Microfounding the Fama–MacBeth Regression

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Abstract

In a new methodological approach to empirically test which factors determine equilibrium asset prices, Berk and Van Binsbergen (2016) find that the Capital Asset Pricing Model would better explain how capital flows into and out of mutual funds. This result is puzzling given that empirical asset pricing tests based on cross-sectional returns favor multifactor models 'a la Fama and French (1993). In this paper, we focus on mutual funds managers' investment decisions instead of mutual funds investors' decisions. Using a structural model, we recover the factor risk premiums from observed fund managers' investment decisions, for a set of well published asset pricing models. We find that Fama and French (1993) expanded by the momentum factor of Carhart (1997), and the liquidity factor of Pástor and Stambaugh (2003), can explain the largest fraction of funds' investment decisions. Most notably, we also find that the macro-finance model a la Chen et al. (1986) is the one that best explains the observed mean-variance efficiency of the market portfolio. We reconcile this apparent paradox, by showing that factors that influence mutual fund managers' asset allocation decisions (eg. value-size investing) may not survive at the aggregate level.

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1 Introduction

In a recent paper, Berk and Van Binsbergen (2016) and Barber et al. (2016) use fund flows to identify the asset pricing model that can explains equilibrium expected returns. As noted by Berk and Van Binsbergen (2016): "The finding that investors' revealed preferences are most aligned with the CAPM despite the fact that the model has been shown to perform poorly relative to other models in explaining cross-sectional variation in expected returns, is an important puzzle for future research". In this paper we argue that this apparent inconsistency can be a consequence of managers and mutual funds' investors using different asset pricing models to determine their posterior beliefs. Moreover, we argue that the finding of managers using a more complex asset pricing model, than the one used by investors to measure the performance of their manager, is consistent with Jegadeesh and Mangipudi (2021).

The importance of studying traders' beliefs to understand financial markets is implicit in different theories of asset pricing. For example, Milgrom and Stokey (1982) show that, abstracting from investors' adjustments of risk return efficiency, trading has to be motivated by informational reasons related to investors' posterior beliefs formation.[1] Using a delegated asset pricing model, Cornell and Roll (2005) show that in order to understand equilibrium expected returns we need to focus on fund managers' beliefs, nor funds investors'.[2] Consequently, in this paper we study active mutual fund managers' beliefs' using a structural approach.

We focus on active mutual funds' asset allocation for two reasons. First, the relative importance of active funds in the stock market: they constitute 57% of the assets under management as of March 2017 (EPFR Global) and 95% of the trading volume (Vanguard). Second, Cremers and Petajisto (2009) suggest that mutual fund decisions are informative of equilibrium asset prices because there is a positive correlation between funds' active shares and fund performance. On the other hand, managers' choices are analyzed at industry level for three reasons. First, it is the most natural disaggregation of the market portfolio. Second, it allows us to be agnostic in term of the assets' characteristics that determine the asset menu, which might favor certain factors over another(Harvey et al., 2016; Daniel et al., 2012). Third, the empirical literature has recognized that mutual funds reallocate their portfolios across industries (Froot and Teo, 2008), industry-selection skill drives fund persistence in relative performance (Busse and Tong, 2012), and investment ability is concentrated among investors that hold portfolios concentrated in a few industries (Kacperczyk et al., 2005).

The analysis of mutual funds' portfolios is conducted through a simple general equilibrium model that can explain the heterogeneity of managers' holdings

[1] In recent times, the neoclassical asset pricing literature has acknowledged that in order to explain the amount of trading observed in financial market, a behavioral or an information friction is needed. Notable examples are Hong and Stein (2007) who show that heterogeneous priors can help to explain trading volume. Also, Daniel et al. (2001) show that investor overconfidence regarding their ability to identify mispricing can also explain trading behavior in the stock market.

[2] This explanation is closely related with the "marginal investor theory", Mayshar (1983).

by heterogeneous beliefs. In our model, funds allocation can be decomposed by beliefs coming from an asset pricing model (common information), and disagreement with respect to the predictions of this model (recovered investors' specific views).[3,4] The main advantage of having a general equilibrium model is that, under our assumption, our model can guide us to construct two criteria to compare the candidate asset pricing models. First, we study if a candidate asset pricing theory can produce beliefs from the Walrasian auctioneer perspective that are consistent with a market portfolio that is risk-return efficient. Therefore, taking the observed market portfolio weights, we can compare the candidate asset pricing models in terms of their implied mean-variance efficiency (Sharpe ratio). Second, to the extent that the implied risk premiums estimated from a candidate factor model contain relevant forward looking information about the stock market equilibrium. Candidate asset pricing models can also be compared in term of their ability to explain the dynamic of the equity risk premium across the business cycle. Finally, given that our procedure relies on a linear factor structure as a representation of the candidate asset pricing theory.[5] Our estimation can be performed by a simple cross-sectional regression of implied expected returns on conditional factor loadings, and for that reason our test can be seen as a microfounded version of Fama and MacBeth (1973).[6]

In estimating our model, the information structure is conditioned by well-known asset pricing theories that are going to add different information to the Capital Asset Pricing Model. A natural benchmark, given that mutual funds investors would be using it to measure performance of mutual funds. The additional factors considered are: size and value (Fama and French, 1993); investment and profitability (Fama and French, 2015); momentum (Carhart, 1997); liquidity (Pástor and Stambaugh, 2003); macro-finance (Chen et al., 1986).

Our results suggest that, consistent with a sophisticated view of mutual fund managers, professional investors would go beyond the CAPM to decide their asset allocation.7 Indeed, we find that the Fama and French (1993) expanded by the momentum factor of Carhart (1997) and the liquidity factor of Pástor and Stambaugh (2003)) is the factor model that can explain a larger fraction of the variance in the cross-section of portfolio weights. However, when asset pricing theories are compared by their ability to explain the observed risk-return trade-off at the market portfolio level, is the macro-finance model à la Chen et al. (1986) the one that produces the market portfolio with the highest implied Sharpe ratio. Interestingly, when we study why the macro-finance model produces a higher Sharpe ratio than, any of the other models, we find

[3]Back (2010) explains how to derive the stochastic discount factor in a heterogeneous priors model by simply taking a "Walrasian auctioneer" or "social planner" as a representative investor that has beliefs that are consistent with a weighted average of participants beliefs.

[4]In our model disagreement is related to perceived mispricing as in Black and Litterman (1991) or Levy et al. (2006).

[5]The assumption about the linear factor representation is innocuous in our case because, if the law of one price holds, we can always write a stochastic discount factor that is a linear combination of the factors (Kozak et al., 2018; Hansen and Jagannathan, 1991).

[6]The implied expected returns are recovered as in Black and Litterman (1991), however, instead of using the market portfolio weights we rely on managers' asset allocation.

that the market risk premium (e.g. the risk premium associated to the CAPM factor) is underestimated when macro-finance factors are omitted. This underestimation occurs mainly during the period before the dot-com bubble and after the Great Recession. On the other hand, the results of our out-of-sample test that compares asset pricing theories by their capacity to explain stock market fluctuations suggest that only the macro-finance model can track a model-free estimation of the Sharpe ratio of the market portfolio. The importance of this result stems from the fact that Chen et al. (1986) have a clear economic interpretation: market procyclicality, economic growth and inflation surprises, credit risk, and interest rate risk. Put simply, the most natural systematic risk factors proposed early by Chen et al. (1986) significantly outperform other factor models that consider risk factors that are difficult to interpret economically speaking.

The paper proceeds as follows: In the second section, we review the literature. The third section explains the structural model, as well as, the econometric challenge when connecting the model with the data. In the fourth section we describe our dataset. The fifth section presents the results and different robustness tests. The final section concludes.

2 Literature

This paper is related to four strands of the finance literature

The empirical asset pricing literature. This literature has mainly focus on identifying models with no asset pricing errors (α) in time-series regressions (Gibbons et al., 1989), or in testing for a positive and theoretically reasonable risk premium given assets' systematic exposure (Fama and MacBeth, 1973). Backed up by these methods, or variations of them, the number of factors went up from 1, aggregated wealth (CAPM) or consumption (CCAPM), to at least 316 factors.[7] In an effort to address the "factor zoo", new methodologies have been being proposed. For example, Harvey et al. (2016) proposed stricter statistical rules for the t-statistic of the traditional Fama and MacBeth (1973) two-stage test. Harvey (2017) proposes a minimum Bayes factor to deal with p-hacking. Feng et al. (2017) apply dimension-reduction techniques (double-selection LASSO) to run a Fama-Macbeth regression with 99 factors. Harvey and Liu (2016) and Fama and French (2016) modify the traditional multiple hypothesis test of Gibbons et al. (1989). Kan et al. (2013) derive the asymptotic distribution of the cross-sectional R^2 on expected returns to discriminate asset pricing models. We particularly follow the relatively new branch of this research agenda that uses new datasets to understand which asset pricing theory can explain equilibrium prices, such as fund flows (Berk and Van Binsbergen, 2016), morningstars rankings (Evans and Sun, 2021), and analysts' recommendations (Brav et al., 2005), to evaluate asset pricing theories. Specifically, we follow the recommendation of a structural approach in empirical asset pricing raised by

[7]Harvey et al. (2016) analyze 31 articles, 250 published, finding 316 different factors.

Kosak et al. (2017) where they claim that specic assumptions about investors beliefs and preferences have to be imposed.

The mutual fund literature that analyze asset management delegation and the value of active versus passive investing. As is well-known, Fama and French (2010) shed doubt on the value of active management from showing that only a small proportion of funds beat the market. While, Sharpe (1992) shows that a limited number of major market indices are required to successfully replicate the performance of an extensive universe of U.S. mutual funds. On the contrary, other studies defend the role of active mutual funds. Avramov and Wermers (2006) state that active management adds value showing that industries are important in locating outperforming mutual funds. Similarly, Kacperczyk et al. (2014) show that mutual funds stock picking or market timing ability fluctuates with the state of the economy.[8] Our methodology exploits active mutual portfolio choices because, regardless of how much consumer surplus extraction exists in the active management industry, they dedicate significant resources to price discovery as is shown by French (2008), and the empirical evidence that suggest that portfolios carry relevant information.In unpublished manuscripts Shumway et al. (2009); Yuan (2007) also use fund manager beliefs on expected stock returns using holdings data. For example, Froot and Teo (2008) find strong evidence of mutual funds reallocation across size, value/growth, and industry/sector portfolios. Busse and Tong (2012) find that the "industry selection" component of mutual funds represents roughly half of portfolios' risk adjusted returns. Kacperczyk et al. (2005) find that industry concentration of mutual funds is positively correlated with performance. Cremers and Petajisto (2009) find that funds with higher active share exhibit strong performance persistence. Therefore, we argue that our results reconcile the idea that investors can perceive value from passive investing because they are not very sophisticated, that in our case would be equivalent to invest in equities using the CAPM model instead of a more sophisticated multifactorial model.

This paper is also related to an incipient structural econometric literature that analyzes portfolio choice problems. Koijen and Yogo (2015) estimate a model with investor demand to illustrate how their model can be used to understand the role of institutions in asset market movements, volatility, and predictability. Koijen (2014) proposes a structural model that disentangle ability, incentives, and risk preferences of mutual fund managers, providing empirical evidence supporting the model's implications for the asymmetric flow-performance relationship. Castañeda and Devoto (2016) estimate a dynamic portfolio choice model for the case of Chilean pension funds, finding that pension fund managers are heavily motivated by relative performance. Branikas et al. (2017) propose and estimate a location choice model, typically used in urban economics, to analyze stock local bias and the performance of local stock picks.

Finally, this paper intends to shed light on the relationship between macroeconomics and asset pricing. The macro-finance literature has taken different

[8] Indeed Kacperczyk et al. (2016) suggest that skill can be linked to attention allocation.

approaches. First, a more structural analysis started with the equity risk premium puzzle of Mehra and Prescott (1985). The authors show that is difficult to reconcile the observed risk and return of the stock market with a reasonable calibrated Lucas (1978)-like model. Similarly, Breeden et al. (1989) rejects the Consumption CAPM. These papers motivated the study of new preferences, Benartzi and Thaler (1995), the inclusion of catastrophic risk in the stock market, Barro (2006), and the use heterogeneous agents models, Mankiw and Zeldes (1991). On the other hand, a reduced form approach have found weak responses of stock prices to macroeconomic news, Chen et al. (1986); Fama (1990); Schwert (1990); Campbell (1996). Nevertheless, other authors have argued that the failure of these tests could be more related with the availability of real-time macroeconomic indicators (Christoffersen et al., 2002; Savov, 2011), statistical adjustments of non-tradable factors (Allena, 2020) or other measurement problems related with time horizons of returns (Parker and Julliard, 2005). Consequently, a new macro-finance research agenda has been proposed by Cochrane (2017).

3 Methodology

3.1 Model

In this section we propose a simple general equilibrium model with heterogeneous priors along the lines of Levy et al. (2006). Investors decide their portfolio according to mean-variance preferences:[9].

$$\begin{aligned} \max_{w_i} \qquad & w_i^\intercal \mu_i - \frac{1}{2}\gamma w_{i,t}^\intercal \Sigma w_i \\ \text{subject to} \qquad & \sum_{l=1}^{L} w_l = 1 \end{aligned} \tag{1}$$

where the portfolio weights of manager i are contained in the Lx1 vector w_i, γ is investor's risk aversion parameter, and Σ is the variance-covariance matrix of the investable assets returns'.

In the presence of a risk-free asset that yields (r_f), the portfolio choice problem has a well-known solution:

$$w_i^* = \frac{1}{\gamma}\Sigma^{-1}(\mu_i - r_f 1) \tag{2}$$

Intuitively, the behavioral model above predicts that an active fund manager i, with risk aversion γ, would invest in a diversified portfolio (w_i) that overweight stocks that have higher risk adjusted returns, in a consistent way with its own

[9]The preference assumption can be justified either by the neuroscience literature that suggests that observed behavior with respect to decision under risk can be reconcile with mean-variance preferences. Or can be seen as a practical simplification given that hedging demands in dynamic portfolio choice problems are small (Ang and Bekaert (2002), Aïtsahali and Brandt (2001), and Brandt (2010)))

beliefs ($\mathcal{B}_i$). The fund manager i forms its expectations about the risk and return of investing in the different investable assets (μ_i and Σ_i) from the information set I. The information set contains the historical returns of the investable assets, as well as, the history of the K state variables included in the linear factor model (M) that endogenously price the assets.[10]. Consequently, following Pástor and Stambaugh (2002) beliefs in this economy are formed by a combination of an asset pricing model and disagreement with respect to the model, as follows:

$$\begin{aligned} E_{i,M}[r] = \mu_i &= r_f 1 + \alpha_i + \beta_M \pi_M \\ \Sigma_M &= \beta_M \Sigma_{f,M} \beta_M + \Sigma_{\epsilon,M} \end{aligned} \tag{3}$$

where $\beta_N \pi_M$ measures the risk premiums associated to systematic factors that belong to model M. Matrices $\Sigma_{f,M}$ and $\Sigma_{\epsilon,M}$ measure the systematic risk implicit in the asset pricing model M and the estimated assets' idiosyncratic risk, respectively. Disagreement in this market arises from α_i, which is a vector that summarizes investors own perceived mispricing. The idea is to capture disagreement about the mispricing across asset prices as in Black and Litterman (1991), where mispricing emerges from managers' disagreement with the prediction of an asset pricing model. As we can see, in our model mispricing is exogenously parametrized as in Levy et al. (2006). This specification is flexible enough to allow for differences in beliefs that arise from heterogeneous private information, partial informativeness of prices, differential interpretation of the same information, or overconfidence.

The market structure described above determines the following financial market equilibrium:

$$\begin{aligned} \sum_{i=1}^{I} w_i^* \omega_i &= \frac{p \cdot q}{\sum_{i=1}^{L} p q_i} \\ \sum_{i=1}^{I} \frac{1}{\gamma} \Sigma^{-1} \Big(\mu_i - r_f 1 \Big) \omega_i &= \frac{p \cdot q}{\sum_{i=1}^{L} p q_i} \\ \frac{1}{\gamma} \Sigma^{-1} \Big(\alpha + \beta_M \pi_M \Big) &= \frac{p \cdot q}{\sum_{i=1}^{L} p q_i} = \hat{w} \end{aligned} \tag{4}$$

where $\sum_{i=1}^{L} p_i q_i$ and $\hat{w}$ are the total market capitalization, which is equal to the sum product between asset prices (p) and the supply of assets (q), and the market weights of the assets, respectively. As we can see, the left hand side of Equation (4) is a well-known result in the heterogeneous belief literature, . Market weights ($\hat{w}$) are equivalent to the optimal portfolio choice of the representative investor or the Walrasian auctioneer with consensus expected returns: expectations derived from the asset pricing model ($\beta \pi_M$) plus a weighted aver-

[10] Assuming a factor model as the source of expected returns in an asset pricing model is a sufficient condition. Since the Fundamental Theorem of Asset Pricing is known that a general equilibrium model of financial markets can be approximated by a factor model (Dybvig and Ross, 2003)

age of managers' specific views (α). The Lx1 vector α contains the consensus mispricing of assets in the economy ($\alpha_l = \sum_{i=1}^{I} \alpha_{l,i}\omega_i$).[11]

Under the assumption that rational expectations hold from the Walrasian auctioneer perspective, the following condition has to hold:

$$\alpha^{\intercal}\alpha = 0$$

The condition above is equivalent to assume that there no-arbitrage opportunities in this economy. Managers' own opinions about the expected returns cancel-out as if managers agree-to-disagree. The factor model, or the "common information", is what price the assets, as in Burnside (2016) methodology to identify the linear stochastic discount factor. Managers' own views do not survive in the aggregate.

We can see that in the studied equilibrium there is an endogenous relationship between assets' risk premiums ($\mu - r_f 1$), assets' total risk ($\Sigma_{f,M}$ and $\Sigma_{\epsilon,M}$), preferences over risk (γ) and market portfolio allocations ($\hat{w}$). Consequently, as in the classical Asset Pricing Theory, risk premiums can be written as a function of factor loadings (β_M) and systematic risk compensations (π_M):

$$\mu - r_f 1 = \gamma\Big(\Sigma_f + \Sigma_\epsilon\Big)\hat{w} \approx \beta\pi_M \tag{5}$$

Finally, the market price of risk can be measured by the Sharpe ratio, which can be written as follows:

$$SR(\hat{w}) = \sqrt{(\mu_M - r_f 1)^T \Sigma_M^{-1}(\mu_M - r_f 1)} \tag{6}$$

3.2 Econometric Problem

In this section we describe our methodology to test which asset pricing model is consistent with the financial market equilibrium described above. Specifically, we propose a two-stage approach. In the first stage, we estimate the latent variables that would be used by portfolio managers at the moment of taking asset allocation decisions. First, we estimate the conditional factor loadings ($\beta_{M,t}$) via Kalman filter as in Adrian and Franzoni (2009). Implicitly, we assume that managers learn about the risk exposure of the assets in a Bayesian way. The statistical model consist of a maximum likelihood estimation of a linear model that relates assets' excess of return and risk factors, where factor loadings ($\beta_{M,t}$), as well as, pricing errors ($c_{M,t}$) follow an AR(1) process:

$$r_{j,t} - r_{f,t} = c_{j,M,t} + \beta_{j,M,t} f_{t,M} + u_{j,t} \tag{7}$$

$$\beta_{j,M,t} = \omega_1 + \beta_{j,M,t-1} + v_{j,t} \tag{8}$$

$$c_{j,M,t} = \omega_2 + \lambda_{j,M,t-1} + \epsilon_{j,t} \tag{9}$$

[11] For a textbook exposition on asset pricing models with heterogenous priors see Back (2010). Gollier and Zeckhauser (2005) refer to the aggregation of individual expectations as consensus beliefs.

where $r_{j,t} - r_{f,t}$ is the excess of return of asset j, $c_{j,M,t}$ is asset j pricing error under model M at time t, $\beta_{j,M,t}$ is asset's j factor loading associated with model M at time t, $f_{t,M}$ describes the evolution of factors under model M at time t, and u, v and ϵ are iid normally distributed error terms.

Second, given the estimated conditional factor loadings, we obtain time-series of assets' idiosyncratic returns by model (M), as follows:

$$u_{j,t,M} = r_t - r_{f,t} - \beta_{M,t} f_{t,M} \tag{10}$$

Based on idiosyncratic returns time-series, we obtain the conditional variance-covariance matrix of idiosyncratic returns ($\Sigma_{\epsilon,M,t}$) from a Multivariate ARCH(1) without conditioning variables in the mean, following Engle (2002) econometric implementation.

Third, the conditional variance-covariance matrix of factors $\Sigma_{f,M,t}$ is estimated using a Multivariate GARCH(1,1) without conditioning variables in the mean, as in Bauwens et al. (2006)).

Combining the estimated conditional factor loadings ($\beta_{M,t}$), conditional variance-covariance matrix of factors ($\Sigma_{f,M,t}$), and the conditional variance-covariance matrix of idiosyncratic returns ($\Sigma_{\epsilon,M,t}$), as in Equation 3. We elicit implied expected returns as in Black and Litterman (1991), such that:[12]

$$\mu_{i,M,t} = r_{f,t} 1 + \Sigma_{M,t} w_{i,t} \tag{11}$$

This transformation is a direct consequence of reverse engineering the solution of managers' asset allocation problem. Given the conditional variance-covariance matrix of assets ($\Sigma_{M,t}$), the observed risk free rate (r_f, t), a normalized risk aversion level (γ) fixed to 1, and manager's i observed asset allocation ($w_{j,t}$).[13]

In the second stage, implied expected returns ($\mu_{i,M,t}$) are disentangled by the predictions of a candidate factor model M plus managers' specific views. The following OLS regression recovers a projection of the factors onto the cross-section of implied expected returns, under a candidate asset pricing model (M):

$$\mu_{t,M} = \beta_{M,t} \widetilde{\pi}_{M,t} + \alpha_{t,M} \tag{12}$$

where $\mu_{t,M}$ is a stacked vector of implied expected returns of managers, calculated under an asset pricing model M; $\widetilde{\pi}_{M,t}$ is a vector that contains estimated consensus risk premiums associated to risk factors embedded in a specific asset pricing model M; $\beta_{M,t}$ is a matrix of conditional factor loadings; $\alpha_{t,M}$ is a stacked vector that contains the "structural errors" that rationalize managers'

[12] The main difference between our approach and Black and Litterman (1991) is that we use manager i observed asset allocation ($w_{j,t}$) at time t instead of the market portfolio weights ($\hat{w}_t$).

[13] Assuming an arbitrary risk aversion parameter is innocuous for our test, given that it could only affect the level of the risk premiums while not the relative differences across the candidate models.

observed decisions given our behavioral assumptions.[14] The OLS estimation implicitly imposes the no-arbitrage condition ($E[\alpha_{t,M} = 0]$), in other words, the estimated implied risk premiums will be such that deviations from the candidate asset pricing model cancel out. As we can see, the proposed test is a microfounded version of the two-pass cross-sectional regression of Fama and MacBeth (1973), such that the dependent variable are implied expected returns instead of realized returns, which allow us to estimate implied risk premiums for different candidate asset pricing models.

3.3 Candidate Asset Pricing Models

We focus on a set of seven reduced form factor models that are important in the empirical asset pricing literature, covering a broad class of theories that intend to explain asset prices: i) CAPM; ii) Fama and French Three Factor Model, Fama and French (1993), FF3; iii) Fama and French Five Factor Model, Fama and French (2015); iv) Fama and French Three Factor Model with momentum, Carhart (1997), FF3 MOM; v) Fama and French Three Factor Model with Pástor and Stambaugh (2003) liquidity factor, FF3 LIQ; vi) Fama and French Three Factor Model with momentum and liquidity factors, FF3 MOM LIQ; vii) An adaptation of the Macro-Finance model of Chen et al. (1986). The risk factors included in the different evaluated models proxy for the following systematic factors that determine asset prices:

1. The market factor (MRP) of the Capital Asset Pricing Model (CAPM) is a natural benchmark. Either matters because of mutual funds' performance measurement reasons, or because it proxy for the aggregated wealth in the economy. Consequently is used in all the evaluated factor models.

2. The size (SMB) and value (HML) factors of Fama and French (1993). Vassalou (2003) suggests that SMB and HML factors contain information related to future GDP growth.

3. The investment (CMA) and profitability (RMW) factors of Fama and French (2015). These factors are important in production based asset pricing models a la Hou et al. (2015).

4. The liquidity factor (LIQ) of Pástor and Stambaugh (2003). Liquidity as a systematic factor in general equilibrium asset pricing models has been mainly related with solvency constraints (Chien and Lustig, 2009), corporations' desire to hoard liquidity (Holmström and Tirole, 2001), and flight to liquidity (Acharya and Pedersen, 2005).

5. The momentum factor (MOM) of Carhart (1997). Momentum has been mainly related with slow information diffusion (Hong and Stein, 1999), or sentiment (Barberis et al., 1998).

[14] The concept of structural error comes from Rust (1987), and is defined by an unobservable (for the econometrician) component of preferences that explain why agents make different choices given the same observables.

6. The macro-finance risk factors proposed by Chen et al. (1986). A growth expectation factor (ExpGrowth), an inflation expectation factor (ExpInfl), a term premium factor (TermPrem), and a credit risk factor (CredRisk). Chen et al. (1986) rationale behind the inclusion of these factors is mainly related with discounted cash flow valuation. For example, cash flow forecasting are captured by economic growth and inflation expectations, and the discount rate is based on market risk, credit risk, and term premium.

3.4 Horse Race of Asset Pricing Models

After estimating our model conditioning on different factor models, the question is, how to evaluate the financial economic validity of a candidate asset pricing model? As has been noted by Jagannathan and Wang (1998), Kan and Zhang (1999) and Lewellen et al. (2010), model comparisons based on the cross-sectional goodness of fit (e.g. the R^2s of Equation 12) of a specific candidate model is problematic if "useless" factors are included, or due to omitted-variable bias.[15] While our estimates suffer from the same potential biases of traditional cross-sectional regressions that use historical returns, we argue that in our setting there is a clear reason of why a higher cross-sectional R^2 is not indicative of the probability of a model being the true asset pricing model that determines equilibrium prices. In our framework, a higher R^2 is indicative of a higher degree of explanatory power of the cross-section of managers investment decisions. However, explaining managers asset allocation better is not necessarily related with understanding the risk premiums required by the Walrasian auctioneer at the aggregate level because trading that is motivated by information which managers agree-to-disagree would cancel-out in the general equilibrium. In other words, in the equilibrium condition presented in Equation (4) we can think about a risk factor that is not included in the factor model (e.g. momentum or liquidity) that can be a source of disagreement about the mispricing of a certain asset, which can explain managers asset allocation but has not influence on equilibrium asset prices. In conclusion, we argue that the R^2 is problematic as an asset pricing criteria, as it does not allow us to differentiate between systematic versus idiosyncratic risks, both important determinants of investment decisions, but not necessarily of equilibrium prices. Consequently, we propose the following two criteria to compare candidate asset pricing models, which are guided by our general equilibrium setting:

1. The maximum implied Sharpe Ratio of the market portfolio: As we have shown in Equation 4, a fundamental general equilibrium condition in our model is that the market portfolio, or the portfolio that holds the Walrasian auctioneer, has to be mean-variance efficient. Thankfully, as under our structural assumptions is well-known that the market price of risk can be simply measured by the Sharpe ratio. In our setting the scientific search of the asset pricing model that explains equilibrium returns can

[15] Sala-i Martin (1997) discusses a similar problem in his study of the causal drivers of economic growth across countries.

focus on the factor model that maximizes Equation 6, which is equivalent to find a factor model can eliminate the evidence of aggregated mispricing (α) as in Gibbons et al. (1989).[16]

The procedure to estimate the implied Sharpe ratio of the aggregated market portfolio is the following. First, we estimate the expected return of the aggregated stock market from the perspective of the representative investor, abstracting from managers' own views (α), or as if only systematic risks are priced:

$$E[R]_{t,M} = \hat{w}_t{}^{\intercal} \beta_{M,t} \widetilde{f}_{M,t} \tag{14}$$

where $E[R]_{t,M}$ is the expected return of the aggregated market at time t under the estimated asset pricing model M; $\hat{w}$ is a vector that contains the observed market sector weights at time t.

Second, we estimate the volatility of the aggregated market as:

$$\sigma[R]_{t,M} = \sqrt{\hat{w}_t{}^{\intercal} \Sigma_{M,t} \hat{w}_t} \tag{15}$$

The ex-ante Sharpe ratio under model M is calculated as:

$$SR_{t,M} = \frac{E[R]_{t,M} - r_{f,t}}{\sigma[R]_{t,M}} \tag{16}$$

Finally, the statistical evaluation of the candidate asset pricing model is trough a simple mean test of the Sharpe ratio time-series by model. Specifically, we test if there is a model that can produce a statistically higher Sharpe ratio than the rest.

2. The second quantifiable criteria is based on the evaluation of the explanatory value of the information captured by the implied risk premiums recovered by different asset pricing models. We specifically focus on the ability to track a model-free measure of the market portfolio Sharpe ratio constructed using historical returns of the market portfolio only. This model-free estimation is constructed combining the following estimates:

    (a) The dynamic of the excess of return of the market portfolio is estimated from the trend component of observed monthly excess returns of the market portfolio ($E[R]_{t,\tau}$) obtained via the Hodrick-Prescott filter.

[16] Gibbons et al. (1989) show that testing for mispricing, measured from the constants of time-series factor regressions, is related with the maximum Sharpe ratio attainable by the test assets (SR^{*}), trough the following relation:

$$\hat{\alpha}^{\intercal} \hat{\Sigma_{\epsilon}} \hat{\alpha} = SR^{*2} - SR^{M2} \tag{13}$$

where SR^{M} is the Sharpe ratio under a factor model M, and $\hat{\Sigma_{\epsilon}}$ is the estimated variance-covariance matrix of idiosyncratic returns.

(b) The dynamic of the volatility of the market portfolio is estimated from the conditional volatility of a fitted GARCH(1,1) process ($\sigma[R]_t^*$).

The model-free ex-ante Sharpe ratio is constructed as follows:

$$SR_{t,\tau} = \frac{E[R]_{t,\tau}}{\sigma[R]_t^*} \tag{17}$$

Finally, the statistical test consist in rejecting if the mean of the estimated Sharpe ratio under model M is equal to the model-free estimation.

4 Data and Summary Statistics

Data used in this paper come from a sample of U.S. equity active mutual funds constructed following Koijen (2014) criteria. Specifically, we use Thomson CDA S12 Mutual Fund Holdings Database, linking it with CRSP Mutual Fund Database using MFLINKS, following Wermers (2000). This allows us to construct a panel database that contains holdings at quarterly/semi-annual frequency, and monthly returns, as well as, other fund level information, such as: portfolio manager identifier, date at which the manager joined the fund, and fees.

We calcualte sector breackdowns by mutual fund aggregating holding data at sector level following the equivalency between SIC codes and GICS sectors proposed by Bhojraj et al. (2003).[17] [18]

The factors that characterize different asset pricing theories, and the historical observed risk free rate, are obtained from different sources. First, from Prof. Kenneth French website we obtain monthly the CAPM market factor, the Fama-French factors, and the momentum factor for the period 1964-2016. The liquidity factor is obtained from Lubos Pastor's website in a monthly frequency for the period 1962-2016. Third, we construct the macro-finance factors. The growth expectation factor (ExpGrowth) is constructed using the first principal component of the University of Michigan Consumer Sentiment Index and the Philadelphia Fed Business Outlook Survey Diffusion Index of General Conditions for the period 1980-2016, which are the activity variables that capture more attention by Bloomberg Terminal users. Following the same criteria of Bloomberg attention, the inflation expectation factor (ExpInfl) is measured by the Conference Board Consumer Confidence Inflation Rate Expectation 12m. The term premium factor (TermPrem) is constructed as the excess of return of the Barclays U.S. Treasury index and a 3-month T-Bills portfolio. The credit

[17] We use the 10 Global Industry Classification Standard (GICS) sectors, a classification widely used by practitioners: Energy, Materials, Industrials, Consumer Discretionary, Consumer Staples, Healthcare, Financials, Information Technology, Telecommunication Services, and Utilities.

[18] We evaluate the quality of the mapping based on sectors comparing the returns of the sector mapped portfolio to their actual return. The mapped portfolio returns overestimate mutual fund gross returns by 16 basis points monthly on average, which is close to the average 2% annual fees. While the contemporaneous correlation is 0.893.

factor (CredRisk) is constructed as the excess of return of the BofA Merrill Lynch US Cash Pay High Yield index and Barclays U.S. Corporate Investment Grade index.[19]

In Table 1, summary statistics of the historical returns of Datastream sector benchmarks is presented. The sector with the highest (lowest) return during the analyzed period is Consumer Staples (Telecom). In term of risk, the sector with the highest (lowest) volatility is IT (Utilities).

In Table 2, summary statistics of the historical evolution of the tradable and non-tradable factors are presented. The non-tradable factors are measured in a different scale, as these are not based on mimicking portfolios but are based on the leading indicators described above.

In Table 3-6, summary statistics of the conditional factor loadings obtained from the proposed Kalman Filter estimation by sectors and asset pricing models. As we can see, on average, betas associated to the same risk factor and sector across models are relatively similar. On the other hand, we can see that conditional betas of some sectors are significantly more volatile than others. For example, while the market beta is constant for Industrial, the standard deviation relative to the unconditional mean for IT's varies between 16-26%. One of the problems of presenting the factor loadings in this way is the comparability of the estimated effect of an unexpected change in the risk factor on sectors returns. This comparability problem comes from the difference in the magnitudes of non-tradable factors (inflation and GDP growth risk), as well as, its variability over time. For example, the momentum factor (MOM) is 3.7 times more volatile than the term premium risk (TermPrem). Therefore, in Table 7-10 we present the standardized estimates based on the historical standard deviation of the risk factor, and the conditional betas. As we can see, based on a comparable unexpected change of the risk factor, the market risk premium explains a higher proportion of cross-section of sector returns.

In Table 11, summary statistics of the sector portfolio weights of the analyzed active mutual funds are documented. The most (least) important sector in the sample, measured by average historical mutual fund allocation is Consumer Discretionary (Telecom). The allocation in the Consumer Discretionary sector is the most variable of the sample, while Financials' is the least dispersed. In Table 12 a comparable table is constructed from the historical aggregated market capitalization of sectors.

5 Results

In this section we start documenting the estimates related to the relevant state variables needed to estimate our model. First, in Table 3-6, we present a summary statistics of the conditional factor loadings from Equation 7 by sectors and asset pricing models. As we can see, on average, betas associated to the same

[19]In the Appendix 8.1, an exploratory data analysis for the constructed non-tradable factors, economic growth expectations and inflation, is documented. Importantly, we show that we can reject non-stationarity in both cases.

risk factor and sector across models are relatively similar. On the other hand, we can see that conditional betas of some sectors are significantly more volatile than others. For example, while the market beta is constant for Industrial, the standard deviation relative to the unconditional mean for IT's varies between 16-26%. One of the problems of presenting the factor loadings in this way is the comparability of the estimated effect of an unexpected change in the risk factor on sectors returns. This comparability problem comes from the difference in the magnitudes of non-tradable factors (inflation and GDP growth risk), as well as, its variability over time. For example, the momentum factor (MOM) is 3.7 times more volatile than the term premium risk (TermPrem). Therefore, in Table 7-10 we present the standardized estimates based on the historical standard deviation of the risk factor, and the conditional betas. As we can see, based on a comparable unexpected change of the risk factor, the market risk premium explains a higher proportion of cross-section of sector returns.

In Table 13 we report the historical means of the sector conditional volatilities by asset pricing model. These are obtained from the diagonal of the variance-covariance matrix of returns by model calculated by Equation 3. The differences with respect to the CAPM estimation vary from -49 basis points for Consumer Discretionary under CRR to +11 basis points for Telecom under FF3 MOM LIQ. In addition, the relative mean absolute difference (RMD) is calculated by asset pricing model. The differences in the estimated volatilities are small, the CRR model produces volatilities with absolute differences (RMD) that are smaller than 8%. On the other hand, Figure 2 presents a correlation analysis of the sectors by asset pricing model. Based on a visual inspection of the correlations, we can see that different asset pricing models estimate similar cross correlations across sectors. Finally, in Table 14 we compare the conditional volatility of the residuals obtained from Equation 10. The differences of the estimated idiosyncratic risk, taking the CAPM as a base, vary from -112 basis points for IT under FF3 MOM LIQ to +15 basis points Materials under CRR.

Taking the estimates presented above, we compute Equation 11 to obtain the implied expected returns by manager. In Table 15-20. As we can see, the implied expected returns that uniquely determine the observed allocation are relatively similar across the different asset pricing models due to the small differences in the variance-covariance matrices under the different candidate models.

Combining the implied expected returns and time-varying factor loadings, we run the cross-sectional regression presented in Equation 12. In Table 23 we document the risk premium estimates by asset pricing model. As we can see, on average, the slopes associated to the same risk factors across asset pricing models are similar. However, the standard deviation of the estimates suggest that conditional expectations of the risk premiums vary significantly over time. The time variation of the estimates is better illustrated in Figure 3-13. Interestingly, a visual inspection of the estimates, suggest that expected risk premiums follow a dynamic that is related to the business cycle. A second important feature of the estimates, is the time-variation of the disagreement across models. For example, Figure 3 suggests that the estimation of the conditional expectation of the market risk premium under the CAPM or the Macro-Finance model diverges mainly during the early 90's and after the Great Recession. Importantly, our results signal that the estimated market risk premium is being underestimated by the regressions when macro-finance factors are omitted. This is consistent with macro-finance factors carrying relevant information that is not contained in other factors regarding equilibrium asset prices, that also correlates with the market portfolio returns.

As we can see, the ability of a specific asset pricing model to explain the asset allocation decisions of mutual funds managers can be evaluated from comparing the cross-sectional R^2s under different estimated models. In Table 24 summary statistics of the time-series of the cross-sectional R^2s are documented. As we can see, consistently with a sophisticated view of mutual funds managers suggested by McLean and Pontiff (2016), they would be using multiple factors into consideration to take investment decisions. Specifically, the CAPM expanded by value-size, momentum, and liquidity factors, is the factor model that explains a high proportion of the variance of the cross-section of implied expected returns, and consequently of managers' decisions. [20]

Since the goodness of fit between the implied expected returns and the factors related to an asset pricing model is not necessarily indicative of its ability to produce a stochastic discount factor that is consistent with the analyzed market equilibrium. In Table 26 we report the estimates for the first criterion to analyze the validity of a factor model. The Table 26 reports the ex-ante Sharpe ratio of the aggregated market portfolio implied by different asset pricing models. Interestingly, we can see that the Macro-Finance model is the one that produces the highest Sharpe ratio, followed by the CAPM.[21] Moreover, Figure 15 confirms the idea that macro-finance factors contain relevant information about the dynamics of the risk-return trade-off of investing in the stock market. On the other hand, when we compare models based on their ability to capture relevant information about the stock market equilibrium. We find that the Macro-Finance model can produce an implied ex-ante Sharpe ratio that tracks significantly better our proposed model-free time-varying Sharpe ratio. From this analysis two important results can be highlighted. First, the correlation between the Macro-Finance Sharpe ratio and its empirical counterpart is 0.73, which compares with a 0.09 for the CAPM (the second highest). Moreover, based on a mean test between model implied Sharpe ratio versus its model-free counterpart, the only model that cannot be rejected is the Macro-Finance model. These results are consistent with the idea of macrofinancial conditions play an important role at determining equilibrium asset prices, while value-size ratios, liquidity and momentum are mainly related to disagreement across stock market investors.

Finally, we analyze the empirical validity of our results from two different perspectives. First, in Figure 16, 17 and 18, we present a residual analysis of the Macro-Finance structural errors, versus the CAPM and FF3 MOM LIQ models

[20]The mean test presented in Table 25 suggests that FF3 MOM LIQ explains a statistically higher proportion of implied expected returns than the CAPM and CRR models.

[21]The difference in means is statistically significant at 1%.

(e.g. the residuals of Equation 12). In other words, we plot non-parametric kernel distributions of the cross-sectional deviations from the asset pricing models by sector. As we can see, most of the managers' expectations would not deviate much of the expected returns predicted by the CAPM or FF3 MOM LIQ. This is inconsistent with the evidence of a large number of investors disagreeing about stocks valuations presented by Cookson and Niessner (2020). On the contrary, the distribution of cross-sectional disagreement produced by the Macro-Finance model are consistent with more managers disagreeing with the expected returns predicted by the Macro-Finance model.Statistically, the Macro-Finance model is the only that is closer to not be rejected by a multivariate normal test (results not reported). Second, in Table 27 the results of traditional time-series factor regressions for the utilized industry portfolios are documented. As we can see, during the analyzed time period, the Macro-Finance model is the only factor model that can produce non-statistically significant mispricing at 95% confidence level, when industries are studied independently.

6 Discussion

In this section, we discuss the potential broader implications of our results. We first relate our findings with Barber et al. (2016); Berk and Van Binsbergen (2016). These two papers provide evidence that is consistent with the idea of mutual fund investors using the CAPM to take their mutual fund investment decisions. Specifically, the authors show that a positive (negative) performance measure based on the CAPM is better related, than other asset pricing models, with fund inflows (outflows). This result raises a puzzle, as Berk and Van Binsbergen (2016) points out that: "The finding that investors' revealed preferences are most aligned with the CAPM despite the fact that the model has been shown to perform poorly relative to other models in explaining cross-sectional variation in expected returns, is an important puzzle for future research". In the rest of this section, we will argue that the apparent inconsistency between the asset pricing model that matters for managers and investors, is consistent with the delegated asset pricing model of Cornell and Roll (2005), which predicts that if investment decisions are delegated, the preferences and beliefs of individuals would be completely superseded by managers'.[22]. Moreover, we argue that the finding of managers using a more complex asset pricing model, than the one that investors use to measure the performance of their managers, is directly related with the functioning of the asset management industry. Being plausible, that this informational advantage, is an important reason behind investors delegating their asset management.

In Table 28, we report the differences in ex-ante and ex-post expected utility of a mean-variance investor that uses a different model than the CAPM to construct her asset allocation. The results take into account short-sale constraints, and a risk aversion of 1. Optimal portfolios are constructed using the beliefs derived from standard in-sample estimates of the evaluated asset pricing models

[22]This explanation is closely related with the "marginal investor theory", Mayshar (1983).

during the period Aug-87 to Dec-15. Such that, expected returns of the assets, and the variance-covariance matrix are estimated as follows:

$$E[r] = \mu = r_f 1 + \beta\mu_f$$
$$\Sigma = \beta\Sigma_f\beta + \Sigma_\epsilon$$

where β is a matrix that contains the betas of individual time-series regressions by factor model; r_f is the average historical risk-free return; μ_f is a vector that contains the in-sample mean of the factors; Σ_f is the in-sample variance-covariance of the factors; Σ_ϵ is the in-sample variance-covariance of the residuals. As we can see in the Table 28, the annualized ex-ante or ex-post gains from using different asset pricing models are similar to the 0.5%-1% annual fees that charge most of the active mutual funds in the US. In other words, when we empirically see that managers aggregate zero value after fees, Fama and French (2010), this can be interpreted as evidence of managers extracting all consumer surplus, as in Berk and Green (2004). In other words, mutual fund investors pay for the additional value that managers add from taking into account additional factors that explain expected returns: macro-finance conditions, size, book-to-market, liquidity and momentum.

7 Conclusion

This paper proposes a new methodology to compare well known asset pricing models based on a structurally estimated financial market model that exploits observable active mutual funds asset allocation. Our method intends to isolate the combination of information and noise that we measure from time-series returns (Black, 1986). Consequently, our methodology produces risk premium estimates that are more stable than the ones produced by traditional cross-sectional regressions based on historical returns. Which allows us to distinguish the relevant systematic risk factors that determine the financial market equilibrium, or the so-called stochastic discount factor.

We find that active mutual fund managers observed asset allocation can be rationalized by beliefs that are formed by a combination of asset pricing theories. On the one hand, the macro-finance factors proposed by Chen et al. (1986) are the ones that would determine equilibrium returns. On the other hand, the size and value factors of Fama and French (1992), the liquidity factor of Pástor and Stambaugh (2003), and the momentum factor of Carhart (1997), appear to contain information that explains managers disagreement.

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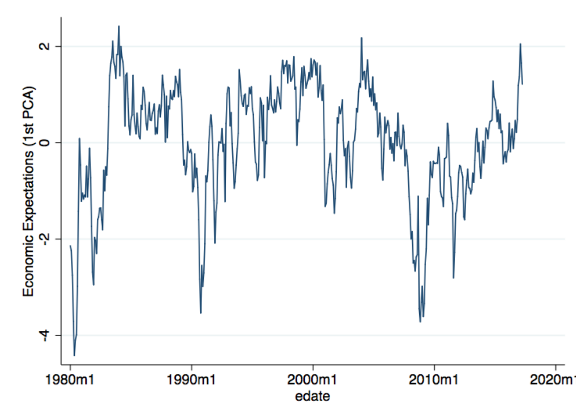
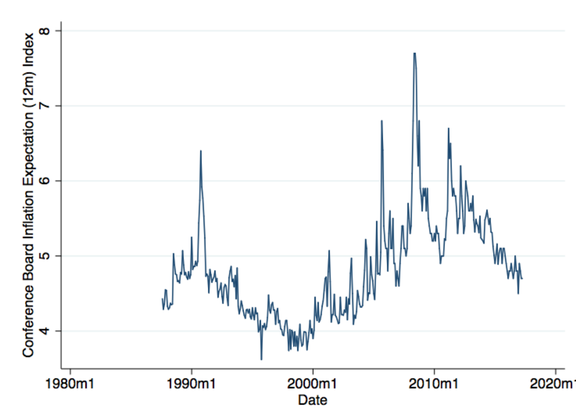
8 Appendix

8.1 Exploratory Analysis: Non-tradable factors

Given the potential concerns with respect to the construction of the adaptation of Chen et al. (1986), CRR. In this section we present the main properties of the non-tradable factors, as they use different information to the one that has been used in the past. As it was mentioned, the main reason to use the University of Michigan Consumer Sentiment Index and the Philadelphia Fed Business Outlook Survey Diffusion Index of General Conditions, in the measurement of economic activity, and the Conference Board Consumer Confidence Inflation Rate Expectation 12m, is the popularity that they have among Bloomberg Terminal users, which are professional traders or fund managers. Given that real-time indexes of economic expectations are divided by households and business, we obtain the first principal component of these two time-series, which explains 74% of the total variance. In Figure 1 the historical evolution of the factors is presented. One potential technical concern when using non-tradable factors is the potential non-stationarity of the time-series. Therefore, we test for the presence of unit root using a traditional Dickey-Fuller. In both cases the null-hypothesis is easily rejected with a MacKinnon approximate p-value lower than 1%.



((a)) Economic Factor



((b)) Inflation Factor

Figure 1: Non-Tradable Factors

8.2 Hodrick-Prescott Filter

The Hodrick-Prescott filter decomposes time-series (y_t) into a trend (τ_t) plus a cyclical component (cy_t).

$$\underset{\tau_t}{\text{minimize}} \quad \sum_{n=1}^{T}(y_t - \tau_t)^2 + \lambda \sum_{n=2}^{T-1}((\tau_{t+1} - \tau_t) - (\tau_t - \tau_{t-1}))^2$$

where the smoothing parameter λ is set fixed to a value. The parameter λ is fixed using Ravn–Uhlig rule, which set $\lambda = 1600p_q^4$, where p_q is the number of period per quarter.

Table 1: Summary Statistics of Sector Indices Returns

Sector	Time Period	N	Mean	Std. Dev.	Median	P25	P75
Consumer Discretionary	Mar-75 / Mar-16	493	1.07%	5.12%	1.09%	-7.25%	9.61%
Consumer Staples	Mar-75 / Mar-16	493	1.20%	4.14%	1.26%	-5.63%	7.61%
Energy	Mar-75 / Mar-16	493	1.07%	5.51%	1.02%	-8.39%	9.73%
Financials	Mar-75 / Mar-16	493	1.10%	5.48%	1.41%	-7.74%	9.42%
Healthcare	Mar-75 / Mar-16	493	1.14%	4.32%	1.35%	-6.31%	7.79%
IT	Mar-75 / Mar-16	493	1.11%	6.76%	1.08%	-9.48%	12.55%
Industrials	Mar-75 / Mar-16	493	1.13%	5.26%	1.43%	-6.88%	9.34%
Materials	Mar-75 / Mar-16	493	1.00%	6.13%	0.87%	-8.77%	11.04%
Telecom	Mar-75 / Mar-16	493	0.95%	5.08%	1.20%	-8.28%	8.52%
Utilities	Mar-75 / Mar-16	493	1.00%	4.10%	1.26%	-5.69%	7.05%

Note: This table documents summary statistics of the historical returns of the 10 Global Industry Classification Standard (GICS) indices.

Table 2: Summary Statistics of Risk Factor time-series

Factors	Time Period	N	Mean	Std. Dev.	Median	P5	P95
MRP	Jul-26 / Dec-16	1086	0.65%	5.37%	1.00%	-7.89%	7.34%
SMB	Jul-26 / Dec-16	1086	0.21%	3.21%	0.08%	-4.22%	4.84%
HML	Jul-26 / Dec-16	1086	0.40%	3.50%	0.20%	-4.21%	5.54%
MOM	Jan-27 / Feb-17	1082	0.66%	4.73%	0.84%	-5.91%	6.54%
LIQ	Jan-68 / Dec-15	576	0.42%	3.51%	0.22%	-5.23%	6.07%
RMW	Jul-63 / Dec-16	642	0.24%	2.23%	-2.90%	0.22%	3.35%
CMA	Jul-63 / Dec-16	642	0.31%	2.01%	0.18%	-2.65%	3.42%
ExpInfl	Ago-87 / Apr-17	357	0.00	0.68	-0.07	-0.84	1.10
ExpGrowth	Ago-87 / Apr-17	357	0.04	1.12	0.11	-2.33	1.59
CredRisk	Ago-87 / Apr-17	357	0.12%	1.95%	0.15%	-2.92%	2.98%
TermPrem	Ago-87 / Apr-17	357	0.24%	1.29%	0.21%	-1.84%	2.34%

Note: This table documents summary statistics of the historical risk factors included in the different evaluated asset pricing models. Statistics are presented as returns for the traded factors and in decimals for the non-traded factors (ExpInfl and ExpGrowth).

Table 3: Summary Statistic of Betas of Kalman Filter Estimation by Model (Panel A)

Factor	Model	Cons. Stap.	Materials	Energy	Cons. Disc.	Industrials
MRP	CAPM	0.68	1.11	0.78	1.03	1.09
		(0.28)	(0.18)	(0.17)	(0.12)	(0)
	FF3	0.74	1.21	0.88	1.05	1.11
		(0.19)	(0.08)	(0.1)	(0)	(0)
	FF5	0.84	1.23	0.93	1.07	1.10
		(0.13)	(0.07)	(0.04)	(0)	(0.03)
	CRR	0.68	1.00	0.69	1.00	1.07
		(0.27)	(0.18)	(0)	(0.01)	(0.06)
	FF3 LIQ	0.75	1.19	0.87	1.05	1.11
		(0.19)	(0.06)	(0)	(0)	(0)
	FF3 MOM	0.77	1.20	0.88	1.07	1.10
		(0.2)	(0.07)	(0.1)	(0.05)	(0)
	FF3 MOM LIQ	0.77	1.19	0.88	1.07	1.10
		(0.21)	(0.00)	(0.00)	(0.05)	(0.00)
SMB	FF3	-0.31	-0.03	-0.15	0.03	-0.09
		(0.00)	(0.05)	(0.09)	(0.19)	(0.00)
	FF5	-0.15	0.06	-0.11	0.05	-0.06
		(0.00)	(0.00)	(0.12)	(0.19)	(0.00)
	FF3 LIQ	-0.31	-0.05	-0.15	0.03	-0.09
		(0.00)	(0.02)	(0.06)	(0.18)	(0.07)
	FF3 MOM	-0.28	-0.02	-0.17	0.00	-0.08
		(0.03)	(0.04)	(0.16)	(0.04)	(0.00)
	FF3 MOM LIQ	-0.28	-0.04	-0.16	0.00	-0.08
		(0.03)	(0.02)	(0.08)	(0.04)	(0.00)

Note: This table documents summary statistics, mean and standard deviations (in parenthesis), of the historical time-varying betas by factor model. The estimation is based on an adaptation of standard multivariate regression models of the historical excess of return by sector on the historical risk factors included in each model. Where the betas are assumed to follow a first order autoregressive process. The estimation is performed by Kalman filtering the betas as in Mamaysky et al. (2008). Details are presented in the Appendix. Cons. Stap. and Cons. Disc. are abbreviations for Consumer Staples and Consumer Discretionary.

Table 4: Summary Statistic of Betas from Kalman Filter Estimation by Sector and Asset Pricing Model (Panel B)

Factor	Model	Cons. Stap.	Materials	Energy	Cons. Disc.	Industrials
HML	FF3	-0.09	0.21	0.36	-0.03	0.02
		(0.34)	(0.39)	(0.57)	(0.28)	(0.14)
	FF5	-0.26	0.26	0.22	-0.01	-0.03
		(0.27)	(0.31)	(0.58)	(0.34)	(0.15)
	FF3 LIQ	-0.09	0.27	0.30	-0.03	0.02
		(0.34)	(0.3)	(0.45)	(0.28)	(0.11)
	FF3 MOM	-0.10	0.20	0.33	-0.04	0.00
		(0.25)	(0.4)	(0.46)	(0.27)	(0.14)
	FF3 MOM LIQ	-0.10	0.27	0.32	-0.04	0.01
		(0.25)	(0.33)	(0.33)	(0.27)	(0.11)
MOM	FF3 MOM	0.05	-0.09	0.04	-0.11	-0.05
		(0.29)	(0.00)	(0.56)	(0.29)	(0.00)
	FF3 MOM LIQ	0.04	-0.09	0.01	-0.11	-0.05
		(0.29)	(0.00)	(0.48)	(0.29)	(0.00)
LIQ	FF3 LIQ	0.01	0.13	0.10	0.03	-0.06
		(0.00)	(0.23)	(0.45)	(0.01)	(0.00)
	FF3 MOM LIQ	0.01	0.12	0.14	0.02	-0.06
		(0.00)	(0.23)	(0.36)	(0.02)	(0.00)
CMA	FF5	0.58	-0.14	0.28	0.03	0.08
		(0.00)	(0.59)	(1)	(0.4)	(0.00)
RMW	FF5	0.60	0.13	0.10	0.21	0.07
		(0.11)	(0.19)	(0.47)	(0.00)	(0.00)
ExpInfl	CRR	0.00	0.00	0.00	0.00	0.00
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
ExpGrowth	CRR	0.00	0.00	0.00	0.00	0.00
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
TP	CRR	0.34	-0.07	0.05	0.01	-0.13
		(0.03)	(0.00)	(0.00)	(0.00)	(0.00)
CredRisk	CRR	-0.10	0.41	0.17	0.12	-0.02
		(0.00)	(0.00)	(0.48)	(0.00)	(0.00)

Note: This table documents summary statistics, mean and standard deviations (in parenthesis), of the historical time-varying betas by factor model. The estimation is based on an adaptation of standard multivariate regression models of the historical excess of return by sector on the historical risk factors included in each model. Where the betas are assumed to follow a first order autoregressive process. The estimation is performed by Kalman filtering the betas as in Mamaysky et al. (2008). Details are presented in the Appendix. Cons. Stap. and Cons. Disc. are abbreviations for Consumer Staples and Consumer Discretionary.

Table 5: Summary Statistic of Betas from Kalman Filter Estimation by Sector and Asset Pricing Model (Panel C)

Factor	Model	IT	Healthcare	Telecom	Utilities	Financials
MRP	CAPM	1.25	0.75	0.71	0.45	1.05
		(0.33)	(0.25)	(0.33)	(0)	(0.21)
	FF3	1.10	0.79	0.82	0.57	1.14
		(0.26)	(0.19)	(0.32)	(0.02)	(0.14)
	FF5	0.99	0.84	0.82	0.59	1.12
		(0.16)	(0.16)	(0.32)	(0.02)	(0.14)
	CRR	1.41	0.75	0.93	0.39	1.03
		(0.32)	(0.24)	(0.3)	(0.11)	(0.2)
	FF3 LIQ	1.07	0.80	0.82	0.56	1.14
		(0.27)	(0.18)	(0.32)	(0.01)	(0.15)
	FF3 MOM	1.09	0.80	0.81	0.60	1.16
		(0.22)	(0.23)	(0.23)	(0.03)	(0.06)
	FF3 MOM LIQ	1.06	0.81	0.82	0.58	1.15
		(0.25)	(0.23)	(0.19)	(0.02)	(0.00)
SMB	FF3	0.09	-0.34	-0.41	-0.25	-0.09
		(0.00)	(0.07)	(0.34)	(0.22)	(0.18)
	FF5	-0.06	-0.24	-0.36	-0.28	-0.11
		(0.03)	(0.00)	(0.32)	(0.21)	(0.16)
	FF3 LIQ	0.09	-0.31	-0.40	-0.26	-0.10
		(0.00)	(0.08)	(0.35)	(0.22)	(0.16)
	FF3 MOM	0.11	-0.32	-0.37	-0.26	-0.11
		(0.00)	(0.05)	(0.32)	(0.22)	(0.18)
	FF3 MOM LIQ	0.11	-0.30	-0.36	-0.24	-0.13
		(0.00)	(0.06)	(0.00)	(0.21)	(0.15)

Note: This table documents summary statistics, mean and standard deviations (in parenthesis), of the historical time-varying betas by factor model. The estimation is based on an adaptation of standard multivariate regression models of the historical excess of return by sector on the historical risk factors included in each model. Where the betas are assumed to follow a first order autoregressive process. The estimation is performed by Kalman filtering the betas as in Mamaysky et al. (2008). Details are presented in the Appendix.

Table 6: Summary Statistic of Betas from Kalman Filter Estimation by Sector and Asset Pricing Model (Panel D)

Factor	Model	IT	Healthcare	Telecom	Utilities	Financials
HML	FF3	-0.66	-0.30	0.05	0.32	0.45
		(0.36)	(0.34)	(0.29)	(0.31)	(0.27)
	FF5	-0.53	-0.41	0.06	0.41	0.63
		(0.21)	(0.28)	(0.35)	(0.5)	(0.29)
	FF3 LIQ	-0.63	-0.30	0.05	0.35	0.43
		(0.35)	(0.34)	(0.29)	(0.28)	(0.23)
	FF3 MOM	-0.66	-0.25	0.04	0.35	0.38
		(0.00)	(0.19)	(0.22)	(0.33)	(0.26)
	FF3 MOM LIQ	-0.66	-0.26	0.04	0.37	0.34
		(0.00)	(0.18)	(0.25)	(0.29)	(0.22)
MOM	FF3 MOM	-0.14	0.00	0.04	0.10	-0.03
		(0.31)	(0.34)	(0.32)	(0.00)	(0.26)
	FF3 MOM LIQ	-0.12	0.00	0.06	0.10	-0.04
		(0.3)	(0.34)	(0.36)	(0.14)	(0.26)
LIQ	FF3 LIQ	-0.05	0.00	0.01	0.00	-0.02
		(0.33)	(0.14)	(0.00)	(0.09)	(0.12)
	FF3 MOM LIQ	-0.04	0.02	-0.01	0.01	-0.02
		(0.29)	(0.19)	(0.02)	(0.07)	(0.11)
CMA	FF5	-0.38	0.45	0.19	-0.10	-0.32
		(0.73)	(0.00)	(0.53)	(0.65)	(0.39)
RMW	FF5	-0.23	0.27	0.08	-0.19	-0.03
		(0.3)	(0.29)	(0.26)	(0.14)	(0.11)
ExpInfl	CRR	-0.01	0.00	0.00	0.01	0.00
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
ExpGrowth	CRR	0.00	0.00	0.00	0.01	0.00
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
TP	CRR	-0.58	0.35	-0.20	1.02	0.40
		(0.00)	(0.00)	(0.00)	(0.00)	(0.04)
CredRisk	CRR	-0.28	-0.09	-0.55	0.05	0.14
		(0.00)	(0.00)	(0.00)	(0.49)	(0.00)

Note: This table documents summary statistics, mean and standard deviations (in parenthesis), of the historical time-varying betas by factor model. The estimation is based on an adaptation of standard multivariate regression models of the historical excess of return by sector on the historical risk factors included in each model. Where the betas are assumed to follow a first order autoregressive process. The estimation is performed by Kalman filtering the betas as in Mamaysky et al. (2008). Details are presented in the Appendix.

Table 7: Standardized Estimates: Contribution of Risk Factors to Sectors Expected Returns by Asset Pricing Model (Panel A)

Factor	Model	Cons. Stap.	Materials	Energy	Cons. Disc.	Industrials
MRP	CAPM	3.18%	5.17%	3.60%	4.79%	5.04%
	FF3	3.46%	5.63%	4.09%	4.88%	5.15%
	FF5	3.89%	5.72%	4.33%	4.94%	5.09%
	CRR	3.15%	4.65%	3.21%	4.65%	4.98%
	FF3 LIQ	3.46%	5.53%	4.02%	4.89%	5.14%
	FF3 MOM	3.57%	5.57%	4.09%	4.98%	5.11%
	FF3 MOM LIQ	3.57%	5.53%	4.07%	4.99%	5.11%
SMB	FF3	-0.94%	-0.08%	-0.45%	0.08%	-0.26%
	FF5	-0.44%	0.17%	-0.33%	0.15%	-0.18%
	FF3 LIQ	-0.94%	-0.15%	-0.44%	0.08%	-0.27%
	FF3 MOM	-0.85%	-0.07%	-0.53%	-0.01%	-0.25%
	FF3 MOM LIQ	-0.85%	-0.12%	-0.50%	0.00%	-0.26%
HML	FF3	-0.26%	0.63%	1.07%	-0.10%	0.06%
	FF5	-0.77%	0.77%	0.67%	-0.02%	-0.09%
	FF3 LIQ	0.02%	-0.37%	0.37%	-0.35%	0.20%
	FF3 MOM	-0.26%	0.81%	0.91%	-0.10%	0.05%
	FF3 MOM LIQ	-0.29%	0.82%	0.96%	-0.12%	0.02%
MOM	FF3 MOM	0.22%	-0.43%	0.21%	-0.52%	-0.23%
	FF3 MOM LIQ	0.21%	-0.41%	0.04%	-0.53%	-0.22%

Note: This table documents the mean of standardized coefficients presented in Table 3-6. The documented estimates in this table are equal to the effect on sectors expected returns given a 1 standard deviation change in the risk factor, obtained from Table 2, and the mean historical betas, obtained from Table 3-6.

Table 8: Standardized Estimates: Contribution of Risk Factors to Sectors Expected Returns by Asset Pricing Model (Panel B)

Factor	Model	Cons. Stap.	Materials	Energy	Cons. Disc.	Industrials
LIQ	FF3 LIQ	0.05%	0.46%	0.36%	0.10%	-0.22%
	FF3 MOM LIQ	0.05%	0.44%	0.49%	0.08%	-0.22%
CMA	FF5	1.17%	-0.28%	4.33%	4.94%	5.09%
RMW	FF5	1.34%	0.30%	4.33%	4.94%	5.09%
ExpInfl	CRR	0.20%	-0.27%	0.01%	-0.17%	0.05%
ExpGrowth	CRR	0.02%	-0.37%	0.37%	-0.35%	0.20%
TP	CRR	0.43%	-0.09%	0.06%	0.02%	-0.17%
CredRisk	CRR	-0.19%	0.79%	0.33%	0.24%	-0.05%

Note: This table documents the mean of standardized coefficients presented in Table 3-6. The documented estimates in this table are equal to the effect on sectors expected returns given a 1 standard deviation change in the risk factor, obtained from Table 2, and the mean historical betas, obtained from Table 3-6.

Table 9: Standardized Estimates: Contribution of Risk Factors to Sectors Expected Returns by Asset Pricing Model (Panel C)

Factor	Model	IT	Healthcare	Teleco	Utilities	Financials
MRP	CAPM	5.80%	3.50%	3.31%	2.08%	4.86%
	FF3	5.12%	3.65%	3.79%	2.64%	5.30%
	FF5	4.61%	3.88%	3.80%	2.76%	5.22%
	CRR	6.54%	3.48%	4.30%	1.79%	4.78%
	FF3 LIQ	4.97%	3.72%	3.81%	2.61%	5.29%
	FF3 MOM	5.04%	3.73%	3.76%	2.77%	5.40%
	FF3 MOM LIQ	4.93%	3.77%	3.81%	2.70%	5.36%
SMB	FF3	0.27%	-1.04%	-1.24%	-0.76%	-0.28%
	FF5	-0.18%	-0.75%	-1.10%	-0.85%	-0.33%
	FF3 LIQ	0.27%	-0.96%	-1.23%	-0.78%	-0.31%
	FF3 MOM	0.34%	-0.97%	-1.14%	-0.78%	-0.34%
	FF3 MOM LIQ	0.35%	-0.90%	-1.10%	-0.73%	-0.41%
HML	FF3	-1.99%	-0.89%	0.16%	0.97%	1.36%
	FF5	-1.58%	-1.24%	0.18%	1.23%	1.90%
	FF3 LIQ	-0.54%	0.10%	-0.16%	0.73%	0.38%
	FF3 MOM	-1.89%	-0.91%	0.16%	1.05%	1.28%
	FF3 MOM LIQ	-1.98%	-0.78%	0.11%	1.10%	1.01%
MOM	FF3 MOM	-0.68%	-0.01%	0.21%	0.48%	-0.16%
	FF3 MOM LIQ	-0.55%	-0.02%	0.29%	0.47%	-0.20%

Note: This table documents the mean of standardized coefficients presented in Table 3-6. The documented estimates in this table are equal to the effect on sectors expected returns given a 1 standard deviation change in the risk factor, obtained from Table 2, and the mean historical betas, obtained from Table 3-6.

Table 10: Standardized Estimates: Contribution of Risk Factors to Sectors Expected Returns by Asset Pricing Model (Panel D)

Factor	Model	Cons. Stap.	Materials	Energy	Cons. Disc.	Industrials
LIQ	FF3 LIQ	-0.16%	0.01%	0.03%	-0.01%	-0.07%
	FF3 MOM LIQ	-0.15%	0.06%	-0.03%	0.02%	-0.06%
CMA	FF5	4.61%	3.88%	3.80%	2.76%	5.22%
RMW	FF5	4.61%	3.88%	3.80%	2.76%	5.22%
ExpInfl	CRR	-0.43%	0.27%	-0.20%	0.50%	-0.01%
ExpGrowth	CRR	-0.54%	0.10%	-0.16%	0.73%	0.38%
TP	CRR	-0.75%	0.45%	-0.25%	1.32%	0.52%
CredRisk	CRR	-0.54%	-0.17%	-1.07%	0.10%	0.28%

Note: This table documents the mean of standardized coefficients presented in Table 3-6. The documented estimates in this table are equal to the effect on sectors expected returns given a 1 standard deviation change in the risk factor, obtained from Table 2, and the mean historical betas, obtained from Table 3-6.

Table 11: Summary Statistics of Historical Mutual Fund Portfolio Weights by Sector

Sectors	Time Period	N	Mean	Std. Dev.	Median	P5	P95
Cons. Disc.	Mar-85 / Dec-14	80025	17.12%	13.02%	15.08%	2.65%	33.62%
Cons. Stap.	Mar-85 / Dec-14	80025	3.80%	4.13%	2.95%	0.00%	10.91%
Energy	Mar-85 / Dec-14	80025	6.12%	7.56%	5.03%	0.00%	14.56%
Financials	Mar-85 / Dec-14	80025	11.37%	9.96%	10.09%	0.00%	26.02%
Healthcare	Mar-85 / Dec-14	80025	6.71%	5.48%	5.84%	0.00%	16.08%
Industrials	Mar-85 / Dec-14	80025	14.26%	8.02%	13.86%	1.51%	26.27%
IT	Mar-85 / Dec-14	80025	17.96%	13.04%	15.91%	0.49%	41.40%
Materials	Mar-85 / Dec-14	80025	12.84%	8.83%	12.10%	0.00%	26.14%
Telecom	Mar-85 / Dec-14	80025	4.78%	6.60%	3.38%	0.00%	13.85%
Utilities	Mar-85 / Dec-14	80025	4.28%	10.30%	1.89%	0.00%	12.32%

Note: This table documents summary statistics of the historical market capitalization weights of mutual fund sector allocation. The sector classification is based on the 10 Global Industry Classification Standard (GICS). The aggregation by sectors is based on the equivalency between SIC codes and GICS proposed by Bhojraj et al. (2003).

Table 12: Summary Statistics of Historical Sector Weights in CRSP Data

Sectors	Time Period	N	Mean	Std. Dev.	Median	P5	P95
Cons. Disc.	Dec-25 / Dec-17	1105	25.13%	6.77%	22.87%	18.09%	40.74%
Cons. Stap.	Dec-25 / Dec-17	1105	6.98%	4.14%	6.87%	1.91%	12.93%
Energy	Dec-25 / Dec-17	1105	4.99%	1.48%	4.71%	3.11%	8.61%
Financials	Dec-25 / Dec-17	1105	5.84%	4.55%	3.91%	1.26%	13.99%
Healthcare	Dec-25 / Dec-17	1105	4.32%	2.72%	4.17%	1.29%	8.52%
Industrials	Dec-25 / Dec-17	1105	19.35%	6.48%	19.03%	9.69%	27.43%
IT	Dec-25 / Dec-17	1105	10.93%	5.41%	12.23%	4.24%	19.33%
Materials	Dec-25 / Dec-17	1105	16.39%	5.86%	16.15%	9.21%	24.47%
Telecom	Dec-25 / Dec-17	1105	1.59%	0.92%	1.16%	0.56%	3.43%
Utilities	Dec-25 / Dec-17	1105	4.47%	2.10%	3.65%	2.37%	9.25%

Note: This table documents summary statistics of the historical market capitalization weights from CRSP individual stock data. The sector classification is based on the 10 Global Industry Classification Standard (GICS). The aggregation by sectors is based on the equivalency between SIC codes and GICS proposed by Bhojraj et al. (2003).

Table 13: Mean Conditional Volatility by Sector and Asset Pricing Model

Volatilities	CAPM	FF3	FF3 LIQ	FF3 MOM	FF3 MOM LIQ	FF5	CRR
Consumer Staples	4.17%	4.17%	4.17%	4.16%	4.20%	4.15%	3.95%
Materials	4.06%	4.11%	4.08%	4.15%	4.12%	4.09%	3.71%
Energy	3.17%	3.22%	3.14%	3.25%	3.16%	3.18%	2.98%
Consumer Discretionary	4.04%	4.03%	4.04%	4.10%	4.13%	4.03%	3.55%
Industrials	3.98%	4.03%	4.03%	4.05%	4.05%	3.96%	3.63%
IT	3.78%	3.68%	3.77%	3.73%	3.87%	3.77%	3.50%
Healthcare	4.07%	4.03%	4.05%	3.99%	4.05%	4.02%	3.77%
Telecom	3.31%	3.35%	3.35%	3.38%	3.41%	3.30%	3.21%
Utilities	2.98%	3.01%	2.93%	2.98%	2.90%	2.93%	2.77%
Financials	4.17%	4.19%	4.13%	4.24%	4.18%	4.10%	3.91%
Mean	3.77%	3.78%	3.77%	3.80%	3.81%	3.75%	3.50%
RMD		1.03%	0.69%	1.57%	1.49%	0.71%	7.26%

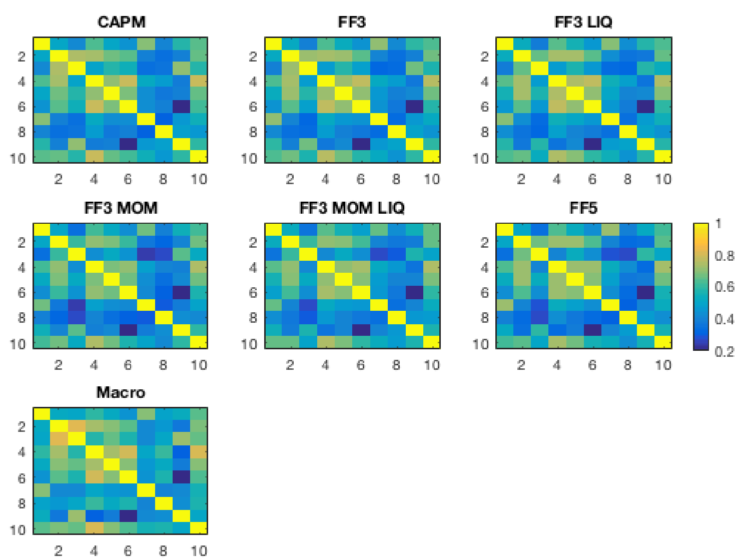
Note: This table documents the historical means of the estimated conditional volatilities by sector and asset pricing model. The estimations are based on the estimated conditional variances and covariances of risk factors, sector dynamic factor loadings, and the conditional variances and covariances of sectors idiosyncratic risk. The mean volatility by asset pricing model, and the relative mean absolute difference (RMD) with respect to the CAPM are documented.

Table 14: Mean Conditional Idiosyncratic Volatility by Sector and Asset Pricing Model

Volality Idiosyncratic Risk	CAPM	FF3	FF3 LIQ	FF3 MOM	FF3 MOM LIQ	FF5	CRR
Consumer Staples	2.43%	2.13%	2.12%	1.79%	1.79%	1.97%	2.44%
Materials	3.45%	2.98%	2.79%	2.84%	2.65%	2.70%	3.60%
Energy	2.21%	1.95%	1.94%	1.68%	1.68%	1.75%	2.21%
Consumer Discretionary	2.14%	2.04%	2.02%	1.99%	2.00%	2.02%	2.02%
Industrials	3.44%	2.97%	2.70%	2.89%	2.70%	2.63%	3.35%
IT	2.51%	1.93%	1.85%	1.55%	1.39%	1.90%	2.47%
Healthcare	3.63%	3.11%	3.09%	2.75%	2.85%	2.86%	3.72%
Telecom	3.60%	3.11%	3.07%	2.97%	2.88%	2.69%	3.18%
Utilities	2.45%	1.83%	1.76%	1.59%	1.56%	1.66%	2.52%
Financials	2.43%	2.13%	2.12%	1.79%	1.79%	1.97%	2.44%
Mean	2.83%	2.42%	2.35%	2.18%	2.13%	2.22%	2.80%
RMD		14.63%	17.07%	22.80%	24.74%	21.70%	3.52%

Note: This table documents the historical means of the estimated conditional idiosyncratic volatilities by sector and asset pricing model. The estimations are based on a multivariate ARCH of the residuals of sectors obtained under each asset pricing model. The mean volatility by asset pricing model, and the relative mean absolute difference (RMD) with respect to the CAPM are documented.

Figure 2: Mean Conditional Correlation of Sectors Returns by Asset Pricing Model



Note: This figure documents the mean correlations of the 10 sectors, estimated by different asset pricing models.

Table 15: Implied Expected Returns: CAPM

Sectors	Time Period	N	Mean	Std. Dev.	Median	P5	P95
Consumer Discretionary	Mar-85 / Dec-14	80025	0.51%	0.24%	0.49%	0.14%	0.92%
Consumer Staples	Mar-85 / Dec-14	80025	0.40%	0.23%	0.39%	0.08%	0.86%
Energy	Mar-85 / Dec-14	80025	0.42%	0.20%	0.42%	0.13%	0.80%
Financials	Mar-85 / Dec-14	80025	0.50%	0.24%	0.47%	0.15%	0.93%
Healthcare	Mar-85 / Dec-14	80025	0.42%	0.23%	0.41%	0.11%	0.86%
Industrials	Mar-85 / Dec-14	80025	0.53%	0.24%	0.51%	0.16%	0.93%
IT	Mar-85 / Dec-14	80025	0.59%	0.28%	0.57%	0.13%	1.07%
Materials	Mar-85 / Dec-14	80025	0.53%	0.23%	0.50%	0.19%	0.94%
Telecom	Mar-85 / Dec-14	80025	0.46%	0.23%	0.48%	0.06%	0.85%
Utilities	Mar-85 / Dec-14	80025	0.37%	0.20%	0.36%	0.06%	0.72%

Note: This table documents summary statistics of the implied expected returns by sectors under a specific asset pricing model. The estimation is based on Equation 10.

Table 16: Implied Expected Returns: FF3

Sectors	Time Period	N	Mean	Std. Dev.	Median	P5	P95
Consumer Discretionary	Mar-85 / Dec-14	80025	0.51%	0.22%	0.50%	0.15%	0.90%
Consumer Staples	Mar-85 / Dec-14	80025	0.40%	0.23%	0.38%	0.08%	0.84%
Energy	Mar-85 / Dec-14	80025	0.44%	0.20%	0.44%	0.13%	0.80%
Financials	Mar-85 / Dec-14	80025	0.52%	0.24%	0.48%	0.16%	0.89%
Healthcare	Mar-85 / Dec-14	80025	0.42%	0.22%	0.40%	0.12%	0.84%
Industrials	Mar-85 / Dec-14	80025	0.53%	0.23%	0.51%	0.16%	0.92%
IT	Mar-85 / Dec-14	80025	0.56%	0.25%	0.56%	0.14%	0.98%
Materials	Mar-85 / Dec-14	80025	0.54%	0.22%	0.52%	0.20%	0.93%
Telecom	Mar-85 / Dec-14	80025	0.46%	0.22%	0.48%	0.06%	0.82%
Utilities	Mar-85 / Dec-14	80025	0.37%	0.19%	0.37%	0.06%	0.68%

Note: This table documents summary statistics of the implied expected returns by sectors under a specific asset pricing model. The estimation is based on Equation 10.

Table 17: Implied Expected Returns: FF3 MOM

Sectors	Time Period	N	Mean	Std. Dev.	Median	P5	P95
Consumer Discretionary	Mar-85 / Dec-14	80025	0.52%	0.23%	0.51%	0.14%	0.91%
Consumer Staples	Mar-85 / Dec-14	80025	0.40%	0.23%	0.38%	0.08%	0.82%
Energy	Mar-85 / Dec-14	80025	0.44%	0.20%	0.44%	0.14%	0.81%
Financials	Mar-85 / Dec-14	80025	0.52%	0.23%	0.49%	0.15%	0.90%
Healthcare	Mar-85 / Dec-14	80025	0.41%	0.21%	0.40%	0.12%	0.83%
Industrials	Mar-85 / Dec-14	80025	0.53%	0.23%	0.51%	0.16%	0.91%
IT	Mar-85 / Dec-14	80025	0.55%	0.25%	0.55%	0.14%	0.98%
Materials	Mar-85 / Dec-14	80025	0.54%	0.22%	0.53%	0.19%	0.92%
Telecom	Mar-85 / Dec-14	80025	0.45%	0.22%	0.47%	0.07%	0.81%
Utilities	Mar-85 / Dec-14	80025	0.38%	0.19%	0.38%	0.07%	0.69%

Note: This table documents summary statistics of the implied expected returns by sectors under a specific asset pricing model. The estimation is based on Equation 10.

Table 18: Implied Expected Returns: FF3 MOM LIQ

Sectors	Time Period	N	Mean	Std. Dev.	Median	P5	P95
Consumer Discretionary	Mar-85 / Dec-14	80025	0.51%	0.22%	0.51%	0.14%	0.89%
Consumer Staples	Mar-85 / Dec-14	80025	0.40%	0.22%	0.39%	0.09%	0.82%
Energy	Mar-85 / Dec-14	80025	0.43%	0.20%	0.44%	0.11%	0.77%
Financials	Mar-85 / Dec-14	80025	0.50%	0.22%	0.49%	0.15%	0.87%
Healthcare	Mar-85 / Dec-14	80025	0.42%	0.21%	0.40%	0.13%	0.82%
Industrials	Mar-85 / Dec-14	80025	0.52%	0.22%	0.51%	0.16%	0.90%
IT	Mar-85 / Dec-14	80025	0.56%	0.24%	0.56%	0.15%	0.96%
Materials	Mar-85 / Dec-14	80025	0.53%	0.22%	0.52%	0.16%	0.93%
Telecom	Mar-85 / Dec-14	80025	0.45%	0.21%	0.47%	0.09%	0.79%
Utilities	Mar-85 / Dec-14	80025	0.37%	0.18%	0.37%	0.07%	0.67%

Note: This table documents summary statistics of the implied expected returns by sectors under a specific asset pricing model. The estimation is based on Equation 10.

Table 19: Implied Expected Returns: FF5

Sectors	Time Period	N	Mean	Std. Dev.	Median	P5	P95
Consumer Discretionary	Mar-85 / Dec-14	80025	0.51%	0.22%	0.50%	0.15%	0.89%
Consumer Staples	Mar-85 / Dec-14	80025	0.41%	0.22%	0.39%	0.09%	0.82%
Energy	Mar-85 / Dec-14	80025	0.43%	0.19%	0.44%	0.13%	0.76%
Financials	Mar-85 / Dec-14	80025	0.50%	0.23%	0.48%	0.15%	0.87%
Healthcare	Mar-85 / Dec-14	80025	0.42%	0.22%	0.40%	0.12%	0.83%
Industrials	Mar-85 / Dec-14	80025	0.51%	0.22%	0.50%	0.17%	0.89%
IT	Mar-85 / Dec-14	80025	0.56%	0.25%	0.54%	0.16%	0.98%
Materials	Mar-85 / Dec-14	80025	0.53%	0.22%	0.52%	0.20%	0.92%
Telecom	Mar-85 / Dec-14	80025	0.45%	0.22%	0.47%	0.06%	0.81%
Utilities	Mar-85 / Dec-14	80025	0.37%	0.18%	0.37%	0.07%	0.68%

Note: This table documents summary statistics of the implied expected returns by sectors under a specific asset pricing model. The estimation is based on Equation 10.

Table 20: Implied Expected Returns: CRR

Sectors	Time Period	N	Mean	Std. Dev.	Median	P5	P95
Consumer Discretionary	Sept-87 / Dec-14	77150	0.59%	0.21%	0.55%	0.33%	0.94%
Consumer Staples	Sept-87 / Dec-14	77150	0.56%	0.19%	0.52%	0.32%	0.87%
Energy	Sept-87 / Dec-14	77150	0.53%	0.18%	0.50%	0.30%	0.84%
Financials	Sept-87 / Dec-14	77150	0.61%	0.21%	0.55%	0.34%	0.99%
Healthcare	Sept-87 / Dec-14	77150	0.57%	0.18%	0.53%	0.32%	0.87%
Industrials	Sept-87 / Dec-14	77150	0.61%	0.21%	0.56%	0.35%	0.98%
IT	Sept-87 / Dec-14	77150	0.61%	0.23%	0.56%	0.34%	1.01%
Materials	Mar-85 / Dec-14	77150	0.62%	0.22%	0.57%	0.35%	0.99%
Telecom	Sept-87 / Dec-14	77150	0.53%	0.19%	0.49%	0.29%	0.88%
Utilities	Sept-87 / Dec-14	77150	0.47%	0.16%	0.45%	0.26%	0.76%

Note: This table documents summary statistics of the implied expected returns by sectors under a specific asset pricing model. The estimation is based on Equation 10.

Table 21: Example of Expected Returns by Asset Pricing Model at Non-Recession Periods

Sectors	CAPM	FF3	FF5	CRR	FF3 LIQ	FF3 MOM	FF3 MOM LIQ	Disagreement
Cons. Stap.	0.40%	0.37%	0.79%	0.47%	0.41%	0.41%	0.42%	0.15%
Materials	0.65%	0.80%	0.85%	0.61%	0.86%	0.70%	0.77%	0.10%
Energy	0.46%	0.66%	0.75%	0.44%	0.68%	0.60%	0.64%	0.12%
Cons. Dis.	0.61%	0.61%	0.64%	0.60%	0.62%	0.56%	0.57%	0.03%
Industrials	0.64%	0.66%	0.64%	0.60%	0.63%	0.61%	0.58%	0.03%
IT	0.73%	0.38%	0.14%	0.66%	0.36%	0.41%	0.39%	0.20%
Healthcare	0.44%	0.34%	0.35%	0.52%	0.35%	0.36%	0.37%	0.07%
Telecom	0.42%	0.50%	0.52%	0.44%	0.51%	0.45%	0.47%	0.04%
Utilities	0.26%	0.47%	0.52%	0.49%	0.47%	0.46%	0.46%	0.08%
Financials	0.62%	0.85%	0.93%	0.72%	0.83%	0.75%	0.71%	0.10%

Note: This table illustrates how different asset pricing models imply different sectors expected returns. Estimates are based on the historical means of the risk factors and the mean betas estimated during non-recession periods by asset pricing model. Disagreement is calculated as the standard deviation of the expected returns across asset pricing models.

Table 22: Example of Expected Returns by Asset Pricing Model at Recession Periods

Sectors	CAPM	FF3	FF5	CRR	FF3 LIQ	FF3 MOM	FF3 MOM LIQ	Disagreement
Cons. Stap.	-0.63%	-0.93%	-0.29%	-0.30%	-0.77%	-0.96%	-0.96%	0.30%
Materials	-1.26%	-1.45%	-1.20%	-0.93%	-1.29%	-1.40%	-1.35%	0.17%
Energy	-0.98%	-1.08%	-0.75%	-1.50%	-0.97%	-1.14%	-1.14%	0.23%
Cons. Dis.	-1.09%	-1.26%	-1.05%	-0.80%	-1.18%	-1.27%	-1.19%	0.16%
Industrials	-1.28%	-1.35%	-1.23%	-1.57%	-1.32%	-1.32%	-1.35%	0.11%
IT	-1.44%	-1.04%	-1.31%	-1.48%	-1.39%	-0.99%	-0.99%	0.22%
Healthcare	-0.72%	-0.91%	-0.57%	-0.47%	-0.89%	-0.92%	-0.98%	0.20%
Telecom	-0.74%	-0.95%	-0.86%	-1.08%	-0.82%	-0.97%	-1.19%	0.15%
Utilities	-0.53%	-0.83%	-1.17%	-0.90%	-0.57%	-0.90%	-0.85%	0.22%
Financials	-1.16%	-1.50%	-1.60%	-1.82%	-1.21%	-1.52%	-1.46%	0.23%

Note: This table illustrates how different asset pricing models imply different sectors expected returns. Estimates are based on the historical means of the risk factors and the mean betas estimated during recession periods by asset pricing model. Disagreement is calculated as the standard deviation of the expected returns across asset pricing models.

Table 23: Factor Premium Estimates by Asset Pricing Model

	CAPM	FF3	FF3 LIQ	FF3 MOM	FF3 MOM LIQ	FF5	CRR
MRP	0.005	0.005	0.005	0.005	0.005	0.005	0.006
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
SMB		-0.001	-0.001	-0.002	-0.002	-0.001	
		(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	
HML		0.000	0.000	0.000	0.000	0.000	
		(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	
MOM				-0.001	-0.001		
				(0.002)	(0.001)		
LIQ			-0.001		-0.001		
			(0.002)		(0.001)		
ExpInfl							0.091
							(0.23)
ExpGrowth							-0.028
							(0.167)
CredRisk							0.000
							(0.002)
TermPrem							0.002
							(0.002)

Note: This table documents the mean and standard deviation, which is shown in parenthesis, of the cross-sectional estimations of the intercepts in Equation (11). These parameters are the expected risk premiums estimates (rows), under the assumption of managers using a specific asset pricing model (columns) to form their expectations.

Table 24: Summary Statistic of cross-sectional R^2 by Asset Pricing Model

	Mean	Std. Dev.	Median	P25	P75
CAPM	0.73	0.10	0.70	0.64	0.81
FF3	0.75	0.10	0.73	0.67	0.85
FF3 LIQ	0.76	0.10	0.75	0.68	0.86
FF3 MOM	0.76	0.10	0.76	0.68	0.86
FF3 MOM LIQ	0.78	0.09	0.79	0.72	0.85
FF5	0.77	0.10	0.76	0.68	0.86
CRR	0.56	0.11	0.56	0.46	0.61

Note: This table documents summary statistics of the cross-sectional R^2s by asset pricing model. Regression model (11).

Table 25: T-test for Equality of Means of Historical cross-sectional R^2

	FF3 MOM LIQ - CRR		FF3 MOM LIQ - CAPM	
	Mean	Std. Err.	Mean	Std. Dev.
Diff.	0.23***	0.01	0.06***	0.004

$*p < 0.1$ $**p < 0.05$ $***p < 0.01$

Note: This table documents the results of a paired sample t-test, which compare means of the cross-sectional R^2s of the model with the highest R^22 in Table 13, Fama and French Three Factor Model with momentum and liquidity factors, FF3 MOM LIQ, versus the proposed adaptation of Chen et al. (1986), CRR, and the CAPM.

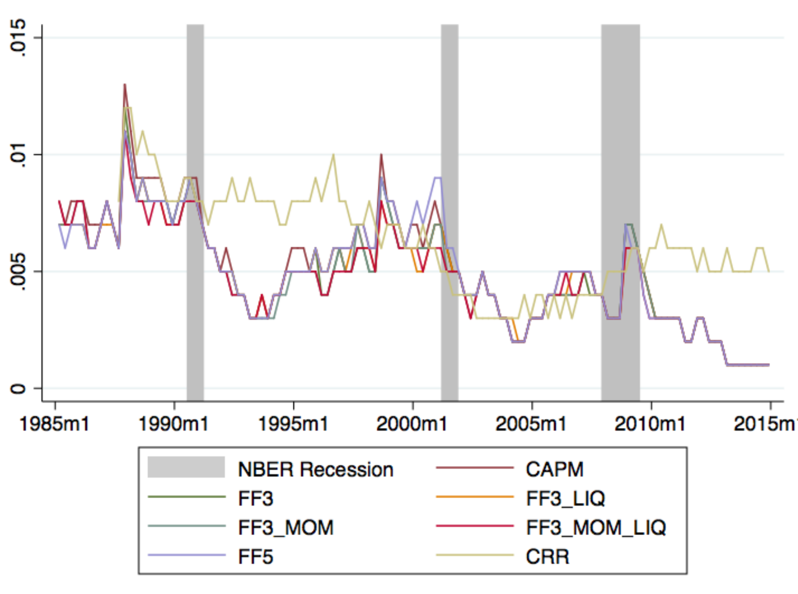
Table 26: Summary Statistic of Model ex-ante Sharpe Ratio and Market Expected Return

Panel A: Sharpe Ratio					
	Mean	Std. Dev.	Median	P5	P95
CAPM	0.12	0.05	0.12	0.04	0.19
FF3	0.11	0.04	0.12	0.04	0.18
FF3 LIQ	0.11	0.04	0.12	0.04	0.18
FF3 MOM	0.11	0.05	0.12	0.04	0.19
FF3 MOM LIQ	0.11	0.05	0.12	0.04	0.19
FF5	0.11	0.05	0.12	0.04	0.18
CRR	0.15	0.06	0.13	0.06	0.27

Panel B: Annualized Expected Return					
	Mean	Std. Dev.	Median	P5	P95
CAPM	6.6%	3.0%	6.3%	1.7%	11.7%
FF3	6.4%	2.8%	6.3%	1.8%	10.8%
FF3 LIQ	6.4%	2.7%	6.2%	1.8%	10.7%
FF3 MOM	6.5%	2.8%	6.4%	1.7%	10.8%
FF3 MOM LIQ	6.4%	2.7%	6.6%	1.8%	10.7%
FF5	6.4%	2.8%	6.4%	1.9%	10.7%
CRR	7.7%	2.7%	7.0%	3.9%	12.0%

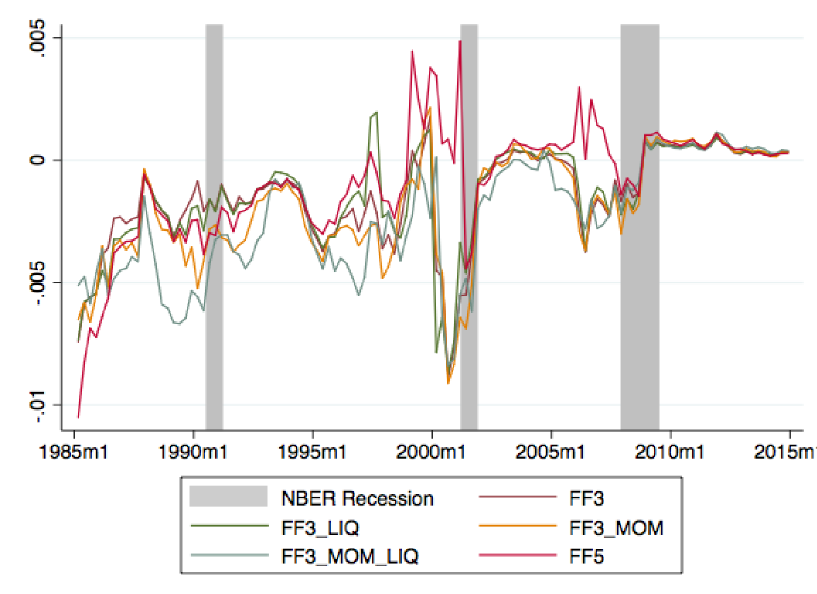
Note: This table documents summary statistics of the model implied ex-ante Sharpe ratio of the market portfolio. The calculations are based on Equation (14) and Equation (12).

Figure 3: Estimated Implied MRP Premium by Model



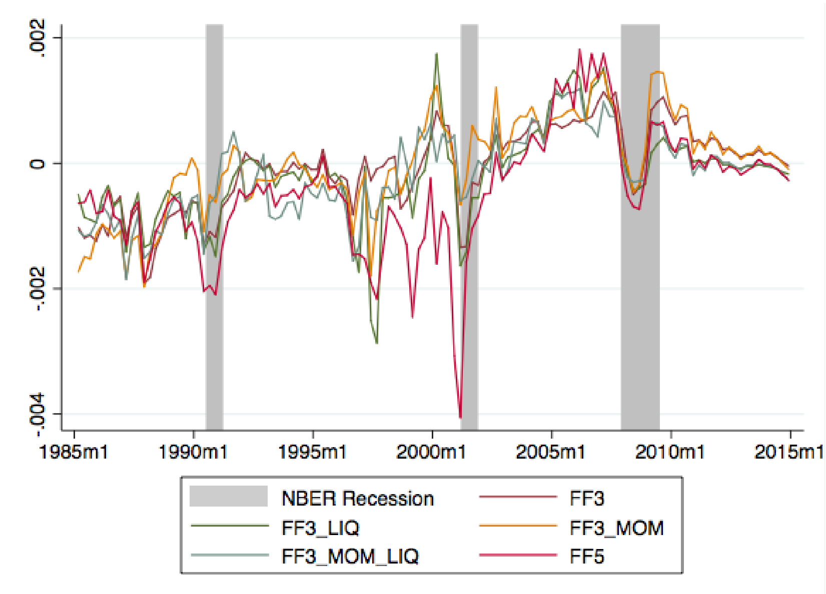
Note: This figure documents the estimated intercept associated with the market risk factor (MRP) by each asset pricing model includes this specific factor.

Figure 4: Estimated Implied SMB Premium by Model



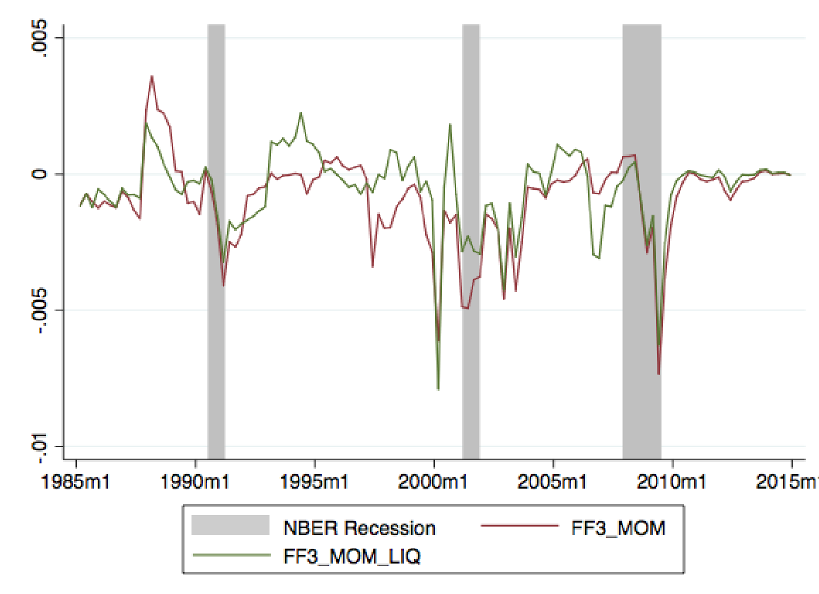
Note: This figure documents the estimated intercept associated with the size risk factor (SMB) by each asset pricing model includes this specific factor.

Figure 5: Estimated Implied HML Premium by Model



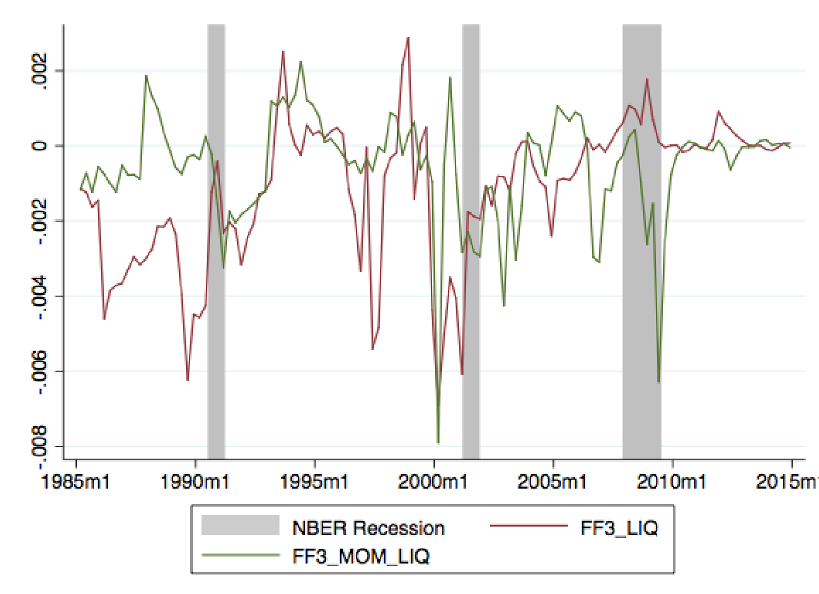
Note: This figure documents the estimated intercept associated with the book-to-market risk factor (HML) by each asset pricing model includes this specific factor.

Figure 6: Estimated Implied MOM Premium by Model



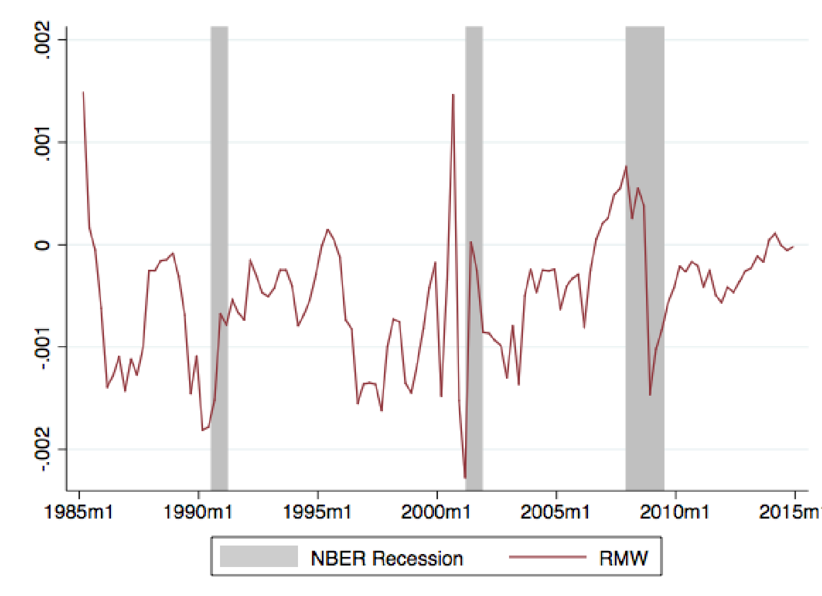
Note: This figure documents the estimated intercept associated with the momentum risk factor (MOM) by each asset pricing model includes this specific factor.

Figure 7: Estimated Implied LIQ Premium by Model



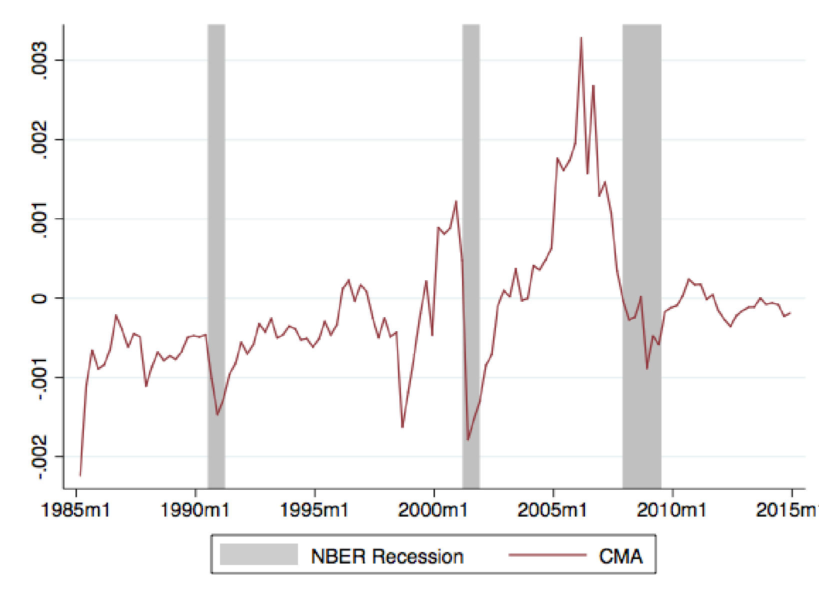
Note: This figure documents the estimated intercept associated with the liquidity risk factor (LIQ) by each asset pricing model includes this specific factor.

Figure 8: Estimated Implied RMW Premium by Model



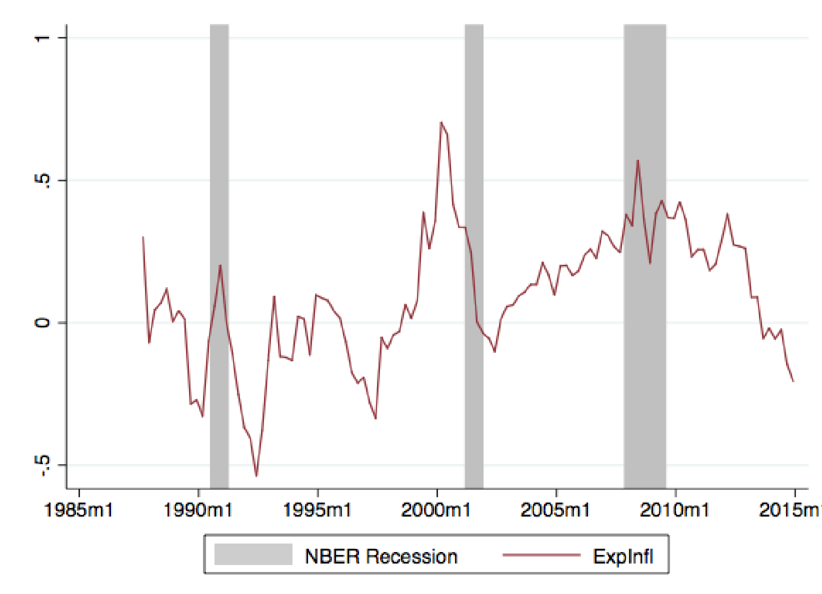
Note: This figure documents the estimated intercept associated with the profitability risk factor (RMW) by each asset pricing model includes this specific factor.

Figure 9: Estimated Implied CMA Premium by Model



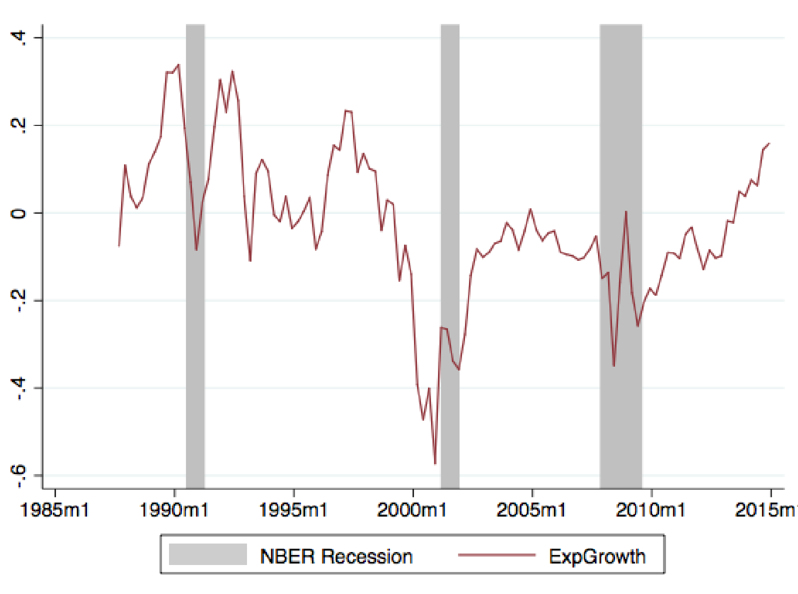
Note: This figure documents the estimated intercept associated with the corporate investment risk factor (CMA) by each asset pricing model includes this specific factor.

Figure 10: Estimated Implied ExpInfl Premium by Model



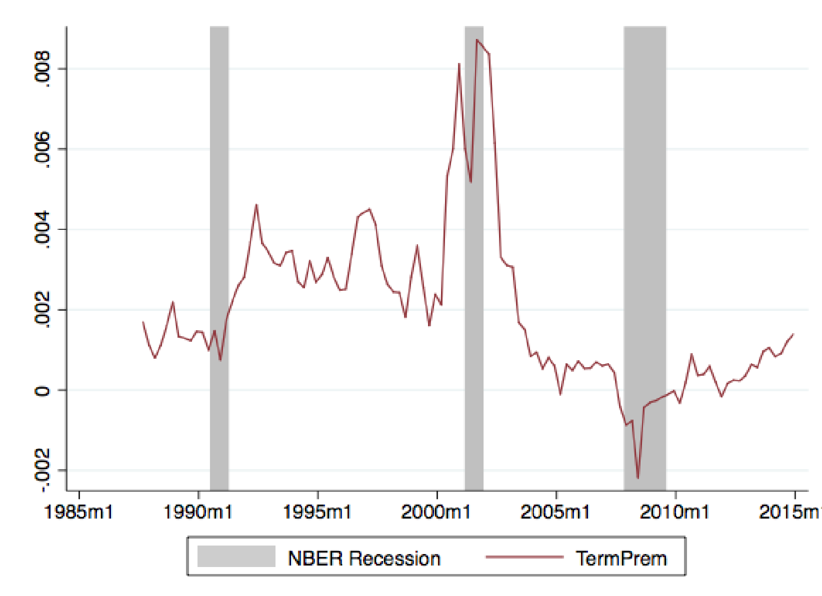
Note: This figure documents the estimated intercept associated with the inflation risk factor (ExpInfl) by each asset pricing model includes this specific factor.

Figure 11: Estimated Implied ExpGrowth Premium by Model



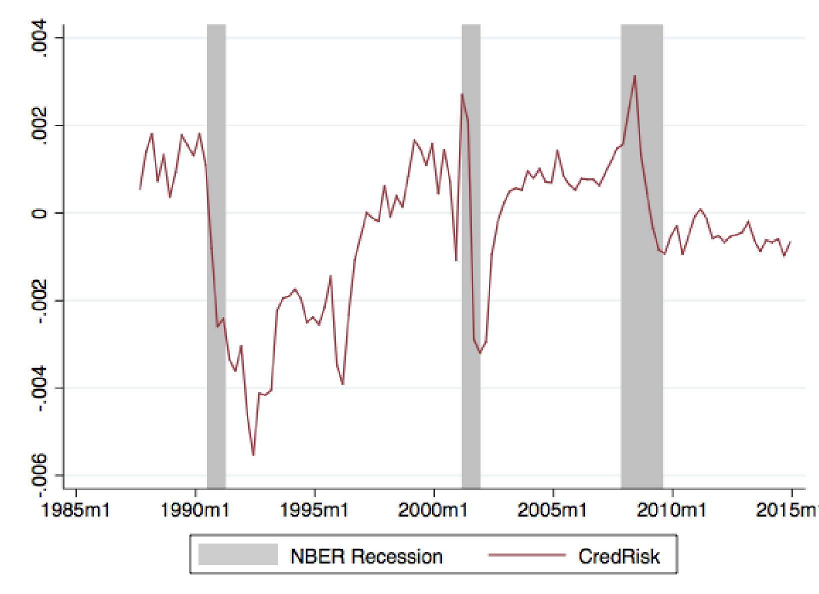
Note: This figure documents the estimated intercept associated with the GDP growth risk factor (ExpGrowth) by each asset pricing model includes this specific factor.

Figure 12: Estimated Implied TermPrem Premium by Model

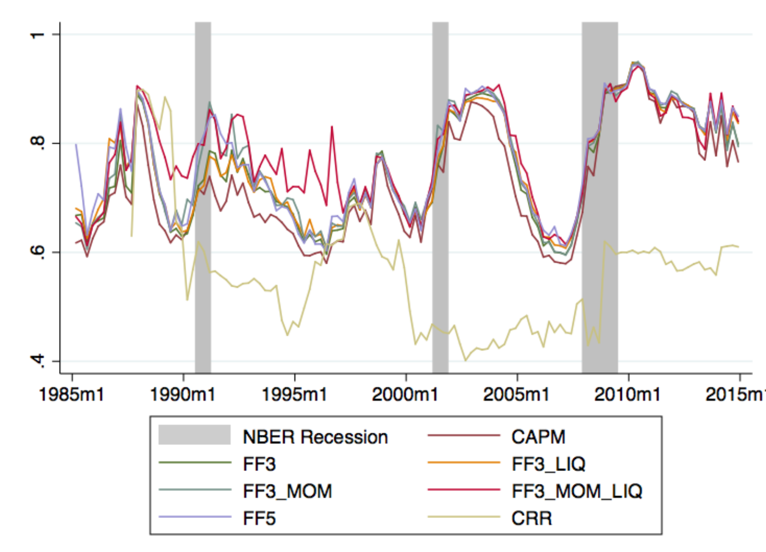


Note: This figure documents the estimated intercept associated with the term premium risk factor (TermPrem) by each asset pricing model includes this specific factor.

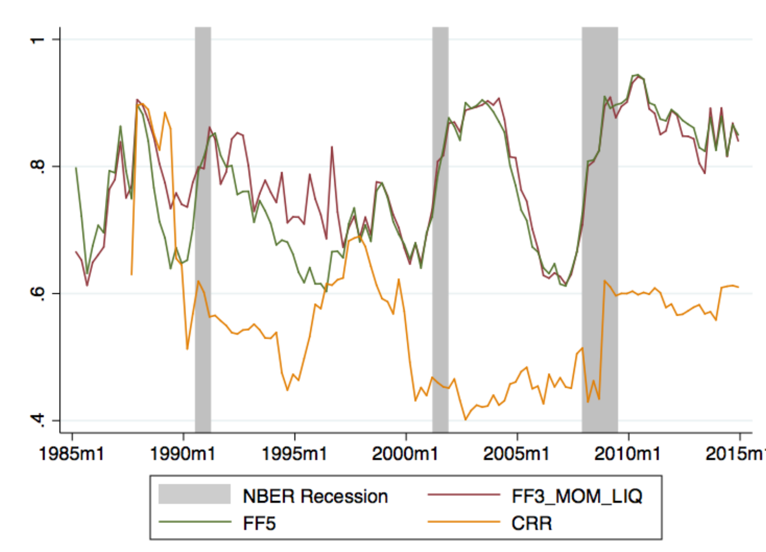
Figure 13: Estimated Implied CredRisk Premium by Model



Note: This figure documents the estimated intercept associated with the credit risk factor (CredRisk) by each asset pricing model includes this specific factor.



((a)) All Models

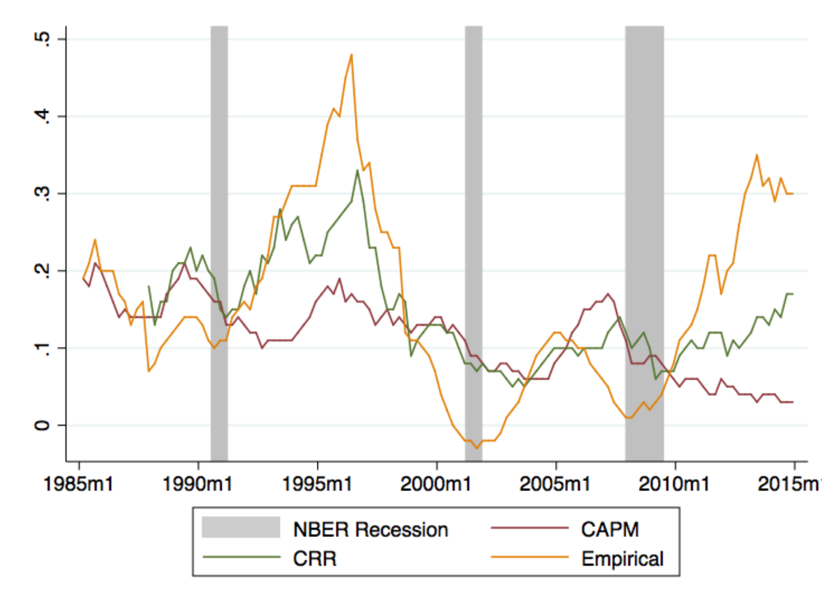


((b)) 5 Factor Models

Figure 14: cross-sectional R^2 of Implied Expected Returns by Asset Pricing Model

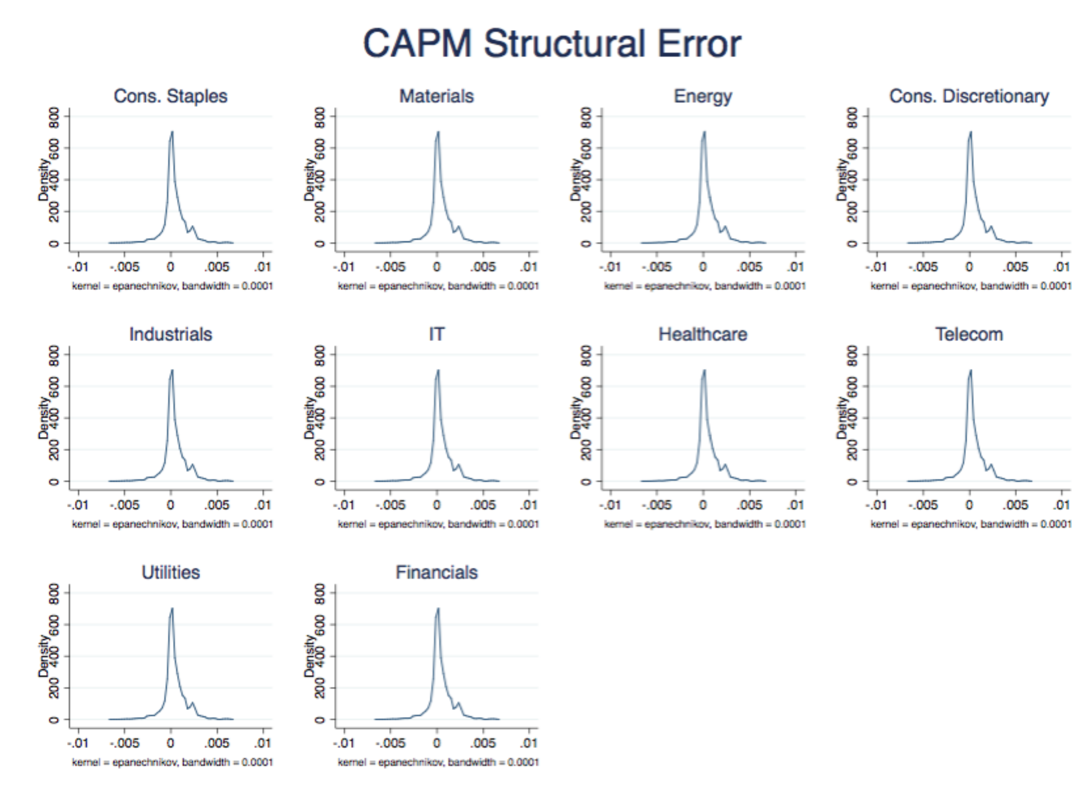
Note: In Panel (a) the historical cross-sectional R^2 of each asset pricing model are documented; In Panel (b) the same time-series are presented but restricting the graph to the models with 5 risk factors only.

Figure 15: Model versus Empirical Estimation of Market Portfolio's Sharpe Ratio



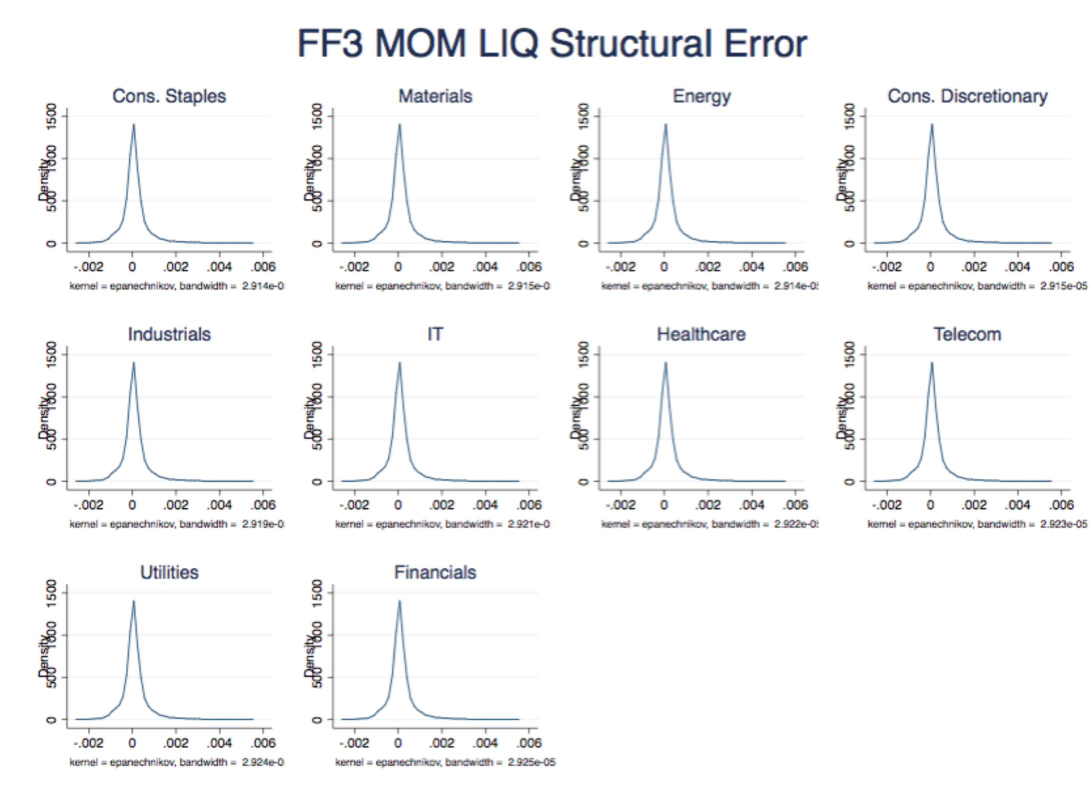
Note: This figure documents the implied Sharpe ratio under the different estimated asset pricing models. The Model estimated Sharpe Ratios are obtained combining the observed market sector weights from CRSP data, the predicted sector expected returns that are consistent with the intercepts by each asset pricing model (Table 12), the conditional betas, and the observed risk free rate. The Empirical estimated Sharpe Ratio is obtained as the ratio of trend of the observed market excess return, obtained by the Hodrick-Prescott filter, and the estimated dynamic volatility, obtained from GARCH (1,1) with a constant mean.

Figure 16: Structural Error Analysis - CAPM Model



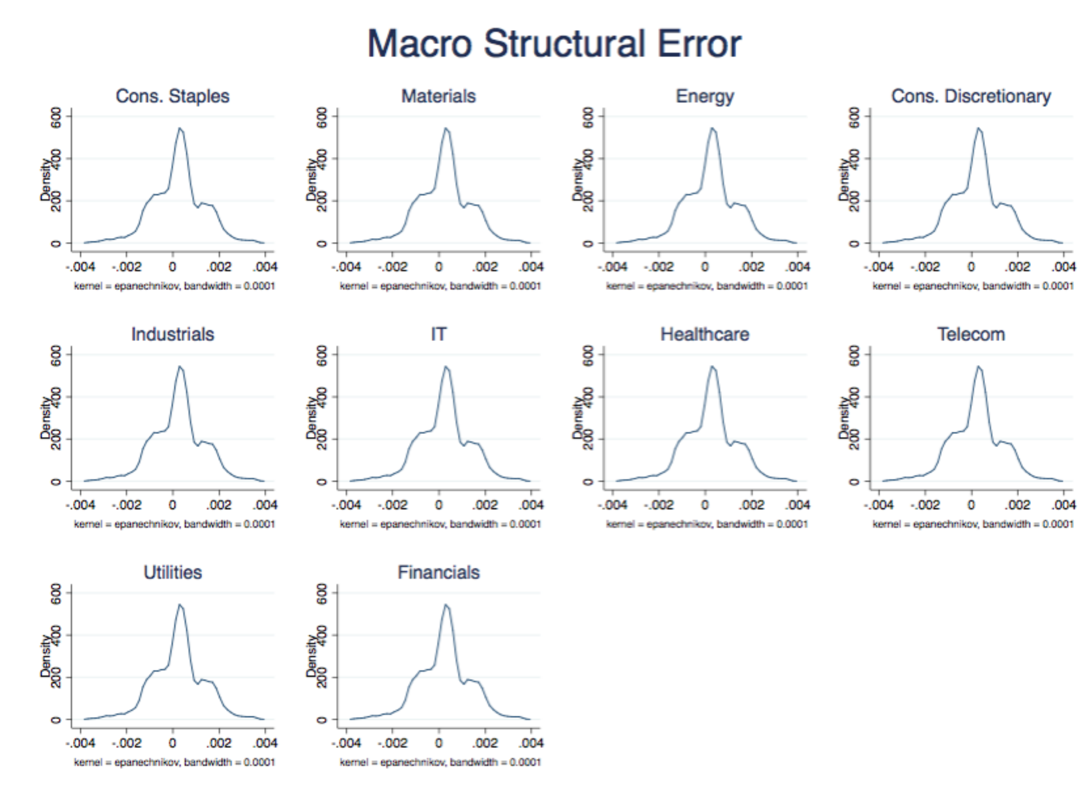
Note: This figure documents the cross-section distribution of the errors of Equation (12) for the CAPM Model.

Figure 17: Structural Error Analysis - FF3 MOM LIQ Model



Note: This figure documents the cross-section distribution of the errors of Equation (12) for the FF3 MOM LIQ Model.

Figure 18: Structural Error Analysis - CRR Model



Note: This figure documents the cross-section distribution of the errors of Equation (12) for the CRR Model.

Table 27: Alphas from Time-Series Regressions (Aug-87 to Dec-15)

	CAPM	FF3	FF3 LIQ	FF3 MOM	FF3 MOM LIQ	FF5	CRR
Consumer Staples	0.43%*	0.41%*	0.43%*	0.34%*	0.36%*	-0.04%	0.33%
Materials	-0.05%	-0.18%	-0.30%	-0.13%	-0.25%	-0.39%	-0.01%
Energy	0.19%	0.09%	-0.03%	0.05%	-0.07%	-0.02%	0.18%
Consumer Discretionary	0.04%	0.00%	0.01%	0.06%	0.06%	-0.08%	0.05%
Industrials	0.09%	0.06%	0.08%	0.09%	0.11%	0.01%	0.13%
Information Technology	0.04%	0.25%	0.25%	0.39%*	0.39%*	0.56%*	0.19%
Healthcare	0.41%*	0.43%*	0.47%*	0.36%*	0.4%*	0.13%	0.30%
Telecommunication Services	0.02%	0.08%	0.09%	0.10%	0.11%	0.06%	0.06%
Utilities	0.30%	0.22%	0.16%	0.13%	0.07%	0.11%	0.04%
Financials	0.05%	-0.12%	-0.09%	-0.08%	-0.04%	-0.09%	-0.06%
N	341	341	341	341	341	341	341

Note: This table documents the intercepts of individual factor regressions by sector and factor model. A $*$ signals that the estimated coefficient is statistically significant from zero with a 95% confidence level.

Table 28: Performance by Asset Pricing Model

Ex-ante	CEQ vs CAPM	Annualized
FF3	0.08%	0.90%
FF5	0.13%	1.61%
FF3 MOM	0.08%	0.90%
FF3 LIQ	0.10%	1.15%
FF3 MOM LIQ	0.08%	0.91%
CRR	0.08%	1.02%
Ex-post	CEQ vs CAPM	Annualized
FF3	0.08%	0.91%
FF5	0.04%	0.46%
FF3 MOM	0.08%	0.91%
FF3 LIQ	0.17%	2.04%
FF3 MOM LIQ	0.07%	0.90%
CRR	0.06%	0.78%

Note: This table documents the difference in ex-ante and ex-post certainty equivalent by each asset pricing model relative to the CAPM. with short sale constraints. Expected returns are calculated using the in sample betas, expected factors, and the variance-covariance factors of the assets.