add additional controls:

$Agg.Disp_{t-1}$ is the monthly β-weighted average of the stock-level disagreement measure which is the standard deviation of analysts' forecasts of long-run EPS growth. $R_{m,t}^{(12)}$, $HML_t^{(12)}$, $SMB_t^{(12)}$, and $UMD_t^{(12)}$ are annualized European market, value, size, and momentum factor returns taken from AQR's Data Library. D/P_{t-1} is the monthly European (including UK) dividend yield index downloaded from Kenneth French's website. $Inflation_{t-1}$ represents the 12-month rolling yearly inflation rate of the group of countries. $TED\ Spread_{t-1}$ is the US dollar denominated TED spread, which is the difference between the 3-month US dollar LIBOR and the 3-month US government debt (T-bills). N shows the number of months.

Dep. Var.	γ_t				η_t				κ_t			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel A: Value-Weighted Portfolios												
Agg.Disp$_{t-1}$	-4.57**	-7.28***	-7.43***	-7.53***	5.03	4.58	4.97	8.69*	6.57***	3.64	3.42	0.05
	(-2.09)	(-3.31)	(-3.24)	(-3.21)	(1.22)	(0.97)	(1.02)	(1.94)	(3.06)	(1.37)	(1.27)	(0.02)
R$_{m,t}^{(12)}$		-0.04	-0.04	-0.03		0.8***	0.8***	0.77***		0.16	0.16	0.18*
		(-0.24)	(-0.24)	(-0.23)		(3.16)	(3.17)	(3.12)		(1.22)	(1.25)	(1.74)
HML$_t^{(12)}$		-0.03	-0.05	-0.05		-0.05	-0.04	0.03		0.14	0.14	0.08
		(-0.09)	(-0.12)	(-0.12)		(-0.08)	(-0.07)	(0.04)		(0.66)	(0.69)	(0.38)

–Continued–

Table 4: (continued)

Dep. Var.	γ_t				η_t				κ_t			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$\text{SMB}_t^{(12)}$		0.89**	0.93**	0.93**		-1.6***	-1.66**	-1.7***		0.53*	0.56*	0.6**
		(2.08)	(2.00)	(2.04)		(-2.40)	(-2.20)	(-2.45)		(1.83)	(1.73)	(2.14)
$\text{UMD}_t^{(12)}$		-0.44	-0.45*	-0.45*		0.21	0.18	0.3		0.34	0.38	0.27
		(-1.61)	(-1.76)	(-1.85)		(0.38)	(0.34)	(0.66)		(1.28)	(1.47)	(1.28)
D/P_{t-1}			0.05	0.05			-0.31	-0.27			0.24	0.21
			(0.27)	(0.26)			(-0.91)	(-0.86)			(1.50)	(1.54)
Inflation_{t-1}			0.74	0.81			-0.82	-3.55			0.11	2.59
			(0.34)	(0.38)			(-0.19)	(-0.91)			(0.05)	(1.31)
Ted Spread_{t-1}				-0.41				16.66				-15.08***
				(-0.06)				(1.57)				(-3.71)
Constant	-0.62	0.9	-0.31	-0.23	2.64	-4.75	-3.23	-6.48	2.43	0.83	0.48	3.42
	(-0.23)	(0.37)	(-0.07)	(-0.05)	(0.51)	(-1.27)	(-0.40)	(-0.75)	(0.89)	(0.42)	(0.10)	(0.80)
N	197	197	197	197	197	197	197	197	197	197	197	197

–Continued–

Table 4: (continued)

Dep. Var.	γ_t				η_t				κ_t			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel B: Equal-Weighted Portfolios												
Agg.Disp$_{t-1}$	-12.55***	-13.17***	-12.91***	-10.34***	18.99***	13.51***	12.78***	13.53***	2.07	-0.85	-0.46	-2.26
	(-4.10)	(-4.80)	(-4.73)	(-3.47)	(4.20)	(4.57)	(4.03)	(3.47)	(0.99)	(-0.60)	(-0.30)	(-1.28)
$R_{m,t}^{(12)}$		-0.09	-0.09	-0.11		1.01***	1.01***	1.01***		0.02	0.02	0.03
		(-0.49)	(-0.50)	(-0.66)		(4.26)	(4.38)	(4.31)		(0.20)	(0.20)	(0.34)
$HML_t^{(12)}$		0.08	0.08	0.13		-0.69*	-0.77*	-0.75*		0.7***	0.74***	0.71***
		(0.27)	(0.30)	(0.52)		(-1.72)	(-1.90)	(-1.94)		(3.64)	(4.03)	(4.40)
$SMB_t^{(12)}$		0.28	0.24	0.21		-0.2	0	-0.01		0.58**	0.46*	0.48*
		(0.61)	(0.50)	(0.43)		(-0.32)	(0.00)	(-0.01)		(2.07)	(1.77)	(1.94)
$UMD_t^{(12)}$		-0.8***	-0.83***	-0.74***		0.59	0.55	0.57		0.11	0.15	0.09
		(-2.61)	(-2.64)	(-2.62)		(1.52)	(1.43)	(1.53)		(0.72)	(0.93)	(0.59)
D/P$_{t-1}$			-0.23	-0.21			0.14	0.15			-0.05	-0.06
			(-1.29)	(-1.12)			(0.53)	(0.56)			(-0.42)	(-0.63)
Inflation$_{t-1}$			-0.43	-2.31			4.18	3.63			-2.43	-1.11
			(-0.26)	(-1.16)			(1.43)	(1.13)			(-1.35)	(-0.65)
Ted Spread$_{t-1}$				11.49***				3.37				-8.06**
				(2.81)				(0.51)				(-2.07)
Constant	4.72	6.26***	7.11***	4.87	-8.59	-14.99***	-21.77***	-22.43***	11.22***	9.24***	13.15***	14.72***
	(1.61)	(3.31)	(2.46)	(1.54)	(-1.59)	(-5.42)	(-4.18)	(-4.23)	(4.29)	(4.63)	(3.52)	(4.45)
N	197	197	197	197	197	197	197	197	197	197	197	197

*,**, and *** indicate 10%, 5%, and 1% statistical significance respectively that the coefficient is different from zero. In brackets beneath each point estimate is the t statistic corresponding to H_0 : coeff. = 0 for which standard errors are Newey and West (1987) robust with 11 lags.

5.3.2 Bonds

Looking at the results for equal-weighted bond portfolios tabulated in Table 5, we do not exactly get what we have hoped for. Again starting with η_t and κ_t, we can conclude that, similarly to our results for stocks, aggregate disagreement does not seem to have any effect on these parameters. We are more concerned with our results for γ_t and we see weak statistical significance in both specifications. Nevertheless, there is economic significance of our negative point estimates because they suggest that aggregate disagreement might indeed have a pervasive negative effect on the curvature of the Security Market Line across asset classes. The most straightforward explanation for the low statistical significance is, however, that we have unfortunately too few quarters and/or too few number of assets. Our results can be compared to those in Hong, Sraer, and Yu (2017). Although, they deal with US Treasuries based on their maturity profiles and thus run regressions on the slope of the term structure our portfolios show similar characteristics: low-beta portfolios have significantly lower average maturity profile compared with the top-beta portfolio (6-7 years vs. 15+ years). The main takeaway of Hong, Sraer, and Yu (2017) is that negative coefficient estimates on aggregate disagreement in the term structure slope regressions are statistically significant only when the bottom-up disagreement measure is augmented by supply of Treasuries. We do not multiply our disagreement proxy because we take bond indices for which such supply measure cannot be quantified. This deviation might explain why we do not see statistically significant results. Furthermore, Hong, Sraer, and Yu (2017) use household inflation forecasts because they "want [their] baseline series to capture as much variation in disagreement as possible, both across forecasters at a point in time and across time." On the contrary, we use professional investors' forecasts to gauge bond market aggregate disagreement which results in much lower variation of disagreement (standard deviation of 0.17%point in our case vs. 1.5%point). Overall, based on the statistically weak regression results we reject Hypothesis 2.

Table 5: Two-Stage Regression Results Testing The Shape of SML for Bonds

Two-stage regressions on sovereign and corporate bond indices. Sovereign indices for the original 12 members of the eurozone plus the UK are Thomson Reuters indices with residual maturity ranging from 2 to 50 years while the corporate indices are iBoxx financial and non-financial corporate indices with residual maturity ranging from 1 to 10+ years and credit rating ranging from BBB to AAA. Daily historical data is retrieved between 2001 and 2017. Index-level pre-ranking market betas for each time t are calculated from contemporaneous and 1 to 5 lagged market returns (equal-weighted average returns) from the preceding 12 months. We exclude indices at t that are not active or do not have at least 100 trading days before t or their prices are completely stale over the estimation period. Indices are sorted every quarter based on pre-ranking beta. Post-ranking betas are daily full-sample estimates of the market beta resulting from OLS regression of the portfolio returns on contemporaneous and 1 to 5 lags of market returns.

Stage 1: we run a cross-sectional regression where 12-month ahead excess returns are regressed on the corresponding post-ranking beta estimates and squared post-ranking betas:

$r^{(12)}_{k,t} = \kappa_t + \eta_t \beta_k + \gamma_t \beta_k^2 + \varepsilon_{k,t}$ k = 1, 2, 3, 4, 5

Stage 2: we run OLS time series regressions where left-hand side variables are the time-series of coefficient estimates obtained in Stage 1:

$\gamma_t = c_1 + \lambda_1 Agg.Disp_{t-1} + \chi_1 controls + u_{1,t}$

$\eta_t = c_2 + \lambda_2 Agg.Disp_{t-1} + \chi_2 controls + u_{2,t}$

$\kappa_t = c_3 + \lambda_3 Agg.Disp_{t-1} + \chi_3 controls + u_{3,t}$

We have 2 specifications where (2) adds an additional control variable:

$Agg.Disp_{t-1}$ is the quarterly first principal component of the standard deviations of 1-year ahead yield forecasts of 2 and 10 year benchmarks of Germany and the UK. Yield forecasts come from Reuters polls. $CP\ factor_{t-1}$ is Cochrane and Piazzesi's (2005) factor constructed from German zero yields that we obtain from Reuters. N shows the number of quarters.

Dep. Var.	γ_t		η_t		κ_t	
	(1)	(2)	(3)	(4)	(5)	(6)
			Equal-Weighted Portfolios			
Agg.Disp$_{t-1}$	-23.51	-29.70	42.55	51.45	-16.57	-19.04
	(-1.07)	(-1.07)	(1.10)	(1.04)	(-0.97)	(-0.87)
CP factor$_{t-1}$		13.42		-19.28		5.33
		(0.42)		(-0.34)		(0.21)
Constant	58.76*	39.83	-104.87*	-77.68	50.51**	42.99
	(1.84)	(0.94)	(-1.87)	(-1.03)	(2.11)	(1.34)
N	53	53	53	53	53	53

*,**, and *** indicate 10%, 5%, and 1% statistical significance respectively that the coefficient is different from zero. In brackets beneath each point estimate is the t statistic corresponding to H_0 : coeff. = 0 for which standard errors are Newey and West (1987) robust with 11 lags.

6 Robustness Checks

In order to further fortify our main findings, we run a series of robustness checks. Additional figures and tables mentioned below are placed in appendices A and B.

Equity Analyst Coverage

Figure A1 displays the impact of our choice of equity analyst coverage threshold. We use 50% coverage ratio threshold for our main analysis, however, additionally we examine the empirical SML with 30% and 70% as well. There are some variations but overall the trends are very similar. It is worth noting especially that with 30% equity coverage ratio (thus including almost all months available in the I/B/E/S database for our analysed countries) surprisingly we see a familiar inverted-U shaped trend even under the low disagreement regime. Or for example, with 70% coverage ratio and under the the high disagreement regime, we have an even stronger downward trend. Therefore, our conclusions made based on visual inspection of the empirical Security Market Line hold.

Alternative Asset Pricing Factors

To avoid the issue of handpicking our factors, we introduce alternative factors for which we summarize the descriptive statistics in Table B1.

Stocks

Table B2 shows the regression results when we use European Fama and French (2015) five factors from Kenneth French's website as control variables in the second stage. The overall statistical significance remains strong for both value- and equal-weighted portfolios, however, there are a few variations. For value-weighted portfolios, similarly to results in Hong and Sraer (2016), the HML is significant although it was not in our main analysis at all which suggests that after all choosing the source of our factors might play a role. In line with the extension of Hong and Sraer's (2016) theoretical model discussed in their paper, the point estimate is significant and has an opposing positive sign (compared to aggregate disagreement). The profitability (RMW) factor is significant through all the regression specifications, while the investment (CMA) factor remains insignificant. For the equal-weighted portfolios, interestingly SMB factor becomes significant while for example the Ted Spread loses its significance compared with our main results. A significant difference from results presented in Hong and Sraer (2016) that inflation remains insignificant for both AQR factors and Fama-French factors.

Bonds

We consider a CP factor constructed from German zero yields to be more accommodative to our main analysis, however, given that we convert all local total return index series to USD we run the regressions also controlling for a CP factor constructed from CRSP Fama-Bliss discount bonds. We present these results in Table B3. Unfortunately, statistical power does not seem to change much as only the constant is significant this case as well. Interestingly, the point estimate in the main table for the CP factor is positive while that is here negative. The magnitude of the point estimate on lagged aggregate disagreement drops in absolute terms though it remains negative.

Alternative Specifications

To prove that the results and findings we show and discuss in subsection 5.3 are not the consequence of sheer chance, we show results for alternative specifications as well.

Table B4 illustrates the 2-stage regression estimation results for the curvature parameter in 3 different panels with alternative setups for value-weighted stock portfolios. Overall, our results seem to be invariant to tweaks to the analyst coverage ratio, number of beta sorted portfolios or the return horizon. By increasing coverage ratio threshold from 50% in our original specification to 70% in panel A, we restrict ourselves to a much smaller sample (roughly half number of months) and the clarity of the results of our regression declines a bit. The negative coefficient estimate on the lagged disagreement is robust, however, there is significant variation in the curvature that we cannot explain, thus, the constant is highly significant in all 4 specifications. In panel B, we show results if we sort the stocks only into 10 beta-sorted portfolios (and equivalently if post-ranking betas are slightly more condensed). The results are almost unchanged since even the point estimates are very close to those in the main table. Same can be concluded for Panel C as well in which we show results if we use the 6-month ahead excess returns as dependent variables in the first stage. Although significance does not change, we should note that the magnitude of the point estimate on the lagged aggregate disagreement is quite smaller in absolute terms than that of in the original setup. In untabulated regressions, we also document that results and significance do not change either if we reduce the analyst coverage threshold to 30%, or only sort stocks into 5 portfolios or increase the horizon to 18 months.

Controlling for Idiosyncratic Volatility

As Hong and Sraer (2016) also discuss it, there is a valid concern that we might be partly re-reporting the findings of the influential paper by Ang, Hodrick, Xing, and Zhang (2009) on the idiosyncratic volatility (IVOL) puzzle. As shown in Table 1, idiosyncratic volatility mostly increases with post-ranking βs and we might just have a low-volatility anomaly that stocks with high idiosyncratic volatility underperform low volatility stocks. To avoid this critique, following Hong and Sraer (2016), we introduce the log of median idiosyncratic volatility in the first stage regression:

$$r_{k,t}^{(12)} = \kappa_t + \eta_t \beta_k + \gamma_t \beta_k^2 + \omega_t \left(\ln \sigma_k^{idiosyncratic}\right) + \varepsilon_{k,t} \qquad \text{k = 1, 2, 3,..., 20} \tag{5}$$

where $\sigma_k^{idiosyncratic}$ is the unconditional mean of the time series of median idiosyncratic volatility of stocks in kth portfolio. Stock-level idiosyncratic volatility at time t is calculated as the standard deviation of the resulting errors in the pre-ranking beta OLS regression (equation (2)) ran at t .

Table B5 displays the regression results after controlling for idiosyncratic volatility as shown in (5). For value-weighted portfolios, there is a small decline in statistical significance compared to that in our main table (for example t stat going from -3.21 to -2.74 in the fourth specification). Aggregate disagreement has an increasing (in absolute terms) significance and negative point estimate from the first regression to the fourth one, with constant being only significant in column (1). Regarding equal-weighted portfolios, we have quite similar results to those in the main table though the constant is generally less significant this case while point estimates on aggregate disagreement are higher in absolute terms. This result means that controlling for idiosyncratic volatility has no significant impact on our findings.

Controlling for Stock-Level Disagreement

A similar concern is that we test and conclude the findings in Diether, Malloy, and Scherbina (2002) on developed European stock markets. Under the theoretical regime of Hong and Sraer (2016) investors disagree on the common factor and stock beta amplifies the disagreement. On the contrary, Diether, Malloy, and Scherbina (2002) only conclude that high-beta stocks have high idiosyncratic disagreement and that stocks with high idiosyncratic disagreement tend to underperform otherwise similar stocks. This means that the empirical shape of the Security Market Line (as shown in Figure 3) is driven purely by idiosyncratic disagreement. To formally address this potential critique, following Hong and Sraer (2016), we introduce the log of monthly average stock-level disagreement in the first stage regression:

$$r_{k,t}^{(12)} = \kappa_t + \eta_t \beta_k + \gamma_t \beta_k^2 + \omega_t \left(\ln \text{AvgDisp}_{k,t}\right) + \varepsilon_{k,t} \qquad \text{k = 1, 2, 3,..., 20} \tag{6}$$

where $\text{AvgDisp}_{k,t}$ is the value-weighted average stock-level investor disagreement of kth portfolio at t.

Table B6 illustrates the regression results after controlling for stock-level disagreement as shown in (6). In line with expectations based on earlier robustness controls, for both value- and equal-weighted portfolios the significance and point estimates of the coefficient on aggregate disagreement decline slightly but remain favourable. Point estimates for lagged aggregate disagreement are still large and negative while the constant remains insignificant in all 4 specifications in the value-weighted case. Overall, our results seem to be completely insensitive to this control. Thus, we can conclude that our findings are different from simply recasting the results in Diether, Malloy, and Scherbina (2002) and that investors' disagreement on the common factor does matter for the shape of the Security Market Line.

Alternative Aggregate Disagreement

Disagreeing about the common factor, or equivalently about the prospect of the whole asset market, can generally be understood as disagreeing about the macro outlook. Following this logic, we replicate our main analysis with an alternative measures for aggregate disagreement. We use the aggregated forecast dispersion of the ECB's Survey of Professional Forecasters database. The description of this measure and its caveats are discussed in subsection 4.3.

Stocks

Table B7 shows the regression results when we substitute the aggregated disagreement measured from the I/B/E/S data with the proxy aggregated from the ECB SPF data. We see absolutely confirming results. First of all, for both value- and equal-weighted portfolios, the high statistical significance of aggregate disagreement remains. Moreover, in Panel A we see that only the coefficient on aggregate disagreement is significant for value-weighted portfolios compared to the main table where the size factor is so as well. On the contrary, in Panel B we see that even though the constant is insignificant other control variables become significant such as the market or the value factor. Especially when we overweight on small stocks, we see that the ECB proxy and the bottom-up proxy seem to capture different information sets on aggregate investor disagreement (which one can also see from the low pairwise correlation presented in Table 2).

Bonds

Table B8 displays the replication of the main results when we use the alternative aggregate disagreement proxy for bonds. We tabulate quite different and intriguing results compared to the original setup. First of all, the coefficients of aggregate disagreement become significant in both specifications which seems like a great improvement at first sight. However, the coefficients of aggregate disagreement turns from negative to positive which means the higher the aggregate disagreement the more convex, thus, more U-shaped the Bond SML is. Though we use a different proxy for the graph, this U-shape of the curve can be seen in Figure 4 for the high disagreement periods. Further, the constant is significant in specification (1) but turns insignificant in (2) which suggests that introducing the CP factor we mitigate our omitted variable bias. These results cast serious doubt whether we can infer anything even in terms of economic significance from the sign of aggregate disagreement at all. Based on information at hand, we are more confident to reject our Hypothesis 2. Although, one should not disregard that the number of observations in this case is still very low (though improved compared to the bottom-up approach). Overall, we believe that the reliability of the results can be greatly improved by finding more suitable pricing factors and having enough and potentially better data at hand.

Individual Countries and Euro Area ex-UK

One could argue that we arbitrarily choose and pool together the original 12 members of the euro area (EA12) and the UK. We argue for our aggregation in section 3 in more detail, however, the main point is that we need a dataset that is vast enough and is expected to be viewed as a homogeneous market by investors. On the one hand, we consider the core members of the eurozone the closest an investor can get in Europe as a vast and homogeneous equity market. On the other and, the UK's financial markets are among the most important ones in Europe given that London is the biggest financial hub, making any cross-regional asset pricing analysis much weaker were the UK to be left out. Nevertheless, here we reproduce our main results as a robustness check for smaller samples, namely the euro area without the UK, France, Germany and the UK alone. We could theoretically expand our analysis to all individual countries, however, we see low potential in taking a country with a fairly small capital market weight. For example, in case of Austria the average number of stocks in a 5 portfolio sorting case is 13-14 and 65 valid months are available which together yield unreliable results unfortunately. Therefore, to present valuable and statistically robust results we constrain ourselves to those aforementioned 4 geographical sub-samples.

As a first insight, in Figure A2 we plot the time series of the aggregate disagreement if we take sub-samples. We observe quite high positive correlations which ultimately further support our argument that on an aggregate level these equity markets are influenced by the same common factor that investors disagree about.

We tabulate the regression results for the curvature parameter (γ_t) in Table B9 for both value- and equal-weighted portfolios. The asset pricing factors included in individual country regressions are country-level AQR factors as well as inflation within those countries. For the euro area we use the same European aggregated AQR factors as in the main regression and inflation is calculated similarly to the original analysis (without the UK). Firstly, looking at panel A, the results for the euro area (EA12) remain strong: the aggregate disagreement stays significant while the constant remains insignificant. This can mainly be accounted for that the EA12 sample is similar to our main sample as both are aggregated and fairly sizeable. Looking at France, Germany and UK individually however, in all cases the statistical significance of the aggregate disagreement vanishes and for example in case of France the point estimates are actually positive. Other factors such as inflation for France or D/P for Germany are significant, although, without a common trend it is difficult to generalize. On the contrary, when it comes to the equal-weighted portfolios, which overweight on small stocks compared to value-weights, we see on panel B that the aggregate disagreement is significant for the individual countries as well with negative signs. The constants are slightly significant under certain runs but overall the results are stronger compared to those for the value-weighted portfolios. In our opinion, this might be due to that small stocks are more prone to the beta-amplified mispricing because relatively more pessimists are sidelined compared to bigger stocks since the more illiquid a stock is the more costly it is to short.

7 Conclusion

In this paper, we follow the influential work of Hong and Sraer (2016) and expand the empirical analysis to developed European equity and bonds markets. We argue that nowadays investors are on average global cross-asset allocators which leads to that agents similarly trade and price assets on both sides of the Atlantic and across asset classes. Essentially, we set ourselves to show and prove that similarly to US equities in Europe the empirical Security Market Line also has a two-regime behaviour both for equities and bonds.

We manage to find conclusive results for equities on an aggregated Compustat historical dataset which consists of the original 12 member states of the eurozone plus UK and covers the period between 1986 and 2017. Our evidence shows that when aggregate disagreement, which we proxy with a bottom-up approach, is low the risk-return trade-off is upward-sloping in line with the classic CAPM. However, when aggregate disagreement is high the Security Market Line resembles an inverted-U shape which means that the excess returns can decline with increasing beta. The idea of the underlying mechanism goes back to Miller (1977) and further explained by Hong and Sraer (2016) that due to short-sale constraints and heterogeneous beliefs on the common factor, which affects all individual stocks, high-beta stocks suffer from mispricing because their market beta amplifies the disagreement. Our empirical findings are confirmed by a battery of robustness checks including substituting our aggregate disagreement measure with a macro disagreement measure.

Nevertheless, we fail to document similar evidence for bonds. We test the theory empirically by deploying a similar methodology and taking Reuters and iBoxx bond indices for the same countries as investable assets between 1999 and 2017. We proxy bond market aggregate disagreement bottom-up this time from Reuters polls. Low statistical significance potentially come from low number of investable assets and/or small sample size since disagreement is available only on quarterly basis. Even though our results are weak, we believe that the potentially pervasive nature of the phenomenon outlined in the previous paragraph should be examined further on a larger dataset in order to confidently embrace or reject the spillover effect we hypothesized in this paper.

In summary, in this paper we provide further empirical evidence for a recent influential academic work that should raise the interest of both practitioners and academics. From the practical side, a better understanding how investors' disagreement affects the risk-return trade-off in financial markets may contribute to taking smart beta investing to the next level. While from an academic point of view, we further shed light on supporting evidence that contemporaneous asset pricing theory has to account for heterogeneous beliefs otherwise it may fail to capture interesting features of the risk-return trade-off. Future research on the one hand could point to an even more comprehensive examination of the available empirical data on stocks in Europe or in other jurisdictions. On the other hand, a more rigorous study, and thus, a deeper understanding whether the recognised phenomenon is pervasive in other asset classes, such as in fixed income, is imperative.

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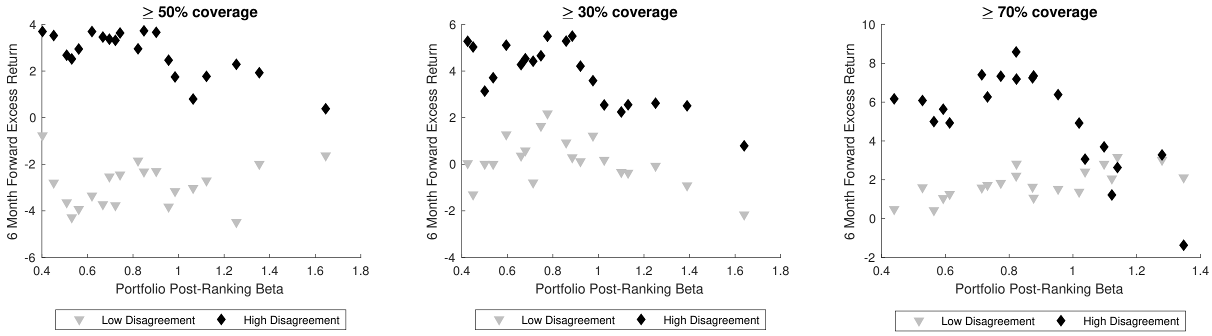
Appendix A Additional Figures

(a) 6-month returns



(b) 12-month returns

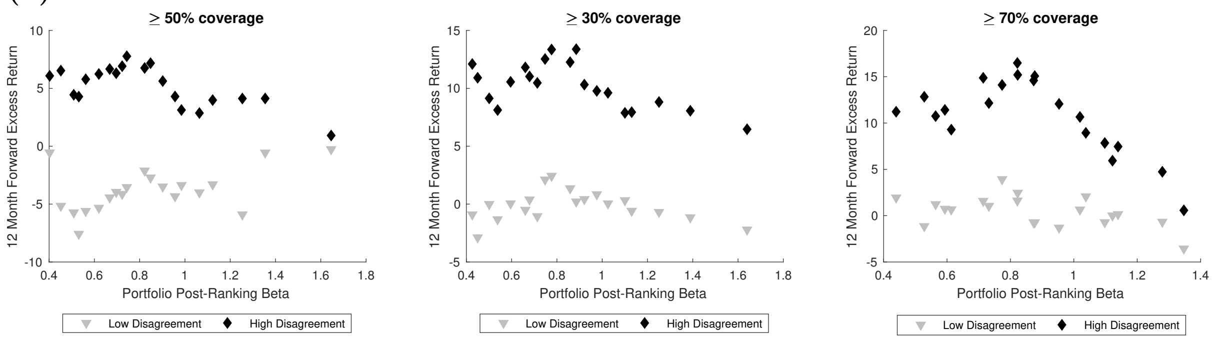


Figure A1: Equities Empirical SML for Different Specifications
The 20 value-weighted portfolios consist of stocks from the Global S&P Compustat database and primarily listed in the original 12 members countries of the eurozone plus UK. Daily historical data is retrieved between 1986 and 2017, excluding penny stocks (price $<$ \$5) and microcaps (market capitalization in the bottom 2 deciles). Stock-level pre-ranking market betas for each time t are calculated from contemporaneous and 1 to 5 lagged market returns from the preceding 12 months. We exclude stocks at t that are not active or do not have at least 100 trading days before t or their prices are completely stale over the estimation period. Stocks are sorted every valid month based on pre-ranking beta. *Portfolio Post-Ranking Beta* is a daily full-sample estimate calculated from portfolio returns regressed on contemporaneous and 1 to 5 lags of market returns. We aggregate investor disagreement bottom-up as a beta weighted average of stock-level disagreement, which is the standard deviation of analysts' forecasts of long-term EPS growth from the unadjusted summary I/B/E/S database. An I/B/E/S observation is valid if the number of long-term EPS growth forecasts is greater than 1 and months are excluded in which the analyst coverage, the relative market capitalization that is covered by valid long-term EPS growth forecast dispersion data, is below our designated threshold. High (low) disagreement months are those for which the aggregate disagreement is in the top (bottom) quartile. Panel (a) and (b) plot 6-month and 12-month ahead average excess returns respectively. The three specifications come from different equity analyst coverage thresholds. First column represents the original specification of 50% threshold while the second and third columns plot 30% and 70% respectively.

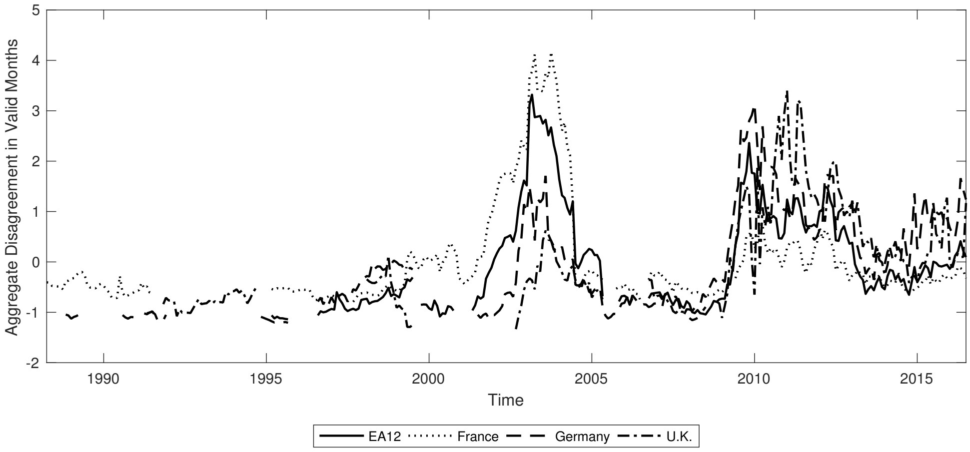


Figure A2: Time Series of Aggregate Disagreement for Individual Countries and The Euro Area

Aggregate disagreement is calculated as a market beta-weighted average long-term EPS growth standard deviation from the unadjusted summary I/B/E/S database. Historical price data is from S&P Compustat for primarily listed stocks. Daily historical data is retrieved between 1986 and 2017, excluding penny stocks (price $<$ \$5) and microcaps (market capitalization in the bottom 2 deciles). Stock-level market betas for each time t are calculated from contemporaneous and 1 to 5 lagged market returns from the preceding 12 months. We exclude stocks at t that are not active or do not have at least 100 trading days before t or their prices are completely stale over the estimation period. An I/B/E/S observation is valid if the number of long-term EPS growth forecasts is greater than 1 and months are excluded in which the analyst coverage, the relative market capitalization that is covered by valid long-term EPS growth forecast dispersion data, is below 50%. *EA12* refers to the original 12 members of the eurozone.

Appendix B Additional Tables

Table B1: Descriptive Statistics of Alternative Time Series Factors

$R_{m,t}^{FF-5F}$, HML_t^{FF-5F}, SMB_t^{FF-5F}, RMW_t^{FF-5F} and CMA_t^{FF-5F} are European market, value, size, profitability and investment factors taken from Kenneth French's Website. $CPfactor_t^{CRSP}$ is Cochrane and Piazzesi's (2005) factor constructed from CRSP Fama-Bliss discount bonds.

	Mean	Std. Dev.	p10	p25	Median	p75	p90	Obs.
$\mathrm{R}_{m,t}^{FF-5F}$	7.8	21.1	-16.26	-5.99	9.91	23.2	30.4	198
HML_t^{FF-5F}	2.5	7.52	-8.63	-3.17	4.1	8.22	10.9	198
SMB_t^{FF-5F}	1.8	11.8	-14.51	-7.14	2.76	10.9	14.8	198
RMW_t^{FF-5F}	4.7	5.77	-2.11	0.44	4.25	8.65	12.8	198
CMA_t^{FF-5F}	1.3	7.85	-6.55	-3.43	0.79	5.56	9.91	198
CP factor_t^{CRSP}	1.7	1.25	-0.15	1.0	1.8	2.86	3.21	54

Table B2: Two-Stage Regression Results Testing The Shape of SML for Stocks – Fama and French (2015) 5-factors

The two-stage regression follows the same methodology as in our main analysis, tabulated in Table 4, except for replacing AQR factors with Fama and French (2015) 5 factors. $R^{(12)}_{m,t}$, $HML^{(12)}_t$, $SMB^{(12)}_t$, $RMW^{(12)}_t$ and $CMA^{(12)}_t$ are the European market, value, size, profitability and investment factors taken from Kenneth French's website. Further description of methodology, variables, control factors is found in the main table.

Dep. Var.	γ_t				η_t				κ_t			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel A: Value-Weighted Portfolios												
Agg.Disp$_{t-1}$	-4.57**	-7.71***	-7.83***	-7.86***	5.03	3.53	3.92	3.99	6.57***	4.89*	4.66*	4.62*
	(-2.09)	(-4.09)	(-4.01)	(-4.00)	(1.22)	(0.82)	(0.92)	(0.90)	(3.06)	(1.84)	(1.80)	(1.71)
$R^{(12)}_{m,t}$		-0.16	-0.16	-0.16		1.26***	1.25***	1.26***		-0.16	-0.15	-0.16
		(-0.99)	(-0.92)	(-0.92)		(3.41)	(3.25)	(3.26)		(-0.69)	(-0.66)	(-0.67)
$HML^{(12)}_t$		1.02***	1.03***	1.05***		-1.83***	-1.86***	-1.9***		0.65**	0.68***	0.7**
		(3.27)	(3.26)	(2.91)		(-3.48)	(-3.58)	(-3.12)		(2.29)	(2.45)	(2.26)
$SMB^{(12)}_t$		-0.44*	-0.44	-0.44		-0.13	-0.12	-0.12		0.63***	0.63***	0.63***
		(-1.77)	(-1.63)	(-1.62)		(-0.28)	(-0.23)	(-0.23)		(2.57)	(2.41)	(2.41)
$RMW^{(12)}_t$		-1.88***	-1.89***	-1.88***		2.75***	2.77***	2.76***		-0.59	-0.6	-0.59
		(-5.03)	(-5.42)	(-5.34)		(3.30)	(3.48)	(3.40)		(-1.13)	(-1.14)	(-1.11)
$CMA^{(12)}_t$		-0.14	-0.05	-0.05		1.11	0.9	0.9		-0.9**	-0.7	-0.7
		(-0.33)	(-0.13)	(-0.13)		(1.42)	(0.95)	(0.94)		(-2.30)	(-1.09)	(-1.08)
D/P$_{t-1}$			-0.08	-0.09			0.16	0.2			-0.18	-0.2
			(-0.13)	(-0.15)			(0.13)	(0.16)			(-0.27)	(-0.30)
Inflation$_{t-1}$			0.1	0.1			-0.33	-0.34			0.2	0.2
			(0.56)	(0.59)			(-0.87)	(-0.92)			(1.09)	(1.13)
Ted Spread$_{t-1}$				0.32				-0.82				0.45
				(0.16)				(-0.21)				(0.21)
Constant	-0.62	7.73***	7.66***	7.08	2.64	-16.49***	-16.26***	-14.79	2.43	4.78	4.65	3.84
	(-0.23)	(2.55)	(2.51)	(1.29)	(0.51)	(-2.97)	(-2.88)	(-1.34)	(0.89)	(1.46)	(1.39)	(0.63)
N	197	197	197	197	197	197	197	197	197	197	197	197

–Continued–

Table B2: (continued)

Dep. Var.	γ_t				η_t				κ_t			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel B: Equal-Weighted Portfolios												
Agg.Disp$_{t-1}$	-12.55***	-14.91***	-14.77***	-14.76***	18.99***	13.58***	13.52***	13.3***	2.07	-0.06	-0.04	0.16
	(-4.10)	(-6.19)	(-5.88)	(-5.94)	(4.20)	(4.16)	(3.86)	(3.78)	(0.99)	(-0.04)	(-0.03)	(0.09)
R$_{m,t}^{(12)}$		0.16	0.16	0.16		0.92**	0.94**	0.93**		0.06	0.05	0.06
		(0.53)	(0.51)	(0.51)		(2.27)	(2.23)	(2.21)		(0.35)	(0.27)	(0.29)
HML$_t^{(12)}$		0.5	0.49	0.48		-0.56	-0.58	-0.47		0.69**	0.71***	0.6*
		(1.16)	(1.14)	(1.07)		(-0.84)	(-0.88)	(-0.67)		(2.24)	(2.36)	(1.94)
SMB$_t^{(12)}$		-0.91**	-0.89**	-0.89**		-0.11	-0.17	-0.16		0.61*	0.66**	0.65**
		(-2.17)	(-2.11)	(-2.11)		(-0.15)	(-0.23)	(-0.22)		(1.85)	(1.97)	(1.99)
RMW$_t^{(12)}$		-0.66	-0.65	-0.65		-0.12	-0.15	-0.13		0.57	0.6*	0.58
		(-0.95)	(-0.91)	(-0.92)		(-0.14)	(-0.19)	(-0.16)		(1.62)	(1.72)	(1.64)
CMA$_t^{(12)}$		0.84	0.86	0.86		-0.17	-0.64	-0.64		-0.03	0.39	0.39
		(1.43)	(1.20)	(1.20)		(-0.19)	(-0.57)	(-0.57)		(-0.07)	(0.70)	(0.72)
D/P$_{t-1}$			-0.05	-0.05			0.56	0.44			-0.49	-0.39
			(-0.10)	(-0.09)			(0.66)	(0.51)			(-1.17)	(-0.92)
Inflation$_{t-1}$			-0.12	-0.12			0.05	0.08			-0.01	-0.04
			(-0.63)	(-0.65)			(0.13)	(0.24)			(-0.09)	(-0.31)
Ted Spread$_{t-1}$				-0.12				2.41				-2.21
				(-0.07)				(0.77)				(-1.48)
Constant	4.72	5.78	5.87	6.09	-8.59	-13.37**	-13.46**	-17.79**	11.22***	5.27*	5.33*	9.31**
	(1.61)	(1.13)	(1.15)	(1.03)	(-1.59)	(-1.97)	(-1.97)	(-2.05)	(4.29)	(1.75)	(1.75)	(2.23)
N	197	197	197	197	197	197	197	197	197	197	197	197

*,**, and *** indicate 10%, 5%, and 1% statistical significance respectively that the coefficient is different from zero. In brackets beneath each point estimate is the t statistic corresponding to H_0 : coeff. = 0 for which standard errors are Newey and West (1987) robust with 11 lags.

Table B3: Two-Stage Regression Results Testing The Shape of SML for Bonds – US Treasuries Implied CP factor

The two-stage regression follows the same methodology as in our main analysis, tabulated in Table 5, except for constructing Cochrane and Piazzesi's (2005) *CP factor* from CRSP Fama-Bliss discount bonds. Further description of methodology, variables, control factors is found in the main table.

Dep. Var.	γ_t		η_t		κ_t	
	(1)	(2)	(3)	(4)	(5)	(6)
Equal-Weighted Portfolios						
Agg.Disp$_{t-1}$	-23.51	-13.05	42.55	24.53	-16.57	-9.57
	(-1.07)	(-0.62)	(1.10)	(0.67)	(-0.97)	(-0.60)
CP factor$_{t-1}$		-17.88		30.81		-11.97
		(-0.93)		(0.95)		(-0.92)
Constant	58.76*	89.18*	-104.87*	-157.29*	50.51**	70.89*
	(1.84)	(1.67)	(-1.87)	(-1.72)	(2.11)	(1.86)
N	53	53	53	53	53	53

*,**, and *** indicate 10%, 5%, and 1% statistical significance respectively that the coefficient is different from zero. In brackets beneath each point estimate is the t statistic corresponding to H_0 : coeff. = 0 for which standard errors are Newey and West (1987) robust with 11 lags.

Table B4: Two-Stage Regression Results Testing The Shape of SML for Stocks – Alternative specifications

The two-stage regression follows the same methodology as in our main analysis (cf. Table 4) except for alternative analyst coverage ratio, number of sorted portfolios and return horizon. Value-weighted portfolios tabulated only. Further description of methodology, variables, control factors is found in the main table.

	Panel A				Panel B				Panel C			
Spec.	20 portf. + 70% cov. requir. + 12M horizon				10 portf. + 50% cov. requir. + 12M horizon				20 portf. + 50% cov. requir. + 6M horizon			
Dep. Var.	γ_t				γ_t				γ_t			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Agg.Disp$_{t-1}$	-12.47*	-16.9***	-15.01***	-14.27***	-3.36	-6.78***	-6.45***	-7.4***	-3.49**	-4.65***	-4.89***	-4.43***
	(-1.82)	(-5.53)	(-6.78)	(-7.50)	(-1.41)	(-2.46)	(-2.47)	(-2.72)	(-2.23)	(-4.80)	(-4.71)	(-3.30)
R$_{m,t}^{(12)}$		0.77*	0.61	0.45		0.05	0.05	0.06		-0.07	-0.06	-0.07
		(1.73)	(1.45)	(1.12)		(0.30)	(0.29)	(0.33)		(-0.76)	(-0.82)	(-0.87)
HML$_t^{(12)}$		0.50	0.76	0.82		-0.01	0.04	0.03		0.28	0.24	0.25
		(0.74)	(1.27)	(1.42)		(-0.02)	(0.11)	(0.06)		(1.55)	(1.38)	(1.47)
SMB$_t^{(12)}$		2.91***	3.01***	3.22***		0.89**	0.78	0.79*		0.34*	0.42**	0.42**
		(3.56)	(3.27)	(4.38)		(2.00)	(1.60)	(1.67)		(1.95)	(2.09)	(2.07)
UMD$_t^{(12)}$		0.16	0.03	0.27		-0.52*	-0.46*	-0.5*		-0.43***	-0.46***	-0.44**
		(0.16)	(0.03)	(0.27)		(-1.93)	(-1.76)	(-1.86)		(-2.35)	(-2.42)	(-2.29)
D/P$_{t-1}$			-1.14***	-1.17***			0.06	0.05			-0.01	-0.01
			(-2.93)	(-3.33)			(0.29)	(0.25)			(-0.10)	(-0.06)
Inflation$_{t-1}$			-1.52	-0.97			-2.65	-1.96			1.78	1.44
			(-0.40)	(-0.30)			(-1.29)	(-0.99)			(1.19)	(0.96)
Ted Spread$_{t-1}$				58.42				-4.24				2.09
				(1.52)				(-0.63)				(0.52)
Constant	-16.98**	-28.2***	-23.47***	-38.29***	-2.57	-1.70	2.50	3.32	0.88	1.24	-1.59	-2.00
	(-2.07)	(-4.93)	(-2.86)	(-4.55)	(-0.88)	(-0.74)	(0.59)	(0.66)	(0.58)	(0.81)	(-0.55)	(-0.66)
N stocks	96	96	96	96	197	197	197	197	197	197	197	197

*,**, and *** indicate 10%, 5%, and 1% statistical significance respectively that the coefficient is different from zero. In brackets beneath each point estimate is the t statistic corresponding to H_0 : coeff. = 0 for which standard errors are Newey and West (1987) robust with 11 lags.

Table B5: Two-Stage Regression Results Testing The Shape of SML for Stocks – Controlling for IVOL

The two-stage regression follows the same methodology as in our main analysis, tabulated in Table 4, except that we control for the idiosyncratic volatility in the first stage:

$$r_{k,t}^{(12)} = \kappa_t + \eta_t \beta_k + \gamma_t \beta_k^2 + \omega_t \left(\ln\, \sigma_k^{idiosyncratic} \right) + \varepsilon_{k,t} \qquad \text{k = 1, 2, 3,..., 20}$$

where $\sigma_k^{idiosyncratic}$ is the unconditional mean of the time series of median idiosyncratic volatility of stocks in kth portfolio. Stock-level idiosyncratic volatility at time t is calculated as the standard deviation of the resulting errors in the pre-ranking beta OLS regression ran at t (Equation 2). Further description of methodology, variables, control factors is found in the main table.

Dep. Var.	γ_t				η_t				κ_t			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
						Panel A: Value-Weighted Portfolios						
Agg.Disp_{t-1}	-4.24*	-7.29**	-7.03**	-8.55***	4.5	4.58	4.33	10.29**	7.02*	3.64	3.96	-1.33
	(-1.69)	(-2.05)	(-2.12)	(-2.74)	(0.84)	(0.67)	(0.68)	(2.01)	(1.75)	(0.78)	(0.94)	(-0.37)
$\text{R}_{m,t}^{(12)}$		-0.07	-0.07	-0.06		0.85***	0.85***	0.81***		0.11	0.11	0.15
		(-0.48)	(-0.49)	(-0.43)		(2.86)	(2.99)	(3.23)		(0.49)	(0.54)	(0.96)
$\text{HML}_t^{(12)}$		-0.31	-0.24	-0.27		0.39	0.26	0.37		-0.23	-0.11	-0.21
		(-0.67)	(-0.51)	(-0.56)		(0.52)	(0.35)	(0.48)		(-0.65)	(-0.33)	(-0.61)
$\text{SMB}_t^{(12)}$		1.23***	1.07***	1.09***		-2.13***	-1.89***	-1.97***		1**	0.76	0.83*
		(2.98)	(2.36)	(2.53)		(-3.15)	(-2.49)	(-2.98)		(2.22)	(1.54)	(1.88)
$\text{UMD}_t^{(12)}$		-0.06	0.05	0		-0.38	-0.6	-0.4		0.86*	1.05***	0.87***
		(-0.19)	(0.17)	(0.01)		(-0.60)	(-1.00)	(-0.75)		(1.93)	(2.56)	(2.48)
D/P_{t-1}			0.33	0.32			-0.76**	-0.7**			0.62***	0.57***
			(1.59)	(1.51)			(-2.17)	(-2.13)			(3.04)	(2.92)
Inflation_{t-1}			-3.81	-2.69			6.3	1.92			-6.02*	-2.13
			(-1.21)	(-0.83)			(1.26)	(0.39)			(-1.78)	(-0.56)
Ted Spread_{t-1}				-6.82				26.68***				-23.71***
				(-1.04)				(2.53)				(-4.61)
Constant	-4.99*	-2.48	3.37	4.7	9.49*	0.55	-8.99	-14.19	-3.47	-3.74	5.44	10.06
	(-1.81)	(-0.82)	(0.53)	(0.66)	(1.84)	(0.12)	(-1.00)	(-1.30)	(-0.91)	(-1.16)	(0.90)	(1.43)
N stocks	197	197	197	197	197	197	197	197	197	197	197	197

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Table B5: (continued)

Dep. Var.	γ_t				η_t				κ_t			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel B: Equal-Weighted Portfolios												
Agg.Disp$_{t-1}$	-14.46***	-15.54***	-15.34***	-12.01***	21.5***	16.61***	15.97***	15.72***	0.07	-3.32	-2.99	-4*
	(-6.46)	(-5.09)	(-5.23)	(-4.03)	(4.89)	(4.85)	(4.55)	(3.86)	(0.03)	(-1.60)	(-1.51)	(-1.67)
$R_{m,t}^{(12)}$		0.05	0.05	0.03		0.82***	0.83***	0.83***		0.17	0.17	0.18
		(0.28)	(0.28)	(0.15)		(3.22)	(3.32)	(3.28)		(1.10)	(1.13)	(1.24)
$HML_t^{(12)}$		0.09	0.09	0.15		-0.71*	-0.77*	-0.78*		0.72***	0.75***	0.73***
		(0.31)	(0.29)	(0.52)		(-1.67)	(-1.70)	(-1.70)		(2.90)	(2.94)	(2.88)
$SMB_t^{(12)}$		0.13	0.12	0.08		-0.01	0.16	0.17		0.42	0.33	0.35
		(0.31)	(0.31)	(0.21)		(-0.01)	(0.28)	(0.29)		(1.37)	(0.99)	(1.03)
$UMD_t^{(12)}$		-0.47	-0.51*	-0.4		0.16	0.13	0.12		0.46*	0.47*	0.44*
		(-1.48)	(-1.66)	(-1.54)		(0.41)	(0.35)	(0.36)		(1.90)	(1.95)	(1.95)
D/P$_{t-1}$			-0.26	-0.23			0.18	0.18			-0.08	-0.09
			(-1.33)	(-1.18)			(0.65)	(0.63)			(-0.48)	(-0.55)
Inflation$_{t-1}$			0.19	-2.25			3.37	3.55			-1.78	-1.05
			(0.08)	(-1.02)			(1.17)	(1.16)			(-0.95)	(-0.52)
Ted Spread$_{t-1}$				14.92***				-1.12				-4.49
				(2.71)				(-0.12)				(-0.67)
Constant	-5.39**	-5.45*	-5.58	-8.49*	4.65	0.35	-5.15	-4.94	0.68	-2.97	-0.07	0.8
	(-1.96)	(-1.90)	(-0.93)	(-1.67)	(1.02)	(0.09)	(-0.85)	(-0.77)	(0.23)	(-1.05)	(-0.02)	(0.21)
N stocks	197	197	197	197	197	197	197	197	197	197	197	197

*,**, and *** indicate 10%, 5%, and 1% statistical significance respectively that the coefficient is different from zero. In brackets beneath each point estimate is the t statistic corresponding to H_0 : coeff. = 0 for which standard errors are Newey and West (1987) robust with 11 lags.

Table B6: Two-Stage Regression Results Testing The Shape of SML – Controlling for Stock-Level Disagreement

The two-stage regression follows the same methodology as in our main analysis, tabulated in Table 4, except that we control for the monthly average stock-level disagreement in the first stage regression:

$r^{(12)}_{k,t} = \kappa_t + \eta_t\beta_k + \gamma_t\beta^2_k + \omega_t \left(\ln \text{AvgDisp}_{k,t}\right) + \varepsilon_{k,t} \qquad \text{k} = 1, 2, 3,..., 20$

where $\text{AvgDisp}_{k,t}$ is the value-weighted average stock-level investor disagreement in kth portfolio at t. Further description of methodology, variables, control factors is found in the main table.

	γ_t				η_t				κ_t			
Dep. Var.	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel A: Value-Weighted Portfolios												
Agg.Disp_{t-1}	-3.47*	-6.35***	-6.52***	-6.33***	3.01	2.94	3.28	6.64	7.7***	4.52*	4.17*	1.69
	(-1.75)	(-2.82)	(-2.72)	(-2.67)	(0.75)	(0.60)	(0.67)	(1.45)	(3.59)	(1.87)	(1.67)	(0.75)
$\text{R}^{(12)}_{m,t}$		-0.02	-0.02	-0.02		0.76***	0.76***	0.74***		0.20	0.20	0.22*
		(-0.13)	(-0.13)	(-0.14)		(3.10)	(3.14)	(3.23)		(1.35)	(1.36)	(1.72)
$\text{HML}^{(12)}_t$		-0.08	-0.09	-0.09		0.02	0.01	0.08		-0.02	-0.03	-0.07
		(-0.20)	(-0.22)	(-0.22)		(0.03)	(0.02)	(0.12)		(-0.06)	(-0.10)	(-0.28)
$\text{SMB}^{(12)}_t$		0.94**	0.98**	0.97**		-1.74***	-1.76***	-1.8***		0.61**	0.66**	0.69***
		(2.30)	(2.21)	(2.24)		(-2.61)	(-2.41)	(-2.64)		(2.04)	(2.06)	(2.34)
$\text{UMD}^{(12)}_t$		-0.20	-0.20	-0.19		-0.41	-0.48	-0.36		0.56**	0.59**	0.5*
		(-0.80)	(-0.80)	(-0.80)		(-0.76)	(-0.89)	(-0.75)		(1.99)	(2.05)	(1.96)
D/P_{t-1}			0.10	0.11			-0.42	-0.39			0.27	0.24
			(0.48)	(0.48)			(-1.02)	(-0.96)			(1.29)	(1.23)
Inflation_{t-1}			0.58	0.44			0.11	-2.35			0.8	2.62
			(0.25)	(0.20)			(0.03)	(-0.56)			(0.36)	(1.16)
Ted Spread_{t-1}				0.87				15.03*				-11.11***
				(0.17)				(1.84)				(-2.99)
Constant	-1.94	-0.63	-1.62	-1.79	5.54	-1.27	-1.16	-4.09	1.55	-0.07	-1.53	0.64
	(-0.78)	(-0.24)	(-0.34)	(-0.35)	(1.16)	(-0.33)	(-0.14)	(-0.45)	(0.58)	(-0.03)	(-0.36)	(0.14)
N stocks	197	197	197	197	197	197	197	197	197	197	197	197

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Table B6: (continued)

Dep. Var.	γ_t				η_t				κ_t			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel B: Equal-Weighted Portfolios												
Agg.Disp$_{t-1}$	-12.57***	-13.66***	-13.31***	-10.63***	18.93***	14.42***	13.54***	14.13***	1.97	-1.45	-0.98	-2.56
	(-4.31)	(-4.80)	(-4.65)	(-3.68)	(4.80)	(4.96)	(4.20)	(3.84)	(0.90)	(-1.12)	(-0.66)	(-1.49)
$R_{m,t}^{(12)}$		-0.03	-0.03	-0.05		0.89***	0.89***	0.89***		0.11	0.11	0.12
		(-0.14)	(-0.14)	(-0.27)		(3.48)	(3.64)	(3.62)		(0.86)	(0.92)	(1.09)
$HML_t^{(12)}$		0.12	0.13	0.18		-0.82**	-0.9**	-0.89**		0.71***	0.76***	0.73***
		(0.44)	(0.50)	(0.75)		(-2.08)	(-2.20)	(-2.24)		(3.84)	(4.11)	(4.49)
$SMB_t^{(12)}$		0.26	0.20	0.16		-0.18	0.06	0.05		0.54**	0.4*	0.42*
		(0.59)	(0.43)	(0.36)		(-0.32)	(0.10)	(0.09)		(2.32)	(1.79)	(1.92)
$UMD_t^{(12)}$		-0.8***	-0.83***	-0.74***		0.57	0.52	0.54		0.14	0.18	0.13
		(-2.61)	(-2.68)	(-2.63)		(1.46)	(1.34)	(1.41)		(0.76)	(0.92)	(0.66)
D/P$_{t-1}$			-0.26	-0.23			0.22	0.23			-0.06	-0.08
			(-1.41)	(-1.24)			(0.78)	(0.79)			(-0.55)	(-0.71)
Inflation$_{t-1}$			-0.85	-2.81			4.78**	4.35*			-2.85**	-1.70
			(-0.49)	(-1.50)			(2.04)	(1.68)			(-1.99)	(-1.19)
Ted Spread$_{t-1}$				12.00***				2.62				-7.06
				(2.49)				(0.30)				(-1.34)
Constant	3.46	4.33**	5.86*	3.52	-5.94	-10.97***	-18.77***	-19.28***	10.14***	7.40***	12.01***	13.38***
	(1.20)	(2.24)	(1.78)	(1.03)	(-1.20)	(-3.68)	(-4.62)	(-4.19)	(3.81)	(3.75)	(4.33)	(5.09)
N stocks	197	197	197	197	197	197	197	197	197	197	197	197

*,**, and *** indicate 10%, 5%, and 1% statistical significance respectively that the coefficient is different from zero. In brackets beneath each point estimate is the t statistic corresponding to H_0 : coeff. = 0 for which standard errors are Newey and West (1987) robust with 11 lags.

Table B7: Two-Stage Regression Results Testing The Shape of SML for Stocks– ECB SPF Disagreement

The two-stage regression follows the same methodology as in our main analysis, tabulated in Table 4, except for substituting our I/B/E/S disagreement data with ECB's SPF data. Agg.Disp$_{t-1}$ is now calculated as the first principal component of the forecast standard deviations from the ECB's SPF database. Further description of methodology, variables, control factors is found in the main table.

Dep. Var.	γ_t				η_t				κ_t			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel A: Value-Weighted Portfolios												
Agg.Disp$_{t-1}$	-3.04	-5.53*	-5.66**	-6.66***	6.96**	2.96	3.11	8.22	4.73*	3.33	3.28	-0.76
	(-1.11)	(-1.91)	(-2.02)	(-2.41)	(2.23)	(0.48)	(0.51)	(1.54)	(1.86)	(1.05)	(1.01)	(-0.30)
R$^{(12)}_{m,t}$		0.17	0.16	0.16		0.49	0.5	0.54		0.23	0.22	0.2
		(1.08)	(1.00)	(1.00)		(1.28)	(1.28)	(1.63)		(1.02)	(1.01)	(1.21)
HML$^{(12)}_t$		-0.25	-0.24	-0.24		0.04	0.01	0.03		0.26***	0.28***	0.26**
		(-1.26)	(-1.23)	(-1.20)		(0.12)	(0.04)	(0.10)		(2.47)	(2.60)	(2.27)
SMB$^{(12)}_t$		0.01	0.02	0.02		-0.16	-0.14	-0.11		0.11	0.09	0.07
		(0.01)	(0.03)	(0.02)		(-0.13)	(-0.10)	(-0.08)		(0.20)	(0.15)	(0.12)
UMD$^{(12)}_t$		-0.33	-0.34	-0.36		0.09	0.11	0.19		0.42	0.42	0.35
		(-0.90)	(-0.96)	(-0.99)		(0.11)	(0.14)	(0.26)		(0.98)	(1.05)	(0.97)
D/P$_{t-1}$			0.19	0.25			-0.38	-0.68			0.18	0.42**
			(0.99)	(1.20)			(-1.06)	(-1.65)			(1.00)	(2.11)
Inflation$_{t-1}$			-0.2	0.54			1.4	-2.39			-0.8	2.19
			(-0.08)	(0.18)			(0.33)	(-0.48)			(-0.42)	(1.07)
Ted Spread$_{t-1}$				-5.1				26.09**				-20.6***
				(-0.78)				(2.01)				(-3.44)
Constant	0.76	1.66	2.09	3.18	-3.91	-6.97	-9.49	-15.08	5.59	2.41	3.84	8.26*
	(0.26)	(0.53)	(0.36)	(0.49)	(-0.81)	(-1.40)	(-0.98)	(-1.30)	(1.44)	(1.03)	(0.98)	(1.73)
N	70	70	70	70	70	70	70	70	70	70	70	70

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Table B7: (continued)

Dep. Var.	γ_t				η_t				κ_t			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel B: Equal-Weighted Portfolios												
Agg.Disp$_{t-1}$	-8.87*	-12.74***	-12.84***	-11.64***	17.82***	14.59***	14.42***	16.93***	0.75	-2.15	-1.9	-4.53***
	(-1.76)	(-4.37)	(-4.28)	(-5.18)	(3.84)	(4.27)	(4.19)	(5.04)	(0.30)	(-1.24)	(-1.05)	(-2.67)
$R_{m,t}^{(12)}$		0.29*	0.28*	0.29*		0.37	0.36	0.38		0.31	0.32	0.3*
		(1.92)	(1.79)	(1.73)		(1.13)	(1.04)	(1.16)		(1.61)	(1.58)	(1.77)
$HML_t^{(12)}$		-0.64***	-0.65***	-0.65***		0.55	0.55	0.56		0.12	0.12	0.11
		(-3.39)	(-3.62)	(-3.59)		(1.56)	(1.57)	(1.63)		(0.72)	(0.70)	(0.68)
$SMB_t^{(12)}$		-0.49	-0.41	-0.4		0.85	0.89	0.91		0.19	0.1	0.09
		(-0.62)	(-0.49)	(-0.46)		(0.62)	(0.58)	(0.62)		(0.28)	(0.14)	(0.13)
$UMD_t^{(12)}$		-0.54*	-0.56**	-0.54*		-0.07	-0.1	-0.05		0.45**	0.48***	0.44***
		(-1.81)	(-1.98)	(-1.91)		(-0.20)	(-0.26)	(-0.16)		(2.22)	(2.37)	(2.58)
D/P$_{t-1}$			-0.11	-0.18			0.15	0			-0.15	0
			(-0.43)	(-0.72)			(0.37)	(0.01)			(-0.64)	(0.01)
Inflation$_{t-1}$			1.67	0.77			0.38	-1.48			-1.06	0.88
			(0.71)	(0.28)			(0.10)	(-0.30)			(-0.50)	(0.36)
Ted Spread$_{t-1}$				6.15				12.83				-13.39**
				(0.95)				(1.05)				(-2.09)
Constant	1.94	4.95	2.12	0.8	-7.95	-13.88***	-14.44***	-17.19***	11.89***	9.35***	11.04***	13.91***
	(0.42)	(1.37)	(0.67)	(0.26)	(-1.44)	(-2.72)	(-2.48)	(-2.88)	(3.37)	(3.34)	(4.10)	(5.22)
N	70	70	70	70	70	70	70	70	70	70	70	70

*,**, and *** indicate 10%, 5%, and 1% statistical significance respectively that the coefficient is different from zero. In brackets beneath each point estimate is the t statistic corresponding to H_0 : coeff. = 0 for which standard errors are Newey and West (1987) robust with 11 lags.

Table B8: Two-Stage Regression Results Testing The Shape of SML for Bonds – ECB SPF disagreement

The two-stage regression follows the same methodology as in our main analysis, tabulated in Table 5, except for substituting our I/B/E/S disagreement data with ECB's SPF data. Agg.Disp$_{t-1}$ is now calculated as the first principal component of the forecast standard deviations from the ECB's SPF database. Further description of methodology, variables, control factors is found in the main table.

Dep. Var.	γ_t		η_t		κ_t	
	(1)	(2)	(3)	(4)	(5)	(6)
Equal-Weighted Portfolios						
Agg.Disp$_{t-1}$	45.00*	46.37*	-79.21*	-81.87*	36.85**	38.00*
	(1.81)	(1.68)	(-1.88)	(-1.73)	(2.08)	(1.90)
CP factor$_{t-1}$		-23.78		46.22		-20.00
		(-0.97)		(1.06)		(-1.09)
Constant	58.26*	92.34	-103.13*	-169.38*	49.92**	78.59*
	(1.73)	(1.61)	(-1.73)	(-1.66)	(1.98)	(1.84)
N	54	54	54	54	54	54

*,**, and *** indicate 10%, 5%, and 1% statistical significance respectively that the coefficient is different from zero. In brackets beneath each point estimate is the t statistic corresponding to H_0 : coeff. = 0 for which standard errors are Newey and West (1987) robust with 11 lags.

Table B9: Two-Stage Regression Results Testing The Shape of SML for Stocks – Individual Countries and Euro Area ex-UK

The two-stage regression follows the same methodology as in our main analysis, tabulated in Table 4, except that this time beta-sorted portfolios are sorted from geographical subsamples. We tabulate results for the original 12 members of the euro area (*Euro area 12*) and individually for *France*, *Germany* and the *UK*. Further description of methodology, variables, control factors is found in the main table.

	Euro area 12				France				Germany				UK			
Dep. Var.	γ_t				γ_t				γ_t				γ_t			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Panel A: Value-Weighted Portfolios																
Agg.Disp_{t-1}	-3.49	-7.01***	-7.23***	-8.06***	5.19	2.67	4.20	2.02	-3.77	-4.22	-6.98	-6.31	-4.56	-3.76	-3.53	-0.96
	(-1.29)	(-2.54)	(-2.50)	(-2.73)	(0.91)	(0.44)	(0.68)	(0.32)	(-0.72)	(-0.81)	(-1.13)	(-0.96)	(-0.57)	(-0.46)	(-0.45)	(-0.10)
$\text{R}_{m,t}^{(12)}$		0.04	0.03	0.03		0.25	-0.11	-0.22		-1.34***	-1.28***	-1.24**		0.48	0.52	0.74
		(0.21)	(0.20)	(0.19)		(0.32)	(-0.16)	(-0.36)		(-2.49)	(-2.36)	(-2.16)		(0.47)	(0.53)	(0.90)
$\text{HML}_t^{(12)}$		-0.38	-0.4*	-0.4*		1.05	0.94	0.76		-0.18	-0.1	-0.01		-0.55	-0.5	-0.51
		(-1.60)	(-1.70)	(-1.70)		(0.90)	(0.75)	(0.67)		(-0.15)	(-0.09)	(-0.01)		(-0.25)	(-0.22)	(-0.23)
$\text{SMB}_t^{(12)}$		0.85*	0.94*	0.95*		-0.85	-1.61	-1.7		-1.40	-1.14	-1.14		-0.60	-0.46	-0.25
		(1.70)	(1.88)	(1.94)		(-0.59)	(-1.02)	(-1.10)		(-1.29)	(-0.97)	(-0.99)		(-0.53)	(-0.32)	(-0.16)
$\text{UMD}_t^{(12)}$		-0.37	-0.43	-0.45		-1.35	-1.33	-1.38		-0.40	-0.39	-0.35		-2.59	-2.42	-2.34
		(-0.90)	(-1.05)	(-1.14)		(-1.44)	(-1.41)	(-1.53)		(-0.78)	(-0.83)	(-0.71)		(-1.23)	(-1.15)	(-1.20)
D/P_{t-1}			0.09	0.08			0.56	0.56			-1.01***	-0.98***			-0.16	-0.06
			(0.35)	(0.33)			(0.65)	(0.66)			(-2.73)	(-2.75)			(-0.18)	(-0.08)
Inflation_{t-1}			2.12	2.58			-10.34***	-8.47*			-6.18	-6.42			-3.29	-3.99
			(0.94)	(1.05)			(-2.54)	(-1.91)			(-0.97)	(-1.00)			(-0.48)	(-0.61)
Ted Spread_{t-1}				-4.17				-15.25				5.50				17.94
				(-0.57)				(-1.08)				(0.51)				(0.52)
Constant	-2.59	0.65	-2.71	-1.40	-8.40	-2.69	12.97	17.97	-1.41	0.55	10.74	8.33	8.41	10.25	18.19	11.66
	(-0.75)	(0.17)	(-0.55)	(-0.26)	(-1.06)	(-0.35)	(1.23)	(1.38)	(-0.22)	(0.09)	(0.81)	(0.53)	(0.77)	(0.89)	(0.91)	(0.54)
N stocks	228	228	228	228	287	287	287	287	246	246	246	246	202	202	202	202

–Continued–

Table B9: (continued)

	Euro area 12				**France**				**Germany**				**UK**			
Dep. Var.	γ_t				γ_t				γ_t				γ_t			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Panel B: Equal-Weighted Portfolios																
Agg.Disp$_{t-1}$	-10.59***	-10.76***	-10.78***	-9.49***	-9.98*	-10.78*	-11.23*	-9.76	-13.5***	-14.84***	-17.46***	-17.06***	-19.1**	-18.7**	-18.07**	-16.74*
	(-2.67)	(-3.16)	(-3.18)	(-2.83)	(-1.73)	(-1.83)	(-1.81)	(-1.54)	(-2.78)	(-3.26)	(-3.97)	(-3.69)	(-2.27)	(-2.18)	(-2.08)	(-1.81)
R$_{m,t}^{(12)}$		0.06	0.05	0.05		0.00	0.06	0.14		0.25	0.32	0.35		-0.86	-0.86	-0.75
		(0.27)	(0.26)	(0.28)		(0.00)	(0.12)	(0.30)		(0.46)	(0.54)	(0.60)		(-0.91)	(-1.07)	(-0.88)
HML$_t^{(12)}$		-0.67***	-0.70***	-0.70***		-0.59	-0.6	-0.48		-2.42*	-2.33*	-2.27*		0.01	0.06	0.06
		(-2.65)	(-2.75)	(-2.69)		(-0.97)	(-0.95)	(-0.69)		(-1.90)	(-1.91)	(-1.75)		(0.01)	(0.04)	(0.03)
SMB$_t^{(12)}$		-0.31	-0.23	-0.25		-0.54	-0.49	-0.43		-1.11	-0.85	-0.85		0.14	-0.28	-0.17
		(-0.54)	(-0.40)	(-0.43)		(-0.57)	(-0.56)	(-0.50)		(-0.90)	(-0.70)	(-0.69)		(0.12)	(-0.22)	(-0.15)
UMD$_t^{(12)}$		-0.75*	-0.83**	-0.80**		0.08	0.06	0.1		0.37	0.38	0.4		-0.58	-0.39	-0.35
		(-1.87)	(-2.08)	(-2.03)		(0.11)	(0.09)	(0.15)		(0.38)	(0.38)	(0.40)		(-0.52)	(-0.41)	(-0.37)
D/P$_{t-1}$			-0.24	-0.23			0.06	0.05			-1.03	-1.01			0.53	0.59
			(-1.01)	(-0.91)			(0.10)	(0.10)			(-1.36)	(-1.28)			(0.89)	(0.97)
Inflation$_{t-1}$			2.02	1.30			2.79	1.53			-5.88	-6.02			-7.37*	-7.74*
			(0.64)	(0.38)			(0.37)	(0.20)			(-1.29)	(-1.34)			(-1.82)	(-1.92)
Ted Spread$_{t-1}$				6.46				10.29				3.31				9.29
				(0.90)				(0.68)				(0.24)				(0.51)
Constant	3.90	7.70**	4.77	2.75	-4.21	-1.70	-5.97	-9.35	11.31*	13.09*	22.82**	21.37	-19.04**	-17.91*	-0.81	-4.20
	(0.89)	(2.12)	(0.80)	(0.50)	(-0.63)	(-0.23)	(-0.47)	(-0.71)	(1.70)	(1.94)	(1.96)	(1.48)	(-1.97)	(-1.87)	(-0.05)	(-0.25)
N stocks	228	228	228	228	287	287	287	287	246	246	246	246	202	202	202	202

*,**, and *** indicate 10%, 5%, and 1% statistical significance respectively that the coefficient is different from zero. In brackets beneath each point estimate is the t statistic corresponding to H_0 : coeff. = 0 for which standard errors are Newey and West (1987) robust with 11 lags.