Intermediary Asset Pricing and Betting Against Beta

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Abstract

From the intuition that the financial intermediaries are the agents most representative of the investors that actually interact on the financial markets and determine the assets' prices, intermediary asset pricing theories build pricing kernels mainly based on intermediaries' funding tightness. At the same time, this is also hypothesized to be key in rationalizing one of the most celebrated pricing anomalies, the CAPM-beta low risk anomaly. The same anomaly is also hypothesized to depend on the different coskewness mechanically brought by assets with different market betas, which is appreciated by the traders, but by the canonical models. Interestingly, because of the asymmetrical effects of the funding tightness, intermediary asset pricing theories predict their risk factors to be related to both. This thesis, after a few preparatory tests of the potential intermediary risk factors informativeness of the intermediary SDF, tests whether the consistency showed by the intermediary factor models on a multitude of assets in previous studies is extendible to the troubling LRA, which are theoretically well connected, and should therefore be explained by it.

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Acronyms

ADF Augmented Dickey-Fuller Test

AEM Adrian, Etula, et al. (2014)

BAB Betting against beta

CAPM Capital Asset Pricing Model

FOF Federal Reserve Flow of Funds

FP Frazzini and Pedersen (2014)

FRED Federal Reserve Economic Data, [Federal Reserve Bank of St. Louis (2018)]

HAC Heteroskedasticity and Autocorrelation Consistent

HKM He, Kelly, et al. (2017)

LRA Low Risk Anomaly

NW Newey and West (1987)

NY Fed Federal Reserve Bank of New York

RQ Research Question

SDF Stochastic Discount Factor

SES Systemic Expected Shortfall

SML Security Market Line

SR Sharpe Ratio

WRDS Wharton Research Data Center [*Wharton Research Data Services* (2018)]

1
Introduction

To understand the dynamics of assets' prices, modern finance theory mainly focuses on modelling the optimal behaviour of a representative investor. While this has been typically assumed to be the average household, recent research developments has started to move the spotlight towards the type of agents that realistically is the most active on the financial markets and thus whose investment decisions are more likely to determine assets' prices, i.e. the financial intermediaries. The exact concerns that guide these agents crucially depend on the financial frictions they are assumed to experience. However, they all eventually boil down to *funding tightness*, that is the availability of capital proportional to the needs of it in that moment. This can be driven by several determinants, such as the profitability of investment opportunities, the urgency of funds to cover losses, the obligation of meeting regulatory requirements, etc, where all tend to be correlated – for instance, investment opportunities of a market tend to be better when it is difficult to fund a trading position in such market. Then, funding tightness is set as key variable of the asset pricing models based on intermediaries.

On the other hand, one of the key factors of funding tightness, namely borrowing constraints, and more broadly funding constraints, are also hypothesized to be the root cause of a *pricing anomaly*, i.e. an error, of the Capital Asset Pricing Model, which is the reference equilibrium model in the literature. This defines a specific relationship between the amount of risk beared by holding an asset and the compensation required to do so. However, it relies on strong assumptions, such as the absence of funding constraints, and is widely violated in reality. Specifically, the borrowing constraints are hypothesized to cause the assets that are defined as riskier by the CAPM, those with higher covariance with the market, to provide lower risk-adjusted returns than the low-risk counterparties. Thus, as the intermediaries' investment decisions and this low-risk-anomaly have a common cause, namely the availability of funds to the majority of investors, which are financial intermediaries themselves, modelling their optimal behaviour should be very informative of assets' prices dynamics, which are not well captured by the CAPM. Further, there is another violation of the CAPM foundations that provides an additional hypothetical explanation of the low risk anomaly, which claims the unexplained returns of the anomaly to represent compensation for risks related to distributional asymmetries in the assets' returns. Interestingly, funding tightness is also predicted to cause asymmetries in assets' returns, thereby ending up being strictly related to the low risk anomaly in another way.

Finally, the goal of this work is then to assess how well the recent asset pricing models based on the intermediaries actually explain such theoretically strictly-related anomaly, exemplified by the trading strategy that is made profitable by the low risk anomaly itself, the betting against beta strategy. Pinning down this relationship may be potentially relevant for both future investment and policy analysis: while the first ones may intuitively benefit from a better pricing kernel model, whose signals enable the most profitable investment strategies, the second ones may gain from an additional tool based market data – for instance the level of profitability of betting against beta, in case it was actually related to marginal value of wealth – to gauge the actual status of funding tightness, which if not monitored and managed can trigger amplification mechanisms that lead to systemic crises such as the recent financial crises.

This thesis is structured as follows: first, I start outlining the main asset pricing theoretical frameworks and predictions based on the intermediaries in chapter 2; then, in chapter 3, I illustrate the empirical methods and evidence of the intermediary asset pricing models; next, in chapter 4, I briefly present the CAPM, as well as the evidence of some of its failures, and the theoretical hypothesized explanations; after that, I set up the empirical analysis by detailing the research questions that I aim to answer with this work and the data used to do so, in chapter 5; in chapter 6 I show the results of the tests executed and their implications; and finally, in chapter 7, I conclude. Further, appendix A shows mathematical passages omitted from the main body of the thesis; appendix B illustrate omitted details about the data used; and lastly, appendix C shows additional tests.

2

Intermediary asset pricing theory

This chapter outlines the main results of the intermediary asset pricing theoretical literature. More details about the models illustrated in this chapter can be found in Appendix A.

2.1 Introduction

Standard consumption-based asset pricing models consider the consumer households as the sole marginal investors and the intermediary sector as a simple pass-through of the direct interactions among households. However, to price all assets with the marginal value of consumption/wealth to the households, they should participate in every market and execute complicated trading strategies. Such assumptions seem to be widely violated in reality,[1] while, on the other hand, financial intermediaries actually trade a wide range of asset classes, often implementing complex investment strategies at high frequencies thanks to low transaction costs, and using continuously-updated models and extensive data to form forward-looking expectations of asset returns at best. Therefore, intermediaries are more likely to be the ultimate marginal investor in most of the asset markets and this motivated the intermediary asset pricing literature to argue that a unified model for jointly pricing of multiple traded assets in the economy is more informative if focused on the marginal utility of wealth to the representative intermediary rather than of consumption to the representative household. In particular, intermediaries are likely to completely take over households as a trader the more sophisticated is the asset, but participation of households in less sophisticated markets, such as equity stocks, do not precludes financial intermediaries from remaining a marginal investor.

Loosely speaking, the need of an additional dollar for an intermediary depends on the scarcity of own funds and on how profitable the employment of the extra dollar would be. The scarcity of funds depends on the availability of funding and the easiness of obtaining it, which are summarized with the term *funding liquidity*. It depends on institution-specific reasons, such as bad credit worthiness, and on the macroeconomic state, which determines the overall supply, while it determines the cost of funds. Anyway, when an intermediary has lower capital, its risk bearing capacity is reduced and so is its trading capacity. Then, when multiple intermediaries face restricted

[1] As showed for instance by Vissing-Jørgensen (2002), who document households' limited stock market participation.

financing, the market(s) in which they participate get less competitive, which leads to higher transaction costs to trade. Markets where the availability of counterparties to trade is low and trading costs are high – where easiness of selling assets is low – are termed of low ”market liquidity”. In such markets, prices may be moved far away from the fundamental value, thus giving rise to theoretical arbitrage opportunities and making more profitable to take part to the market. Nonetheless, it can also work the other way around: if few participants take part in a specific financial market, it is difficult to redeem any investment in such market – to fund other trades for example, thus less funds would be provided for trading activity in that market, making such funds more expensive. To sum up, scarcity can drive up the costs of capital while making investments more profitable, thus increasing the value of additional funds. Thus, as usual, in equilibrium the cost and profitability of a resource, funds in this case, are equal and represent two sides of the same coin, namely its marginal value.

In a world without financial frictions an intermediary would always be able to fund any profitable position or, at least, there would be a competing intermediary to take its place. There would be a perfectly efficient market-making, arbitrage-free markets, and asset pricing would be trivial. Nevertheless, in the real financial markets the liquidity issues just described occur and at times have huge effects, such as when they trigger *liquidity spirals*. These are episodes where negative price shocks get enormously amplified because market illiquidity and funding illiquidity reinforce each other. Specifically, when a price shock is negative enough: the funding providers worry about risk exposure thus reducing available funds and forcing further sales, which further depress prices; the other traders sell as well,[2] further depressing the price and making trading costs surge. Therefore financial frictions, namely funding constraints, are a key determinant of wealth marginal value and they are crucial to build a pricing kernel consistent with the reality.

Since marginal wealth value is not directly measurable, as neither are funding and market liquidity, to obtain testable predictions the intermediary asset pricing literature pinned down the SDF by relating it to intermediaries' balance sheets information, which instead is readily observable. More precisely, leverage has been hypothesized to be the key variable related to the wealth marginal value and their relation has been derived in general equilibrium models of economies prone to liquidity spirals due to funding constraint.[3] Strikingly, the conclusions of these models are at odds depending on the nature of the constraint, whether on equity or debt raising. The following sections will present the asset pricing predictions and contextualize the differences.

2.2 Equity constraint framework

The most recent examples of this line of research are He and Krishnamurthy (2013) and Brunnermeier and Sannikov (2014).[4] In these models, the inter-

[2]Positive-feedback trades may be due to: momentum strategies, predatory trading, hedging strategies, or, simply, crowded trading strategies.

[3]Leverage is defined as total assets, which must equal the total liabilities, i.e. debt plus equity, divided by equity capital – the intermediary's net worth.

[4]This framework originates with net worth-based based models such as Bernanke and Gertler (1989) and Kiyotaki and Moore (1997). Their models focus on linear approximations around a

mediary has a preference on the capital structure, as higher leverage implies higher returns and risk, but their raising of equity is restricted, which can be motivated by agency or informational frictions. As a result, when an adverse shocks hit the intermediary sector's assets and its equity shrink, the intermediaries can restore the optimal target level of leverage-risk only by reducing its debt financing. Such operation is performed with a lag and is funded with the sale of assets. If the precautionary assets sale is enough to trigger a liquidity spiral, the amplification mechanisms offset the de-leveraging of the intermediary by reducing the asset prices until a boundary condition is met – e.g. all of the assets are owned by the less-productive households, or enough positive shocks enable the intermediary to get back healthy. As the de-leveraging lags and the only possible equity in-flow is from assets returns, the equilibrium leverage following a negative shock is higher than what preferred by the intermediary, who then requires a higher risk premium because of the higher risk implied and the need of funds. Therefore, in this framework, leverage increase when funds are needed the most, while on the other hand, a positive shock to the assets increases the intermediaries' equity, thereby mechanically decreasing leverage and possibly easing the constraints on new equity raising, which may be used to buy other assets or leveraging up, creating anyway buying pressure on prices. In a few words, *leverage is counter-cyclical.*

A simple intermediary pricing kernel

To illustrate more formally the main asset pricing predictions of this class of models, I will go through a simplified, single-period model inspired by He, Kelly, et al. (2017) (HKM). The economy of this model is populated by two representative agents, a household and a financial intermediary, but to derive the equilibrium price of the assets in the economy only the marginal utility of consumption to the representative intermediary is considered, since it is assumed to be the only marginal investor in risky assets. The intermediary maximizes the stream of utility over a period, which begins "today" at time t and ends "then" at $t+1$, subject to a budget constraint:

$$\begin{aligned} &\max_{c_t,\theta_t} \mathbb{E}_t \left[u(c_t) + e^{-\rho} u(\tilde{c}_{t+1})\right] \\ \text{s.t.} \quad & c_t + \theta_t \cdot p_t = w_t, \quad \tilde{c}_{t+1} = \theta_t \cdot \tilde{x}_{t+1} \end{aligned} \tag{2.1}$$

with c_t being the consumption at time t, $u(\cdot)$ the instantaneous utility of consumption,[5] $e^{-\rho}$ the discount rate applied to the $t+1$ utility, w_t the initial endowment, θ_t the amount invested in a risky asset with price p_t that gives the right to the stochastic payoff x_{t+1} in the second period. The random variables are marked as $\tilde{\bullet}$ and are defined on the typical filtered probability space $(\Omega, \mathcal{F}, \mathbb{P})$ and measurable with respect to $\mathcal{F}_t$. The first order conditions directly provide the pricing equation where the Stochastic Discount Factor (SDF) $\tilde{M}_{t+1}$ projects the future uncertain payoff into the current asset price:

$$p_t = \mathbb{E}_t \left[e^{-\rho} \frac{u'(\tilde{c_{t+1}})}{u'(c_t)} \cdot \tilde{x}_{t+1} \right] = \mathbb{E}_t \left[\tilde{M}_{t+1} \cdot \tilde{x}_{t+1} \right] \tag{2.2}$$

deterministic steady state, while newer research typically solve fully stochastic models.

[5] The utility function is assumed to be well-behaved and concave

Note that if there are no arbitrage opportunities in the economy, i.e. multiple risky assets are traded and no profits can be done trading them without investing any portion of wealth, then a unique SDF must price all of the risky securities.[6] That is, the pricing kernel of representative investor must price the risk consistently across all of the available assets.

To link the current consumption-based formulation to intermediary's wealth, a first-order approximation is used: consumption c_t is assumed to be proportional to intermediary's wealth W_t^I, $c_t = \beta W_t^I$, where β is a positive constant. Further, if W_t is the aggregated wealth in the economy, that is $W_t = W_t^I + W_t^{HH}$, then the intermediary's share of wealth η_t can be defined as $W_t^I = \eta_t \cdot W_t$.[7] Since $c_t = \beta \cdot \eta_t \cdot W_t$, the SDF can be stated as:

$$\tilde{M}_{t+1} = e^{-\rho} \frac{u'(\beta\ \tilde{\eta}_{t+1} \tilde{W}_{t+1})}{u'(\beta\ \eta_t\ W_t)} \tag{2.3}$$

As long as the intermediary is risk averse, its marginal utility is higher when intermediary wealth is lower; in other words, when aggregate wealth W_t and/or intermediary's wealth share η_t are low, an additional dollar gets more valuable for the intermediary. As the SDF is higher the higher is the expected marginal utility of the state (and time) in which the payoff will be paid, it follows that a payoff paid in low-wealth states is more valuable than the same payoff paid in high-wealth states. More formally, the compensation required by the representative intermediary to hold an asset whose payoff covary with its future wealth, in the form of expected return in excess of the risk-free rate, is the following:

$$\mathrm{E}_t[\tilde{R}_{t+1}] - R_f = -\ \mathrm{Cov}_t \left[\frac{\tilde{M}_{t+1}}{\mathbb{E}_t[\tilde{M}_{t+1}]}, \tilde{R}_{t+1} \right] \tag{2.4}$$

Here, the future intermediary wealth enters the equation through the SDF as showed in Equation 2.3. The covariance term shows how an asset whose returns are lower when the SDF is higher – the "bad" states, is expected (unconditionally) to provide a higher return.

Finally, to relate the pricing kernel to the intermediary's leverage, the intermediary's wealth share is equated to its capital ratio, which is simply the reciprocal of leverage as defined in footnote 3:

$$\frac{W_t^I}{W_t} = \eta_t = \frac{\mathrm{Equity}_t^I}{\mathrm{Assets}_t^I} \tag{2.5}$$

Such critical relationship holds exactly only under stylized assumptions: (1) intermediary assets represent all of the net wealth in the economy, so the households cannot directly own any risky asset; (2) the intermediary equity amounts to the intermediary's net wealth only (more specifically to the wealth of the financial expert that runs it), so households cannot own any equity share of the intermediary, though they can have shares of the intermediary debt. For instance, He and Krishnamurthy (2013) build on the assumption that households can only invest in a zero-net-supply risk-free asset or in the intermediary's equity. Specifically, the last kind of investment may be

[6] Here I am also assuming market completeness.

[7] W_t^{HH} is the wealth of the households.

constrained, since it cannot be higher than a fixed share of the wealth invested by the financial experts who manage the intermediary themselves.[8] Therefore, in this model condition (1) is always met by construction, while, about condition (2), it can be noted that in the constrained states the intermediary's wealth share is mapped into the capital ratio.[9] In Brunnermeier and Sannikov (2014), intermediaries cannot issue equity to households, so condition (2) always holds, but households can hold risky assets at a cost, so condition (1) does not hold exactly. However, as outlined in the introductory section, the buyback of debt lags behind the reduction in intermediaries' capital, so the capital ratio co-move with the intermediary's wealth share.[10]

Plugging the right-hand side of Equation 2.5 into 2.3 and then into 2.4, it can be clearly seen that an asset paying systematically less when capital ratio is low, which is when leverage and the value of an additional dollar is high, requires a higher expected return. It can also be seen that *leverage risk*, that is, the risk of an asset's return to positively covary with leverage, has a negative price (commands a lower expected returns) because it helps agents smoothing consumption through out the economic cycle. At the end of the day, this pricing kernel relies crucially on two components – two *factors*:

- The economy's total wealth, W_t, which is led by the canonical productivity shocks that affect the fundamentals of the whole economy. It is related to the usual economic growth term used in consumption-based asset pricing models and is negatively related to marginal utility (marginal utility is low when W_t is high), because of risk aversion.

- The intermediary's capital ratio, η_t, which may be led both by changes in the capital structure implemented by the intermediary – in theory mainly through debt issuing/buybacks – and by shocks to the intermediary's assets that get channelled to the capital ratio through the equity. As η_t decreases, intermediary wealth decreases thus increasing its marginal utility and the absolute risk aversion.[11] Therefore, risky assets get sold, making the returns covary negatively with the SDF, and the price of this risk factor positive.

Utility of managers, who practically price and trade the assets, is aligned with the intermediary net worth utility with the following mechanisms:

- Monetary incentives and legal actions threat: as long as managers' compensation is mostly paid through stocks their own wealth suffers when intermediary's wealth decreases. Similarly, if his maladministration can be persecuted, he will be sensible to losses of the intermediary's wealth.

- Regulatory capital requirements: as equity shrinks, financial institutions may be forced by authorities to forgo profitable but risky investments. Therefore, the lower the capital the higher the potential opportunity cost.

[8] In a companion paper, He and Krishnamurthy (2012), the authors derive the optimal share by solving a moral hazard problem between the expert and the investor household.

[9] HKM, footnote 16.

[10] As showed in chapter 3, the empirical tests rely only qualitatively on the SDF specification, so HKM claims the co-movement to be a sufficient condition.

[11] Assuming constant relative risk aversion.

2.3 Debt constraint framework

This line of research is exemplified by Brunnermeier and Pedersen (2009) and Adrian and Shin (2010), among others.[12] In this set-up, equity issuance is ruled out by assumption and the focus is on credit availability, which is time-varying and depends on market conditions. In the case of Brunnermeier and Pedersen (2009), trading margins are endogenously determined, so when the market is hit by a significant decline, the lender tries to limit the exposure to the borrowers' default by increasing it.[13] Such action forces the trading intermediaries to liquidate assets to fund the margin call, thereby de-leveraging.[14] This, in turn, creates further selling pressure that potentially makes the cycle start all over again, moving prices away from the fundamentals. Once again, the result is that following (or preceding!) a negative shock to asset prices, due to precautionary motives, available funds are the least exactly when they are needed the most – funding constraints are the tightest, though this time it is credit availability that decreases, together with leverage. On the other hand, when the economic outlook improves, lenders lower margins, increasing credit availability and leverage, finally generating buying pressure on assets. Therefore, the leverage in this setting is *pro-cyclical*.

A simple intermediary pricing kernel

In the style of Adrian, Etula, et al. (2014), I present some of the results of Brunnermeier and Pedersen (2009) to show more formally the asset pricing implications of the framework just described. The economy of this model is composed by bank customers, who arrive sequentially to the market; speculators, who provide market liquidity smoothing price fluctuations; and financiers, who simply fund the speculators' trades with collateralized borrowing and set the margins to control their value-at-risk. Given the role similarity to the real-world financial intermediaries, the intermediary pricing kernel here is based on the representative speculator. There are two periods – three points in time, and the risk-neutral speculator just maximize its final wealth, given that its wealth must be higher than the margins required on its trading position (funding constraint) at any time:[15]

$$\theta_t \cdot m_t \leq W_t$$

where θ_t is the position in the risky asset at time t, m_t is the margin and W_t is the wealth. Then, at time 0, the problem can be described as maximizing the wealth at time 1 times the shadow cost/value of capital at that time ϕ_1:

$$\begin{aligned} &\max_{\theta_0} \mathbb{E}_0 \left[\tilde{\phi}_1 \cdot \tilde{W}_1 \right] \\ \text{s.t. } &\tilde{W}_1 = W_0 + (\tilde{p}_1 - p_0)\theta_0 + \tilde{\gamma}_1 \end{aligned} \tag{2.6}$$

[12]Shleifer and Vishny (1997) is a related pioneer work.

[13]The margin is the percentage of a trading position that must be deposited by the trader, required by the lender. The rest of the trading position is funded with the lender's capital, which is essentially credit to the trader.

[14]The intermediaries are essentially required to increase the equity deposited at the lender.

[15]I only consider one risky security to make notation simpler; the paper multiple securities are considered.

where p_t is the price of the risky asset, γ_1 is a zero-mean shock to final wealth due to exogenous and independent events, and the variables marked as $\tilde{\bullet}$ are random variables defined on the typical filtered probability space $(\Omega, \mathcal{F}, \mathbb{P})$ and measurable with respect to $\mathcal{F}_1$. Then, ϕ_1 essentially determines the value of wealth by itself since it is reflects the profitability of wealth in the next period, as long as the intermediary is not bankrupt:

$$\tilde{\phi}_1 = 1 + \frac{|\tilde{v}_1 - \tilde{p}_1|}{\tilde{m}_1} \tag{2.7}$$

where v_1 stands for the fundamental value of the risky assets at time 1, so $\frac{|\tilde{v}_1 - \tilde{p}_1|}{\tilde{m}_1}$ is essentially the profits per dollar that can be earned by trading the mispriced securities. In the model of Brunnermeier and Pedersen (2009), it increases following a rise in *de-stabilizing margins*, which, forcing speculators to sell assets in order to meet margin calls, makes mispricings increase.[16] Therefore, the dynamics of ϕ_1 is strictly related to the market liquidity – the availability of counterparties to trade, since the more liquid a market, the less sales have an impact on the price. At the end, intuitively, the value of wealth at time 1 is higher when investment opportunities are especially good and available funding is relatively low.

Generalizing the result of the first order conditions from the time frame (0, 1, 2) to $(t,\, t+1,\, t+2)$, the SDF is simply:

$$\tilde{M}_{t+1} = \frac{\tilde{\phi}_{t+1}}{\mathbb{E}_t\left[\tilde{\phi}_{t+1}\right]} \tag{2.8}$$

This SDF weights more in the price the payoffs of the states when the shadow value of capital is high relatively to its expected value. Then, expressing the related pricing equation in terms of the expected return from a risky asset

$$\mathbb{E}_t[\tilde{R}_{t+1}] - R_f = -\frac{\mathrm{Cov}_t\left[\tilde{\phi}_{t+1}, \tilde{R}_{t+1}\right]}{\mathbb{E}_t[\tilde{\phi}_{t+1}]} \tag{2.9}$$

It is clear that the lower are the asset's returns when funding conditions are bad and shadow value of an additional dollar is high, the greater the compensation the agent will require (and expect) to hold such asset instead of an asset that do not covary with the SDF – the risk-free asset.

Finally, to relate the pricing kernel to leverage, AEM rely on the fact that at time $t+1$ the margin constraint is always binding, so ϕ_{t+1} is monotonically decreasing with time $t+1$ leverage (and increasing with the margin), i.e. as capital become more abundant. So, they specify:

$$\phi_{t+1} \approx a - b\ \ln(\text{leverage}_{t+1}) \tag{2.10}$$

Therefore, the final relation between expected returns and leverage is:

$$\mathbb{E}_t[\tilde{R}_{t+1}] - R_f = b\ \frac{\mathrm{Cov}_t\left[\ln(\widetilde{\text{leverage}}_{t+1}), \tilde{R}_{t+1}\right]}{\mathbb{E}_t\left[\tilde{\phi}_{t+1}\right]} \tag{2.11}$$

[16] To comply with the margin constraint, when it binds, θ_t needs to be lower to accommodate a higher m_t.

Here, an asset whose returns are low when leverage is low – and relative need for funding is high, is required to have a high expected excess returns, i.e. the *leverage risk* has a positive price. Essentially, assets that covary with leverage worsen the consumption pattern making it less smooth, thus a positive compensation is required. Note that there is no aggregate wealth nor consumption, therefore, as AEM literally state, "It is important to note that leverage–not wealth–is the key measure of the marginal value of wealth in these models".

2.4 Discussion on leverage cyclicality

The two lines of research just presented get very different results. To sum up, while the equity constraint models find that tighter funding is related to higher intermediary's leverage, and thereby attach a higher marginal value to wealth in high-leverage states and ask a higher compensation for *negative covariance* with leverage, the debt constraint models find that the funding constraints are tighter when leverage is low, and thereby attach a higher marginal value to wealth in low-leverage states and ask a higher compensation for *positive covariance* with leverage.

At the root of the differences there is the fact that the two types of constraint entails two exclusive types of balance sheet dynamics, illustrated in Figure 2.1, where model 2 refers to equity-constraint models dynamics and model 3 to debt-constraint ones. Specifically, only one element of the liabilities is assumed to be driven by precautionary motives and thus engage with the assets in a mutual-negative-feedbacks loop, that is, a liquidity spiral. This automatically implies which element will be mostly affected by a (sufficiently) negative shock of the assets and whether leverage is pro- or counter cyclical. However, as AEM and He and Krishnamurthy (2013) point out, the real-world intermediaries are likely to be heterogeneous to some degree and experience the constraints in different states and extents. Indeed, one of the hypothesis is that heterogeneity may depend on the type of intermediary: for example, during a downturn, when the marginal value of wealth is likely to be high for all intermediaries, the margin requirements may become binding for hedge funds forcing them to sell their assets – acting closer to what described by debt-constraint models – while commercial banks may buy such assets, enlarging the balance sheet with external funds – acting more closely to what described by the equity-constraint models. In such case, the hedge fund was likely employing all of the debt capacity, while the commercial bank likely had some spare capacity, reflective of the different purposes – and managers' incentives – of the two institutions. Then, the leverage of these two intermediaries would move in opposite directions, leading the overall intermediary sector to behave in a much more nuanced and complex way than what predicted by either class of models. This potential heterogeneity poses some empirical challenges, since as long as leverage is used to proxy marginal utility, the relationship between these two must be univocal for the considered set of agents.

Empirical evidence

Recently, several empirical analysis have been carried out to provide evidence on the cyclicality of leverage, with the following results:

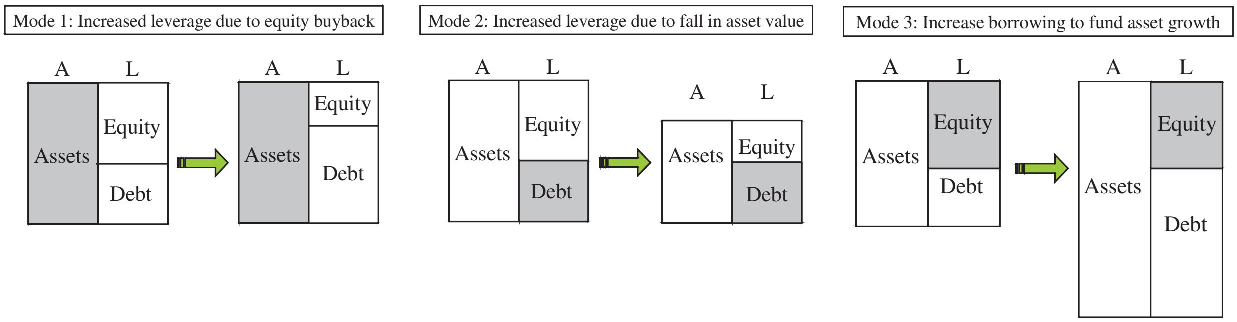


Figure 2.1: Modes of levereging up. The shaded area indicates the balance sheet component that is held fixed. Source: Adrian and Shin (2014).

Pro-cyclical leverage

- Adrian and Shin (2010) and Adrian and Boyarchenko (2013) provide evidence based on book values, of a highly pro-cyclical leverage of the broker/dealer sector.[17]
- He, Khang, et al. (2010) and Ang et al. (2011) document that hedge funds during the last financial crises, when marginal utility of funds was likely to high for all of the intermediaries, reduced the assets de-leveraging.

Counter-cyclical leverage

- Ang et al. (2011) provide evidence based on market values of a higher leverage of the broker/dealer sector during the 2008 crisis.
- He, Khang, et al. (2010) show that the book leverage of commercial banking sector increased significantly during the 2008 financial crises.
- Gatev and Strahan (2006) and Pennacchi (2006) document the counter-cyclicality of inflow funds to banks.

It is clear then that there is a wide heterogeneity in the leverage dynamics, depending on the type of intermediary category, which is reflective of a re-intermediation scheme in the sector.

[17] Adrian and Boyarchenko (2013) also show the leverage of the non-bank financial sector is a-cyclical.

3

Intermediary pricing kernel empirical tests

The main empirical evidence supporting the intermediary asset pricing theory as a whole is provided by AEM and HKM, since both find strong cross-sectional evidence in favour of a pricing kernel based on intermediaries' balance sheets.[1] However, the results of the two studies, like the two classes of theoretical models showed in chapter 2, are at odds about the risk premium related to the intermediary leverage risk factor.

3.1 Data and empirical strategies

In this section I summarize the theoretical framework, empirical methodology and data employed in the two studies.

Adrian, Etula, et al. (2014)

Similarly to section 2.3, AEM specify an SDF that is affine in a leverage factor

$$M_t = 1 - b \cdot lvg_t^{\Delta,BD} \tag{3.1}$$

which ends up generating the linear factor model

$$\mathbb{E}[r_t^e] = b \text{ Cov}\left[r_t^e, lvg_t^{\Delta,BD}\right] = \lambda_{lvg}\beta_{lvg} \tag{3.2}$$

where $r_t^e = R_t - R_f$; $\beta_{lvg} = \text{Cov}(r_t^e, lvg_t^{\Delta,BD})/\text{Var}(lvg_t^{\Delta,BD})$ captures the exposure of the risky asset to $lvg_t^{\Delta,BD}$; and λ_{lvg} represents the price of risk associated with $lvg_t^{\Delta,BD}$. This leverage factor model is then tested with the cross-sectional regression

$$\hat{\mathbb{E}}[r_{i,t}^e] = a + \hat{\boldsymbol{\beta}}_{i,\mathbf{f}}' \, \boldsymbol{\lambda}_{\mathbf{f}} + \varepsilon_i \tag{3.3}$$

where the test assets portfolios are indexed with i,[2] $\boldsymbol{\lambda}_{\mathbf{f}}$ is the vector of risk premia associated to the risk factors tested – included in the vector $\mathbf{f}_t$, and the vector $\boldsymbol{\beta}_{i,\mathbf{f}}$ is estimated with the time series regression

$$r_{i,t}^e = c_i + \boldsymbol{\beta}_{i,\mathbf{f}}' \, \mathbf{f}_t + \epsilon_{i,t} \tag{3.4}$$

[1] Further evidence is provided by Adrian, Moench, et al. (2016), which test the forecasting power of four different intermediary pricing kernels and find evidence mostly according to AEM.

[2] The asset classes can be studied separately including only the portfolios from one asset class, or pooled, including all of the portfolios in one regression.

The main focus of AEM's analysis clearly is on the case $\mathbf{f}_t = lvg_t^{\Delta,BD}$.

The leverage factor employed by the authors as a proxy of the shocks to the SDF consists in the innovations to the *aggregate leverage ratio* lvg_t^{BD} of all the institutions in the security broker-dealers sector – indexed by i, which is computed as:

$$lvg_t^{BD} = \frac{\sum_i \text{Financial assets}_{t,i}}{\sum_i \text{Financial assets}_{t,i} - \text{Financial liabilities}_{t,i}} \tag{3.5}$$

Specifically, the *leverage risk factor* was built as real-time seasonally-adjusted log differences in the level of lvg^{BD}:

$$lvg_t^{\Delta,BD} = \left[\Delta \ln \left(leverage_t^{BD}\right)\right]^{SA} \tag{3.6}$$

The authors estimate it using quarterly seasonal dummies in an expanding-window regression at each date, using the data up to that date.

The data is based on book values from the Federal Reserve Flow of Funds (FOF), have quarterly frequency and cover the period from 1968 to 2009.[3] The test assets included in the analysis are: 25 size and book-to-market (value) portfolios, 10 momentum portfolios, and 6 Treasury bond portfolios sorted by maturity.

He, Kelly, et al. (2017)

HKM essentially assume the SDF showed in section 2.2, where the marginal utility of time t is standardized to 1:

$$M_t = e^{-\rho}\ u'(\beta\ \eta_t^{\Delta} W_t) \tag{3.7}$$

which the authors claim to test qualitatively with the factor model:

$$\mathbb{E}[r_t^e] \approx\ \text{Cov}\left[\eta_t^{\Delta}, r_t^e\right] +\ \text{Cov}\left[W_t, r_t^e\right] = \lambda_\eta \beta_\eta + \lambda_W \beta_W \tag{3.8}$$

λ_i and β_i being the premium of and the sensibility of the asset to the risk factors $[\eta^{\Delta}, W]$, respectively. $[\eta^{\Delta}, W]$ represent the shocks to the aggregate wealth – the market risk, and to the tightness of the intermediaries' fundings – the intermediary leverage/capital ratio risk.

The authors compute the intermediary quasi-market capital ratio η_t aggregating the balance sheets of the Federal Reserve Bank of New York's (NY Fed) *primary dealers* – indexed with i; and the intermediary capital risk factor η_t^{Δ}, as the AR(1) innovations of η_t, scaled by the lagged value η_{t-1}:[4]

$$\eta_t = \frac{\sum_i \text{Market equity}_{i,t}}{\sum_i \left(\text{Market equity}_{i,t} + \text{Book Debt}_{i,t}\right)} \tag{3.9}$$

$$\eta_t^{\Delta} = u_t^{\eta}/\eta_{t-1} \quad \text{where} \quad u_t^{\eta} = \eta_t - \phi_0^{\eta} - \phi_1^{\eta} \cdot \eta_{t-1} \tag{3.10}$$

Then the authors perform the regressions 3.3 and 3.4 focusing on $\mathbf{f} = [R_W, \eta^{\Delta}]$. The test assets set is comprised of a wide range of asset classes: 25 size-

[3] The available data actually spanned the period from 1952 to 2009, but the first 16 years were dropped because the authors considered the resulting leverage ratios unreasonably high, with the equity being negative for several years.

[4] More about the NY Fed primary dealers in section 3.3

and value- sorted equities portfolios, 10 maturity-sorted US government and corporate bonds portfolios, 6 sovereign bonds portfolio,[5] 54 moneyness- and maturity- sorted options leverage-adjusted portfolios, 20 credit default swaps spreads-sorted portfolios, 23 commodities portfolios, and 12 currencies portfolios.[6]

3.2 Results

In this section I summarize the contrasting results of the two studies, whose differences will be further debated in the next section.

Adrian, Etula, et al. (2014)

Pooling all of the test assets portfolios in the single-factor cross-sectional regression, AEM find a low and insignificant intercept (12 basis points, t-stat: 0.06); and a positive and significant risk premium related to the leverage factor (62%, t-stat: 4.6), where the adjusted R^2 is 77%.[7] The mean absolute pricing error (MAPE) is around 1% per annum, and the most problematic portfolios, those with the highest MAPE, are the highest momentum portfolio (pricing error of 7%) and the small-growth portfolio (3% pricing error). The authors then perform a series of comparison tests:

- They include the canonical market risk factor, thus test a two-factor model similar to HKM: it does not change any of the statistics of the previous results and the market risk price only ends up with a t-statistics of 1.75
- They test the CAPM and the Fama and French (1993) three-factor models: they have a cross-sectional intercept that is both statistically and economically significant, as it is over 3% per annum with t-statistics over 3, and a far lower adjusted R^2, of 0.10 and 0.16 respectively
- They test a five-factor model that includes the Carhart (1997) momentum factor and the bond pricing factor of Cochrane and Piazzesi (2008), which are the shocks to the first principal component of the yield curve: it is the only model that matches the performances of the leverage single-factor model in terms of intercept (0.66%, t-stat: 1.14); and adjusted R^2 (0.81). However, the authors also test whether all of the pricing errors could be jointly equal to 0, and the single-factor model shows a lower statistic than this five-factor model.[8]

Finally, they also find that leverage shocks are uncorrelated to the measure of innovations to market liquidity proposed by Pástor and Stambaugh (2003) and that the presented results hold both in ”good” and ”bad” times, showing that broker-dealers may be borrowing-constrained in period of non-crises as well.

[5] These portfolios are created double-sorting the assets by their covariance with the US equity market returns and S&P bond's credit rating.

[6] 6 based on Lettau et al. (2014) interest-differential-sorting and 6 on momentum-sorting.

[7] Rates are quarterly and the t-statistics are computed as in Fama and Macbeth (1973).

[8] The test statistic associated to the leverage factor model is $\chi^2_{N-2} = 68$, while for the five-factor the statistic is $\chi^2_{N-6} = 110$. Note how the statistic is lower for the leverage factor model even if it has the least degrees of freedom among the tested models.

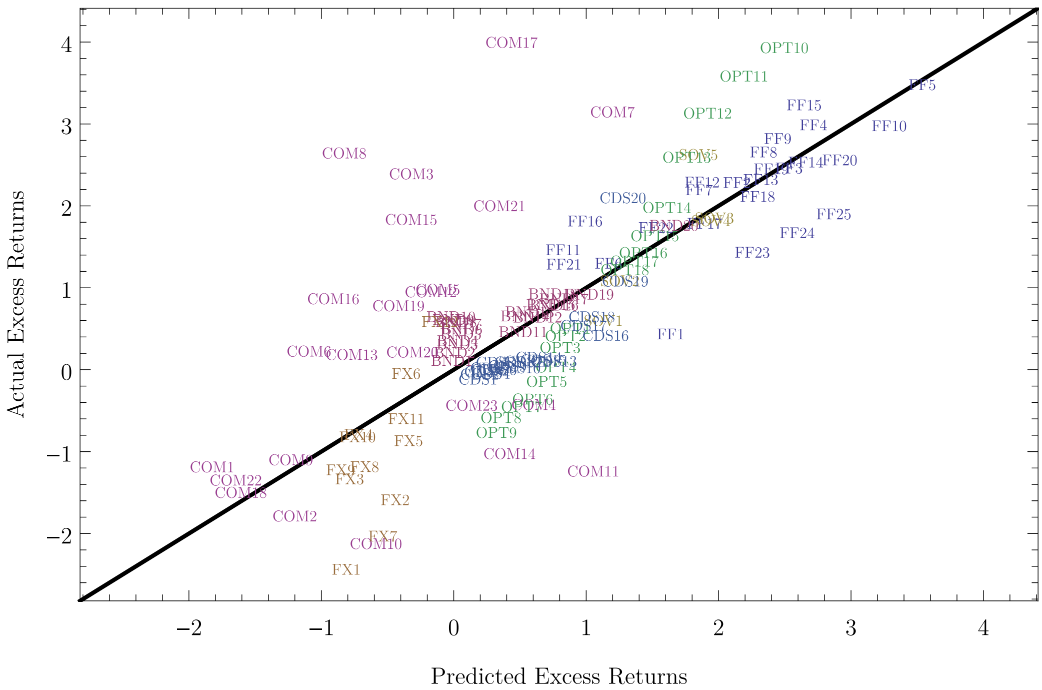


Figure 3.1: Pricing errors of HKM. Actual average percent excess returns on all tested portfolios versus the expected returns predicted by the pooled cross-sectional regression based on risk exposures to the intermediary capital risk factor and the market excess returns. Portfolios are abbreviated based on their asset class: equities (FF), US bonds (BND), foreign sovereign bonds (SOV), options (OPT), CDS, commodities (COM), and foreign exchange (FX). Source: He, Kelly, et al. (2017).

He, Kelly, et al. (2017)

HKM find a significant exposure to intermediary capital risk of all the asset classes. Specifically, when the cross-sectional analysis is performed on the asset classes separately, the estimated class-specific risk premia, which can be observed in figure 3.2a, are always positive and statistically significant at the 5% level, a part from the sovereign bonds and the commodities where it is anyway significant at the 10% level.[9] As can also be seen in Figure 3.1, commodities is the asset class that in general the model fits the worst (R^2 of 25%), while the closest fit is achieved with option portfolios (R^2 of 99%). The premia range from 7% for equities to 22% for options, and when all of the asset classes are included contemporaneously in the (pooled) cross-section analysis, the estimated price of intermediary capital risk is 9.35%.[10] Interestingly, the hypothesis that risk price is 9% for any of the individual asset classes cannot be rejected at the 5% significance level, while the hypothesis of all the separate risk premia being 0 can be rejected at 10% level of confidence. Homogeneity of the intermediary capital risk premia is crucial to support intermediary asset pricing theories because it confirms that the leverage risk factor successfully proxy the SDF of a marginal investor active in all the markets. In other words, it confirms that at least the set of intermediaries considered in the intermediary risk factor are marginal in all of the asset markets, thus strengthening the case of a unique pricing kernel based on their

[9] The t-statistics are respectively 1.66 and 1.90. These are GMM t-statistics, which are used in order to correct for cross-correlation and first-stage estimation error in betas.

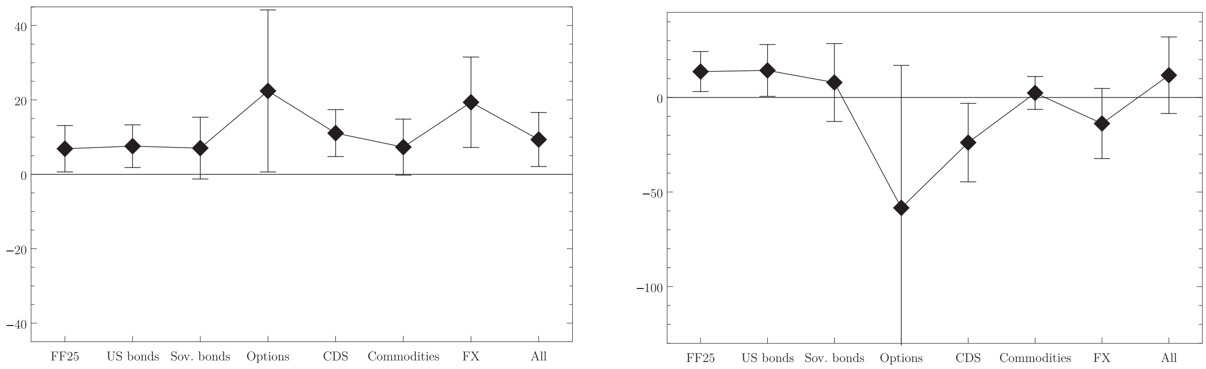
[10] With a t-statistic of 2.52 and a R^2 equal to 71%. The rates are quarterly.

wealth for all risky assets (which implies no arbitrage exist). If instead some of the considered intermediaries specialized in a specific asset class, their leverage would entail a different pricing kernel, which could not price all the risky assets. The authors argue that evactly this failure could explain the higher estimates for options and FX. Moreover, the authors also estimate the MAPE for each of the asset classes and a restricted version of the MAPE (MAPE-R) in which the pricing errors are computed using the risk premia estimated in the pooled cross-sectional regression. The resulting differences between the MAPE-R and the MAPE are modest: the proportionally and absolute highest difference is with options, 0.54% (MAPE: 0.14%), and the lowest is with equities, 0.06%(MAPE: 0.34%). So, again, allowing risk prices to vary across asset classes brings little gains in pricing ability, strengthening the hypothesis of a pricing kernel based on the intermediary capital to efficiently price all of the financial assets.

In the pricing kernel tested by HKM, contrary to AEM, also shocks to aggregate wealth – proxied by the excess market returns, are considered.[11] Empirically, the estimated price of market risk is positive in all asset classes, though significant only in the foreign exchange test. As the intermediary capital risk coefficient remains definitely significant while controlling for the market return, the authors claim that it can be stated that the pricing kernel tested statistically improves on the CAPM for all of the tested asset classes. The authors also directly compare the pricing power of the intermediary capital ratio factor to the plain CAPM, the Fama and French (1993) three- and the Fama and French (2015) five-factor models, the Carhart (1997) momentum factor, the Pástor and Stambaugh (2003) liquidity factor, and the Lettau et al. (2014) down-side risk CAPM models. The first relevant result is that every time the intermediary capital risk factor is included in the regressions of the aforementioned models, the MAPE decreases of 22±2 basis points, where the MAPEs of those models ranged from 0.82 to 0.87. The second one is that the adjusted R^2s moves as well: from 0.32 to 0.71 in the CAPM, from 0.65 to 0.80 in the three-factor model, from 0.65 to 0.69 in the five-factor model, from 0.27 to 0.73 in the momentum model, from 0.50 to 0.71 in the down-side CAPM, while the liquidity model is the only one to show no improvements in the adjusted R^2. The intermediary capital risk factor is always significant at 10% and at 5% in the CAPM, the five-factor and momentum models. At the same time, the highest t-statistic reached by any of the peculiar factors of the compared models is only 1.46, which reached by the High-Minus-Low factor in the five-factor model.

Finally, as capital ratio shocks can be driven both by changes in the debt and in the equity values, the authors test whether one of the two components has a greater influence. They do so performing a three-factor version of the model – the three factors are: market returns, log-innovations in intermediary market equity, log-innovations in intermediary book debt – on the asset classes separately and pooled. When all asset classes are tested together, the equity risk factor is significant at 5% and of a similar magnitude to the two-factor test (9.7%), while the debt risk factor has a coefficient and a t-statistic close to 0, thereby suggesting that the intermediary capital risk factor is mainly driven by the market equity innovations. Nonetheless, when asset classes are tested separately, equity innovations always have coefficients higher than 4.7%,

[11] AEM test a specification where the market risk is included only as a robustness check.



(a) HKM (b) AEM

Figure 3.2: Intermediary capital risk premia per asset class, comparison of the results from HKM and AEM. AEM only performed a pooled cross-section analysis, the class-specific risk premia showed in panel (b) have been estimated by HKM with their methodology, using the data provided by AEM. Source: He, Kelly, et al. (2017).

but significant only in the foreign exchange class (at 1% level), while debt innovations have a negative coefficient in 5 of the 7 asset classes, statistically significant at 5% only on the sovereign bonds and CDS classes. To sum up, market equity seems to be the most important component of the analysis, but debt definitely has a role in some asset class.

3.3 Making sense of the conflict

As illustrated in the previous section, the estimation of the risk premium associated to the intermediary capital ratio differs significantly between HKM and AEM. Specifically, it is positive for both of the papers, but where one uses the capital ratio as a risk factor, the other one uses leverage, which, being the reciprocal, should bring opposite results to be consistent with the first study. Then, HKM have tested with their methodology and wide-ranging test assets the AEM leverage factor, and the result is that the risk premia associated to the leverage factor changes sign depending on the asset class and is not significant for many asset classes, as it is shown in Figure 3.2. This is strongly inconsistent with the theories, which predict a common risk factor to price all of the traded assets.[12] Moreover, in the pooled cross-sectional analysis, the AEM leverage risk factor is not significant.

As the empirical results' divergence resembles the divergence in the predictions of the theories showed in chapter 2, the cause of the divergence is expected to be strictly related to the arguments explained in section 2.4, where the theories are re-connected. In facts, as can be seen in Figure 3.3, the leverage measures that underlie the leverage risk factors at the core the two papers are markedly conflicting in terms of cyclicality: the correlation between the HKM *capital ratio* and the AEM *leverage* measure is positive

[12] It must be reported though that on the classes equities and treasury bonds, the AEM performance is superior to HKM, as reflected in their higher cross-sectional R^2 (respectively 0.70 vs 0.53, 0.87 vs 0.84). AEM is relatively successful in explaining average returns among momentum-sorted equity portfolios, which HKM state to be unable to explain.

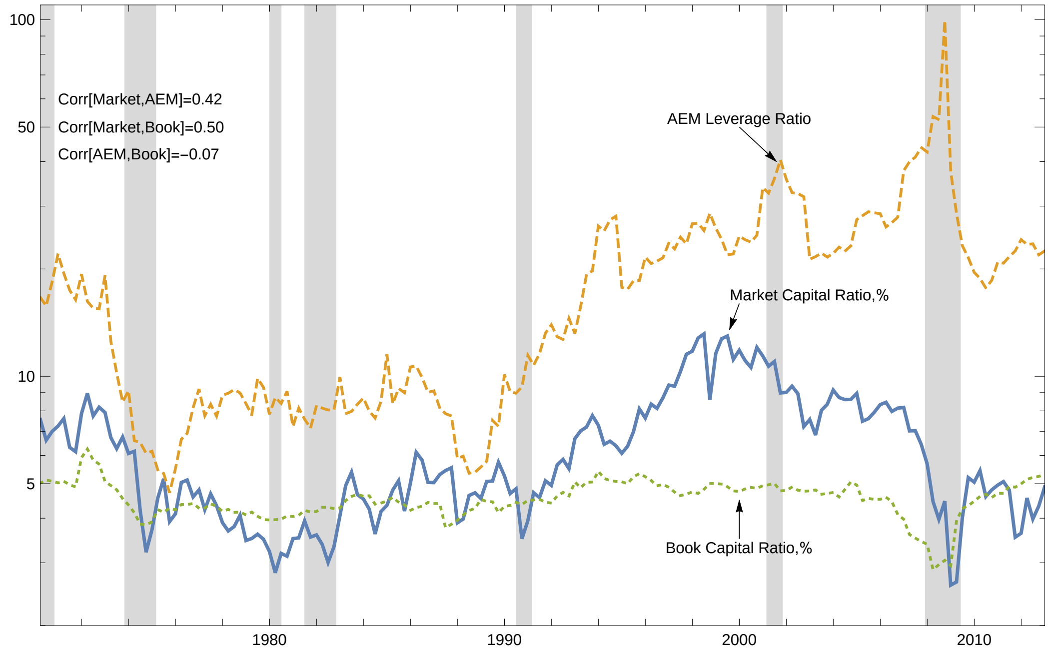


Figure 3.3: Comparison of leverage measures from HKM and AEM in levels. Source: He, Kelly, et al. (2017).

both in levels (42%) and in innovations (14%).[13] The potential reasons of this discrepancy in the estimated leverage are illustrated in the following paragraphs, which are mainly based on He, Kelly, et al. (2017).

Book vs. market values

The first difference to note in the used data is that HKM use quasi-market data (market equity, book debt), while AEM use book data. In order to reflect the forward-looking information contained in the assets' prices, HKM argue that most of the theories would suggest using market values. However, as broker-dealers are required to mark the books to market frequently, one would still expect a positive correlation between market values and book values. In such case not huge differences would be expected. In facts, the correlation between the HKM market capital ratio and the Compustat book capital ratio of primary dealers is positively correlated both in levels (50%) and in innovations (30%). Therefore, the source of the results differences is more likely coming from the composition of the set of intermediaries considered.

Broker-dealer subsidiaries vs. primary dealers holding companies

The second difference in the data used to build the leverage/capital ratio factor takes place in the the set of intermediaries included: AEM consider the whole universe of the intermediaries in the securities broker-dealers sector, while HKM only include the primary dealers, which are the trading counterparties of the NY Fed in its implementation of monetary policy. Nonetheless, as

[13]It must be remembered that capital ratio is the reciprocal of leverage. Therefore, a positive correlation between the aggregate capital ratio measure from HKM and the leverage measure of AEM implies a negative correlation between the two measures when expressed in the same terms.

already illustrated in section 2.4, different types of financial intermediaries are expected to show very different relationships between leverage and wealth marginal utility, and thereby different prices of leverage/capital ratio risk. Indeed, the correlation between the capital ratio of primary dealers and that of non-primary dealers is -9%.

The NY Fed primary dealers form a relatively small group of institutions that is composed by the largest and most active broker-dealers, while, as described by HKM, "non-primary dealers tend to be smaller, standalone broker–dealers with little activity in derivatives markets". This leads the primary dealers to be more likely to represent the marginal investor in most of the financial markets and, on these terms, it also comes natural to choose them as focus of the empirical test of an intermediary pricing kernel, which is expected to price all of the risky assets in the economy. Indeed, when HKM test the non-primary dealer capital ratio factor, equities and CDS show a significantly positive price of capital ratio risk, while the estimated price of capital risk in all the other asset classes is insignificant or even significantly negative, in the case of options. This again confirms that there is a high degree of heterogeneity in the intermediary sector but also, at the opposite, that the primary dealers are quite homogeneous. To directly test the homogeneity of primary dealers, HKM compute the correlation of the "equal-weighted average capital ratio" and the the "value-weighted" measure for primary dealers, which is 97.8%;[14] while this correlation is only 56% for non-primary dealers.

A further difference in the selection of the intermediaries included in the computation of the leverage risk factor is the observed economical unit: AEM, by using the FOF data, focus on the broker-dealer *subsidiaries*, while HKM, by hand-checking the correspondence, look at the *holding companies* of the primary dealers. As HKM point out, capital markets within the financial conglomerates can make this fact play a role in the gap between the two papers, as they potentially diversify and transmit adverse financial shocks across subsidiaries.[15] Specifically, when a subsidiary suffers large trading losses, it gets reflected in the FOF anyhow, but if the parent company is thriving and the subsidiary has access to the internal capital market, then it does not affect much the availability of funds nor the related marginal value of additional capital. On the other hand, a negative shock to a different division that put the holding company in distress may impair internal capital flow thereby reducing the available funds to the healthy broker-dealer subsidiary, which may have to reduce profitable positions. Clearly, if internal capital markets represent a significant source of funds for the broker-dealer subsidiaries, the capital ratio of the holding company would be a much better proxy for the intermediary sector pricing kernel. Also from a legal perspective, it can be observed that both the holding company and (many of) the subsidiaries are subject to the regulatory capital requirements, but only the holding company raises equity, which then distribute to the subsidiaries. So, once again, the financial distress should observed at the holding level. Moreover, the holding company may impact the subsidiaries' financial soundness (where the opposite is still less likely) even when the internal capital market is not affected, for

[14]The equal-weighted average capital ratio corresponds to the plain mean of the capital ratios of the primary dealers, i.e. a weighted average of the capital ratios where each intermediary has weight 1, irrespective of the size. On the other hand the "value-weighted" measure essentially refers to η_t as previously showed.

[15]Scharfstein and Stein (2000)

example through the reputation, since the subsidiary's funding ability in the short-term debt market is influenced by the perceived risk of the entire conglomerate.

3.4 Systemic risk

The focus of the intermediary asset pricing theories is the marginal utility of wealth to intermediaries, which crucially relies on the availability of funding to them. Interestingly, the capitalization status of the financial intermediaries is also the key variable of the financial systemic risk literature, which is concerned with how vulnerable is the financial system to propagation of losses. Several empirical contributions have proposed different measures to gauge how high is the risk of a systemic event, that is a default contagion among institutions that interrupts the proper functioning of the whole financial system, then hurting the real economy.[16] Among those, there is a measure that relates especially well with the intermediary asset pricing theories: the systemic expected shortfalls (SES), proposed by Acharya et al. (2017), which equals the expected losses conditional on critical market conditions. As the SES of an institution increases, so do the funds needed to survive the crises. Thus, if managers' incentives/constraints are aligned, the higher value of financing will be reflected in asset prices.

An issue with this claim concerns government insurance: in the occurrence of systemic events, the government typically intervenes to mitigate the systemic risk externalities on the real economy. In such cases the risk of undercapitalization is not beared by the intermediaries and moral hazard may take place. Then, SES would perfectly capture the value/scarcity of funds in the overall economy, but the managers of the intermediaries would not experience a higher need of funds, thereby leaving the intermediary SDF unaffected. However, when government intervention seems less likely, a higher SES implies a higher risk of not being able to perform the basic transactions or meeting the capital requirements when it is most relevant – in crises. Therefore, its informativeness about the level of funding needs of the intermediaries is expected to provide anyway some precious information, and juxtaposed with leverage.

The SRISK and empirical evidence

Acharya et al. (2017) propose an estimator of the SES based on structural assumptions and that requires observing a realization of a systemic crisis, thus such methodology is not the first-best ex-ante. Brownlees and Engle (2017) propose a forward-looking version of the SES, called SRISK, based on publicly available information.

Following the original paper, capital shortfall of firm i on day t is

$$\mathrm{CS}_{i,t} = k \cdot \mathrm{assets}_{i,t} - \mathrm{equity}_{i,t} \tag{3.11}$$

where k is the prudential capital fraction, e.g. following Basel Accords $k = 8\%$, and $\mathrm{assets}_{i,t} = \mathrm{equity}_{i,t} + \mathrm{debt}_{i,t}$. Then, a systemic event is defined as a multiperiod (from time $t+1$ to $t+h$) arithmetic market return below the

[16]See Bisias et al. (2012) for a thorough survey of the systemic risk measures.

threshold C, $\{R_{M,t+1:t+h} < C\}$, where the authors set C=60%.[17] Finally, the expected capital shortfall in case of systemic risk with horizon h is named SRISK, which computed as:

$$\begin{aligned}\text{SRISK}_{i,t} &= \mathbb{E}_t(\text{CS}_{i,t+h}|R_{M,t+1:t+h} < C)\\ &= k \cdot \mathbb{E}_t(\text{debt}_{i,t+h}|R_{M,t+1:t+h} < C)\\ &\quad - (1-k)\mathbb{E}_t(\text{equity}_{i,t+h}|R_{M,t+1:t+h} < C)\end{aligned} \tag{3.12}$$

It is assumed that debt cannot be renegotiated, so that the expected amount of debt at the horizon $t+h$ is equal to debt at time t. SRISK then:

$$\text{SRISK}_{i,t} = \text{equity}_{i,t}[k \cdot \text{lvg}_{i,t} + (1-k)\text{LRMES}_{i,t} - 1] \tag{3.13}$$

where $\text{lvg}_{i,t} = \frac{\text{debt}_{i,t} + \text{ equity}_{i,t}}{\text{equity}_{i,t}}$, and LRMES is the Long Run Marginal Expected Shortfall, that is the expected multiperiod arithmetic return given that the market experience a crises

$$\text{LRMES}_{i,t} = 1 - \mathbb{E}_t(R_{i,t+h}|R_{M,t+1:t+h} < C) \tag{3.14}$$

Estimation of LRMES requires a model for the returns of market and firm: several methodologies can be used, and Acharya et al. (2017) use the GARCH-DCC specification.[18] It can be seen from Equation 3.13 that SRISK increases with the size of the firm, its leverage, and its expected equity return conditional on a systemic event, which depends on the specific assets and liabilities that compose the balance sheet. A limitation reported by the authors is that off-balance sheet information is not employed, so the true asset structure of a firm might be not appropriately captured.

The authors test the predictive power of SRISK, over the period 2003-2012, with respect to capital injections, industrial production growth, and unemployment rate.[19] SRISK is used in log-levels in the regression of capital injection, and obtain a t-statistic higher than 2 despite including several alternative predictors as additional regressors. The real-economy variables instead are regressed on the log-differences of SRISK, and SRISK results having a significative role in predicting both, especially at horizons longer than 6 months where it is always significant at 1% level, also including autoregressive terms of the series and other canonical regressors.

Further relevant evidence on systemic risk is provided by Giglio et al. (2016). They study how a broad set of financial distress and systemic risk measures affect the real economy. Among the variables included there are the leverage of the 20 biggest financial intermediaries, market liquidity measures, and the one-step-ahead SES illustrated in Brownlees and Engle (2017), though not the SRISK. They shrink all of these in a single measure, with two different approaches and use it to forecast macroeconomic shocks. The main result is that the synthetic measure that include systemic risk, intermediary leverage and market liquidity, has most of the predictive power on the negative part of macroeconomic shocks distribution rather than its central tendency. Similarly, Jensen et al. (2017) provide evidence of the asymmetric relation of leverage with the real economy, as they show that firms' and households' leverage

[17]So, to be crystal clear, the critical rate of return is $r^C = C - 1 = -40\%$.
[18]The main reference provided for the GARCH-DCC is Engle (2009).
[19]The information used in the SRISK calculations started from January 2000.

induce negative skewness in the business cycle. Since the real economic shocks are typically reflected in asset prices, this evidence further strengthen the claim that tighter funding constraints are related to negative skewness of returns, which the theories of chapter 2 predicted, even without the fundamental value being skewed.

4

Betting against beta

This chapter introduces the Low Risk Anomaly (LRA) related the risk priced by Capital Asset Pricing Model (CAPM), the beta. Then, a trading strategy that takes advantage of the LRA, and helps studying it, is introduced, as well as two theoretical explanations to rationalise it.

4.1 Introduction: the CAPM

The reference equilibrium model in the asset pricing literature to specify the relationship between risk and return is the CAPM. This predicts that the expected return of an asset i is equal to the risk-free return rate R^f plus a risk premium, the expected return of the whole market R_M in excess of R^f, times the asset's sensitivity to systematic risk, which is the non-diversifiable risk to be beared to hold the asset and which is quantified with the OLS-regression beta:

$$\mathbb{E}[R_i] = R^f + \beta_i \, \left[\mathbb{E}[R_M] - R^f\right] \quad \text{where} \quad \beta_i = \frac{\text{Cov}[R_i, R_M]}{\text{Var}[R_M]} = \frac{\sigma_{i,M}}{\sigma_M^2}$$

$$\mathbb{E}[R_i] - R^f = \frac{\left[\mathbb{E}[R_M] - R^f\right]}{\sigma_M} \cdot \underbrace{\rho_{i,M} \cdot \sigma_i}_{\text{amount of risk}} = \text{SR} \cdot \frac{\sigma_{i,M}}{\sigma_M} \tag{4.1}$$

The CAPM, however, relies on the premise that all agents are rational, so all of them only invest in the single portfolio with the highest expected return per unit of risk. Specifically, all agents are expected to invest in the portfolio that gives the highest expected return per unit of volatility – the highest Sharpe Ratio (SR), which, if a risk-free asset exist, is simply a combination of this and the whole market,[1] meaning essentially that the agents only leverage or de-leverage the market portfolio to accommodate their specific risk preferences. Therefore, at the end, to have no arbitrage, any risky asset must provide the same SR, which translates in a return proportional to the risk, proxied by the covariance of the asset with the market, scaled by the market volatility. This framework follows from two specific assumptions, namely:

Mean-variance optimization i.e. expected utility of investors only depends on the first two moments of the portfolio returns. However, taking the Taylor expansion of the utility that agents get out of the wealth at

[1] Since in equilibrium demand equals supply and all of the agents' demand is on a single risky portfolio, that must be the market.

the end of an investments, around its expected value $\mu W_0 = \mathbb{E}[R_i]W_0$, it can be seen that higher moments play a role as well:

$$\begin{aligned} U(R_i W_0) = U(\mu W_0) + (R_i - \mu) \cdot W_0 \cdot U'(\mu W_0) + \\ + (R_i - \mu)^2 \cdot \frac{W_0^2}{2} \cdot U''(\mu W_0) \ + \ \dots \\ + (R_i - \mu)^n \cdot \frac{W_0^n}{n!} \cdot U^{(n)}(\mu W_0) + \ \dots \end{aligned} \tag{4.2}$$

Exact mean-variance optimization only happens when one of the following two conditions is true:

Quadratic utility The agents' utility function is quadratic, which has no derivatives with order higher than the second one.

Separating distribution of returns The returns' distribution belong to a specific set of distributions that includes the elliptical class, whose members can essentially be characterized by their first two moments and whose most prominent examples are the normal distribution and the Student's t.

No borrowing constraints such as the mandatory cash holdings of mutual funds, which do not allow agents to leverage the optimal portfolio, thereby distorting the efficient frontier of the portfolio choice.

4.2 Evidence of the low beta-risk anomaly

One of the empirical implications of the CAPM is that

$$\alpha_i = \mathbb{E}[r_i^e] - \beta_i \ \mathbb{E}[r_M^e] = 0 \tag{4.3}$$

where $E[r_i^e] = \mathbb{E}[R_i] - R^f$. Since Miller and Scholes (1972) and Black et al. (1972), however, this is proved to not hold true in practise. Specifically, when the *security market line* (SML) outlined by the CAPM is tested empirically with a cross-sectional regression similar to the one showed in section 3.1

$$\hat{\mathbb{E}}[r_i^e] = \gamma_0 + \gamma_1 \ \hat{\beta}_i + \epsilon_i \tag{4.4}$$

where γ_0 essentially estimates α_i and should be 0, while γ_1 should be equal to $\hat{\mathbb{E}}[R_m^e]$; then γ_0 ends up being significantly higher than 0 and γ_1 significantly lower than $\hat{\mathbb{E}}[R_m]$.[2] Therefore, the SML results being flatter than what predicted by the CAPM and lower-beta stocks seem to provide higher risk-adjusted returns than stocks with a higher beta, on average. Another way to observe this is by separately analysing portfolios of beta-sorted stocks, i.e. groups of stocks separated by their beta. Doing so, Frazzini and Pedersen (2014) (FP) find the average excess returns of groups with different betas being similar, i.e. a flat SML, across several asset classes – international stocks, US treasury and corporate bonds, credit, foreign exchange, and commodities.[3] Furthermore, FP find that CAPM alphas and the SR of the beta-sorted stocks

[2] In Black et al. (1972) the results are contrasting only for the period 1931-1939.

[3] On the US stocks only, Black et al. (1972) obtain similar results.

portfolios decrease almost monotonically from low-beta to high-beta ones; in particular, for the US stocks, the alpha and the annualized SR of the lowest beta ranking stocks are 0.52% monthly (t-statistic: 6.3) and 0.70, where the alpha and SR of the highest beta ranking stocks is -0.10% (t-statistic: -0.5) and 0.28, respectively. This higher market-risk-adjusted compensation for assets with lower risk is only one of the different Low Risk Anomalies observed in the financial market, where the risk is proxied by variables other than the market beta, such as the idiosyncratic volatility.[4]

Betting against beta

Based on the evidence of higher risk-adjusted returns in low-beta stocks than high-beta stocks, FP consider the "betting against beta" (BAB) trading strategy: this forms a portfolio (the BAB factor) that is short in high-beta stocks and long in low-beta stocks, where both positions are de/leveraged such that the portfolio is market-neutral, i.e. is has the same beta-exposure in the long positions and in the short ones. More precisely, every month all of the securities (per asset class) are ranked by their beta, and then assigned to either the high-beta or low-beta sub-portfolio depending on whether they rank above or below the average beta. The weights of the securities in the sub-portfolios are hold in the vectors $\mathbf{w}_H$ and $\mathbf{w}_L$, and each security has a weight $w^i_\bullet$ that is proportional to the beta ranking itself, i.e. high*er* beta stocks have a high*er* weight in the high-beta sub-portfolio w^i_H, while low*er* beta stocks have high*er* weights in the low-beta sub-portfolio w^i_L. Finally, a long position is taken in the low-beta sub-portfolio and a short position is taken in the high-beta sub-portfolio, where the positions in the sub-portfolios are inversely proportional to the weighted average of the betas of the stocks it contains. Therefore, both sub-portfolio positions have an offsetting beta of one, and the whole BAB portfolio is (theoretically) not affected by market movements – beta-neutral. The factor is also self-financing since the long position is funded shorting the risk-free asset (borrowing), while the short funds an investment in the risk-free asset. Therefore, the rate of return of the BAB factor is:

$$r^{BAB}_{t+1} = \frac{1}{\beta^L_t}(r^L_{t+1} - r^f) - \frac{1}{\beta^H_t}(r^H_{t+1} - r^f) \tag{4.5}$$

where $r^L_{t+1} = \mathbf{w}'_L \mathbf{r}_{t+1}$, $r^H_{t+1} = \mathbf{w}'_H \mathbf{r}_{t+1}$, and $\beta^L_t = \mathbf{w}'_L \boldsymbol{\beta}_t$, $\beta^H_t = \mathbf{w}'_H \boldsymbol{\beta}_t$ – being $\mathbf{r}$ and $\boldsymbol{\beta}$ the vectors of returns and betas of all the assets in the market.

Over the sample 1931-2017, the BAB portfolio for US equities results being on average long \$1.4 in the low-beta sub-portfolio and \$0.7 in the high-beta one. The authors then test this BAB factor by regressing it on the CAPM single risk factor – the market excess returns, the Fama and French (1993) three factors – market, size and value, the Carhart (1997) four factors – the three factors plus momentum, and a five factors model – the four-factor plus the Pástor and Stambaugh (2003) market liquidity measure. The alpha resulting from these tests is always positive and statistically significative: 0.73% monthly in both the CAPM and the three-factor tests (t-statistics above 7) and 0.55% in the four- and five-factor tests (t-statistics 5.6 and 4.1 respectively). Interestingly, the alpha's point estimate and the level of

[4]More details in N. L. Baker and Haugen (2012) and M. Baker et al. (2011).

significance in the CAPM and three-factor tests is very similar to the plain average excess returns of the BAB factor (0.70%, t-statistic: 7.1), which is the result of good estimates of the ex-ante betas, which in turn allows to get closer to an actual market neutrality.[5] Finally, the estimated annualized SR of the US equities' BAB factor is 0.78, while, for comparison, the annualized SR of the US equities over the same sample is 0.44. As the authors obtain statistically significant alphas for the other asset classes as well, it can be concluded that there is clear evidence of the CAPM beta not being able to capture all of the risks priced by the investors.

4.3 Funding constraints

One of the risks that is commonly regarded as the economic driver ot the BAB anomaly, is related to the borrowing constraints. Practically, in the market there are agents that cannot borrow to leverage the optimal portfolio and reach the desired risk level, so they end up overweighting the riskier assets to achieve the target level of return. Then, because of the buy pressure, in equilibrium the riskier assets offer a lower risk-adjusted return, of which an unconstrained agent can take advantage using a BAB strategy. Black (1972) has been the first to model constrained agents, then FP built on that, related the funding constraint to investments' margins, and extended the analysis to explicitly explain the BAB anomaly. Their theoretical predictions about the relationship between funding constraints and the BAB factor, as well as the empirical results are outlined in the next section; more details on the model are in Appendix A.

Frazzini and Pedersen (2014) model and empirical evidence

Consider an overlapping generations economy, populated by agents indexed by i that born with wealth W_t^i and die in $t+1$. Such agents can trade S securities, indexed by s, with prices $\mathbf{P}_t$, which pay dividends δ_t^s and that has $x^{s,*}$ outstanding shares. Then, at each time t, young agents can choose portfolio weights $\mathbf{x}^i$ and invest the remaining wealth in the risk-free asset, with r^f rate of return, solving the following problem:

$$\max_{\mathbf{x}^i} \mathbf{x}^{i\prime} \left(\mathbb{E}_t \left[\tilde{\mathbf{P}}_{t+1} + \tilde{\boldsymbol{\delta}}_{t+1} \right] - (1+r^f)\mathbf{P}_t \right) - \frac{\gamma^i}{2} \mathbf{x}^{i\prime} \boldsymbol{\Omega_t} \mathbf{x}^i$$
$$\text{subject to} \quad m_t^i \left(\mathbf{x}^{i\prime}\ \mathbf{P}_t \right) \leq W_t^i \tag{4.6}$$

where $\boldsymbol{\Omega_t}$ is the variance-covariance matrix of the future uncertain payoff $\tilde{\mathbf{P}}_{t+1} + \tilde{\boldsymbol{\delta}}_{t+1}$, then $\mathbf{x}^{i\prime}\boldsymbol{\Omega_t}\mathbf{x}^i$ is the variance of the agent's portfolio, and γ^i is the aversion of agent i to variance – the risk. So, the agent, through the objective function, is essentially maximizing the excess returns of its holdings while minimizing the variance of the portfolio, practically making a mean-variance optimization. Next, m_t^i is the exogenously-set margin – the share of any

[5]The authors also report the realized betas of the 10 beta-sorted portfolios, which, indeed, never differ of more than 20% from the ex-ante estimates. The betas are estimated by splitting the correlation's and the standard deviations' processes. For the former they use a longer window (750 trading days instead of 120) and three-days returns (rather than single-day) in the rolling estimation.

position that the agent has to hold in the form of equity, so the sum of the margins on total holdings $m_t^i \left(\mathbf{x}^{i'}\ \mathbf{P}_t\right) = \sum_s m_t^i x^{i,s} P_t^s$ has to be less than the endowed wealth. Similarly to the debt-constraint intermediary asset pricing literature, a higher margin, given W_t^i, forces agent i to decrease her portfolio positions to meet the budget constraint. For instance, if m^i=1, no leverage is allowed, if it is 0.5 then the agent can hold twice his wealth in risky assets. The pricing equation resulting from the first order and the equilibrium conditions is

$$\mathbf{P}_t = \frac{\mathbb{E}_t\left[\tilde{\mathbf{P}}_{t+1} + \tilde{\boldsymbol{\delta}}_{t+1}\right] - \gamma\Omega\mathbf{x}^*}{1 + r^f + \psi_t} \tag{4.7}$$

which can be expressed in terms of the excess returns, so to describe a new SML:

$$\begin{aligned} \mathbb{E}_t[\tilde{r}^s_{t+1}] - r^f &= \psi_t + \beta_t^s(\mathbb{E}_t[\tilde{r}^M_{t+1}] - r^f - \psi_t) && (4.8)\\ &= (1 - \beta_t^s)\psi_t + \beta_t^s(\mathbb{E}_t[\tilde{r}^M_{t+1}] - r^f) && (4.9) \end{aligned}$$

where γ is the aggregate risk aversion $\frac{1}{\gamma} = \sum_i \frac{1}{\gamma^i}$, aggregate tightness of funding ψ_t is a weighted average of individual restriction levels, $\sum_i \frac{\gamma}{\gamma^i}\psi_t^i$, and security's beta it the CAPM beta $\beta_t^s = \frac{\sigma_{s,M}}{\sigma_M^2}$. From Equation 4.8, it can be seen that when the funding constraints get tighter, the SML gets higher and flatter, thereby closing the gap between the CAPM and the SML empirically observed. That means that to obtain the level of returns of the tangency portfolio, constrained agents have to hold riskier assets. Further, in the CAPM-like formulation of Equation 4.9, the intercept is explicitly function of the asset's beta and the funding constraint tightness, and it gets higher, as well as the expected excess return does, when:

- Funding constraints are tighter – lower funding liquidity, making portfolio choices more distorted
- The asset's beta is lower – it is less risky, providing less expected returns.

Moreover, two peculiar results should be noted:

- The market portfolio is a weighted average of all investors' portfolios, essentially averaging the portfolios of both the unconstrained agents – the tangency portfolio, and the constrained agents, which have higher risk than the tangency portfolio. Therefore, the market portfolio in equilibrium has to have higher risk, and lower SR, than the tangency portfolio. As a result, the tangency portfolio, the portfolio with the best SR, has a beta lower than 1.
- An asset that does not covary with the market should anyway provide a return higher than the risk-free asset. The authors relate this to the fact that constrained agents escape such securities for more risky ones, while at the same time unconstrained agents, who hold the tangency portfolio, would see their diversification harmed, thus they ask a compensation for that. Specifically, the tangency portfolio contains zero-beta assets, so zero-beta assets would actually have some covariance with the unconstrained agents' holdings, thereby making them bear a higher risk even if the security has zero beta, and then ask a compensation for that.

The predicted return on the BAB factor is:

$$\mathbb{E}_t[r_{t+1}^{BAB}] = \frac{\beta_t^H - \beta_t^L}{\beta_t^L \beta_t^H} \psi_t \tag{4.10}$$

which is positive by definition, and increasing with the ex-ante beta spread $\frac{\beta_t^H - \beta_t^L}{\beta_t^H \beta_t^L}$ and the ex-ante funding constraints tightness ψ_t. Tighter funding, following an increase in the margin requirements for instance, implies a higher expected returns of the BAB factor because agents, being more constrained, tilt more the portfolios toward high-beta stocks, increasing the convenience of low-beta stocks. However, it follows that the effect of higher constraints on the contemporaneous return of the BAB factor is opposite: as constraints get tighter, prices of high-beta assets get pushed up while low-beta ones get pushed down even more, thus making the BAB factor realizing a loss, i.e. a negative return. In other terms, one may observe that higher expected returns mechanically decrease prices because of the higher discounting.

FP test these predictions regressing the BAB factor returns on the contemporaneous change in the TED spread and the lagged value of the TED. The TED spread is the difference between the 3-month LIBOR rate, which is the rate at which major banks expect to obtain funding, and the 3-month US treasury bill interest rate, at which US government, regarded as the global safest borrower, obtain funding. Thereby, measuring how relatively expensive are the funds for the banking sector, it broadly indicates how difficult is to obtain funds for intermediaries and how tight funding constraints are – the ψ_t of the model.[6] Surprisingly, both the coefficients of the lagged TED level and the contemporaneous TED change are negative for the BAB factor returns of US stocks, international stocks, and the pool of all the assets in the study.[7] Further, when the authors perform a more robust regression including different control variables, the two coefficients double in magnitude – the contemporaneous change also in t-statistics.[8] This would mean that tighter funding constraints do decrease contemporaneous returns of a BAB strategy, but so does the past level of funding tightness, which strongly contrast the theory. The authors suggest that the interpretation of TED may be a bit different, namely that a high TED may represent a *worsening* in the funding constraint, which may lead to a gradual intensification of funding tightness over time keeping the BAB factor loose over time.

Further evidence related to the link between the BAB factor and funding constraints is provided by AEM, who claim their leverage factor to (1) correlate with the BAB factor (at 10% level of significance) as well as other funding constraint proxies such as volatility, the Baa-Aaa spread, and asset growth and (2) explain the cross-section of returns sorted on betas.[9]

[6] TED is, in a related manner, also interpreted as a proxy of how much risky the banking sector, and the economy more in general. Moreover, since it depends on the US treasury yield, it inherit the convenience yield effect, thereby potentially overestimating the spread at times.

[7] Coefficients and t-statistics for US stocks: -0.025 (-5.3) and -0.019 (-2.6) respectively.

[8] The additional explanatory variables were the market returns, to account for noise in the beta estimation; the 1-month lagged beta, to account for potential momentum in the BAB factor; the ex-ante beta spread; the short volatility return – a portfolio of straddles on the S&P500; and the lagged inflation. Only the market returns and the short on the straddles had a t-statistic larger than 1 in magnitude.

[9] No statistics are provided about the second statement.

4.4 Systematic skewness

The CAPM is built on a proxy of the SDF that is linear in the market return,

$$M_{t+1} = a^{CAPM} + b^{CAPM} R_{M,t+1} \tag{4.11}$$

Then the coefficients are related to the first two terms of the Taylor's series expansion of the SDF – the intertemporal marginal rate of substitution $\frac{U'(W_t R_{t+1})}{U'(W_t)}$, around the null $t+1$ rate of return on wealth:

$$M_{t+1} = 1 + \frac{W_t\ U''(W_t)}{U'(W_t)}(r_{t+1}) + \frac{W_t^2\ U'''(W_t)}{2\ U'(W_t)}(r_{t+1})^2 + o(W_t) \tag{4.12}$$

where $o(W_t)$ represents the remainder of the expansion. So, $a^{CAPM} = 1 + o(W_t)$ and $b = \frac{W_t\ U''(W_t)}{U'(W_t)}$, which is the relative risk aversion. As $U''(W)$ is negative to reflect economic satiation, b is negative as well, which consistently means that in periods of high returns, and high wealth, the intertemporal marginal rate of substitution is low. This kind of SDF proxy, combined with the standard first order condition of the representative agent showed in Equation 2.2, generates the CAPM. Nonetheless, this is exact only when the conditions outlined in section 4.1 are met, while it is an approximation in the other cases. In facts, as argued by Harvey and Siddique (2000), several elements may induce skewness in the investments' returns, for example limited liability and other agency problems related to investments' management. Therefore, they specify a non-linear pricing kernel that includes the squared market returns:

$$M_{t+1} = a + bR_{M,t+1} + cR_{M,t+1}^2 \tag{4.13}$$

Comparing this to the Taylor's series expansion of the SDF, it can be observed that a and b are similar to the CAPM specification, while c is related to the term $\frac{W_t^2\ U'''(W_t)}{2\ U'(W_t)}$: if the agent has non-increasing absolute risk aversion, which Kimball (1993) claim being an essential feature of realistic risk-averse agents, this is positive. From that SDF specification, Schneider et al. (2016) derive a *skewness-aware* SML, in a fashion similar to the CAPM:

$$\mathbb{E}_t^{skew}[R_{t+1}^e] = \beta_t^{skew} \cdot \mathbb{E}_t[R_{M,t+1}^e] \tag{4.14}$$

where

$$\beta_t^{skew} = \frac{b \cdot \sigma_{i,M,t} + c \cdot \sigma_{i,M^2,t}}{b \cdot \sigma_{M,t}^2 + c \cdot \sigma_{M,M^2,t}} \tag{4.15}$$

Here, $\sigma_{i,M^2,t}$ is the covariance between $R_{i,t}^e$ and ${R_{M,t}^e}^2$, i.e. the asset coskewness, while $\sigma_{M,M^2,t}$ is the covariance between $R_{M,t}^e$ and ${R_{M,t}^e}^2$, that is the market skewness. As claimed by the authors, $|b \cdot \sigma_{M,t}^2|$ is generally greater than $|c \cdot \sigma_{M,M^2,t}|$ by several orders of magnitude, therefore, at the end, a higher risk premium is required from security i when it has higher covariance and lower coskewness with the market. In other words, in this skew-aware framework, a higher compensation is required for assets whose returns happen to be low when market returns are low and highly volatile, which are states of low utility and high marginal utility. Indeed, note that adding such an asset to the agent's portfolio would increase its undiversified variance and shrink more when volatility is high – having a higher undiversified skewness.

If the real world is better represented by the skew-aware model, the CAPM implies a pricing error defined as

$$\alpha_{i,t+1} = \mathbb{E}_t^{skew}[R_{i,t+1}^e] - \mathbb{E}_t^{CAPM}[R_{i,t+1}^e] + \epsilon_{i,t+1}^{skew} \quad \text{where} \quad \mathbb{E}[\epsilon_{i,t+1}^{skew}] = 0 \tag{4.16}$$

which in expectations amount to the CAPM regression's alpha, and amounts to:

$$\begin{gathered} \mathbb{E}_t[\alpha_{i,t+1}] = (\sigma_{i,M^2,t} - \beta_{i,t}^{CAPM} \cdot \sigma_{M,M^2,t}) \cdot B_t \cdot \mathbb{E}_t[R_{M,t+1}] \\ \text{where} \quad B_t = \frac{c}{b \cdot \sigma_{M,t}^2 + c \cdot \sigma_{M,M^2,t}} \end{gathered} \tag{4.17}$$

Then, since market skewness $\sigma_{M,M^2,t}$ and B_t are typically negative, the last equation implies that the higher the CAPM-beta, the (more) negative should be the alpha on average, which matches the empirical evidence showed in section 4.2. Meanwhile, also the coskewness not captured by the CAPM, and thereby left in the residuals, is derived:

$$\sigma_{\alpha_i,M^2,t} = \sigma_{i,M^2,t} - \beta_{i,t}^{CAPM} \cdot \sigma_{M,M^2,t} \tag{4.18}$$

Residuals' coskewness is higher the higher is $\beta_{i,t}^{CAPM}$ because more of the negative coskewness in asset i is due to correlation with the negatively skewed market, thus, adjusting for the market, residuals get more positively coskewed the higher the beta. Finally, plugging the mispricings' coskewness into the expected alpha,

$$\mathbb{E}_t[\alpha_{i,t+1}] = \sigma_{\alpha_i,M^2,t+1} \cdot B_t \cdot \mathbb{E}_t[R_{M,t+1}] \tag{4.19}$$

So, the CAPM alpha of an asset is lower the more positively coskewed its returns are with the market and this is argued to be the reason why high-beta stocks have lower alphas. Economically, positive coskewness is a distributional feature that agents appreciate, and for which they pay in terms of lower risk premium. However, coskewness is not among the risk factors considered and thus gauged by the CAPM, to which then CAPM fails to attach a value in terms of predicted excess return.

Low Risk Anomalies?

Schneider et al. (2016) then illustrate how considering the CAPM mispricing related to coskewness can account for the returns of the BAB strategy, which in expectations are:

$$\begin{aligned} \mathbb{E}_t[\alpha_{BAB,t+1}] &= \mathbb{E}_t[\alpha_{L,t+1}] - \mathbb{E}_t[\alpha_{H,t+1}] \\ &= (\sigma_{\alpha_L,M^2,t+1} - \sigma_{\alpha_H,M^2,t+1}) \cdot B_t \cdot \mathbb{E}_t[R_{M,t+1}] \qquad (4.20) \\ &= \big((\sigma_{L,M^2,t+1} - \sigma_{H,M^2,t+1}) - \big(\beta_{L,t}^{CAPM} - \beta_{H,t}^{CAPM}\big) \cdot \sigma_{M,M^2,t}\big) \\ &\quad \cdot B_t \cdot \mathbb{E}_t[R_{M,t+1}] \end{aligned} \tag{4.21}$$

As the CAPM underestimates the risk and the required return from holding low-beta stocks and overestimates them for high-beta stocks, implementing a BAB strategy implies bearing the risk ignored by the CAPM on both sides of the strategy and earning the relative compensation – it is essentially comparable to selling protection from negative coskewness. Indeed, from

Equation 4.20 it can be seen that the average excess returns of the BAB factor increase with lower residuals' coskewness of low-beta stocks, on which the strategy is long, $\sigma_{\alpha_L, M^2, t+1}$, as well as with higher residual coskewness of high-beta stocks, which are shorted, $\sigma_{\alpha_H, M^2, t+1}$. The role of the CAPM beta can be directly seen in Equation 4.21, where, assuming that the coskewness of the low-beta and high-beta portfolios is identical as well as market skewness is negative, the BAB factor's alpha is higher the higher the beta spread is: this happens because the BAB portfolio inherit even more negative skewness from shorting high-beta stocks, as well as less positive skewness from investing in low-betas, which can be checked in Equation 4.18.

In the empirical analysis of Schneider et al. (2016), it is actually found that the coskewness of high-beta stocks is lower than that of low-beta stocks – figure 4.1a.[10] However, this only mitigates the positive effect of accounting for the market skewness, so the residuals of high-beta stocks are indeed found to have a higher coskewness than the low-beta stocks – figure 4.1b. So, the relationship between alphas and residuals' coskewness is strongly confirmed, as showed in 4.1c. To perform an empirical test of the skew-aware pricing kernel, the authors build three skewness factors, based on ex-ante skewness, to capture the coskewness risk.[11] Specifically, they create ten portfolios with stocks sorted by their ex-ante risk-neutral skewness, which is estimated with option data; then, those portfolios are combined in three different ways, to build the skewness factors.[12] Those factors are then included in the CAPM regression test,[13] resulting in significantly lower alphas – figure 4.1d, specifically, the alpha's t-statistic decreases from the 2.87 of the plain CAPM test, to between 1.87 and 1.06 in the CAPM extended with the skewness factors.[14]

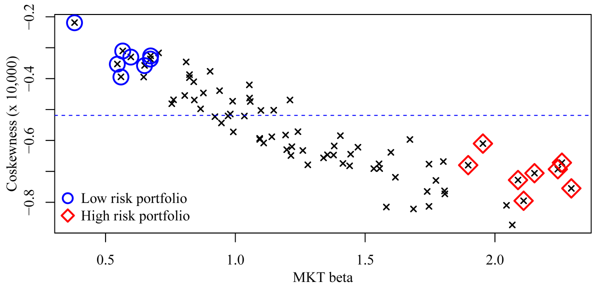
[10] The authors include in the analysis portfolios of stocks sorted by measures of risk different from the CAMP beta, which still give rise to LRAs.

[11] The authors also illustrate how ex-ante skewness is strictly related to residuals realized coskewness.

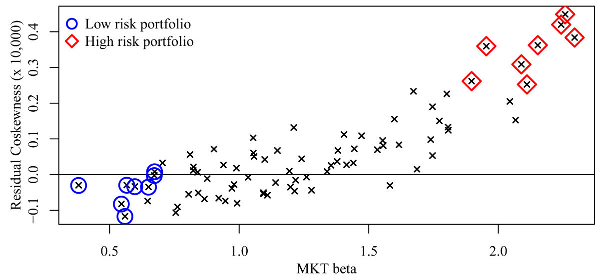
[12] Skewness is computed from data on call and put options, thus the *upper-*, *lower-*, and total (the sum of upper- and lower-) skewness of returns are observed. One factor, "SK_{1+10}-SK_{5+6}, is long the highest and the lowest total-skewness-sorted stocks deciles and short the central two deciles; the other two are long the most skewed decile and short the lowest one, where the skewness is either the upper-, factor "USK", or the lower-, factor "LSK", one.

[13] Further analysis are performed extending the Fama and French (1993) and Carhart (1997) models, with similar results.

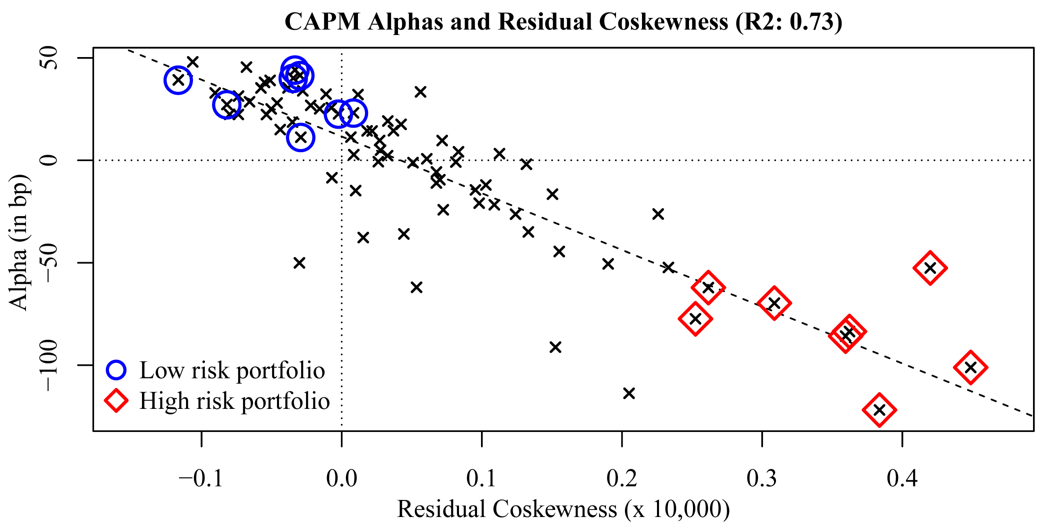
[14] The best result is achieved by including both the USK and LSK factors.



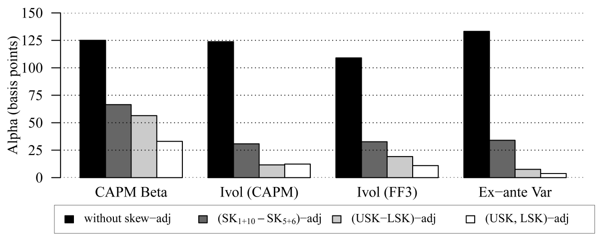
(a) CAPM betas - returns coskewness



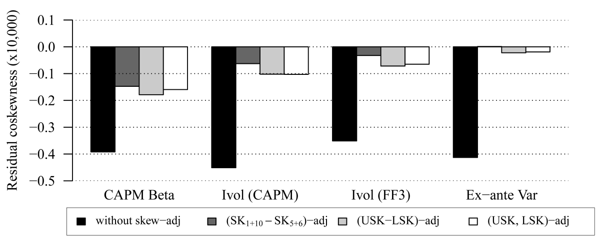
(b) CAPM betas - residuals' coskewness



(c) Residuals' coskewness - CAPM alphas



(d) Skew-adjusted alphas



(e) Skew-adjusted residuals' coskewness

Figure 4.1: Tests on coskewness and LRAs. Source: Schneider et al. (2016).

5

Analysis set-up

The main goal of this thesis is to test the intermediary pricing kernel on the CAPM-beta low risk anomaly. The link should be now trivial: tightness of funding is the key determinant of both the marginal value of wealth to intermediaries, which defines the intermediary pricing kernel, and the betting against beta factor returns. Therefore, an SDF that efficiently gauge the soundness of intermediaries' funding should solve the LRA and being able to price the risk compensated with the BAB returns. The study is structured in three research questions (RQs), whose goal and data are further described in this chapter. The term "intermediary risk" stands for "intermediary leverage risk", or indistinctly, as should be clear by now, "intermediary capital ratio risk".

5.1 Research questions formulation

RQ 1: which intermediary risk factor specifications explain the most of variables related to the intermediaries' true SDF?

Clearly, there is no measure of the intermediaries' marginal value of wealth against which a proxy can be tested directly, otherwise there would not be any need of the proxy itself. However, the wealth marginal value is proven to depend on a few drivers – among which undercapitalization, funding and market liquidity, for which proxies exist. Therefore, assuming the true SDF has a strong relationship with these, I make an introductory assessment of the risk factors representativeness of the SDF by testing their ability to explain the other supposedly-related proxies. This will also be indicative of the cyclicality of the leverage specifications used and is preparatory for the following research question. The answer to this question relies on the proxies of the Systemic Expected Shortfall, funding liquidity, and market liquidity; namely the SRISK, the TED spread, and the liquidity measure of Pástor and Stambaugh (2003).

RQ 2: can an intermediary pricing kernel explain the beta-CAPM low risk anomaly and consistently price it?

Firstly I further test the ability of intermediary risk factors to explain a proxy of funding tightness, and thus being related to it, by testing them directly on the BAB factor, which crucially relies on funding constraints. This leverages on the precise theoretical relationship showed in section 4.3, which has been difficult to pin down by other tests. Then, after having showed how the intermediary risk factors relate to elements supposedly connected to the intermediary SDF, I move on using these factors to test the SDF itself, and its ability to price multiple asset simultaneously, especially those most commonly associated to funding tightness. Therefore, the ultimate questions are two:

1. Is the SDF able to provide a consistent pricing kernel, which is the ultimate goal of any SDF? Or, better, how consistent is the intermediary SDF over different assets?

2. Is the intermediary SDF able to price low risk anomalies, which are supposed to depend exactly on the key factor on which the intermediary SDF in founded – funding tightness? Or, better, how good is the intermediary SDF in pricing such anomalies with respect to other models that not theoretically built on such premises?

This last hypothesis is explicitly verified with a cross-sectional asset pricing test on a variety of test assets, including the beta-sorted stocks portfolios and the troubling BAB factor.

RQ 3: do the intermediary risk factors also capture the coskewness risk?

Another theoretical explanation for the CAPM-beta LRA is provided by the existence of a compensation required by investors for the risk of assets' returns being negatively coskewed with the market. This is proved being related to the skewness of the asset itself, which, at the same time, intermediary asset pricing theory predicts to be related to funding tightness, independently of the fundamental asset's distribution.[1] Further, empirical evidence relates leverage and other measures of financial distress to asymmetries in real economic shocks, i.e. negative skewness of the fundamentals. Therefore, it is natural to test whether the intermediary pricing kernel specifications already tested, which theoretically capture funding tightness, are able to account also for this risk. To do so, I essentially test whether the mispricings of the previous intermediary pricing kernel application are related to coskewness like the CAPM residual are proved doing.

5.2 Data

I have focused on the USA and the data have been collected from multiple sources, listed in table 5.1. More details about some of the series are provided in Appendix B.

Intermediary risk factors

The authors of AEM make available the quarterly leverage factor $lvg_t^{\Delta,BD}$ defined in section 3.1, which in the meanwhile has been updated following the FOF revision in 2017. Performing an Augmented Dickey-Fuller Unit Root Test (ADF), the series results being stationary at 1% level of significance. However, despite the seasonal adjustments, the series shows significant autocorrelation:

[1] Namely because of the asymmetrical amplification mechanisms that yield liquidity spirals. These make liquidity and prices drop quickly and recover slowly.

Table 5.1: Data sources, frequencies, and time spans. D, M, and Q stand for daily, monthly, and quarterly, respectively.

Variable	**Source**	**Frequency**	**Timespan**
η_t and η_t^{Δ}	He, Kelly, et al. (2017)	M, Q	1/1970 – 10/2017
$lvg_t^{\Delta,BD}$	Adrian, Etula, et al. (2014)	Q	1968q1 – 2017q3
SRISK	Brownlees and Engle (2017)	D	2/6/2000 – 9/1/2014
TED spread	FRED	D	2/1/1986 – 6/4/2018
$m.liq_t$	Pástor and Stambaugh (2003)	M	8/1962 – 12/2016
BAB factor	Frazzini and Pedersen (2014)	D	1/12/1930 – 29/12/2017
Other risk factors and 1-month T-Bill	French (2018)	M	7/1926 – 3/2018
Characteristic-sorted stocks portfolios	French (2018)	M	7/1963 – 3/2018
US bonds	WRDS	M	1/1969 – 5/2018
Test assets other than US stocks and bonds	He, Kelly, et al. (2017)	M, Q	1/1970 – 12/2012

performing the Box-Ljung test with lags equal to the yearly frequency of the series, i.e. 4 in this case, the series proves to have autocorrelation at 1% level of significance; ACF and PACF plots in Appendix B.

HKM instead make available both the primary dealers capital ratio η_t described in section 3.1 and the relative intermediary capital risk factor η_t^{Δ}. Their capital ratio measure depends both on book values and market data, so these series are provided at daily, monthly, and quarterly frequencies.[2] As only in the quarterly series all the information used is updated at every observation, I will mainly rely on this for my analysis. However, I will use the monthly series for robustness checks in Appendix C because, as illustrated in section 3.2, the prevalent driver of the series is the equity, i.e. the part that is updated more frequently. The quarterly series of η_t^{Δ} is stationary at 1% level of confidence and non autocorrelated; for further details about the other series, please refer to Table 5.2 and Appendix B.

Analogously to HKM, and from the capital ratio series provided by them, I compute the intermediary sector leverage (lvg_t) and the intermediary leverage risk factor (lvg_t^{Δ}) as:

$$lvg_t = \frac{1}{\eta_t} = \frac{\sum_i \left(\text{Market equity}_{i,t} + \text{Book Debt}_{i,t}\right)}{\sum_i \text{Market equity}_{i,t}} \tag{5.1}$$

$$lvg_t^{\Delta} = \hat{u}_t^{lvg}/lvg_{t-1} \text{ where } \hat{u}_t^{lvg} = lvg_t - \hat{\phi}_0^{lvg} - \hat{\phi}_1^{lvg} \cdot lvg_{t-1} \tag{5.2}$$

As leverage and capital ratio point at the same economic quantity, the interpretation of results are unaltered, but I consider both because the econometric performance may differ and, more importantly, because the intermediary leverage in levels conveniently results being stationary at 10%, contrary to

[2]The authors also provide data at daily and yearly frequency, which are not used in this work.

Table 5.2: Intermeciary capital ratios time-series characteristics. The level of significance of stationarity is based on the outcome of an Augmented Dickey–Fuller test while the autocorrelation (Autocorr) level of significance is determined with a Box-Ljung test where the number of lags tested is equal to yearly frequency of the series tested (12 for monthly data, 4 for quarterly data).

		Quarterly		*Monthly*	
	Definition	**Stationary**	**Autocorr**	**Stationary**	**Autocorr**
η_t	Equation 3.9	No	Yes***	No	Yes***
η_t^Δ	Equation 3.10	Yes***	No	Yes***	Yes*
lvg_t	Equation 5.1	Yes*	Yes***	Yes**	Yes***
lvg_t^Δ	Equation 5.2	Yes***	No	Yes***	No
$lvg_t^{\Delta,BD}$	Equation 3.6	Yes***	Yes***	–	–

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 5.3: Summary statistics of quarterly and monthly intermediary data. ρ measures the the Pearson correlation.

	Quarterly					*Monthly*			
	$lvg_t^{\Delta,BD}$	η_t	η_t^Δ	lvg_t	lvg_t^Δ	η_t	η_t^Δ	lvg_t	lvg_t^Δ
Min	-30.1	0.026	-0.437	7.61	-0.311	0.022	-0.280	7.46	-0.295
1st Qu.	-3.0	0.045	-0.066	13.10	-0.084	0.045	-0.040	13.09	-0.043
Median	1.0	0.057	0.017	17.67	-0.029	0.057	0.001	17.61	-0.007
3rd Qu.	5.2	0.076	0.078	22.06	0.060	0.076	0.040	22.03	0.037
Max.	33.3	0.132	0.445	38.46	0.739	0.134	0.397	44.84	0.385
Mean	0.7	0.062	0.004	18.36	-0.002	0.063	0.001	18.20	-0.001
SD	8.0	0.024	0.125	6.52	0.140	0.024	0.068	6.43	0.068
$\rho(\eta_t, \bullet)$	-0.06	–	–	–	–	–	–	–	–
$\rho(\eta_t^\Delta, \bullet)$	0.01	0.29	–	–	–	0.16	–	–	–
$\rho(lvg_t, \bullet)$	0.01	-0.92	-0.35	–	–	-0.91	-0.19	–	–
$\rho(lvg_t^\Delta, \bullet)$	-0.06	-0.44	-0.96	0.48	–	-0.25	-0.98	0.26	–
T	199	191	191	191	190	574	573	574	573

the capital ratio in levels, which is not.[3] Thus, it can be used limiting the risk of spurious relationship, in a factor model that I will illustrate in the next chapter. Quarterly lvg_t^Δ results being both stationary at 1% and non autocorrelated.

The aggregated intermediary balance sheet measures differ markedly: the correlation between $lvg_t^{\Delta,BD}$ and η_t^Δ is 0.01, while between $lvg_t^{\Delta,BD}$ and lvg_t^Δ is -0.06. This is consistent with the evidence from HKM – Figure 3.3, and confirms how crucial is the composition of the set of representative intermediaries. Further descriptive statistics of the quarterly and monthly series can be found in Table 5.3.

[3] 10% is generally considered enough to reject the unit root hypothesis because of the low power of the ADF test.

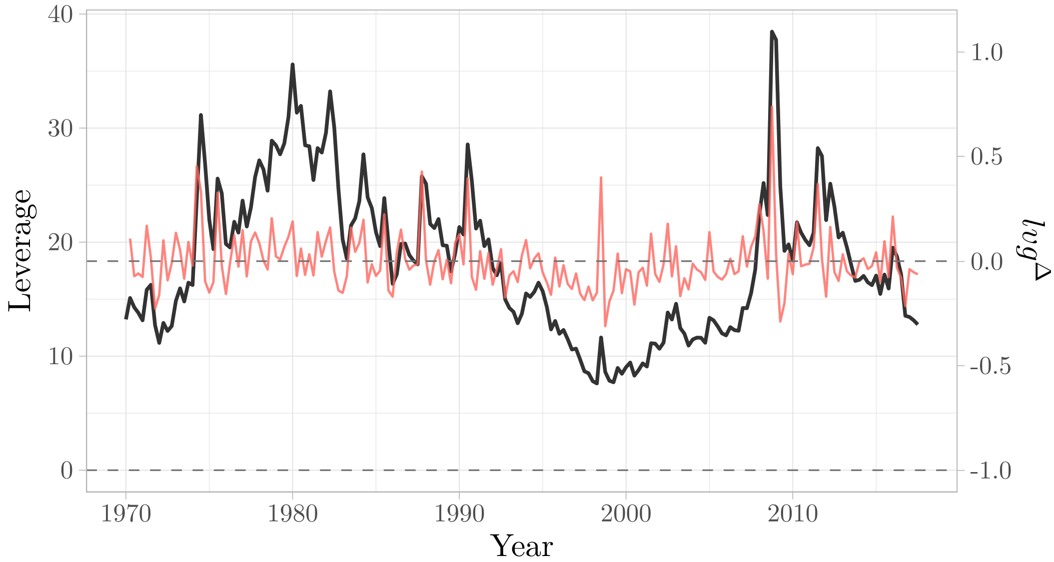


Figure 5.1: Plot of lvg_t (in black) and lvg_t^{Δ} (in red). lvg_t is measured on the left axis, while lvg_t^{Δ} on the right axis.

SRISK, TED, and market liquidity measure

SRISK has been introduced in section 3.4. It is provided in real-time at https://vlab.stern.nyu.edu [Engle et al. (2018)], and the data is at firm level, with daily frequency. To aggregate daily firm-level data to US-wide daily data, I have followed page 53 of Brownlees and Engle (2017), i.e. I have summed up only the positive values of each day. This type of aggregation has a specific rationale: during a severe downturn, over-funded institutions – those with a negative SRISK – are not likely to buy or generically supply capital to the under-funded institutions, therefore, the total capital needed by the financial system to overcome the crises, likely supplied by the government, amounts to what derived in this way. Then, I have aggregated daily data into monthly data, which is the time unit used by Brownlees and Engle (2017), by averaging 15 calendar daily values centred at the end of each month. This is only one of the adjustments that I have implemented on this dataset; the others consist of the removal of problematic dates with limited underlying-data coverage and the time span reduction to match the starting date of Brownlees and Engle (2017). The full procedure and the reasons for that are explained in section B.2. Finally, quarterly frequency data is obtained by simply taking the last monthly observation of each quarter. SRISK is non-stationary and autocorrelated, thus it will not be used in the analysis to avoid spurious relationships. Instead, accordingly to Brownlees and Engle (2017) and consistently with the use of innovations for intermediary capital ratio, the log differences $\Delta \ln(\text{SRISK}_t)$ will be used, which are conveniently both stationary and non-autocorrelated, at least at quarterly frequency.

The TED spread has been introduced in section 4.3 and it is provided by the Federal Reserve Bank of St. Louis (2018). TED is provided with daily frequency, so lower frequencies are obtained keeping the last observation available. This rate is expected to be especially informative about the debt funding liquidity, as well as more in general of the funding tightness. Since the pricing kernel is tested in terms of shocks to the intermediary capital

Table 5.4: SRISK, TED and Market Liquidity time-series characteristics. The level of significance of stationarity is based on the outcome of an Augmented Dickey–Fuller test while the autocorrelation level of significance is determined with a Box-Ljung test where the number of lags tested is equal to the yearly frequency of the series tested, 4 and 12.

	Quarterly		*Monthly*	
	Stationary	**Autocorr**	**Stationary**	**Autocorr**
SRISK_t	No	Yes***	No	Yes***
$\Delta \ln(\text{SRISK}_t)$	Yes***	No	Yes***	Yes***
ΔTED_t	Yes***	Yes***	Yes***	Yes***
TED_t^Δ	Yes***	Yes*	Yes***	Yes***
$m.liq_t^\Delta$	Yes***	No	Yes***	Yes***

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 5.5: Summary statistics of SRISK, TED, and market liquidity. l(SR) stands for $\Delta \ln(\text{SRISK}_t)$, and ρ measures the the Pearson correlation.

	Quarterly				*Monthly*			
	$\text{l(SR}_t)$	ΔTED_t	TED_t^Δ	$m.liq_t^\Delta$	$\text{l(SR}_t)$	ΔTED_t	TED_t^Δ	$m.liq_t^\Delta$
Min.	-0.048	-0.018	-0.011	-0.256	-0.062	-0.010	-0.461	-0.392
1sr Qu.	-0.023	-0.001	-0.001	-0.023	-0.023	-0.001	-0.054	-0.023
Median	0.004	0.000	-0.001	0.001	0.004	0.000	-0.020	0.007
3rd Qu.	0.037	0.001	0.001	0.029	0.037	0.001	0.007	0.029
Max.	0.430	0.022	0.023	0.116	0.430	0.020	0.198	0.280
Mean	0.017	-0.000	-0.000	-0.002	0.015	-0.001	-0.029	0.000
SD	0.073	0.003	0.003	0.055	0.058	0.230	0.061	0.055
$\rho(\Delta\text{TED}_t, \bullet)$	0.06	–	–	–	0.12	–	–	–
$\rho(\text{TED}_t^\Delta, \bullet)$	0.11	0.95	–	–	0.20	0.96	–	–
$\rho(m.liq_t^\Delta, \bullet)$	-0.28	-0.12	-0.26	–	-0.31	-0.19	-0.24	–
N	45	129	130	218	133	387	653	653

ratio, the changes in TED, ΔTED_t, are used. I also consider the the AR(1) innovations TED_t^Δ to remove the remarkable autocorrelation of TED, which is reported in Table 5.4. However, the correlation between the changes and the innovations amounts to 0.96.

The MARKET LIQUIDITY MEASURE $m.liq_t$ provided by Pástor and Stambaugh (2003) is an average of the US individual stocks' liquidity measures. These measures are based on the the short-term reversal of stocks' returns, which is greater in magnitude the more sensible the returns are to the order flow, which depends on the liquidity in the market. The authors provide the ARIMA innovations of $m.liq_t$, which I define $m.liq_t^\Delta$ and use, to be consistent with the intermediary risk factors measures, similarly based on the innovations.

Interestingly, the correlation between market liquidity innovations and TED innovations is -0.26, that is, negative market liquidity shocks tend to happen when funding liquidity suffers negative shocks as well. This is reflective of the self-reinforcing mechanisms that generate liquidity spirals. Similarly, the correlation between TED changes and market liquidity innovations is -0.12. As the TED innovations do not appear to bring additional information with respect to the changes, and are also more redundant as they are generally more correlated with other proxies, in the next analysis I will only use the latter, following FP.

Other risk factors

The risk factors considered in this work other than those related to the intermediaries' balance sheets are: the market excess returns; Small-Minus-Big (SMB) and High-Minus-Low (HML) from Fama and French (1993); and momentum (UMD), from Carhart (1997). All of these are obtained from the web library of professor French, at French (2018), with monthly frequency from 1926 to 2018. The quarterly series are obtained taking the geometric sum over the period.

Test assets

The test assets included in this analysis are the following portfolios:

(a) * the US-equity BAB factor presented in section 4.2

(b) * 10 of US stocks sorted on CAPM beta

(c) 25 of US stocks sorted on value and size (also named FF25)

(d) * 10 of US stocks sorted on momentum

(e) 7 of US government bonds sorted on maturity

(f) 10 of US corporate bonds sorted on yield spread

(g) 6 of sovereign bonds sorted on covariance with the US equity market and default probabilities from S&P ratings

(h) 18 of S%P 500 index options sorted on moneyness and maturity; 9 of calls, 9 of puts

(i) 6 of currencies sorted on interest rate differential

(j) 6 of currencies sorted on momentum

(k) 23 of commodities

(l) 20 of individual-name 5-year CDSs, sorted by spreads

(a) is obtained from the authors of FP; (b), (c), (d) from French (2018); (e) from *Wharton Research Data Services* (2018); the remaining ones from HKM, whose analysis does not include the test assets marked with *. Quarterly returns of portfolios are computed with a geometric sum; descriptive statistics of the test assets are provided in Table 6.5.

6

Empirical tests

The intermediary factor models

Four factor models based on intermediary risk factors are specified as follows:

IFM1 includes only the leverage factor lvg_t^{Δ}, thereby essentially replicating the AEM specification, but based on HKM's primary dealers data

IFM2 is based on HKM, and as such it includes the capital ratio risk factor η_t^{Δ} and the market excess returns

IFM3 is the most complex model: it includes the market excess returns, lvg_t^{Δ}, the absolute contemporaneous primary-dealers leverage level lvg_t, and the interaction term $lvg_t^{\Delta} \cdot lvg_t$

IFM4 is based on AEM, and as such it includes their leverage factor $lvg_t^{\Delta,BD}$ only

where IFM is just the shorthand for Intermediary Factor Model. IFM2 and IFM4 have been widely discussed in chapter 3, and the first specification is one of the robustness checks of HKM, which join their data with the AEM specification. Thereby, IFM1 is then not expected to provide results too far from IFM2. However, it may have a different empirical performance and, most importantly, it works as a direct benchmark to the third specification, which is introduced only now. The aim of the third specification is to test the hypothesis that leverage does not impact homogeneously the SDF, but rather the impact depends on the level of leverage in place. Thus, the focus of this specification is on the interaction term $lvg_t^{\Delta} \cdot lvg_t$: this is higher the higher are the intermediary leverage risk factor and the leverage level, with the effect of magnifying the leverage shocks in higher-leverage states. My choice of multiplying the leverage level with the scaled innovations instead of the innovations themselves is quite arbitrary, but I relied on HKM, which identifies the scaled innovations to the capital ratio, and not the absolute innovations, as fundamental shocks to the intermediary capital risk.[1] Then, this interaction term should capture the difference, if there is any, between the risk associated to shocks realized in different leverage-level states.

[1]Moreover, to remove the autocorrelation from the absolute innovations – p-value higher than 10% in Box-Ljung test with 4 lags – at least an ARMA(1,2) model of leverage is required, while for scaled innovations an AR(1) suffices, thus strengthening the argument in favour of scaled innovations as fundamental shocks to the leverage process.

Table 6.1: Regression results: capital risk factors – SRISK. NW HAC-SEs in parenthesis; RMSE is the shorthand for Root Mean Squared Errors. Models are, in order: IFM1, IFM2, IFM3, IFM4.

	Δ log SRISK	Δ log SRISK	Δ log SRISK	Δ log SRISK
(Intercept)	0.024^{*}	0.026^{**}	0.061	0.026^{*}
	(0.010)	(0.009)	(0.033)	(0.011)
lvg_t^{Δ}	0.118		0.410^{**}	
	(0.061)		(0.122)	
η_t^{Δ}		-0.164^{**}		
		(0.058)		
lvg_t			-0.002	
			(0.002)	
$lvg_t^{\Delta} \cdot lvg_t$			-0.009^{**}	
			(0.003)	
$lvg_t^{\Delta,BD}$				0.002
				(0.001)
R^2	0.112	0.159	0.201	0.058
Adj. R^2	0.091	0.139	0.143	0.017
AIC	-128.7	-131.2	-129.5	-125.2
BIC	-123.3	-125.8	-120.5	-119.8
Num. obs.	45	45	45	45
RMSE	0.055	0.054	0.054	0.058

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

6.1 Research question 1

Here I make a battery of basic tests to assess how well the intermediary risk factors explain proxies of undercapitalization, funding liquidity, and market liquidity, widely recognized as causes and symptoms of the funding tightness.

Undercapitalization

The test is performed with OLS regressions on quarterly data, using the Newey and West (1987) (NW) standard errors, which account for heteroskedasticity and autocorrelation of residuals (HAC). The results relative to SRISK are shown in Table 6.1. The first striking result comes from IFM4, whose performance is definitely the worst one, with the worst R^2, just above 5%, AIC, BIC and root mean squared errors (RMSE) values. Moreover, differently from AEM, the results show that the AEM leverage factor is positively related to higher undercapitalization states – higher distress states, thus covarying with the factor of HKM as well. On the other side, the specification that simply explain the most of SRISK log differences is the IFM3, with an R^2 of 20%, that is the double of IFM1 and 5% higher than IFM2. The model also has the best AIC, however, considering the more parsimonious BIC, the best model in the group is IFM2, which indeed has the same RMSE of IFM3, but obtains it with two parameters less. In general, all of the models show that a negative

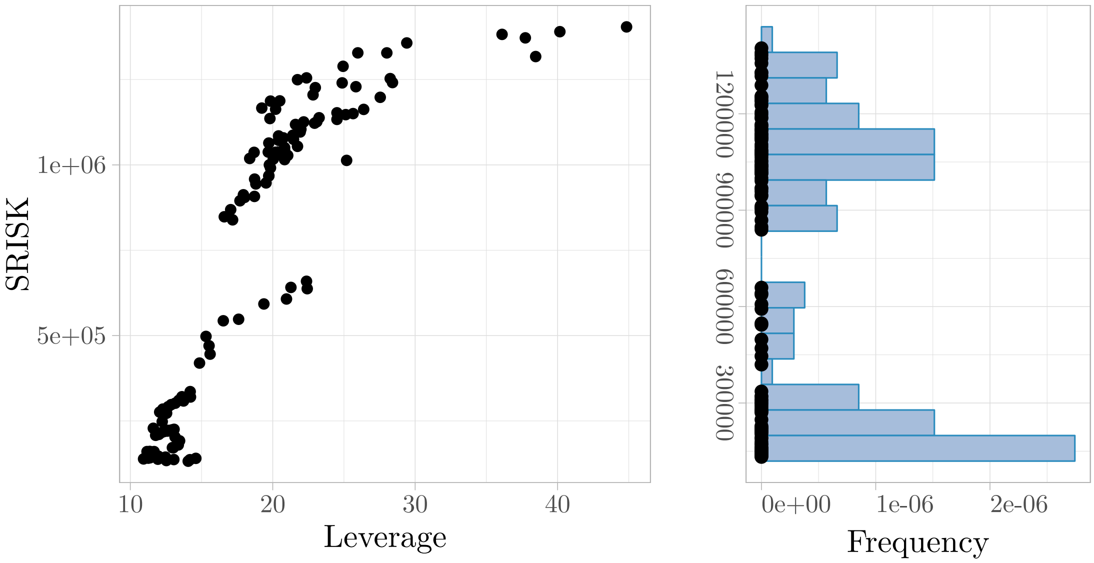


Figure 6.1: Monthly SRISK-leverage scatterplot (on the left) and SRISK histogram (on the right). Dots in the y axis of the histogram are monthly observations of SRISK.

shock to leverage is associated with a higher funding level, therefore, at least with this set of aggregate capital ratios, the predominant dynamics is that of the equity-constraint model where lower leverage implies higher utility (and lower marginal utility).

Interestingly, the leverage factor at the base of IFM1 is not statistically significant until a discriminant of the level of leverage (IFM3) is introduced. Then, it is highly significant, as well as the interaction term with the leverage level. This would seem to confirm the relevance of considering the leverage absolute level. Nonetheless, being the interaction term negative, it implies that a positive shock to leverage would have less and less effect the higher is the level of leverage, which in general contradict the prediction of higher leverage implying more financial distress. This may be due to the interventions of government, if these impact the log differences of SRISK when leverage is high. Looking at Figure 6.1, it may hypothesized that if interventions of government take place when SRISK is high, then they will likely take place when also leverage is high. However, since SRISK is non-stationary, it cannot be said much of statistically significant about the relationship between SRISK and leverage, and this hypothesis. Moreover, the leverage required to make its shocks having a negative relation with SRISK log differences is 47.1, which has never been observed. Figure 6.1 also broadly supports what predicted by Brunnermeier and Sannikov (2014), that is the economy spends most of the time in two regimes, a stable one and a crisis one: in facts, two distinct clusters can be observed in the chart, one of low SRISK and the other one of high SRISK, which even split the probability density showed in the histogram.[2] Notably, the two clusters are also quite well distinct in terms of leverage, and if leverage was to actually have two regimes like SRISK, it would provide further motivation to include the level of leverage as an intermediary capital risk factor. The last consideration about this test only covers a limited

[2]Notably, it is really similar to the probability density drawn in figure 4 of Brunnermeier and Sannikov (2014).

Table 6.2: Regression results: capital risk factors – TED. NW HAC-SEs in parenthesis; RMSE is the shorthand for Root Mean Squared Errors. Models are, in order: IFM1, IFM2, IFM3, IFM4.

	Δ TED$_t$	Δ TED$_t$	Δ TED$_t$	Δ TED$_t$
(Intercept)	-0.010	-0.007	0.172^{**}	-0.007
	(0.018)	(0.013)	(0.060)	(0.017)
lvg_t^{Δ}	-0.263		2.110^{***}	
	(0.530)		(0.485)	
η_t^{Δ}		0.037		
		(0.465)		
lvg_t			-0.008^{*}	
			(0.003)	
$lvg_t^{\Delta} \cdot lvg_t$			-0.097^{***}	
			(0.026)	
$lvg_t^{\Delta,BD}$				0.015
				(0.010)
R^2	0.012	0.000	0.202	0.107
Adj. R^2	0.004	-0.008	0.182	0.100
AIC	85.09	86.65	62.28	72.38
BIC	93.60	95.15	76.46	80.89
Num. obs.	126	126	126	126
RMSE	0.334	0.336	0.303	0.317

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

amount of time, thus relying only on 45 observations, which may weaken the reliability of results.

Funding liquidity

The regression results of the analysis on TED changes are in Table 6.2; as for the other tests, standard errors are NW HAC. The outcome overturn in some respects the previous test: the model that better performed under the BIC in the test before, IFM2, here is the worst under all measures; it has a negative adjusted R^2, the highest AIC and BIC, and the higher RMSE of the group. At the same time, the worst performing specification of the first test, IFM4, now explains the second most of the variation of TED in the group, with 10% of R^2. Notably, this is only half ot the R^2 of the best specification, which is again IFM3. This explains the most variance in TED, plus having the lowest RMSE, AIC, and BIC, and highly significant parameters, though including the intercept. Indeed, another fact that is not overturned is the significance of the interaction term, which also makes the leverage factor lvg^{Δ} becoming highly significant. Again, the interaction term is negative, meaning that the higher the leverage level, the less leverage positive shocks are associated with positive TED changes – lower funding liquidity. This is rather puzzling especially because the positive shocks are already associated to negative TED changes when leverage is above 21.75, which happened in 9% of observations. In any case, it is appreciable that this specification is able

Table 6.3: Regression results: capital risk factors – market liquidity. NW HAC-SEs in parenthesis; RMSE is the shorthand for Root Mean Squared Errors. Models are, in order: IFM1, IFM2, IFM3, IFM4.

	$m.liq_t^\Delta$	$m.liq_t^\Delta$	$m.liq_t^\Delta$	$m.liq_t^\Delta$
(Intercept)	-0.003	-0.003	-0.025	-0.003
	(0.005)	(0.005)	(0.018)	(0.005)
lvg_t^Δ	-0.113^{**}		-0.093	
	(0.034)		(0.101)	
η_t^Δ		0.115^{***}		
		(0.032)		
lvg_t			0.001	
			(0.001)	
$lvg_t^\Delta \cdot lvg_t$			-0.002	
			(0.004)	
$lvg_t^{\Delta,BD}$				0.001^{*}
				(0.000)
Adj. R^2	0.074	0.059	0.083	0.004
AIC	-552.3	-549.3	-552.1	-538.6
BIC	-542.6	-539.6	-535.9	-528.9
Num. obs.	187	187	187	187
RMSE	0.055	0.055	0.054	0.057

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

to capture this asymmetry, while IFM1 coefficients is negative and not even statistically significant. All in all, the two specifications that better perform by far, IFM3 and IFM4, both agrees on associating higher TED – lower funding liquidity – with higher leverage, thus once again showing dynamics more comparable to those described by the equity-constraint framework.[3]

Market liquidity

The tests performed on the market liquidity measure are showed in Table 6.3. The results here are more ambiguous because there is not a specification that outperform the others in the majority of the statistics. Specifically, IFM3 is the one that explains the most of market liquidity variation, having the highest R^2 and the lowest RMSE. Nonetheless, its AIC is slightly lower than IFM1, which also has a far better BIC, and comparable R^2 and RMSE. Under the parsimonious BIC, also IFM2 performs better than IFM3, which implies IFM3 may be the most at risk of overfitting. Furthermore, IFM3 has no significant coefficients, and the opposite of the past test happens: when the interaction term factor is included, the leverage factor lvg^Δ becomes insignificant. However, the hypothesis of all the coefficients of IFM3 being 0 is rejected, by far, at the 1% level of confidence, with a p-value of 0.0003. IFM4 is not only the worst model under any measure, but is also the only

[3] IFM3 and IFM4 are also the only 2 to have a F statistic significant at 1% level, while the p-values of IFM1 and IFM2 are higher than 0.2.

model not significant, at any level. This is also the only one predicting a pro-cyclical leverage – higher leverage associated with higher market liquidity. So, at the end of the day, only IFM1, IFM2 and IFM3 show a weak, though still statistically significant, relation the market liquidity and they all predict a counter-cyclical leverage, as in the previous tests.

6.2 Research question 2

Since (1) the performances of IFM1 and IFM4 were quite bad in RQ1; (2) IFM1 is extremely close to IFM2 and nested in IFM3, thus quite redundant; and (3) IFM4 proved being a poor proxy of the intermediary pricing kernel also in HKM tests, I do not test these two specifications further. Instead, to answer RQ2 I only apply IFM3, which has had the best overall performance, and IFM2, of which HKM have extensively proved the goodness in the ultimate asset pricing test, in addition to having an easier interpretation and greater theoretical support than IFM3.

A direct test on the BAB factor of risk factors representativeness

Before testing the consistency of the intermediary factor models in pricing the BAB factor and more in general the CAPM-beta LRA, I further test the ability of the risk factors to gauge funding liquidity, this time directly on the BAB factor. This leverage on the relationship predicted by the theory showed in section 4.3, which tests fail to confirm though. Then, similarly to FP, I regress the BAB excess returns on the current risk factors, on their 1-lag value, and on the market returns, for robustness reasons:

$$r_t^{BAB} - r_{f,t} = \beta_0 + \boldsymbol{\beta}_1 \mathbf{f}_t + \boldsymbol{\beta}_2 \mathbf{f}_{t-1} + \beta_3 r^e_{M,t} + \epsilon_t \tag{6.1}$$

The regression is performed with the OLS method and standard errors are NW HAC; results are in Table 6.4. IFM3 (first column) performs better than the HKM specification under any measure: AIC, BIC, R^2, and RMSE. Since the market coefficient in the first IFR3 specification is statistically insignificant, a version without the market variables is estimated, showed in the second column. No performance statistic worsen significantly, while the BIC even slightly improves.

The contemporaneous factors that have a statistically significant coefficient are η_t^{Δ} and the interaction term $lvg_t^{\Delta} \cdot lvg_t$. The first one has a positive coefficient, which is consistent with the view that higher capital ratio, i.e. lower leverage, implies looser funding constraint. Then, as current funding constraints get looser, low-beta asset prices increases, high-beta prices drop, lowering the expected returns of the BAB portfolio, while making the BAB strategy realize a contemporaneous positive return. Next, the interaction term is negative, which agrees with the first one, despite a different interpretation: current positive shocks to leverage are associated with lower BAB returns, the higher is the leverage. This perfectly agrees with the intuition of the theory: as leverage is higher, and marginal utility of wealth increases, shocks to wealth have heavier implications. Interestingly, the contemporaneous leverage factors lvg_t^{Δ} have positive coefficients, which instead diametrically contradicts the theory, but are totally insignificant.

Table 6.4: Regression results: BAB factor – intermediary factor models. The dependant variable is r_t^{BAB}, standard errors are Newey-West HAC.

	IFM3	**IFM3-mkt**	**HKM**	**FP**	**IFM3-mkt**
(Intercept)	-0.019	-0.017	0.026^{***}	0.066^{***}	-0.007
	(0.025)	(0.026)	(0.007)	(0.010)	(0.037)
$r^e_{M,t}$	-0.169		-0.120		
	(0.150)		(0.147)		
lvg_t^{Δ}	0.023	0.089			0.082
	(0.091)	(0.114)			(0.135)
lvg_{t-1}^{Δ}	-0.330^{**}	-0.361^{**}			-0.413^{***}
	(0.113)	(0.118)			(0.106)
lvg_t	0.006	0.007			0.008
	(0.006)	(0.006)			(0.011)
lvg_{t-1}	-0.003	-0.005			-0.006
	(0.006)	(0.005)			(0.009)
$lvg_t^{\Delta} \cdot lvg_t$	-0.014^{***}	-0.015^{***}			-0.014^{*}
	(0.004)	(0.004)			(0.006)
$lvg_{t-1}^{\Delta} \cdot lvg_{t-1}$	0.008	0.010^{*}			0.012^{**}
	(0.004)	(0.005)			(0.004)
η_t^{Δ}			0.158^{*}		
			(0.068)		
η_{t-1}^{Δ}			0.069		
			(0.072)		
Δ TED$_t$				-0.044^{**}	
				(0.013)	
TED$_{t-1}$				-0.073^{***}	
				(0.015)	
R^2	0.217	0.199	0.094	0.179	0.204
Adj. R^2	0.187	0.173	0.074	0.166	0.164
AIC	-515.3	-513.0	-493.8	321.8	-314.14
BIC	-486.1	-487.0	-474.3	-310.5	-291.5
Num. obs.	189	189	190	126	126
RMSE	0.060	0.061	0.064	0.066	0.065

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Similar to the results of FP, the lagged proxies of funding tightness, which in this case are the capital-related risk factors lvg_{t-1}^{Δ} and η_{t-1}^{Δ}, do not have positive coefficients – but neither are significant. The only partial exception is with the IFM3-mkt model, where the lagged interaction term is significant at the 5% level.[4] Then, as $t-1$ leverage increases, positive $t-1$ shocks to leverage are more and more positively related to higher BAB returns in t. Interestingly, when $t-1$ leverage reaches 37.0, positive shocks to $t-1$ leverage finally predict higher BAB returns in the next period, which is consistent with the view that higher leverage is related to tighter funding – higher marginal utility of wealth. Despite the fact that such a high realization of leverage only occurred in 2 quarters in whole sample – slightly more than 1% of observations

[4]In IFM3 it has a p-value of 0.078.

– this seems a step closer towards what predicted by FP.

In the last two columns IFM3 and the FP's specification are directly compared, where the sample size is reduced to match the time span of the TED time series.[5] The intermediary model outperforms the TED model in terms of variance explained – R^2, however, the TED-based specification results being better considering adjusted R^2, AIC and BIC. Notably, in the smaller sample the lagged interaction term of the leverage-model becomes more significant both statistically and economically: in this case a leverage of 0.52 is enough for a positive lagged shock to be associated with higher future BAB returns. So, despite being less powerful in explaining the BAB returns per se, and since no leverage observation is lower than 7, in the shorter sample the intermediary model risk factors successfully show the relationship between funding tightness and BAB returns predicted by the theory. To be precise, this is true assuming that the leverage measure on which the intermediary risk factors are based, are counter-cyclical, which has wide support from RQ1 and other coefficients here. Nonetheless, it must be noted that the interaction term seems to be quite fragile, as its direction changes across this and the previous tests, even though it may also be due to the structural relationship. In any case, even if fragile, it consistently appears to be useful in explaining dependant series.

Cross-sectional asset pricing test

To test the ability of the intermediary pricing kernel to price consistently all the assets in the economy, I perform the two-stage procedure employed by both HKM and AEM:

1. I estimate the risk exposure of each test asset over the whole sample, in terms of covariance with the risk factors, with the regression showed in Equation 3.4.

2. Having the average risk exposures of the test assets to the risk factors, I regress the cross-sections of average excess returns on average exposures, i.e. betas estimated over the whole sample, with the regressions showed in Equation 3.3.

Note that this procedure differs from the canonical period-by-period estimation of betas employed commonly to perform 2-stage tests similar to this. Specifically, here the estimated risk prices are unconditional averages over the sample, thus ignoring state-dependant effects, which are a matter of second order for this investigation. Moreover, a technical note: the standard errors of the risk premia estimated in the second stage need to account for the potential bias due to autocorrelation and cross-sectional correlation between test assets that may make betas biased, thus I follow Petersen (2009), using the NW HAC SE estimator, and set the lag to T-1. To use such estimator, instead of actually regressing the expected excess return estimated over the whole sample, i.e. the average return, of each test asset on the relative full-sample betas, I regress period-by-period the excess returns of the test assets on the full-sample betas. Then, the average risk premium of a risk factor is derived taking the mean of regression coefficients of the relative beta, over the whole

[5]The results of the HKM specification in the shorter sample is not reported because essentially identical to those of the full sample.

Table 6.5: Test assets characteristics by category. Quarterly rates, in percentage. The count of observation for the category "all" is an average of all the portfolios.

	Beta	FF25	Mom	US Bonds	Sov Bonds	Options	CDS	Comm	FX	All
Mean R^e	1.936	2.312	1.703	1.212	1.974	1.113	0.281	0.366	-1.011	1.054
SD(•)	0.203	0.611	0.885	0.522	1.125	1.472	0.521	1.703	0.817	1.392
Mean SR	0.409	0.433	0.371	0.847	0.615	0.226	0.204	0.058	-0.440	0.290
SD(•)	0.103	0.116	0.184	0.667	0.281	0.305	0.365	0.226	0.333	0.456
Mean α^{CAPM}	0.173	0.498	-0.000	1.039	1.351	-0.165	0.149	0.025	-1.112	0.193
SD(•)	0.523	0.775	1.143	0.620	0.814	1.224	0.458	1.765	0.769	1.162
Mean α^{HKM}	0.226	0.613	0.070	1.107	1.419	-0.164	0.264	-0.072	-1.244	0.222
SD(•)	0.514	0.901	1.084	0.561	0.847	1.274	0.516	1.797	0.788	1.219
Mean α^{IFM3}	-0.583	-1.102	-1.044	0.667	-2.645	-1.048	-0.615	2.375	3.313	0.105
SD(•)	2.015	1.517	2.089	0.503	1.505	0.823	0.457	3.142	0.991	2.347
Mean β_M^{CAPM}	1.078	1.110	1.046	0.113	0.339	0.819	0.105	0.197	0.067	0.533
SD(•)	0.335	0.192	0.220	0.115	0.226	0.167	0.069	0.214	0.047	0.477
Mean β_M^{HKM}	1.038	1.028	0.992	0.075	0.108	0.818	0.041	0.327	0.174	0.518
SD(•)	0.330	0.288	0.223	0.065	0.131	0.120	0.035	0.244	0.040	0.458
Mean $\beta_{\eta^\Delta}^{HKM}$	0.037	0.075	0.049	0.034	0.207	0.001	0.055	-0.114	-0.094	0.014
SD(•)	0.027	0.118	0.083	0.050	0.127	0.048	0.035	0.099	0.025	0.110
Mean β_M^{IFM3}	1.039	1.017	1.004	0.099	0.137	0.829	0.042	0.286	0.255	0.523
SD(•)	0.342	0.272	0.235	0.078	0.115	0.098	0.036	0.254	0.033	0.452
Mean $\beta_{lvg^\Delta}^{IFM3}$	0.000	0.001	0.001	0.000	0.003	0.000	0.001	-0.001	-0.002	0.000
SD(•)	0.001	0.001	0.001	0.000	0.002	0.001	0.001	0.002	0.000	0.001
Mean β_{lvg}^{IFM3}	-0.038	-0.127	-0.016	0.046	-0.192	-0.060	-0.024	0.376	0.307	0.047
SD(•)	0.097	0.096	0.038	0.029	0.105	0.042	0.053	0.243	0.075	0.218
Mean $\beta_{lvg \cdot lvg^\Delta}^{IFM3}$	0.000	0.002	-0.001	-0.003	-0.001	0.003	-0.001	-0.013	-0.005	-0.003
SD(•)	0.004	0.003	0.002	0.002	0.008	0.002	0.002	0.012	0.003	0.007
Mean R^2_{CAPM}	0.841	0.765	0.808	0.107	0.224	0.779	0.510	0.034	0.016	0.454
Mean R^2_{HKM}	0.843	0.777	0.813	0.118	0.307	0.781	0.632	0.043	0.042	0.483
Mean R^2_{IFM3}	0.846	0.780	0.812	0.141	0.352	0.793	0.756	0.075	0.169	0.523
Quarters	193	193	193	168	65	103	47	105	135	133

sample. As mentioned, this is the same procedure as HKM, though the SEs are estimated differently. A consequence of this procedure is that when the available time span of the test assets is not homogeneous, the period-by-period risk premia are estimated on different ranges of assets, thus overweighting the pricing dynamics of assets that are more present in the dataset. In the case of HKM, the predominant asset class was US stocks, in the form of value- and size-sorted portfolios. In this work, such test assets are still predominant but so are the BAB factor, the momentum-, and beta-sorted US stocks portfolios, and the maturity-sorted US government bonds portfolios as well.[6] The results of the first-stage regressions, as well as the number of observations and other descriptive statistics per asset class/sorting-characteristic are reported in Table 6.5.

The results of the second-stage regression of the HKM and IFM3 factor models are reported in Table 6.6, together with the results of the same two-stage procedure for the CAPM, the Fama and French (1993) three-factor model (FF3), and the four-factor model of Carhart (1997) (C4). Firstly, as the CAPM market risk premium is lower than the sample average market excess return, which is 1.72%, and the intercept is positive and statistically significant, it can be noted the flatness of the CAPM's SML mentioned in section 4.2. Then, moving to the intermediary risk factor models, it can be noted that the intercept is even higher than the CAPM, with the IFM3 being the highest one, which is a general sign of relatively worse fit. Next, it can be noted that the market risk premium is significant only for HKM, consistently with their analysis, despite being half a percentage point lower in this sample. Finally, HKM results having a significant positive risk premia for the capital risk, again consistent with HKM results, as well as IFM3 ends up having two out of three factors' premia significantly different from 0. Specifically, the significant IFM3 premia are the level of leverage and the interaction term, both with negative sign. This indicates that the more negatively an asset covary with leverage, the higher is the required return from it, since it is negatively covarying with the marginal utility of wealth, consistently with all the previous results and the HKM specification. More precisely, the covariances are with the level of leverage, and the shocks scaled by the leverage level. The magnitude of the risk premia is remarkable, 6.97% and 128.19% quarterly. However, the risk exposures are relatively low: for instance, the average FF25 portfolio, ignoring the extremely insignificant risk premium of the risk factor lvg_t^{Δ}, earns per quarter $(-6.97\%) \cdot (-0.127) + (-128.19\%) \cdot 0.002 = 0.629\%$ from the exposure to these risk factors, which is nothing monstrous but more likely the opposite.

Looking at the overall performances, the R^2 of HKM is higher than those of the CAPM and FF3, while the R^2 of IFM3 is the highest of all of the five models showed. Then, moving to the ultimate measure of pricing accuracy, the mean absolute pricing error (MAPE), HKM only outperform the CAPM, while IFM3 is the second lowest among the specifications, loosing solely to the C4. So, this evidence seems to suggest that the two intermediary factor models definitely do a better job than the CAPM, but not that better than the FF3, and unlikely better than the C4, which has both the lowest intercept and MAPE of the group of models. This provides a first answer to the first

[6]The series of maturity-sorted US government bonds portfolios have been updated with respect to HKM, equating the length of stocks' series. In Table 6.5 it is reported having as few as 168 observation because government bonds are grouped with the US corporate bonds, whose time span is shorter.

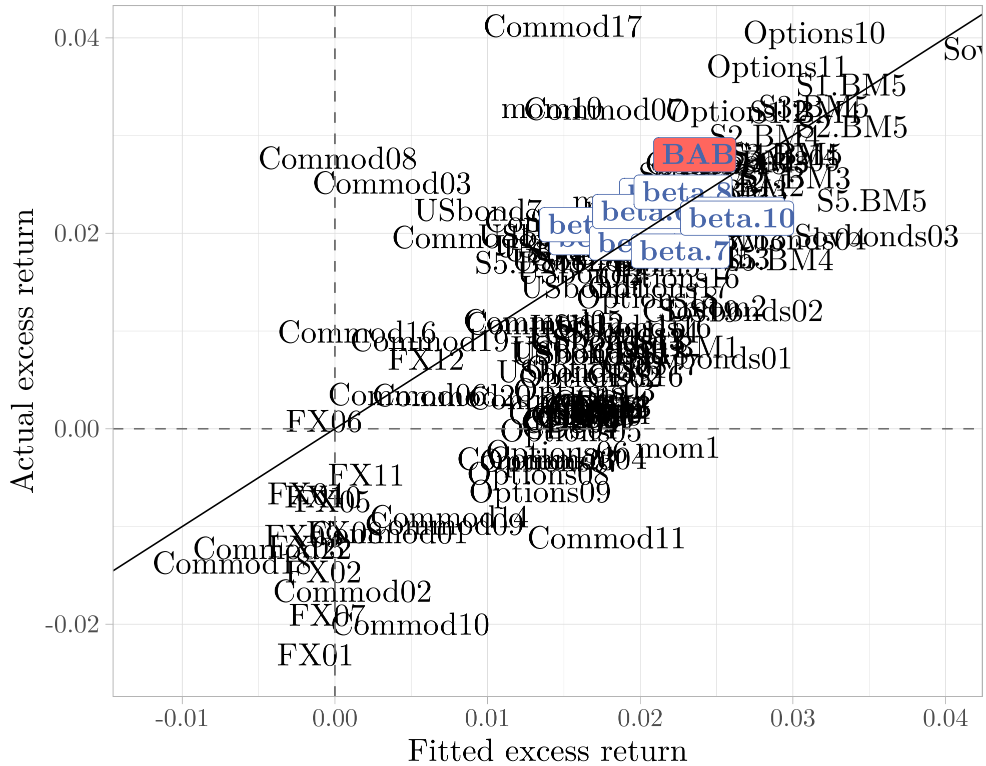
Table 6.6: Prices of risk. Quarterly returns, expressed in percentage. Newey and West (1987) SEs, R^2 computed as in He, Kelly, et al. (2017), that is variance of predicted excess returns divided by variance of actual excess returns.

	CAPM	**FF3**	**C4**	**HKM**	**IFM3**
(Intercept)	0.54^{***}	0.41^{***}	0.25^{*}	0.65^{***}	1.11^{***}
	(0.11)	(0.12)	(0.11)	(0.10)	(0.20)
$\bar{\lambda}_M$	1.31^{***}	1.21^{***}	1.47^{***}	0.96^{***}	0.42
	(0.23)	(0.30)	(0.29)	(0.22)	(0.44)
$\bar{\lambda}_{SMB}$		0.22	0.29		
		(0.18)	(0.19)		
$\bar{\lambda}_{HML}$		1.65^{***}	1.79^{***}		
		(0.25)	(0.27)		
$\bar{\lambda}_{mom}$			1.32^{*}		
			(0.61)		
$\bar{\lambda}_{\eta^{\Delta}}$				6.46^{***}	
				(0.72)	
$\bar{\lambda}_{lvg^{\Delta}}$					10.37
					(137.59)
$\bar{\lambda}_{lvg}$					-6.97^{***}
					(0.67)
$\bar{\lambda}_{lvg^{\Delta}\cdot lvg}$					-128.19^{***}
					(31.65)
R^2	0.201	0.291	0.382	0.367	0.453
Adj. R^2	0.197	0.279	0.368	0.361	0.442
Num. obs.	191	191	191	191	191
MAPE	0.908	0.810	0.761	0.823	0.799
MAPE-betas	0.489	0.315	0.232	0.367	0.320

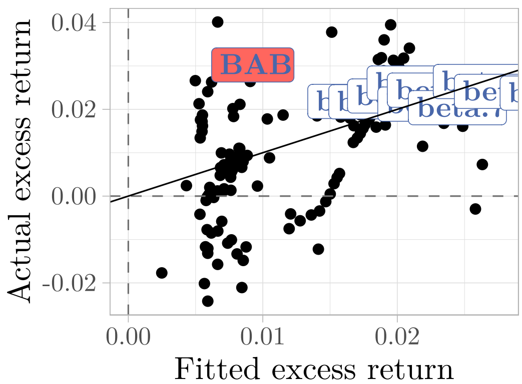
$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

part of RQ2; to move on and reply to the second part, the MAPE of the 10 beta-sorted US stocks portfolios and the BAB factor can be observed in Table 6.6. The lowest one is of C4, which is essentially half the MAPE of the CAPM. Then, midway through the C4 and the CAPM, FF3 and IFM3 perform similarly, while HKM follows. It can be noted how all the models price the beta-sorted portfolios (including the BAB factor) quite well relatively to the average portfolio of all the test assets included. So, one may consider the difference between the overall MAPE and the beta-MAPE as a measure of goodness in pricing the portfolios "affected" by the CAPM-beta LRA. However, the intermediary pricing kernel specifications here tested do not excel in this metric either, being ranked third and fourth after FF3 and C4. The only point related to beta-LRA pricing in which intermediary models outperform other models, can be observed in Figure 6.2, where it can be noted that the BAB factor is best priced within the IFM3 model set up (0.54% against 1.03% of C4, the best competitor).

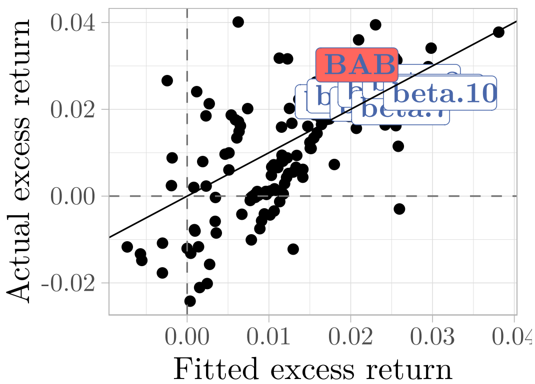
One of the issues to be considered using these results is that the test assets are extremely imbalanced in terms of asset classes, overweighting the US stocks, which are theoretically less strictly related to intermediaries'



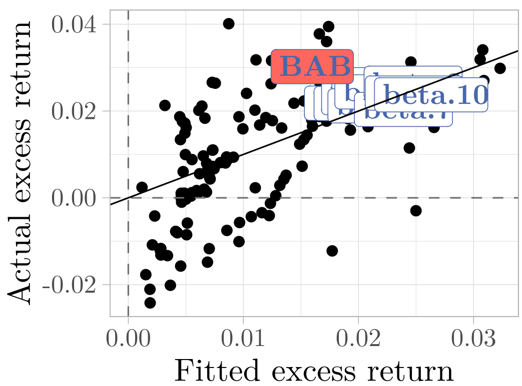
(a) IFM3 – Intermediary pricing kernel



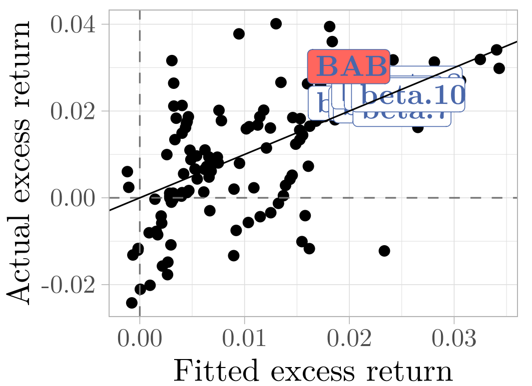
(b) CAPM



(c) HKM – intermediary pricing kernel



(d) FF3



(e) C4

Figure 6.2: Pricing errors scatter plots comparison. On the x-axis the average excess return predicted by the models, on the y-axis the actual value. In the (a) panel "beta.•", "S•.BM•", "mom•", "USbonds•", "SovBonds•", "Commod•", "Option•", "FX•", and "CDS•" stand for beta-sorted, FF25, momentum-sorted, US bonds, Sovereign bonds, Commodities, Options, Foreign Exchange, and CDS portfolios

Table 6.7: Prices of risk. Quarterly returns, expressed in percentage. Newey and West (1987) SEs.

	Beta-sorted + BAB				*Other test assets*			
	CAPM	**C4**	**HKM**	**IFM3**	**CAPM**	**C4**	**HKM**	**IFM3**
(Intercept)	2.20***	1.61**	1.74***	1.78***	0.42***	0.21	0.57***	1.15***
	(0.22)	(0.50)	(0.23)	(0.30)	(0.11)	(0.11)	(0.10)	(0.21)
$\bar{\lambda}_M$	−0.21	0.11	0.03	0.04	1.46***	1.51***	1.06***	0.38
	(0.31)	(0.66)	(0.28)	(0.47)	(0.23)	(0.30)	(0.22)	(0.43)
$\bar{\lambda}_{SMB}$		0.66***				0.30		
		(0.18)				(0.19)		
$\bar{\lambda}_{HML}$		1.86*				1.70***		
		(0.86)				(0.27)		
$\bar{\lambda}_{mom}$		0.04				1.24*		
		(1.26)				(0.61)		
$\bar{\lambda}_{\eta^\Delta}$			4.95***				6.25***	
			(1.08)				(0.68)	
$\bar{\lambda}_{lvg^\Delta}$				−253.15*				30.75
				(102.33)				(142.02)
$\bar{\lambda}_{lvg}$				−6.49***				−6.44***
				(1.02)				(0.68)
$\bar{\lambda}_{lvg^\Delta \cdot lvg}$				−108.22***				−100.47**
				(26.78)				(36.63)
R^2	0.103	0.504	0.587	0.594	0.224	0.375	0.363	0.476
Adj. R^2	0.099	0.493	0.582	0.585	0.220	0.362	0.356	0.465
Num. obs.	191	191	191	191	191	191	191	191
MAPE	0.230	0.134	0.146	0.138	0.924	0.800	0.841	0.847

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

SDFs. However, using only the observations with all the test assets would reduce the sample to approximately 30 periods only, concentrated between 2001 and 2009, which would yield results hardly generalizable. Nevertheless, a useful perspective, especially with respect to the second part of RQ2, may be provided by analysing the beta-LRA related portfolios (beta-sorted and BAB factor) and all of the other portfolios separately. The results of this analysis is showed in Table 6.7. In the panel related to all of the test assets other than the beta-related ones, as one could expect, results are very similar to the pooled regression. At the same time, in the beta-portfolios panel there are a few notable differences concerning: the intercepts, which are all significantly higher; the sign of the market risk premium in the CAPM, which is negative; the loading on the SMB factor, which becomes extremely significant; the risk premia in the HKM model, where market becomes insignificant and capital risk premium gets lower; and finally the gigantic risk premium for leverage shocks lvg_t^Δ in IFM3, which is significant in this set-up. To give a sense of the results of the last specification, the quarterly risk premium related to intermediaries' leverage risk factors that an average beta-portfolio is predicted to earn is $(-253.15\%) \cdot (0.00045) + (-6.49\%) \cdot (-0.038) + (-108.22\%)(0.000001) = 0.133\%$, which is quite insignificant in economical terms, especially compared to the intercept. Looking at the performances of the models, the intermediary factor specifications present remarkably higher R^2, both capturing almost 60% of the returns in beta-portfolios. This is also translated in a significantly lower MAPEs, though the C4's MAPE is still slightly lower. Another relevant observation is that IFM3's alpha increases of only 0.67%, while C4 of as much as 1.36%, with HKM increasing as well, of 1.09%. Thus, again, intermediary models perform well, but not better than C4, under different measures.

All in all, across the three cross-sectional analysis, IFM3 generally performs better and shows more uniform estimations of risk premia than HKM. Where the latter shows significantly different intercepts and risk premia, the first results being the model whose intercepts change the least of all 5 specifications and having all the risk premia which cannot be excluded to be exactly the same across all three the regressions. Then, relatively to the other models, the intermediary specifications perform well under several measures, but never peaking C4. Therefore, in a few words, these models perform quite well and in a decently consistent way, but do not outperform other models, not even limiting the analysis to portfolios related to the beta-LRA, where they should show some sort of advantage theoretically.

6.3 Research question 3

As can be observed in Table 6.9, when the CAPM regression is performed on the beta-sorted portfolios singularly, the resulting alphas decrease almost monotonically from the low-beta portfolios to the high-beta ones. At the opposite, still from low-beta to high-beta portfolios, coskewness of residuals changes sign from negative to positive. Indeed, as confirmed in the first column of Table 6.8 and in the first panel of Figure 6.3, the CAPM alphas of the beta-sorted stocks portfolios result being negatively correlated with residuals' coskewness, consistently with Schneider et al. (2016). Thus expected CAPM mispricings' expectations (alphas) are related to their covariance with the market (coskewness), similar to any other risk factor. Interestingly, the BAB factor fits in this linear relationship almost perfectly.

I test whether the intermediary risk factors are able to capture the coskewness of portfolio's returns thus eventually pricing it and leaving no correlation between alphas and residuals' coskewness with the market. To do so, I make the same computations for the HKM and IFM3 models: I regress the individual portfolios' returns on these two pricing kernel specifications, and then compute the correlations between alphas and residuals' coskewness. A few interesting facts already emerge from the regressions, whose results can be observed in average for all the beta-portfolios in the first column of Table 6.5 and for each beta-portfolio in Table 6.9:

- The alpha of the BAB factor when tested with the CAPM and the HKM specifications is significantly positive and different from 0, while with IFM3 it is not significant at any level. A further evidence of the peculiar pricing ability of IFM3 with respect to the BAB factor, is provided by the R^2, which is a remarkable 0.101 against the 0.033 of HKM and the 0.001 of CAPM
- Alphas over all the beta-portfolios are on average positive for both CAPM and HKM, while they are negative for IFM3

Table 6.8: Alphas - coskewness relation in beta-sorted portfolios. SE of correlations are computed from 10,000 bootstrapped samples.

	CAPM	**HKM**	**IFM3**
Mean(α)	0.388	0.456	-0.330
SD(α)	0.867	0.905	2.087
Mean(σ_{ϵ,M^2})	1.768	1.842	-0.000
SD(σ_{ϵ,M^2})	102.314	102.383	0.000
$\rho(\alpha, \sigma_{\epsilon,M^2})$	-0.877***	-0.863***	0.604***
	(0.105)	(0.108)	(0.228)

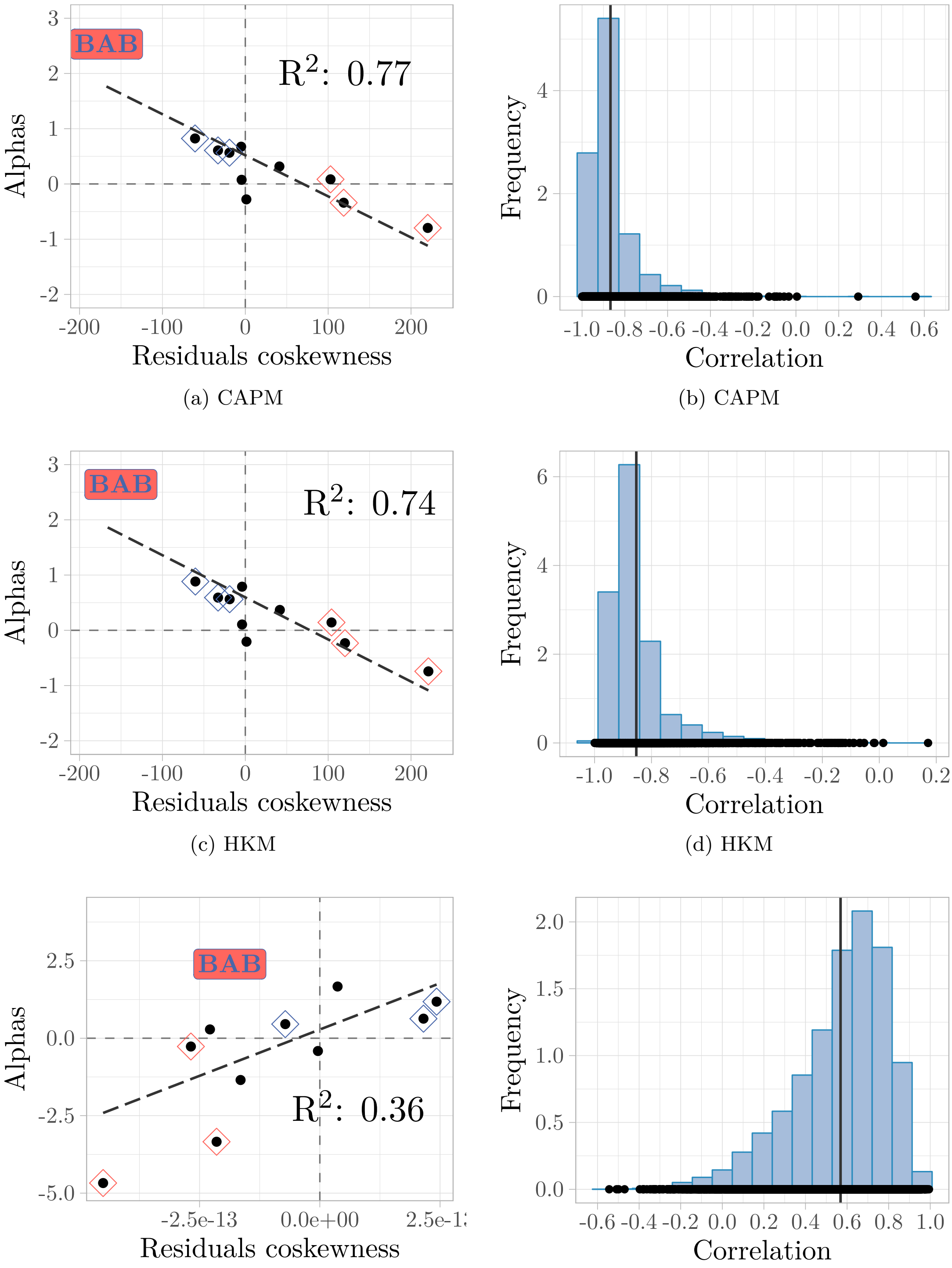
- Coskewness of beta-portfolios' residuals, when tested with CAPM and HKM are extremely close, approximately ranging from $-60 \cdot 10^{-6}$, $-167 \cdot 10^{-6}$ including the BAB factor, to $220 \cdot 10^{-6}$. On other hand, in the test of IFM3, these are incredibly smaller, ranging from $-7 \cdot 10^{-20}$ to $2 \cdot 10^{-19}$

Finally, the correlations between alphas and residuals' coskewness: while the relation estimated applying the HKM specification is essentially identical to the one of CAPM, it is extremely different for IFM3, for which is even reversed, as the correlation is a positive 0.604. Then, to assess the statistical significance of this difference, I compute the standard errors of the correlations from 10,000 bootstrapped samples of the 11 portfolios' alpha-residual coskewness couples, whose resulting distributions can be seen on the right of the panels in Figure 6.3. The t-statistics of the difference between HKM's correlation and IFM3's correlation or between CAPM's correlation and IFM3's correlation, either assuming homogeneous or heterogeneous variance of the population, are all higher than hundreds. Alternatively it can also be observed that the confidence intervals of HKM and IFM3 do not touch until the level of confidence is xxx. Therefore, while it cannot be generalized to both the intermediary pricing kernel specifications, the IFM3 model, and thus the risk factors used in it, seems significantly affect the relationship alpha - residual coskewness, capturing the coskewness risk.

Table 6.9: Beta-sorted and BAB portfolios statistics. Quarterly rates in percentage, coskewness multiplied by 10^6. Standard Errors in parenthesis, Heteroskedasticity Consistent for betas and alphas. R^e is for excess return, $\bar{R}^2$ for adjusted R^2.

	P1 (low)	P2	P3	P4	P5	P6	P7	P8	P9	P10 (high)	BAB
R^e	1.79	1.78	1.91	2.21	1.73	2.05	1.64	2.25	2.02	1.98	2.63
	(6.47)	(7.21)	(7.81)	(8.64)	(9.09)	(9.55)	(10.60)	(12.14)	(13.38)	(16.04)	(6.65)
SR	0.55	0.49	0.49	0.51	0.38	0.43	0.31	0.37	0.30	0.25	0.79
α^{CAPM}	0.82***	0.61**	0.57**	0.68***	0.08	0.32	-0.28	0.08	-0.34	-0.80*	2.53***
	(0.28)	(0.29)	(0.23)	(0.23)	(0.21)	(0.22)	(0.23)	(0.30)	(0.36)	(0.47)	(0.51)
α^{HKM}	0.88***	0.59*	0.56**	0.79***	0.11*	0.37	-0.21	0.14	-0.23	-0.74	2.76***
	(0.29)	(0.31)	(0.25)	(0.23)	(0.21)	(0.23)	(0.24)	(0.31)	(0.39)	(0.49)	(0.53)
α^{IFM3}	0.46	0.63	1.18	1.67**	-0.41	0.28	-1.35*	-0.27	-3.34**	-4.67***	2.20
	(1.02)	(1.17)	(0.96)	(0.84)	(0.81)	(0.73)	(0.80)	(1.27)	(1.40)	(1.71)	(1.75)
β_M^{CAPM}	0.604***	0.724***	0.830***	0.941***	1.002***	1.056***	1.175***	1.316***	1.436***	1.696***	0.059
	(0.037)	(0.042)	(0.037)	(0.028)	(0.033)	(0.031)	(0.035)	(0.049)	(0.055)	(0.073)	(0.083)
β_M^{HKM}	0.556***	0.727***	0.825***	0.852***	0.974***	1.019***	1.129***	1.270***	1.355***	1.672***	-0.117
	(0.064)	(0.070)	(0.062)	(0.045)	(0.055)	(0.044)	(0.053)	(0.076)	(0.088)	(0.099)	(0.124)
$\beta_{\eta^\Delta}^{HKM}$	0.044	-0.004	0.004	0.081***	0.025	0.034	0.043	0.043	0.074	0.023	0.161**
	(0.038)	(0.036)	(0.032)	(0.028)	(0.027)	(0.024)	(0.033)	(0.043)	(0.053)	(0.056)	(0.075)
β_M^{IFM3}	0.542***	0.717***	0.819***	0.858***	0.965***	1.022***	1.112***	1.279***	1.377***	1.698***	-0.171
	(0.063)	(0.076)	(0.063)	(0.044)	(0.053)	(0.046)	(0.053)	(0.078)	(0.086)	(0.097)	(0.120)
$\beta_{lvg^\Delta}^{IFM3}$	0.000	0.000	-0.000	-0.000	0.000	0.000	0.001	0.000	0.002*	0.002**	0.001
	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
β_{lvg}^{IFM3}	-0.016	0.023	0.101*	-0.032	0.030	0.011	-0.012	-0.097	-0.164**	-0.222**	0.067
	(0.055)	(0.067)	(0.059)	(0.052)	(0.044)	(0.045)	(0.055)	(0.062)	(0.080)	(0.101)	(0.106)
$\beta_{lvg \cdot lvg^\Delta}^{IFM3}$	-0.002	-0.001	-0.005*	-0.001	-0.003	-0.002	-0.002	0.003	0.004*	0.009***	-0.012***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.004)
$\bar{R}^2_{CAPM}$	0.651	0.750	0.840	0.881	0.903	0.908	0.913	0.874	0.856	0.830	0.001
$\bar{R}^2_{HKM}$	0.652	0.748	0.839	0.886	0.903	0.908	0.914	0.874	0.857	0.830	0.033
$\bar{R}^2_{IFM3}$	0.651	0.746	0.843	0.887	0.903	0.908	0.915	0.873	0.859	0.838	0.101
$\sigma_{\epsilon,M^2}^{CAPM}$	-60.645	-32.952	-19.133	-5.011	-4.446	41.146	1.265	102.865	118.724	220.213	-167.571
$\sigma_{\epsilon,M^2}^{HKM}$	-60.258	-32.849	-18.898	-3.918	-3.914	41.675	1.452	104.064	120.316	220.971	-166.081
$\sigma_{\epsilon,M^2}^{IFM3}$	-0.000	0.000	0.000	0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$



(a) CAPM (b) CAPM

(c) HKM (d) HKM

(e) IFM3 (f) IFM3

Figure 6.3: Alphas – coskewness models comparison. On the left the scatter plots of the doubles alpha-residuals coskewness of each beta-portfolio. Red diamonds indicate the three highest-beta stocks portfolios, blue the three lowest-beta stocks portfolios. On the right the histogram of 10,000 bootstrapped samples, from which the standard deviation is obtained: the vertical solid line is placed at the bootstrapped average, while each dot on the X axis represents a bootstrapped sample value.

7
Conclusion

This work studies the relation between the intermediary asset pricing models and the CAPM-beta low risk anomaly. In the theoretical premises it is made clear the key role of intermediary leverage as a determinant of intermediaries' funding tightness, and thus of their marginal utility and pricing kernel. However, depending on how financial frictions are modelled, leverage has diametrically opposing dynamics, either pro- or counter-cyclical, thereby generating pricing kernels in direct contradictions. This is also reflected in opposing empirical evidence, which agree on the significance of intermediary funding tightness as a relevant risk factor, but with opposing estimates of the leverage price. This is rationalized taking a deeper look at the intermediary sector and the representative members considered, which may experience different constraints, incentives and ultimately leverage dynamics.

Then it is introduced the CAPM and its assumptions because two violations of these provide the theoretical justification of the differential in risk-adjusted returns differential between assets with different market betas. One directly relying on a funding tightness, similarly to the intermediary asset pricing models, and the other relying on returns distributional features not captured by the CAPM, namely the asymmetry, the skewness. Despite not being directly related to funding tightness, also the second violation is related to it because of amplification mechanisms, which asymmetrically affect assets return, and the real returns' skewness, due to leverage. Therefore, the issues are all interestingly theoretically connected.

The final part empirically test the connection between the theories, considering different intermediary factor models and comparing them to proxies of other variables that drive the intermediary marginal utility of wealth. The core of the analysis is the cross-sectional test of two intermediary pricing kernel specifications on several test assets, included test assets related to the CAPM-LRA, which should be strictly connected. The models prove to be definitely better than the standard reference model, the CAPM, and being generally consistent. However, a superior performance on the test assets that should be theoretically best explained by this type of pricing kernel is not observed. Finally, the coskewness is proved to be captured by one of the risk factors, but not by the other main alternative specification.

Further investigations would surely be insightful if investigated the nonlinearities of leverage and the SDF, the cross-country differences intermediary risk premium and the direct comparison with risk factors that account for coskewness.

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Appendices

A
Models' details

This appendix shows the mathematical passages omitted in the main body of the thesis.

A.1 Section 2.2

The optimization problem faced by the intermediary

$$\begin{aligned}
&\max_{c_t,\theta_t} \mathbb{E}_t \left[u(c_t) + e^{-\rho} u(\tilde{c}_{t+1})\right] \\
\text{s.t.} \quad & c_t + \theta_t \cdot p_t = w_t, \quad \tilde{c}_{t+1} = \theta_t \cdot \tilde{x}_{t+1}
\end{aligned} \tag{A.1}$$

is solved maximizing the following Lagrangian:

$$\mathcal{L} = \mathbb{E}_t \left[u(c_t) + e^{-\rho} u(\theta \cdot \tilde{x}_{t+1})\right] + \lambda \left[w_t - c_t - \theta_t \cdot p_t\right] \tag{A.2}$$

The resulting first order conditions are:

$$\frac{\partial \mathcal{L}}{\partial c_t} = u'(c_t) - \lambda = 0 \rightarrow \ u'(c_t) = \lambda \tag{A.3}$$

$$\begin{aligned}
\frac{\partial \mathcal{L}}{\partial \theta_t} &= \mathbb{E}_t \left[e^{-\rho} u'(\tilde{c}_{t+1}) \cdot \tilde{x}_{t+1}\right] - \lambda \ p_t = 0 \\
&\rightarrow \ \mathbb{E}_t \left[e^{-\rho} u'(\tilde{c}_{t+1}) \cdot \tilde{x}_{t+1}\right] = \lambda \ p_t
\end{aligned} \tag{A.4}$$

Finally, assuming the utility function is concave, to obtain the the single-period asset pricing equation it suffices plugging Equation A.3 in A.4:

$$\begin{aligned}
p_t &= \mathbb{E}_t \left[e^{-\rho} \frac{u'(\tilde{c}_{t+1})}{u'(c_t)} \cdot \tilde{x}_{t+1}\right] \\
&= \mathbb{E}_t \left[\tilde{M}_{t+1} \cdot \tilde{x}_{t+1}\right]
\end{aligned} \tag{A.5}$$

To express Equation A.5 in terms of returns, it is assumed a risk-free bond which pays 1 at $t+1$ in every state, whose price is then

$$B_t = \mathbb{E}_t \left[\tilde{M}_{t+1} \cdot 1\right] = \mathbb{E}_t \left[\tilde{M}_{t+1}\right] = \frac{1}{R_f} \tag{A.6}$$

Then:

$$
\begin{aligned}
p_t &= \mathbb{E}_t\left[\frac{1}{R_f}\frac{\tilde{M}_{t,t+1}}{\mathbb{E}_t[\tilde{M}_{t+1}]}\cdot \tilde{x}_{t+1}\right] \\
p_t \cdot R_f &= \mathbb{E}_t\left[\frac{\tilde{M}_{t,t+1}}{\mathbb{E}_t[\tilde{M}_{t+1}]}\cdot \tilde{x}_{t+1}\right] \\
R_f &= \mathbb{E}_t\left[\frac{\tilde{M}_{t+1}}{\mathbb{E}_t[\tilde{M}_{t+1}]}\cdot \tilde{R}_{t+1}\right] \quad \text{where} \quad \tilde{R}_{t+1} = \tilde{x}_{t+1}/p_t = 1 + r_{t+1} \\
&= \mathbb{E}_t\left[\frac{\tilde{M}_{t+1}}{\mathbb{E}_t[\tilde{M}_{t+1}]}\right]\cdot \mathbb{E}_t\left[\tilde{R}_{t+1}\right] + \mathrm{Cov}_t\left[\frac{\tilde{M}_{t+1}}{\mathbb{E}_t[\tilde{M}_{t+1}]}, \tilde{R}_{t+1}\right] \qquad \text{(A.7)}
\end{aligned}
$$

Which, applying the law of iterated expectations to $\mathbb{E}_t\left[\frac{\tilde{M}_{t+1}}{\mathbb{E}_t[\tilde{M}_{t+1}]}\right]$, brings to:

$$
\mathbb{E}_t\left[\tilde{R}_{t+1}\right] - R_f = -\,\mathrm{Cov}_t\left[\frac{\tilde{M}_{t+1}}{\mathbb{E}_t[\tilde{M}_{t+1}]}, \tilde{R}_{t+1}\right] \qquad \text{(A.8)}
$$

A.2 Section 2.3

The problem solved by financial experts in the two-period model, time = (0,1,2), is:

$$
\max_{\theta_0} \mathbb{E}_0\left[\tilde{\phi}_1 \cdot \tilde{W}_1\right] \qquad \text{(A.9)}
$$

$$
\text{s.t.} \quad \tilde{W}_1 = W_0 + (\tilde{p}_1 - p_0)\theta_0 + \tilde{\gamma}_1 \qquad \text{(A.10)}
$$

The problem can be solved via the Lagrangian

$$
\mathcal{L} = \mathbb{E}_0\left[\tilde{\phi}_1 \cdot (W_0 + (\tilde{p}_1 - p_0)\theta_0 + \tilde{\gamma}_1)\right] \qquad \text{(A.11)}
$$

whose first order condition, since γ_1 is independent and 0 in expectations, is

$$
\begin{aligned}
\frac{\partial \mathcal{L}}{\partial \theta_0} &= \mathbb{E}_0\left[\tilde{\phi}_1 \cdot (\tilde{p}_1 - p_0)\right] = 0 && \text{(A.12)} \\
\rightarrow \mathbb{E}_0\left[\tilde{\phi}_1 \cdot \tilde{p}_1\right] &= \mathbb{E}_0\left[\tilde{\phi}_1 \cdot p_0\right] && \text{(A.13)} \\
p_0\, \mathbb{E}_0\left[\tilde{\phi}_1\right] &= \mathbb{E}_0\left[\tilde{\phi}_1 \cdot \tilde{p}_1\right] && \text{(A.14)} \\
p_0 &= \frac{\mathbb{E}_0\left[\tilde{\phi}_1 \cdot \tilde{p}_1\right]}{\mathbb{E}_0\left[\tilde{\phi}_1\right]} && \text{(A.15)} \\
p_0 &= \frac{\mathbb{E}_0\left[\tilde{\phi}_1\right]\cdot \mathbb{E}_0\left[\tilde{p}_1\right] + \mathrm{Cov}_0\left[\tilde{\phi}_1, \tilde{p}_1\right]}{\mathbb{E}_0\left[\tilde{\phi}_1\right]} && \text{(A.16)} \\
p_0 &= \mathbb{E}_0\left[\tilde{p}_1\right] + \frac{\mathrm{Cov}_0\left[\tilde{\phi}_1, \tilde{p}_1\right]}{\mathbb{E}_0\left[\tilde{\phi}_1\right]} && \text{(A.17)}
\end{aligned}
$$

Then, the price of a risk-free asset whose $p_1^B = 1$ in every state is

$$p_0^B = 1 + \frac{\mathrm{Cov}_0\left[\tilde{\phi}_1, 1\right]}{\mathbb{E}_0\left[\tilde{\phi}_1\right]} = 1 = \frac{1}{R_f} \to R_f = 1 \tag{A.18}$$

Then, dividing Equation A.17 by p_0, it can be expressed in returns:

$$1 = \mathbb{E}_0[\tilde{R}_1] + \frac{\mathrm{Cov}_0\left[\tilde{\phi}_1, \tilde{R}_1\right]}{\mathbb{E}_0\left[\tilde{\phi}_1\right]} \quad \text{where} \quad \tilde{R}_1 = \tilde{p}_1/p_0 = 1 + \tilde{r}_{t+1} \tag{A.19}$$

$$\mathbb{E}_0[\tilde{R}_1] - R_f = -\frac{\mathrm{Cov}_0\left[\phi_1, \tilde{R}\right]}{\mathbb{E}_0\left[\phi_1\right]} \tag{A.20}$$

A.3 Section 4.3

As in the previous models, the optimization problem

$$\begin{gathered}\max_{\mathbf{x}^i} \mathbf{x}^{i\prime}\left(\mathbb{E}_t\left[\tilde{\mathbf{P}}_{t+1} + \tilde{\boldsymbol{\delta}}_{t+1}\right] - (1+r_f)\mathbf{P}_t\right) - \frac{\gamma^i}{2}\mathbf{x}^{i\prime}\boldsymbol{\Omega}_t\mathbf{x}^i \\ \text{subject to} \quad m_t^i\left(\mathbf{x}^{i\prime}\ \mathbf{P}_t\right) \leq W_t^i\end{gathered} \tag{A.21}$$

can be solved with the Lagrangian:

$$\begin{aligned}\mathcal{L} = \mathbf{x}^{i\prime}&\left(\mathbb{E}_t\left[\tilde{\mathbf{P}}_{t+1} + \tilde{\boldsymbol{\delta}}_{t+1}\right] - (1+r_f)\mathbf{P}_t\right) - \frac{\gamma^i}{2}\mathbf{x}^{i\prime}\boldsymbol{\Omega}_t\mathbf{x}^i \\ &+ \lambda_t\left[W_t^i - m_t^i\left(\mathbf{x}^{i\prime}\ \mathbf{P}_t\right)\right]\end{aligned} \tag{A.22}$$

The resulting first order condition is:

$$\frac{\partial\mathcal{L}}{\partial\mathbf{x}^i} = \mathbb{E}_t\left[\tilde{\mathbf{P}}_{t+1} + \tilde{\boldsymbol{\delta}}_{t+1}\right] - (1+r_f)\mathbf{P}_t - \gamma^i\boldsymbol{\Omega}_t\mathbf{x}^i - \underbrace{\lambda_t m_t^i}_{\psi_t^i}\mathbf{P}_t = 0 \tag{A.23}$$

So, rearranging, the resulting individual optimal position is:

$$\mathbf{x}^i = \frac{1}{\gamma^i}\boldsymbol{\Omega}_t^{-1}\left(\mathbb{E}_t\left[\tilde{\mathbf{P}}_{t+1} + \tilde{\boldsymbol{\delta}}_{t+1}\right] - (1+r_f+\psi_t^i)\mathbf{P}_t\right) \tag{A.24}$$

The equilibrium is defined as supply of shares equal total demand $\sum_i \mathbf{x}^i = \mathbf{x}^*$, thus:

$$\mathbf{x}^* = \frac{1}{\gamma}\boldsymbol{\Omega}_t^{-1}\left(\mathbb{E}_t\left[\mathbf{P}_{t+1} + \boldsymbol{\delta}_{t+1}\right] - (1+r_f+\psi_t)\mathbf{P}_t\right) \tag{A.25}$$

Where aggregate risk aversion $\frac{1}{\gamma} = \sum_i \frac{1}{\gamma^i}$, and aggregate tightness of funding $\psi_t = \sum_i \frac{\gamma}{\gamma^i}\psi_t^i$ is a weighted average of individual restriction levels. Finally, rearranging, the pricing equation shows up:

$$\mathbb{E}_t\left[\tilde{\mathbf{P}}_{t+1}+\tilde{\boldsymbol{\delta}}_{t+1}\right]-(1+r_f+\psi_t)\mathbf{P}_t=\gamma\boldsymbol{\Omega}_t\mathbf{x}^*$$

$$\mathbb{E}_t\left[\tilde{\mathbf{P}}_{t+1}+\tilde{\boldsymbol{\delta}}_{t+1}\right]+\gamma\boldsymbol{\Omega}_t\mathbf{x}^*=(1+r_f+\psi_t)\mathbf{P}_t$$

$$\mathbf{P}_t=\frac{\mathbb{E}_t\left[\tilde{\mathbf{P}}_{t+1}+\tilde{\boldsymbol{\delta}}_{t+1}\right]-\gamma\boldsymbol{\Omega}_t\mathbf{x}^*}{(1+r_f+\psi_t)} \tag{A.26}$$

To derive an expression of assets' individual returns, only the row s of the system in Equation A.26 is considered. Using the definition $r_{s,t+1}=\frac{P_{s,t+1}+\delta_{s,t+1}}{P_{s,t}}-1$ and the vector $\mathbf{e}_s$ composed by zeros and a 1 only in row s, and then dividing Equation A.26 by $P_{s,t}$, it brings:

$$\mathbf{e}_s'\mathbf{P}_t(1+r_f+\psi_t)=\mathbf{e}_s'\mathbb{E}_t\left[\tilde{\mathbf{P}}_{t+1}+\tilde{\boldsymbol{\delta}}_{t+1}\right]-\mathbf{e}_s'\gamma\boldsymbol{\Omega}_t\mathbf{x}^*$$

$$P_{s,t}(1+r_f+\psi_t)=\mathbb{E}_t\left[\tilde{P}_{s,t+1}+\tilde{\delta}_{s,t+1}\right]-\gamma\mathbf{e}_s'\boldsymbol{\Omega}_t\mathbf{x}^*$$

$$\frac{1}{P_{s,t}}\gamma\mathbf{e}_s'\boldsymbol{\Omega}_t\mathbf{x}^*=\mathbb{E}_t[\tilde{r}_{s,t+1}+1]-(1+r_f+\psi_t)$$

$$\mathbb{E}_t[\tilde{r}_{s,t+1}]-r_f=\frac{1}{P_{s,t}}\gamma\mathbf{e}_s'\boldsymbol{\Omega}_t\mathbf{x}^*+\psi_t \tag{A.27}$$

where $\mathbf{e}_s'\boldsymbol{\Omega}_t=\mathrm{Cov}_t\left[\tilde{P}_{s,t+1}+\tilde{\delta}_{s,t+1},\left(\tilde{\mathbf{P}}_{t+1}+\tilde{\boldsymbol{\delta}}_{t+1}\right)'\right]$. Next:

$$\begin{aligned}\mathbb{E}_t[\tilde{r}_{s,t+1}]-r_f&=\psi_t+\gamma\ \mathrm{Cov}_t\left[\frac{\tilde{P}_{s,t+1}+\tilde{\delta}_{s,t+1}}{P_{s,t}},\left(\tilde{\mathbf{P}}_{t+1}+\tilde{\boldsymbol{\delta}}_{t+1}\right)'\right]\mathbf{x}^*\\&=\psi_t+\gamma\ \mathrm{Cov}_t\left[\tilde{r}_{s,t+1},\left(\tilde{\mathbf{P}}_{t+1}+\tilde{\boldsymbol{\delta}}_{t+1}\right)'\right]\mathbf{x}^*\\&=\psi_t+\gamma\ \mathrm{Cov}_t\left[\tilde{r}_{s,t+1},\left(\left(\tilde{r}_{M,t+1}+1\right)\left(\mathbf{P}_t\right)\right)'\right]\mathbf{x}^*\\&=\psi_t+\gamma\ \mathrm{Cov}_t\left[\tilde{r}_{s,t+1},\tilde{r}_{M,t+1}\right]\mathbf{P}_t'\mathbf{x}^*\end{aligned} \tag{A.28}$$

where it is used the fact that $P_{s,t+1}+\delta_{s,t+1}=(1+r_{s,t+1})P_{s,t}$ so $\mathbf{P}_{t+1}+\boldsymbol{\delta}_{t+1}=(1+r_{s,t+1})\mathbf{P}_t$. The return of the market depends on the sum of the market securities' returns, weighted by their value share of the whole market (market portfolio weights)

$$w_s=\frac{x_s^*P_{s,t}}{\mathbf{x}^{*\prime}\mathbf{P}_t} \tag{A.29}$$

So, multiplying Equation A.28 by w_s and summing over s bring

$$\sum_{s\in S}w_s\cdot\left(\mathbb{E}_t[\tilde{r}_{s,t+1}]-r_f\right)=\sum_{s\in S}w_s\cdot\psi_t+\sum_{s\in S}w_s\cdot\left(\gamma\ \mathrm{Cov}_t\left[\tilde{r}_{s,t+1},\tilde{r}_{M,t+1}\right]\mathbf{P}_t'\mathbf{x}^*\right)$$

$$\begin{aligned}\mathbb{E}_t[\tilde{r}_{s,t+1}]-r_f\cdot\left(\sum_{s\in S}w_s\right)&=\psi_t\cdot\left(\sum_{s\in S}w_s\right)\\&\quad+\gamma\ \mathbf{P}_t'\mathbf{x}^*\cdot\left(\sum_{s\in S}w_s\cdot\mathrm{Cov}_t\left[\tilde{r}_{s,t+1},\tilde{r}_{M,t+1}\right]\right)\end{aligned}$$

$$\mathbb{E}_t[\tilde{r}_{M,t+1}]-r_f=\psi_t+\gamma\mathbf{P}_t'\mathbf{x}^*\mathrm{Var}_t[\tilde{r}_{M,t+1}]$$

$$\mathbb{E}_t[\tilde{r}_{M,t+1}]-r_f-\psi_t=\gamma\mathrm{Var}_t[\tilde{r}_{M,t+1}]\mathbf{P}_t'\mathbf{x}^* \tag{A.30}$$

Finally, as

$$\frac{\mathbb{E}_t[\tilde{r}_{M,t+1}] - r_f - \psi_t}{\gamma \mathrm{Var}[\tilde{r}_{M,t+1}]} = \mathbf{P}_t'\mathbf{x}^*$$

the equilibrium risk premium for any security s of Equation A.28 is

$$\begin{aligned} \mathbb{E}_t[\tilde{r}_{s,t+1}] - r_f &= \psi_t + \mathrm{Cov}_t\left[\tilde{r}_{s,t+1}, \tilde{r}_{M,t+1}\right] \frac{\mathbb{E}_t[\tilde{r}_{M,t+1}] - r_f - \psi_t}{\mathrm{Var}[\tilde{r}_{M,t+1}]} \\ &= \psi_t + \beta_{s,t}(\mathbb{E}_t[\tilde{r}_{M,t+1}] - r_f - \psi_t) \\ &= (1 - \beta_{s,t})\psi_t + \beta_{s,t}(\mathbb{E}_t[\tilde{r}_{s,t+1}] - r_f) \end{aligned} \tag{A.31}$$

The expected BAB return is:

$$\begin{aligned} \mathbb{E}_t[\tilde{r}^{BAB}_{t+1}] &= \mathbb{E}_t\left[\frac{1}{\beta^L_t}(\tilde{r}^L_{t+1} - r_f) - \frac{1}{\beta^H_t}(\tilde{r}^H_{t+1} - r_f)\right] \\ &= \mathbb{E}_t\Bigg[\frac{1}{\beta^L_t}((1-\beta^L_t)\psi_t + \beta^L_t(\mathbb{E}_t[\tilde{r}_{M,t+1}] - r_f)) \\ &\quad - \frac{1}{\beta^H_t}((1-\beta^H_t)\psi_t + \beta^H_t(\mathbb{E}_t[\tilde{r}_{M,t+1}] - r_f))\Bigg] \\ &= \left(\frac{1-\beta^L_t}{\beta^L_t} - \frac{1-\beta^H_t}{\beta^H_t}\right)\psi_t \\ &\quad + \left(\frac{\beta^L_t}{\beta^L_t} - \frac{\beta^H_t}{\beta^H_t}\right)(\mathbb{E}_t[\tilde{r}_{M,t+1}] - r_f) \\ &= \left(\frac{1}{\beta^L_t} - 1 - \frac{1}{\beta^H_t} + 1\right)\psi_t \\ &= \frac{\beta^H_t - \beta^L_t}{\beta^L_t\beta^H_t}\psi_t \end{aligned} \tag{A.32}$$

B

Data

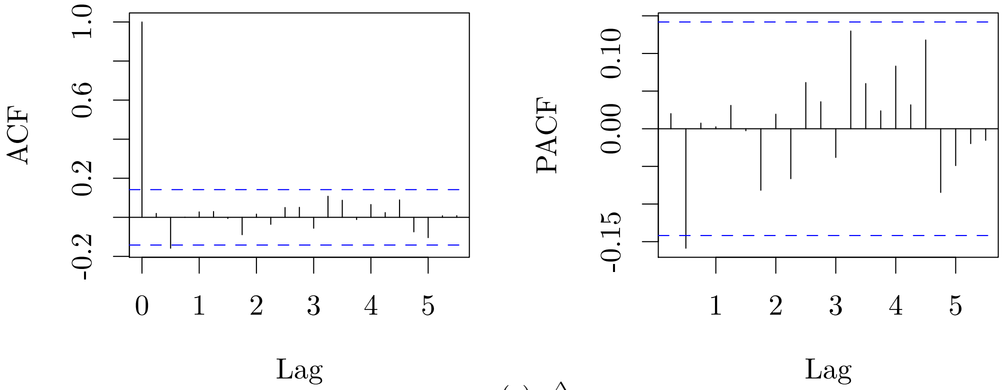
B.1 Autocorrelation capital risk factors

The results for the quarterly series are shown in Figure B.1.

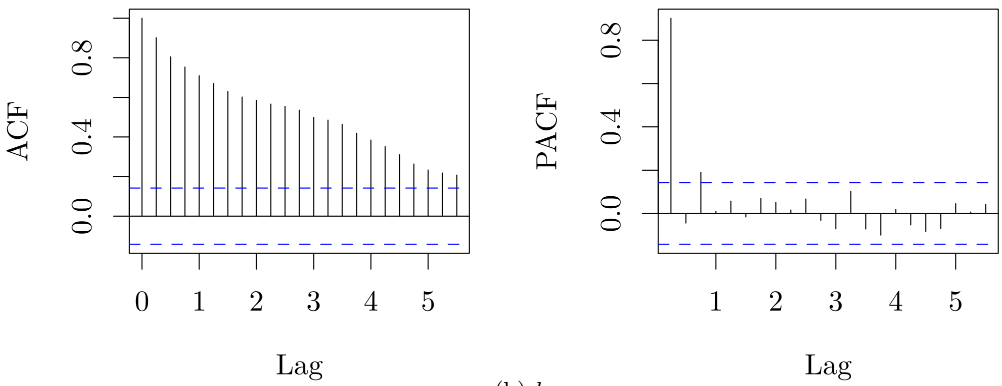
B.2 SRISK

As can be seen in Figure B.4a, the available data on US SRISK presents huge single-day drops and back-to-previous-level increases, whose relative log-differences dominate the time series. As claimed by Brunnermeier and Oehmke (2013), systemic risk should be slow-moving, therefore I considered these enormous consecutive drops-surges realizations highly unlikely to be structural, but rather being data aberrations. Looking for the sources of this aberrations in order to delete the problematic dates, I have checked the number of firms that compose the aggregate measure, Figure B.4b, and the log-difference of each year-day across all the years in the sample, Figure B.4c. The number of firms that compose the SRISK are indeed highly volatile and present huge drops as well, however changes in number of firms shows some only little correlation with the log differences of SRISK, 0.27, therefore, it cannot be used as rationale to identify the problematic dates, despite being related. Figure B.4c shows average, minimum and maximum log-differences observed in each day across years. There, it can be observed that days right after Christmas and around the end of March, when accounting years typically close, shows (a) extreme values, (b) extreme increases right after extreme decreases. Therefore, I consider the the availability of balance sheet information to be the real cause of the big swings in SRISK, and thus I proceed eliminating such changes to remove data non actually related to changes in SRISK.

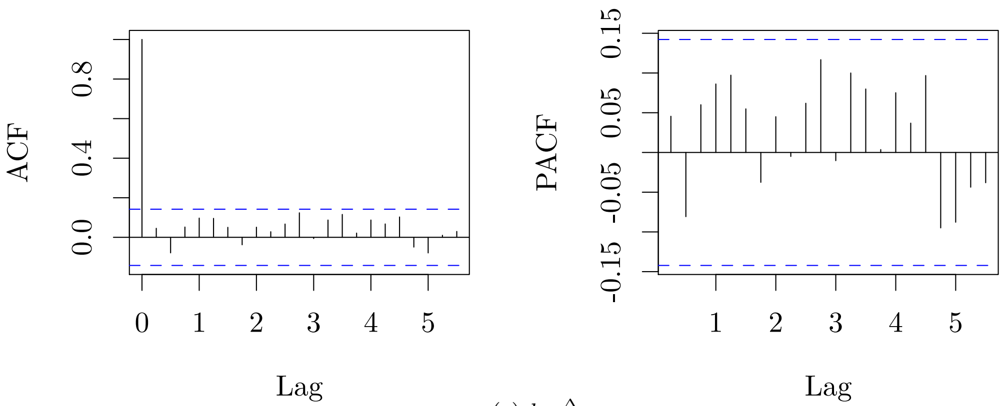
The cleaning procedure I implemented consists in removing all the observations on the 26$^{\text{th}}$ December in the sample and all the observations that generated log-differences lower than -20% on the same day *and* more than +20% on the following calendar day. Performing the procedure, the final attrition rate has been 2.84% (97 days out of 3422). The resulting series is plotted in Figure B.3. Finally, the ex-post SD of the log-differences is 9.80%, therefore the single-day observations that I deleted were less likely than than two 2-sigma consecutive events, assuming a normal distribution. Clearly, I am not assuming SRISK is normally distributed, but since the literature consider the systemic risk to be a slow-moving variable, this comparison should provide



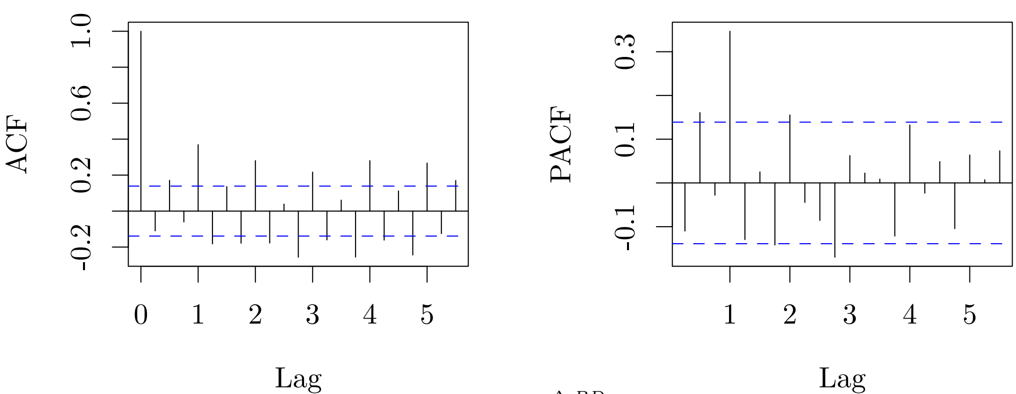
(a) η_t^{Δ}



(b) lvg_t

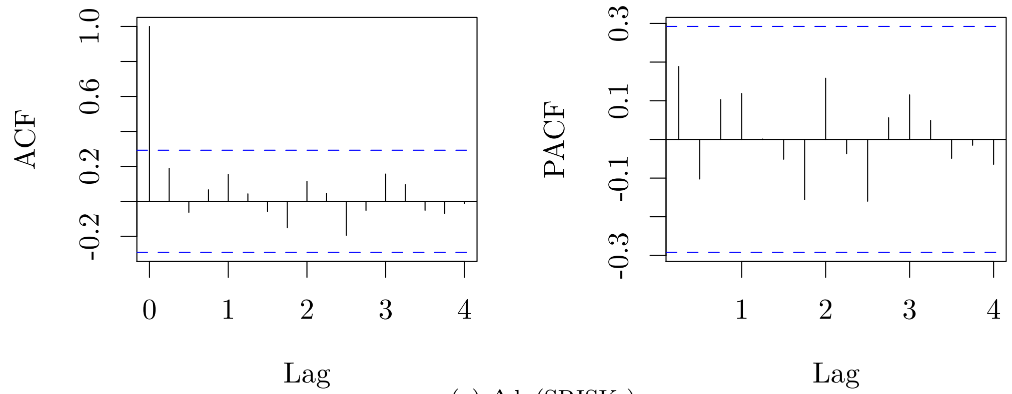


(c) lvg_t^{Δ}

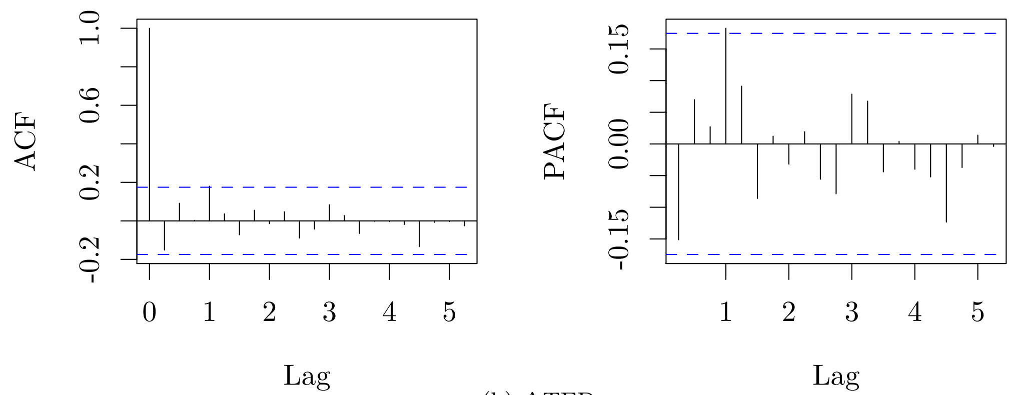


(d) $lvg_t^{\Delta,BD}$

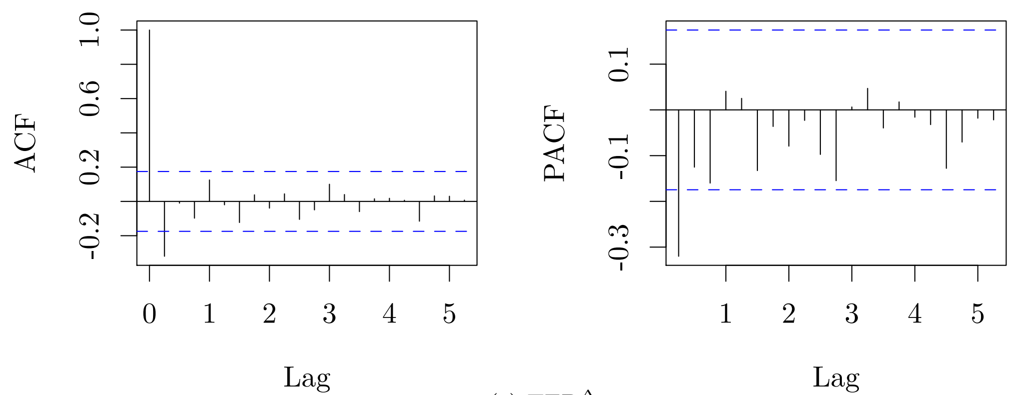
Figure B.1: Quarterly series ACFs and PACFs



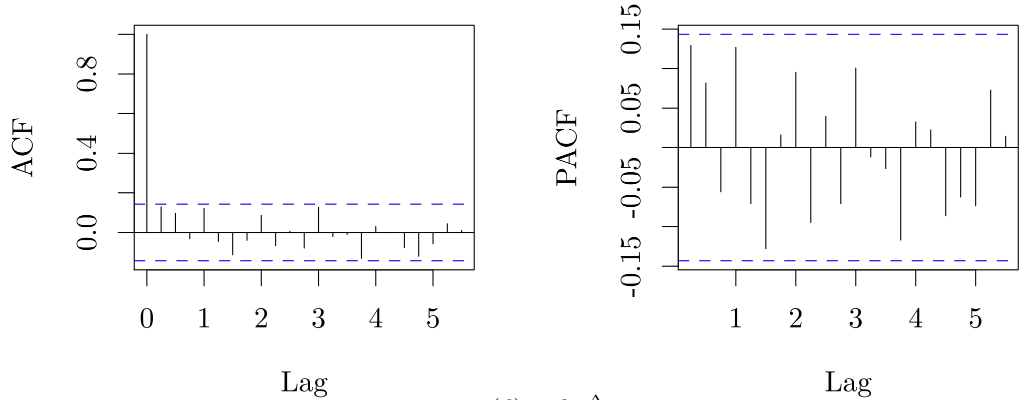
(a) $\Delta \ln(\text{SRISK}_t)$



(b) ΔTED_t



(c) TED_t^{Δ}



(d) $m.liq_t^{\Delta}$

Figure B.2: Quarterly series ACFs and PACFs

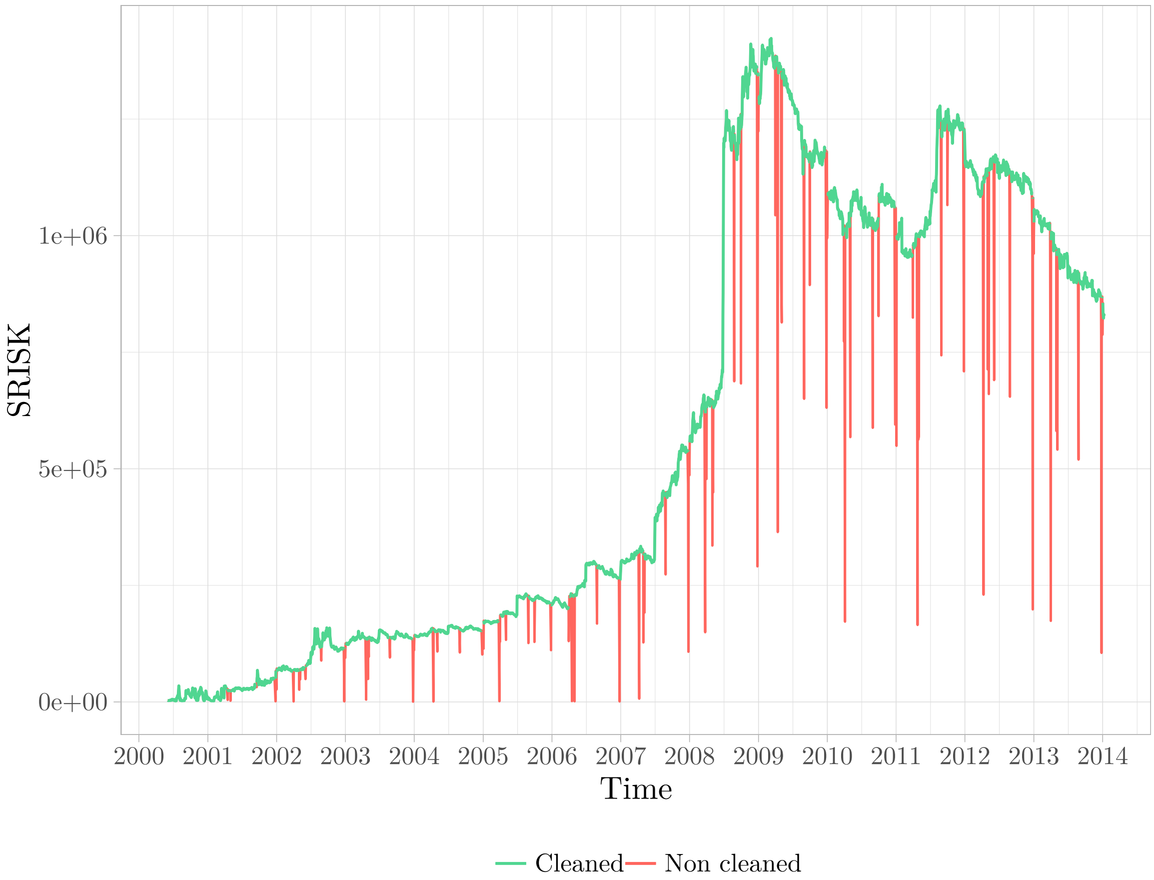
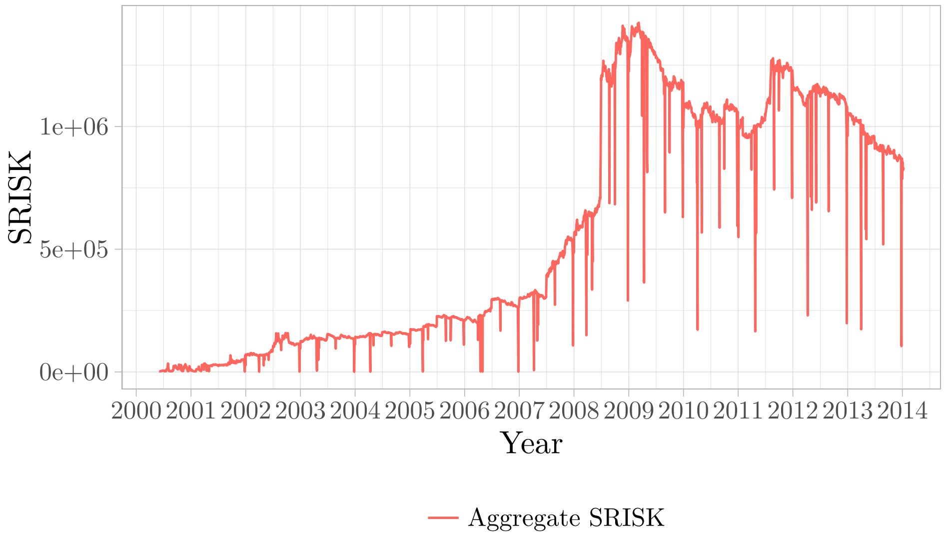


Figure B.3: SRISK cleaned-non cleaned comparison.

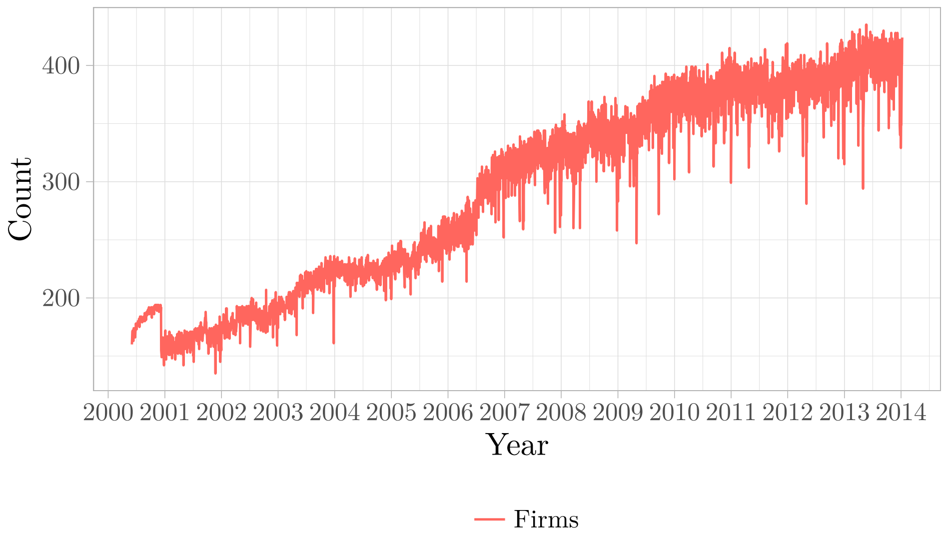
a feeling of how unlikely those *daily* observations were to be from the actual SES distribution.[1]

Furthermore, after the main procedure, almost all of the first observations of July show an increase then maintained in the next days. I did not perform any sort of cleaning of these days as I they were not as clearly unlikely as the other aberrations. However, I followed the authors of Brownlees and Engle (2017), using only the observations from 2003 and, lastly, to reduce the measurement errors, which mid-year surges are likely to be, I performed the monthly aggregation by taking the 2-week average, centered on the last days of the month, which I consider an efficient trade-off between smoothing of data aberrations and promptness of the information.

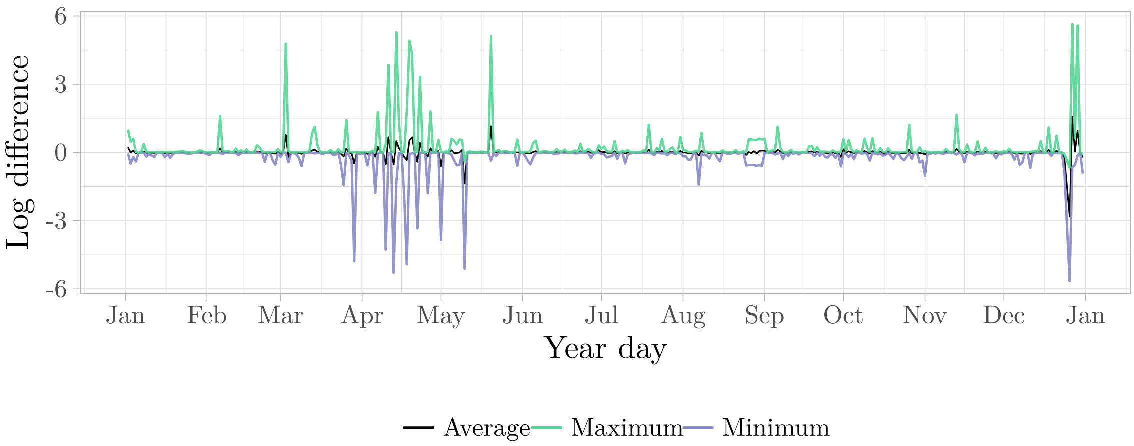
[1] In several observations, SRISK dropped to near 0 for a single day and then came back to the previous values, realizing proportional *daily* changes of -100% and consecutively even +28,300%.



(a) As is SRISK



(b) Firms count



(c) SRISK year-day log-differences

Figure B.4: Non cleaned SRISK, daily frequency.

C

Additional tests

C.1 Research question 1

Table C.1, Table C.2, Table C.3 the monthly tests equivalent to those performed in the main body of the thesis. These tests further confirm the relevance of the considered risk factors specification, though showing a less prominent role of the interaction term, partly substituted by the sole-leverage level factor in the TED series.

	Δ log SRISK	Δ log SRISK	Δ log SRISK
(Intercept)	0.014^{*}	0.014^{*}	0.035^{**}
	(0.006)	(0.006)	(0.012)
lvg_t^{Δ}	0.341^{***}		0.887^{***}
	(0.090)		(0.172)
η_t^{Δ}		-0.356^{***}	
		(0.085)	
lvg_t			-0.001
			(0.001)
$lvg_t^{\Delta} \cdot lvg_t$			-0.020^{***}
			(0.005)
Adj. R^2	0.154	0.159	0.200
Num. obs.	133	133	133
RMSE	0.054	0.054	0.052

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Table C.1: Regression results: SRISK-leverage

	Δ TED$_t$	Δ TED$_t$	Δ TED$_t$
(Intercept)	-0.000	-0.000	0.069^{*}
	(0.009)	(0.008)	(0.033)
lvg_t^{Δ}	0.439		0.981
	(0.334)		(0.581)
η_t^{Δ}		-0.459	
		(0.311)	
lvg_t			-0.004^{*}
			(0.002)
$lvg_t^{\Delta} \cdot lvg_t$			-0.023
			(0.040)
Adj. R^2	0.014	0.015	0.023
Num. obs.	381	381	381
RMSE	0.230	0.230	0.229

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Table C.2: Regression results: TED-leverage

	$m.liq_t^{\Delta}$	$m.liq_t^{\Delta}$	$m.liq_t^{\Delta}$
(Intercept)	-0.001	-0.001	-0.004
	(0.002)	(0.002)	(0.008)
lvg_t^{Δ}	-0.225^{***}		-0.441^{***}
	(0.059)		(0.113)
η_t^{Δ}		0.216^{***}	
		(0.051)	
lvg_t			0.000
			(0.000)
$lvg_t^{\Delta} \cdot lvg_t$			0.010
			(0.007)
Adj. R^2	0.073	0.066	0.080
Num. obs.	563	563	563
RMSE	0.055	0.055	0.054

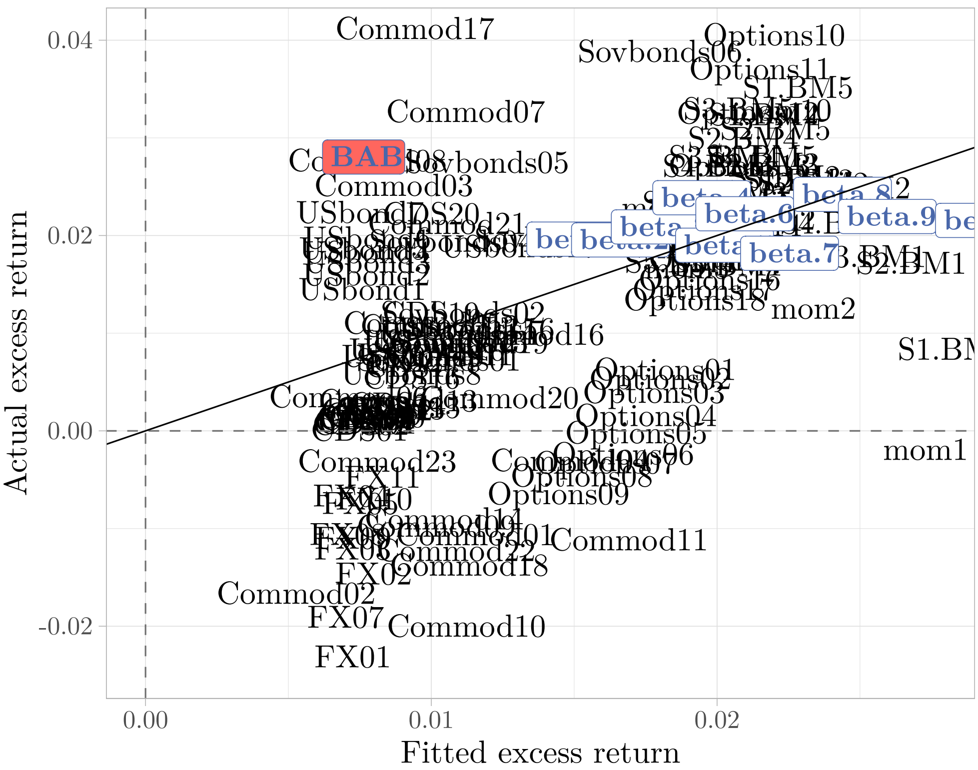
$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Table C.3: Regression results: market liquidity-leverage

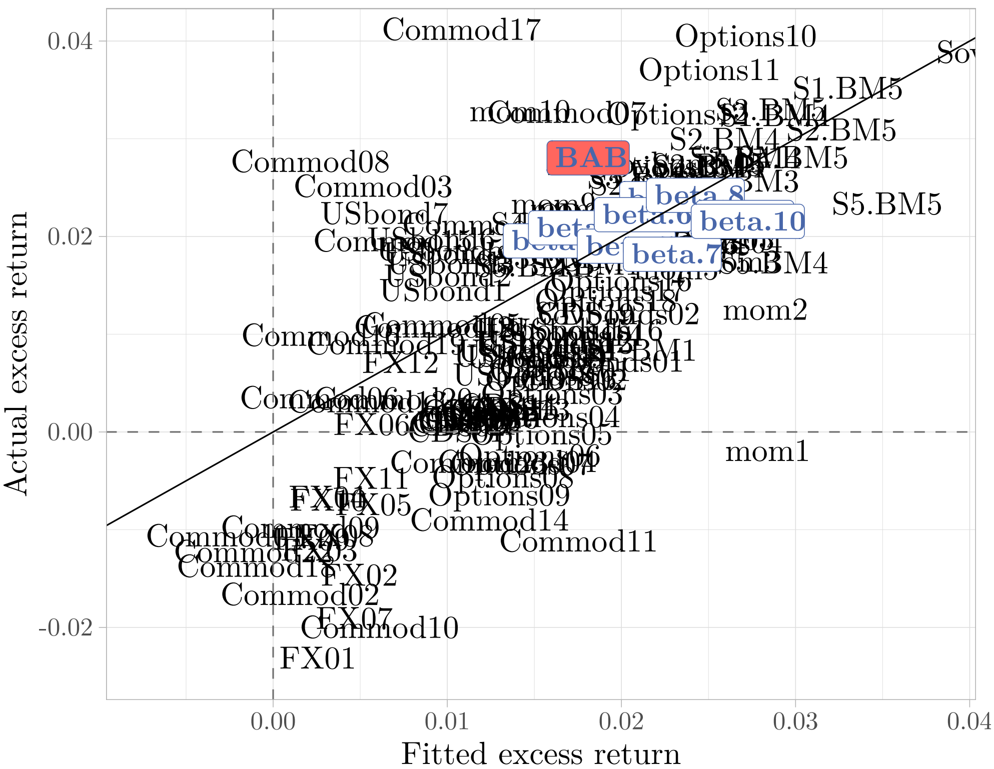
C.2 Research question 2

Quarterly mispricings

Figure C.1 and Figure C.2 show the quarterly plots of chapter 6, with the portfolios labels.

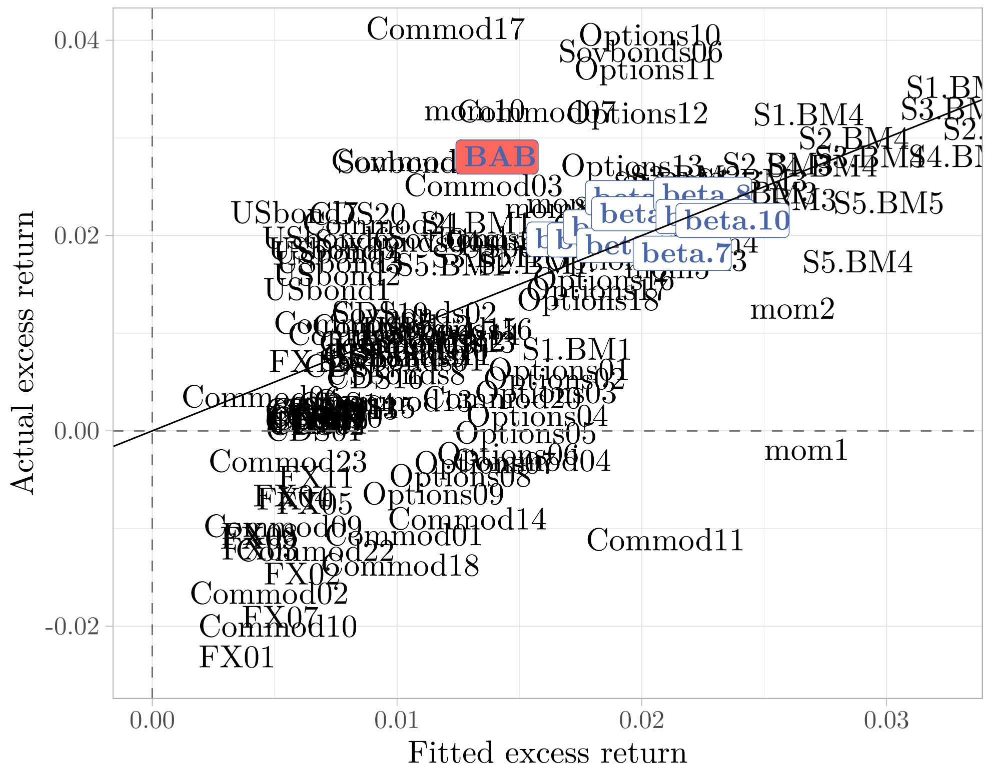


(a) CAPM

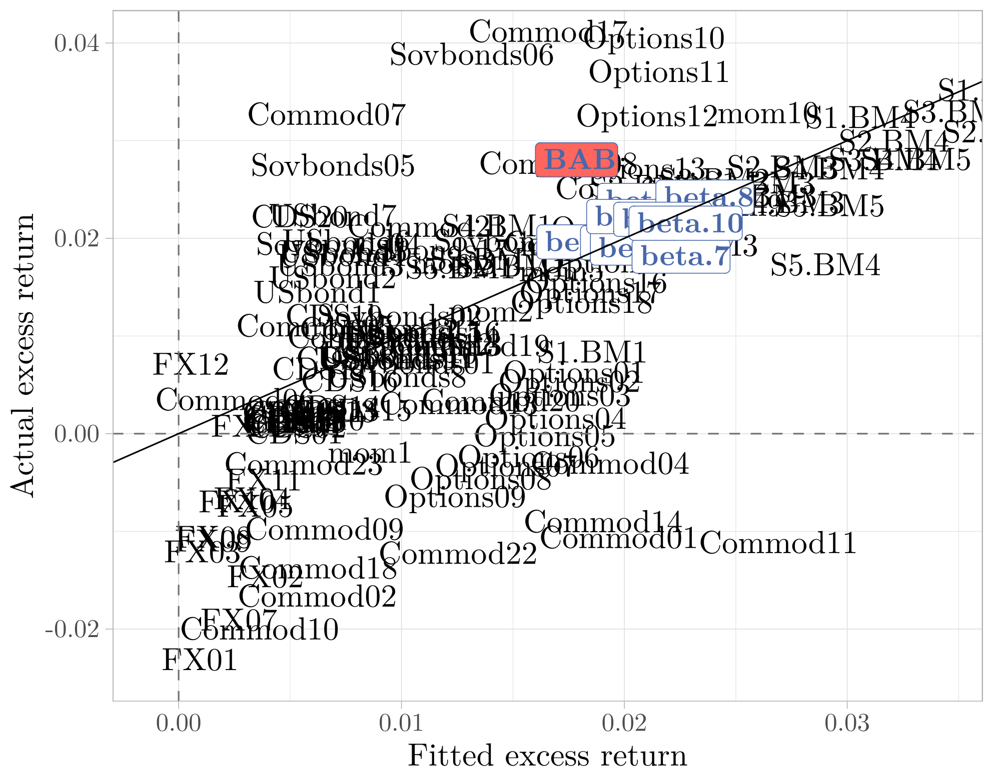


(b) HKM

Figure C.1: Pricing errors comparison.



(a) FF3



(b) FF4

Figure C.2: Pricing errors comparison.

Monthly time series test

Table C.4 contains the analysis of Table 6.4, for monthly series. For reasons related to space, the regressors not significant are omitted. Results are weaker but in the shorter sample test the lagged interaction value of the the past quarter, $t - 3$, is still significant. This is partly due to the frequency with which data is completely updated, which is quarterly.

	IRF3-mkt	**IRF3-mkt**	**HKM**	**FP**	**IRF3-mkt**
(Intercept)	-0.016	-0.004	0.009^{***}	0.022^{***}	-0.030^{*}
	(0.011)	(0.010)	(0.002)	(0.003)	(0.014)
lvg^{Δ}_{t-2}	-0.240^{**}				-0.298^{***}
	(0.078)				(0.088)
lvg^{Δ}_{t-4}	-0.261^{***}				-0.303^{***}
	(0.071)				(0.073)
lvg_t	$0.024^{\cdot}$	0.025^{*}			0.050^{***}
	(0.014)	(0.012)			(0.013)
lvg_{t-1}	-0.027	-0.025^{*}			-0.055^{*}
	(0.021)	(0.114)			(0.027)
lvg_{t-4}	0.025^{*}				0.036^{***}
	(0.010)				(0.010)
lvg_{t-5}	-0.010				-0.021^{***}
	(0.007)				(0.005)
$lvg_t \cdot lvg^{\Delta}_t$	-0.026^{*}	-0.028^{**}			-0.046^{***}
	(0.012)	(0.010)			(0.012)
$lvg_{t-1} \cdot lvg^{\Delta}_{t-1}$	-0.003			0.006	
	(0.012)	(0.003)			(0.015)
$lvg_{t-3} \cdot lvg^{\Delta}_{t-3}$	0.014^{-}				0.016^{*}
	(0.006)				(0.008)
η^{Δ}_t			0.060^{-}		
			(0.032)		
ΔTED_t				-0.018^{*}	
				(0.009)	
TED_{t-1}				-0.025^{***}	
				(0.005)	
R^2	0.159	0.080	0.064	0.085	0.233
Adj. R^2	0.131	0.070	0.057	0.080	0.195
AIC	-2321.1	-2309.2	-2308.0	-1463.9	-1482.1
BIC	-2234.3	-2274.4	-2281.9	-1448.2	-1403.5
Num. obs.	568	572	573	380	376
RMSE	0.031	0.032	0.032	0.035	0.033

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{-}p < 0.10$

Table C.4: Regression results: BAB-leverage

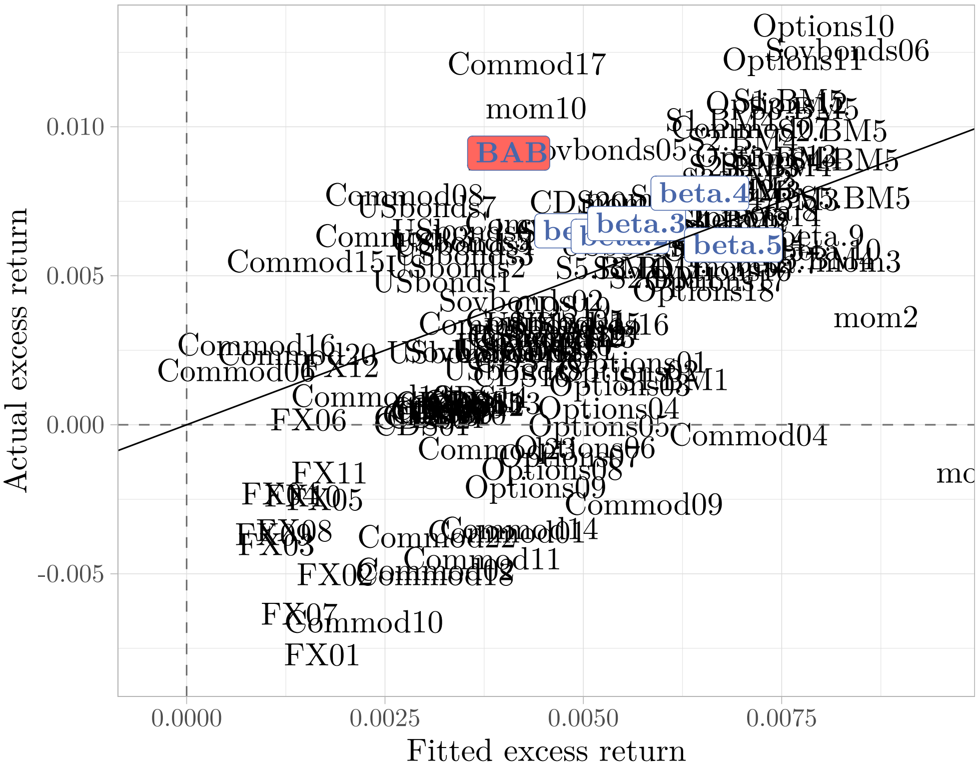
Monthly cross-sectional test

Performing the monthly test on beta- and non-beta-portfolios separately brings the same comparisons as in Table 6.7.

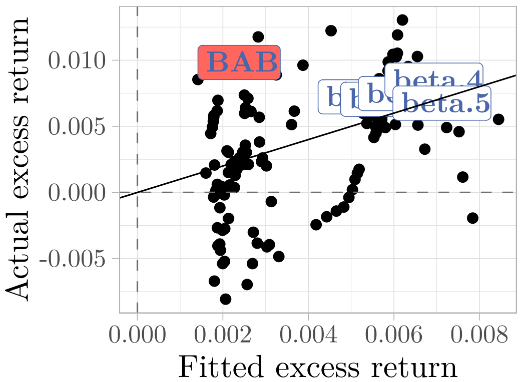
Table C.5: Prices of risk. Quarterly returns, expressed in percentage. Newey and West (1987) SEs, R^2 computed as in He, Kelly, et al. (2017), that is variance of predicted excess returns divided by variance of actual excess returns.

	CAPM	**FF3**	**FF4**	**HKM**	**IRF3**
(Intercept)	0.17^{***}	0.14^{*}	0.08	0.16^{***}	0.20^{***}
	(0.07)	(0.06)	(0.06)	(0.06)	(0.06)
$\bar{\lambda}_M$	0.42^{*}	0.33^{*}	0.46^{**}	0.40^{***}	0.32^{**}
	(0.13)	(0.14)	(0.14)	(0.12)	(0.12)
$\bar{\lambda}_{SMB}$		0.20	0.17		
		(0.11)	(0.11)		
$\bar{\lambda}_{HML}$		0.46^{***}	0.52^{***}		
		(0.10)	(0.11)		
$\bar{\lambda}_{mom}$			0.84^{***}		
			(0.16)		
$\bar{\lambda}_{\eta^{\Delta}}$				1.34^{*}	
				(0.17)	
$\bar{\lambda}_{lvg^{\Delta}}$					54.22
					(221.11)
$\bar{\lambda}_{lvg}$					-1.54^{**}
					(0.53)
$\bar{\lambda}_{lvg^{\Delta}\cdot lvg}$					-37.61^{***}
					(8.72)
R^2	0.185	0.262	0.414	0.218	0.216
Adj. R^2	0.181	0.250	0.402	0.210	0.199
Num. obs.	574	574	574	574	574
MAPE	0.292	0.261	0.225	0.291	0.286
MAPE-betas	0.213	0.219	0.112	0.200	0.179

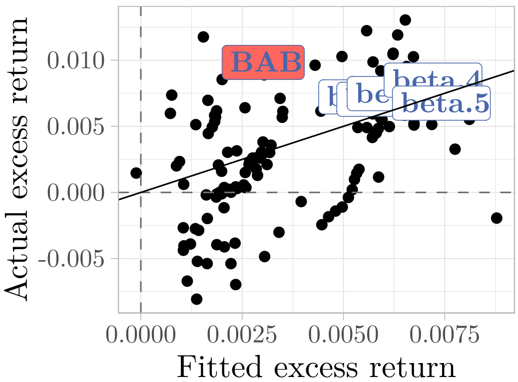
$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$



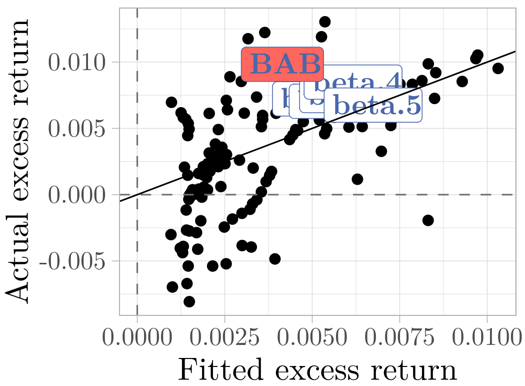
(a) Intermediary pricing kernel



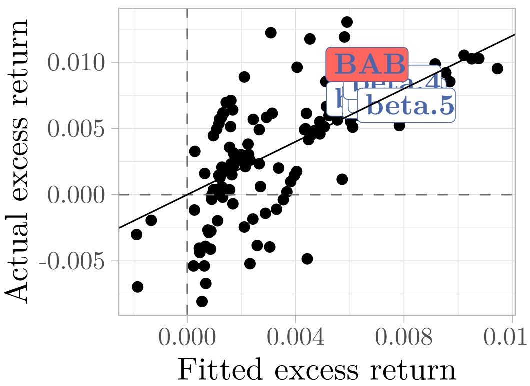
(b) CAPM



(c) HKM intermediary pricing kernel



(d) FF3



(e) FF4

Figure C.3: Pricing errors comparison. D

C.3 Research question 3

Table C.6 shows results of Table 6.8, for monthly data. Results are weaker, but the difference between the correlations are still statistically significant.

Table C.6: Alphas - coskewness in beta-sorted portfolios. SE of correlations are computed from 10,000 bootstrapped samples. Coskewness multiplied by 10^6

	CAPM	**HKM**	**IFR3**
Mean(α)	0.253	0.260	0.172
SD(α)	3.684775e-01	3.740770e-01	7.601519e-01
Mean(σ_{ϵ,M^2})	-2.100	-2.393	-1.99
SD(σ_{ϵ,M^2})	16.118	16.074	15.845
$\rho(\alpha, \sigma_{\epsilon,M^2})$	-0.434***	-0.411***	-0.297***
	(0.082)	(0.080)	(0.095)