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JEL Classification: G10, G12

Keywords: Leverage Cycles, intermediary asset pricing, Macro-Finance

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Dynamic Leverage Asset Pricing*

Tobias Adrian Emanuel Moench Hyun Song Shin

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*Adrian is with the International Monetary Fund, Moench is with the Deutsche Bundesbank and with Goethe University Frankfurt, Shin is with the Bank for International Settlements. The authors would like to thank Markus Brunnermeier, Richard Crump, Gary Gorton and Tyler Muir for valuable feedback. Evan Friedman, Nora Lamersdorf, Daniel Stackman, and especially Tobias Stein provided excellent research assistance. The views expressed in this paper are those of the authors and do not necessarily represent those of the International Monetary Fund, the Bundesbank, the Eurosystem, or the Bank for International Settlements.

1 Introduction

Financial frictions have been the subject of intensive study as economists have refined their theoretical models to capture key aspects of the Great Financial Crisis and its aftermath. Although the building blocks used in these models share many common elements, a systematic study of the comparative *empirical* impact of financial frictions is far from complete. Our paper attempts to redress the balance by exploring the empirical implications of financial frictions in an asset pricing context.

The question that we address in this paper is whether the key state variable for intermediary asset pricing is *net worth* or *leverage*, where leverage is defined as the ratio of assets to net worth. The literature emphasizing the importance of net worth (encompassing the work of Bernanke and Gertler (1989), Holmström and Tirole (1997) and Kiyotaki and Moore (1997)) is not necessarily limited to financial intermediaries. It could equally be aimed at households and non-financial corporates, as well as banks. The insights have been developed in the asset pricing context by Gromb and Vayanos (2002), He and Krishnamurthy (2013), and Brunnermeier and Sannikov (2014) by interpreting the borrower as an intermediary. The focus is not necessarily on the lending activity of intermediaries but rather on their borrowing cost. Indeed, in many of these models, the "bank" holds the real assets directly or holds equity claims on the real assets, rather than providing loans.

In contrast, Geanakoplos (2010) and Fostel and Geanakoplos (2008) address the role of intermediaries as *lenders*, and emphasize the role of leverage as the gauge of the ease of credit supply. When the bank's own funds are given, lending is determined by leverage. In these models, leverage is the key state variable. They emphasize how leverage falls during downturns, mirroring the increased collateral requirements (increased "haircuts") imposed by lenders, and how the risk bearing capacity of the financial system fluctuates with changes in collateral requirements. Similarly, Gorton (2010) and Gorton and Metrick (2012) have explored the analogy between classical bank runs and the modern run in capital markets driven by increased collateral requirements and the reduced capacity to borrow that comes from a reduction in permitted leverage.

The contrasting perspectives on the importance of net worth and leverage in modeling financial frictions are potentially very important, as the empirical predictions of the two approaches are quite different. Specifically, models based on intermediary net worth as the state variable predict that assets which comove positively with shocks to equity have higher average returns. At the same time, high intermediary equity is associated with low expected returns. In sharp contrast, models based on risk based leverage constraints imply that assets which are exposed to intermediary leverage should have high average returns. Moreover, in these models high intermediary leverage is associated with low expected future returns. Our task in this paper is to investigate empirically which theory is more consistent with observed asset prices, and how the variation in intermediary balance sheets affects risk premiums in the economy. Among other things, finding an answer to our question may reveal to what extent financial frictions affect asset prices through the external finance premium of borrowers or the credit supply decisions of intermediaries.

To answer the question of whether it is net worth or leverage that is key to asset pricing, we put the models through their paces in tailored empirical investigations. Specifically, we test reduced forms of alternative intermediary pricing models. The intermediary asset pricing models can be distinguished by their risk factors (the cross-sectional pricing factors) and the price of risk factors (the forecasting factors that capture the time variation in risk premiums). Importantly, both types of pricing model imply time variation of risk premiums as a function of intermediary balance sheet conditions. In addition to the standard cross-sectional regressions, it is therefore important to use the time series of returns to discriminate empirically among the alternative models. We do so in three different ways: by means of predictive return regressions, the linear dynamic asset pricing model (DAPM) approach of Adrian, Crump, and Moench (2015), and the non-linear return forecasting approach of Adrian, Crump, and Vogt (2019). Our cross-section of test assets includes size, book-to-market, and momentum sorted equity portfolios, as well as Treasury portfolios sorted by maturity.

We find the dynamics of broker-dealer leverage, not net worth, to be consistent with asset prices. In particular, we show that models with innovations to broker-dealer book leverage as a cross-sectional pricing factor and the lagged level of broker-dealer book leverage as price of risk variable generate highly significant risk premiums. These tests are suggestive evidence in favor of asset pricing theories that feature intermediaries with risk based leverage constraints such as value at risk constraints, which give rise to leverage as a state variable in equilibrium (e.g. the theories of Brunnermeier and Pedersen (2009), Adrian, Moench, and Shin (2010); Adrian and Shin (2014) and Adrian and Boyarchenko (2013)).

Consistent with these theories, our analysis shows that the price of risk associated with exposure to book leverage innovations is positive, and that higher leverage predicts lower future returns. Both of these findings reflect the procyclicality of leverage. The price of risk is positive as unexpectedly large leverage shocks correspond to states of the world when the marginal value of wealth is high. Leverage is associated with lower future returns as high leverage is associated with asset price booms, when expected returns are compressed. In contrast, we find that innovations to broker-dealers' book equity are associated with a negative price of risk, while the level of book equity predicts returns with a positive sign.

These findings are at odds with the predictions of the theoretical literature highlighting the role of intermediary equity in the spirit of He and Krishnamurthy (2013). They are also at odds with the empirical results of He, Kelly, and Manela (2017) (HKM henceforth). These authors study the empirical asset pricing properties of market equity, as part of intermediaries' enterprise value (the sum of market equity and book debt). They document that innovations to this ratio are associated with a positive price of risk, while a high intermediary equity ratio predicts excess returns with a positive price of risk.

There are several important differences between our measurement of intermediary balance sheet constraints and that of HKM. Most importantly, they measure intermediary equity for around 20 primary dealers that act as counterparties with the Federal Reserve Bank of New York. Instead, we focus on the book equity of all US-based broker-dealers as captured by the Financial Accounts of the United States. In addition to the largest banks included in the list of primary dealers, our intermediary universe thus also includes many medium-sized brokers and dealers which may not be publicly traded entities but could still arguably represent the marginal investor in some assets. As another important difference, the HKM factor is based on a ratio of *market* equity to the sum of market equity and book debt, while our broker-dealer factors are based on *book* equity and assets.

Running horse races between our broker-dealer leverage and equity pricing factors as well as the HKM factor, we find that all are individually significant. While broker-dealer book equity commands a significant negative price of risk, the HKM factor features a positive risk premium, confirming the results of HKM. However, the HKM factor loses its significance and switches to a negative sign in a joint regression with the broker-dealer pricing factors that also controls for the standard Fama-French factors. We find a similar result when using a market-based measure of broker-dealer equity as pricing factor.

Our results are consistent with Adrian, Etula, and Muir (2014) who document a positive price of risk for broker-dealer book leverage in the cross-section of equity and Treasury returns. We complement their analysis by showing that book leverage predicts future excess returns on risky assets with the expected negative sign. Moreover, we document that while measures of book equity have strong cross-sectional and predictive explanatory power, the coefficients imply that intermediary book equity is countercyclical, contrary to the theory of He and Krishnamurthy (2013). While measures of market equity command risk premiums whose sign is consistent with this theory, we show that the significance of the estimated risk premium is sensitive to the inclusion of equity ratios based on book values and the inclusion of standard asset pricing factors.

The remainder of the paper is organized as follows. In Section 2, we provide a brief review of the alternative intermediary asset pricing theories, and present our empirical approach. In Section 3, we describe the data and measurement. Section 4 presents our empirical evidence which helps to discriminate between alternative intermediary asset pricing theories. Section 5 concludes.

2 Intermediary Asset Pricing: Theory and Tests

2.1 Intermediary Asset Pricing Theory

One approach to intermediary asset pricing, proposed by He and Krishnamurthy (2013), rests on intermediary *equity* as the relevant state variable. Specifically, in their model intermediary equity relative to all household wealth in the economy represents the asset pricing factor when financial constraints bind while the standard capital asset pricing model holds when constraints are not binding.

According to this model, the intermediary equity ratio should be both a cross-sectional asset pricing factor, and a return forecasting factor. It is a cross-sectional pricing factor as riskiness in the economy is proxied by the intermediary equity capital. Specifically, the risk premium in the He and Krishnamurthy (2013) economy is given by the covariance of the asset return with intermediary consumption growth which in turn depends on intermediary equity. The more an asset comoves with intermediary equity, the higher the risk premium in this model. The model by He and Krishnamurthy (2013) further predicts that the intermediary equity ratio (intermediary equity to total wealth) is a return forecasting factor, as the risk premium rises with the adversity of the state. As intermediary equity falls relative to total wealth in the economy, the risk premium rises. In the model, this relation is nonlinear: the risk premium is proportional to the inverse of the squared intermediary capital ratio.

Note that the model of He and Krishnamurthy (2013) features only one shock for analytical tractability. To ensure that we capture both aspects of their model in our empirical tests, we consider both the intermediary equity relative to total wealth and the market return as pricing factors. This allows us to assess the incremental explanatory power of intermediary market equity growth over and above the return on the market portfolio. In our empirical analysis, we use nominal GDP as a measure of total wealth in the economy.

To summarize, in the theory of He and Krishnamurthy (2013), the risk premium associated with the intermediary equity ratio is predicted to be positive in cross-sectional asset pricing regressions, indicating procyclical intermediary equity capital. In the time-series, a higher intermediary equity ratio is predicted to be associated with lower expected returns giving rise to a negative coefficient in predictive return regressions. Conversely, higher intermediary leverage should predict higher future expected returns in this model.

HKM document support for the cross-sectional predictions using a measure of intermediary market equity relative to intermediary enterprise value (market equity plus debt). They further find that higher intermediary market leverage (the inverse squared HKM ratio) is associated with higher future returns. Instead of market equity, in our empirical analysis we focus on book values. Book equity is the owner's own stake in the portfolio, and lending conditions in the economy are captured by the haircut applied to collateralized lending through, for instance, a repurchase agreement (repo). A repo haircut of 5 percent means that 5 cents of each dollar's worth of securities must be funded by the owner's stake, so that maximum achievable leverage is 20. For securities that are traded in liquid markets, the repo haircut gives a good marked-to-market snapshot of funding conditions that (together with book equity) influences risk-taking and portfolio choice.

An alternative measure of equity is market capitalization, which is the discounted value of all future free cash flows. Both book equity and market equity capture important economic dimensions of intermediary net worth. Book and market equity can diverge even in perfect markets—for instance when one bank has a higher fee income than another even when they hold identical portfolios of loans and securities. For the purpose of asset pricing choices, marked-to-market book equity together with the haircut on collateralized lending is a better indicator of overall risk-taking and portfolio choice by intermediaries. In this way, book equity is more closely related to the way in which firms are managed. Market values are largely outside the control of firms, fluctuating with market risk premiums. For these reasons, in our empirical approach, we use book equity as the baseline, but also report results with market equity as a cross-check.

Furthermore, we use broker-dealer balance sheets to measure intermediary behavior. Broker-dealers are fully marking their balance sheets to market, and hence the difference between book and market equity is the present discounted value of intangibles such as fee income. In intermediary asset pricing theories, such intangible assets are not modeled, and hence book equity of institutions that are marking to market are closer to the theory. It is worth reiterating that book equity is what firms manage, while the value of market equity is largely outside of the control of firms.

As already discussed, the assumption of equity as the key state variable has a long tradition starting with the seminal work by Bernanke and Gertler (1989), Holmström and Tirole (1997) and Kiyotaki and Moore (1997). While these early papers focused on the equity of borrowers (typically non-financial firms or households), the more recent literature has emphasized the equity of financial intermediaries. Intermediary asset pricing models that follow the equity approach include Gromb and Vayanos (2002), and Brunnermeier and Sannikov (2014), in addition to the work by He and Krishnamurthy (2013) mentioned above. The common thread among these theories is that the pricing of risk depends directly on intermediary equity, with the prediction that intermediary equity is a procyclical variable.

A second approach to intermediary asset pricing emphasizes the role of *leverage*. Brunnermeier and Pedersen (2009) propose a model where shocks to the pricing kernel are proportional to the financial intermediary's Lagrange multiplier on its leverage constraint, in addition to the market factor. A specification that is consistent with Brunnermeier and Pedersen (2009) is to proxy this Lagrange multiplier by the leverage of the intermediary sector, such that higher leverage corresponds to tighter funding constraints. When funding constraints tighten, intermediaries are forced to deleverage by selling off assets they can no longer finance.

Risk premiums can vary also in leverage based intermediary asset pricing models, for example by emphasizing the role of margin constraints. In such models, the pricing factor is the market return, and the price of risk depends on the Lagrange multiplier of margin constraints. Garleanu and Pedersen (2011) is a recent exposition of such an approach. Empirically, the tightness of the margin constraint is difficult to observe directly, but Adrian and Etula (2011) discuss how theories with margin constraints compare to models that use intermediary leverage as state variable. A more directly testable approach is presented by Danielsson, Shin, and

Zigrand (2012) who consider risk-neutral financial intermediaries that are subject to a value at risk (VaR) constraint. In their model, the intermediaries' demand for risky assets depends on the Lagrange multiplier of the VaR constraint that reflects effective risk aversion. In equilibrium, asset prices depend on the leverage of the intermediaries, which determines the level of effective risk aversion—times of low intermediary leverage are times when effective risk aversion is high. As a result, financial intermediary leverage directly enters the equilibrium pricing kernel. The pricing factor is therefore the market return, while the price of risk depends on intermediary leverage, reflecting the time varying effective risk aversion of intermediaries. Importantly, leverage—not equity —is the key measure of time varying effective risk aversion in these models.

A pricing kernel in which the pricing of risk varies as a function of leverage over time, and in which shocks to leverage are cross-sectional pricing factors, can be motivated from the equilibrium asset pricing model of Adrian and Boyarchenko (2013). They study an economy in which financial intermediaries have risk based leverage requirements, forcing them to deleverage when volatility increases. Volatility endogenously increases when intermediaries reduce the size of their balance sheet, thus generating a feedback mechanism. In equilibrium, the price of risk can be expressed as varying as a function of leverage, while the model implies that the relevant risk factors are shocks to intermediary leverage and the market return. In this theory leverage is procyclical with a positive price of leverage risk, and higher leverage forecasting lower future returns.

Importantly, in the theory of Adrian and Boyarchenko (2013) there are only two shocks: to time preferences of households, and to firms' productivity. Hence, fluctuations in leverage are entirely due to shocks that emanate outside the intermediary sector, and leverage is an endogenous variable that reflects the effective risk aversion of intermediaries. The reduced form asset pricing prediction of Adrian and Boyarchenko (2013) is that expected returns depend on the covariation of returns with intermediary leverage. Of course, that covariation is in and of itself endogenous in the theory, which is a feature that we abstract from in our unconditional asset pricing tests. Put differently, the theory gives rise to a conditional asset pricing prediction with time varying intermediary betas, but we test the unconditional version of that prediction, with in sample constant betas.

A closely related intermediary asset pricing theory is presented by Elenev, Landvoigt, and Van Nieuwerburgh (2018). In their model, the corporate sector is hit by an aggregate productivity shock and by shocks to the cross-sectional dispersion of idiosyncratic firm productivity. Intermediaries face occasionally binding constraints on their leverage (and indirectly also net worth), which limit their short-term debt to a fraction of the market value of their assets (corporate loans). In this model, intermediary leverage and net worth are endogenous. The constraint restricts how much risk-bearing capacity the intermediary sector provides, not only when it is binding but also when it is not binding since risk averse intermediaries will try to stay away from the constraint at all times. Another closely related recent model is by Santos and Veronesi (2018). They generate pro-cyclical leverage in a multi-agent frictionless general equilibrium model that features time-varying risk preferences. Aggregate debt increases in expansions when asset prices are high, volatility is low, and levered households enjoy a "consumption boom." The model is consistent with intermediaries' leverage being a priced factor.

Leverage can be measured at book values as total assets to book equity, or at market values as the ratio of enterprise value to market equity. Enterprise value is the analogue of total assets, defined as the sum of market capitalization and debt. Enterprise value addresses the question "how much is the bank worth?" In contrast, total assets address the question "how much does the bank lend?" or "how much does the bank hold in terms of securities?" Clearly, the latter set of questions is the more relevant one for risk-taking and portfolio choice with financial intermediation and hence we opt for the book definition of leverage in our empirical analysis, but compare the results with those using market equity to compute leverage.

In summary, in models where intermediary leverage is the key state variable, leverage is predicted to be a procyclical metric, with a positive price of risk in the cross-section, and a negative sign in predictive return regressions. In contrast, in models where intermediary net worth is the key state variable, net worth should be associated with a positive and leverage with a negative price of risk in the cross-section. Moreover, net worth should feature a negative and leverage a positive sign in predictive return regressions in such models. An empirical analysis of these starkly contrasting theoretical predictions is the focus of our paper. Importantly, both types of models imply that risk premiums vary as a function of intermediary balance sheet conditions. A proper assessment of these models thus requires a framework which explicitly allows for time variation of risk premiums.

2.2 Testing Intermediary Asset Pricing Theories

The discussion above highlights that the two competing intermediary asset pricing theories make starkly different predictions for the cross-section and time-series of asset returns. We test these predictions by first estimating cross-sectional and predictive return regressions separately. We then combine the cross-sectional and time-series dimensions in a dynamic asset pricing model. Finally, we assess the role of nonlinearities in risk premiums. We now discuss each of the empirical approaches in turn.

2.2.1 Cross-sectional Regressions

To study the ability of the various pricing factors in explaining the cross-section of risky asset returns, we estimate the following standard linear asset pricing model:

$$X_{j,t+1} = \mu_j + \phi_j X_{j,t} + v_{j,t+1} \qquad \forall j \in \{1, .., k\} \tag{1}$$

$$R^i_{t+1} = \alpha_i + \beta_i' \hat{v}_{t+1} + e^i_{t+1} \tag{2}$$

$$\bar{R}_{t+1} = \hat{\beta}\lambda + \nu_{t+1}. \tag{3}$$

Hence, $v_{j,t+1}$ denotes the AR(1) innovation to pricing factor X_j, $\hat{\beta}$ the vector of factor risk exposures estimated in the first-pass regression of Equation (2), $\bar{R}_{t+1}$ the $n \times 1$ vector of average excess returns, $\hat{\beta}$ the $N \times k$ matrix of estimated factor risk exposures and λ the $k \times 1$ vector of associated prices of risk estimated in the second-pass regression of Equation (3). In line with standard asset pricing restrictions, we do not include a constant in the cross-sectional regression of average excess returns on factor risk exposures.

The parameter of interest in this model is λ. It indicates whether a proposed pricing factor is associated with variation in expected returns, and what sign this relation has. We estimate this model using the standard two-pass regression approach. We compute standard errors via GMM that adjust for cross-correlation and first-stage estimation uncertainty in betas. The results of the cross-sectional asset pricing tests are provided in Section 4.1.

2.2.2 Predictive Return Regressions

We assess the ability of different intermediary balance sheet indicators to explain time variation in risk premiums by running simple time-series regressions of excess returns on one-quarter lagged balance sheet proxies, controlling for benchmark return predictor variables:

$$R^i_{t+1} = c + \gamma' F_t + \delta' Z_t + \epsilon^i_{t+1}, \tag{4}$$

where R^i_{t+1} is the excess return on asset i, F_t denotes the (vector of) intermediary predictor variables and Z_t a vector of controls. Based on these regressions, the coefficient of interest γ will allow us to assess if a given intermediary variable significantly drives risk premiums, and if so what the sign of the relation is. We estimate these regressions using standard OLS and report Newey-West standard errors which adjust for serial-correlation and heteroskedasticity of the residuals. The results of the predictive return regressions are provided in Section 4.2.

2.2.3 Dynamic Asset Pricing Model

The intermediary asset pricing theories have implications for both the cross-sectional and the time-series variation of returns. The reduced-form representations of such models can be cast in the *Dynamic Asset Pricing Model* (DAPM) framework of Adrian, Crump, and Moench (2015). The DAPM framework features an affine pricing kernel, and can be viewed as a first order approximation to the true nonlinear pricing kernel. In the DAPM framework, systematic risk in the economy is captured by a $K \times 1$ vector of state variables X_t that follow a stationary vector autoregression (VAR).

State variables can be "risk" factors, "price of risk" factors, or both. Risk factors refer to variables that explain the cross-section of asset returns, but do not predict future excess returns. Price of risk factors refer to variables that significantly predict excess returns in the time-series, but do not comove with returns contemporaneously.[1] Finally, some state variables can be contemporaneously correlated with returns and also predict returns, implying that they act as both a price of risk and a risk factor. In the DAPM, the state variables are therefore partitioned into three categories:

$$\begin{aligned} X_{1,t} &\in \mathbb{R}^{K_1} : \text{risk factor only} \\ X_{2,t} &\in \mathbb{R}^{K_2} : \text{risk and price of risk factor} \\ X_{3,t} &\in \mathbb{R}^{K_3} : \text{price of risk factor only} \end{aligned}$$

Define

$$C_t = \begin{bmatrix} X_{1,t} \\ X_{2,t} \end{bmatrix}, \quad F_t = \begin{bmatrix} X_{2,t} \\ X_{3,t} \end{bmatrix}, \quad u_t = \begin{bmatrix} v_{1,t} \\ v_{2,t} \end{bmatrix},$$

where "C_t" is for "cross-section" and "F_t " is for "forecasting".

Assuming a linear pricing kernel and prices of risk that are affine in the forecasting factors F_t, the beta representation of the DAPM is given by

$$R^i_{t+1} = \beta_i' (\lambda_0 + \Lambda_1 F_t) + \beta_i' u_{t+1} + e^i_{t+1}, \tag{5}$$

$$X_{t+1} = \mu + \Gamma X_t + v_{t+1}, \qquad t = 1, \ldots, T. \tag{6}$$

The realized excess return, R^i_{t+1}, can thus be decomposed into the time varying expected excess return, $\beta_i' (\lambda_0 + \Lambda_1 F_t)$, which depends on the *level* of the forecasting factors, a component that is conditionally correlated with the *innovations* to the risk factors, $\beta_i' u_{t+1}$, and a return pricing error, e^i_{t+1}.

[1]In the fixed income literature, such price of risk factors are sometimes referred to as "unspanned" factors, see Joslin, Priebsch, and Singleton (2012), and Adrian, Crump, and Moench (2013).

Significant coefficients in the matrix Λ_1 will indicate which factor is driving time variation of market prices of risk. By studying which elements of the estimator $\bar{\lambda} = \lambda_0 + \Lambda_1 \bar{F}_t$ are statistically different from zero, one can further assess which factor risk exposures are priced. Moreover, Wald tests of rows of Λ_1 being equal to a vector of zeros can be used to study whether there is significant time variation in the price of risk of a given factor.

Adrian, Crump, and Moench (2015) propose a regression-based estimator for the parameters of the model and show that it is consistent and asymptotically normal. They further derive asymptotic standard errors that are robust to heteroskedasticity in the return pricing errors. This estimator nests the popular Fama-MacBeth two-pass regression estimator when both $\Lambda_1 = 0$ and $\Gamma = 0$. That is, the DAPM estimator can be thought of as a generalized Fama-MacBeth estimator that explicitly allows for state variables and prices of risk to be time-varying.

We use the DAPM approach to test the cross-sectional and time series predictions of the competing intermediary asset pricing theories in a unified framework. Consistent with these models, the intermediary variables will be X_2-type factors, that is their innovations will be priced risk factors and their levels forecasting factors. Additional factors such as the MKT return will be X_1-type factors. These results are presented in Section 4.3.

2.2.4 Sieve Reduced Rank Regressions

As discussed above, in both competing intermediary asset pricing theories the price of risk is a nonlinear function of intermediary leverage or net worth, respectively. We test for nonlinearities in the prices of risk by computing expected returns based on a flexible nonlinear function of return forecasting factors F:

$$R^i_{t+1} = a_i + b_i \phi\left(F_t\right) + \varepsilon^i_{t+1}. \tag{7}$$

We estimate $\phi\left(F_t\right)$ using the Sieve reduced rank (SRR) regressions approach of Adrian, Crump, and Vogt (2019). SRR regressions exploit the fact that the price of risk, $\phi(F_t)$, is a common component that drives time-variation across all expected excess returns. We remain nonparametric about the shape of $\phi(\cdot)$ by relying on the method of sieves.This method involves basis function approximations to the unknown function ϕ that grow slowly with the sample size. A prototypical approximation for ϕ has the form $\tilde{\phi}(v) = \sum_{j=1}^{m_T} \tilde{\gamma}_j B(v)$, where $B(v)$ are basis functions (B-splines in our empirical implementation). The number of basis functions used in the approximation is required to grow slowly with the sample size ($m_T \to \infty$ slowly as $T \to \infty$), allowing ever-increasing flexibility in approximating the true ϕ. Asymptotically, the basis function approximations become arbitrarily flexible and close to ϕ in the sense formalized in Adrian, Crump, and Vogt (2019).[2] SRR estimates $\hat{\phi}(F_t)$ thus have a shape that is simultaneously informed by the cross-section and time-series of returns. We standardize the sign of $\phi(\hat{F}_t)$ so that they are increasing functions.

3 Data and Measurement

We draw on three types of data for our empirical exercise in this paper. The first are excess returns for equity and Treasury bond portfolios. The equity returns are decile portfolios sorted on book-to-market, market capitalization, and momentum, respectively, from Kenneth French's website. The Treasury returns are the constant maturity returns for maturities $n = 1, 2, 5, 7, 10$ years, obtained from unsmoothed Fama-Bliss zero coupon yields as constructed in Le and Singleton (2013).

We collect intermediary balance sheet data from two different sources. We obtain book values of financial assets and total equity for Securities Brokers and Dealers ("broker-dealers") from the Federal Reserve Flow of Funds (Table L.130).[3] We compute book leverage as the

[2] To guard against overfitting, the flexibility of $\phi(\cdot)$ is chosen to minimize predictive errors. In our application, we find that a global cubic approximation performs best.

[3] The Flow of Funds are now officially labeled "Financial Accounts of the United States". For simplicity, we will continue to refer to them as "Flow of Funds (FoF)".

ratio of financial assets and equity:[4]

$$Leverage^{BD} = \frac{FinancialAssets^{BD}}{Equity^{BD}}$$

and focus on the log of this series as our measure of book leverage.

As discussed in Section 2, in net worth-based intermediary asset pricing models in the spirit of He and Krishnamurthy (2013), the relevant state variable is intermediary net worth relative to total wealth in the economy. To account for non-tradable wealth, we normalize the equity of broker-dealers with nominal U.S. GDP obtained from the Bureau of Economic Analyses (BEA):

$$Equity\ ratio^{BD} = \frac{Equity^{BD}}{GDP}$$

and also use the log of this ratio as our measure of broker-dealer equity. A detailed account of the data construction is provided in Appendix A. We discuss robustness with respect to an alternative normalization in Section 4.1.

For both broker-dealer measures, we focus on the equity of U.S.-based broker-dealers. Global banks headquartered outside the United States will be subject to capital allocation decisions that reflect global conditions, not only U.S. securities markets. For this reason, we focus on broker-dealer variables that are most likely to be relevant for the U.S. securities examined here. We obtain the equity of U.S.-based broker-dealers by subtracting the equity of foreign banks in U.S.-domiciled broker-dealers from the total equity of the U.S. broker-dealer sector. The former series is constructed by the Bureau of Labor Statistics (BLS) as part of their foreign direct investment (FDI) calculations (FA663192005) and is used as a subcomponent of broker-dealer equity in the FoF calculations.[5] While we focus on the leverage and equity ratio

[4]Financial assets represent the vast majority of assets of broker-dealers, time-series variation in leverage based on total assets or total financial assets is therefore essentially identical.

[5]Starting with the third quarter of 2016, the equity of the aggregate broker-dealer sector in the FoF includes the equity of broker-dealer subsidiaries of foreign banks. Before 2016Q3, the equity of foreign banks in U.S.-domiciled broker-dealers was accounted for as liabilities in the FoF. To reconstruct measures of broker-dealer leverage used in prior research (e.g. Adrian and Shin (2010) and Adrian, Etula, and Muir (2014)) based on FoF data published after 2016Q3, one therefore needs to subtract the FDI series from the total equity series as we do here.

of U.S.-based broker-dealers in our main analysis, we also study the asset pricing properties of all U.S.-domiciled broker-dealers in Section 4.5.

A first inspection of the (log) book equity ratio series as well as the corresponding leverage series for U.S. broker-dealers in Figure 1 shows that both appear nonstationary due to breaks or trends. These likely reflect structural changes to the financial sector over the past forty years. Such breaks are a common feature in economic and financial time series. Lettau and Van Nieuwerburgh (2007) find strong empirical evidence in support of shifts in the steady state of the economy and propose a simple adjustment to financial ratios such as the dividend yield to account for such shifts. They suggest applying the test for multiple structural breaks proposed by Bai and Perron (1998), and to demean the original series by subtracting the different subsample means. We follow Lettau and Van Nieuwerburgh (2007) and apply the Bai-Perron test to the log level of the broker-dealer book leverage series, shown in the upper-left panel of Figure 1. The test results are provided in Table 8 in Appendix A. They suggest four structural breaks since 1968, the last one occurring in 1992Q2, around the time when the public started discussing the repeal of the Glass-Steagall Act. The break-adjusted series is provided in the top right panel of Figure 1 and serves as the input into our time-series and cross-sectional asset pricing regressions. We show robustness of the results with respect to the number of identified breaks in Appendix B.

In contrast to broker-dealer book leverage, the log equity ratio (upper-right panel) features a nonlinear trend rather than structural breaks. To render the series stationary, we follow Cooper and Priestley (2008) and compute the deviations of the log equity ratio from a trend that features both a linear and a quadratic component. The resulting detrended series is shown in the lower-right panel and is further used in our asset pricing tests.[6]

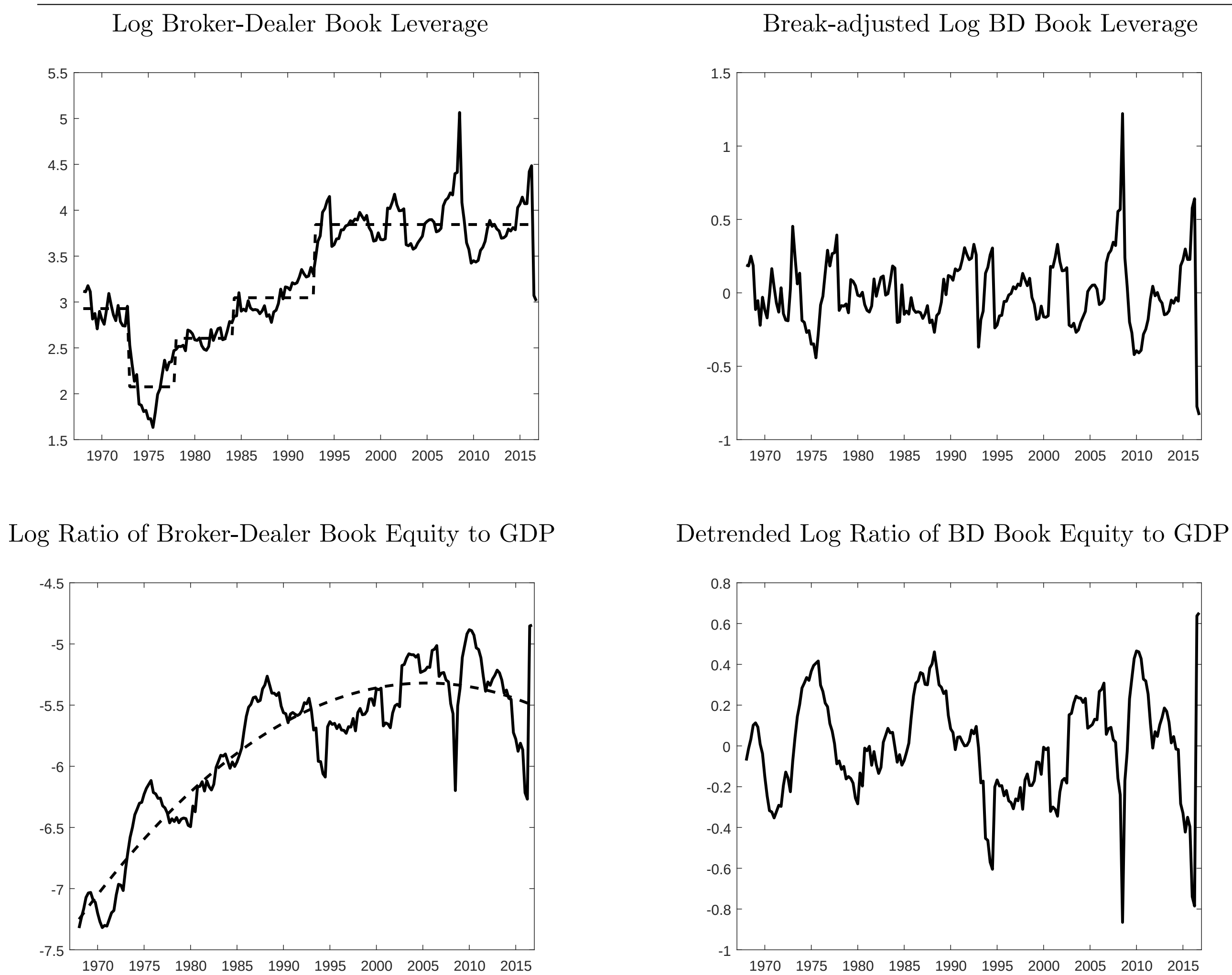
We use the the break- and trend-adjusted log levels of the broker-dealer leverage and equity ratio series as return predictors. We label them “BDblev” and “BDbe2gdp”, respectively.[7] As

[6] We confirm that standard unit root tests fail to reject the Null of stationarity of the trend-adjusted series.

[7] As discussed in HKM, a simplified version of the model in He and Krishnamurthy (2013) suggests that the risk premium is inversely related to the squared intermediary equity ratio. We first study the predictive ability of the broker-dealer equity ratio in linear settings and test for nonlinearities in the pricing of risk in Section 4.4.

Figure 1: **Break and Trend Adjustment – BD Book Leverage and Equity Ratio**

The top panel plots the log U.S. broker-dealer book leverage ratio (solid line) along with its subsample means as identified by the Bai and Perron (1998) procedure (dashed line) on the left, and the difference between the two series on the right. The bottom panel plots the log U.S. broker-dealer book equity to GDP ratio (solid line) as well as its linear-quadratic trend (dashed line) on the left, and the difference between the two series on the right.



pricing factors in our cross-sectional asset pricing tests, we use the innovations of the adjusted log level series in an autoregression (AR) of order one and label them "BDblev factor" and "BDbe2gdp factor", respectively. This is in line with the common practice in the literature (see e.g. Adrian, Etula, and Muir (2014) and HKM) and captures the main premise of conditional asset pricing models that only unexpected innovations to state variables should be priced.

We compare the cross-sectional pricing power of the resulting broker-dealer pricing factors with that of two other intermediary asset pricing factors that have been proposed in the literature. First and most importantly, we contrast our factors' pricing ability to the primary dealer market equity ratio proposed in HKM. We obtain their factor (labeled "HKM factor" henceforth) and excess return data from Asaf Manela's website. The construction of the HKM factor differs from ours in several dimensions. First, HKM use the group of around 20 primary dealers that act as counterparties with the Federal Reserve Bank of New York in their implementation of monetary policy as the relevant intermediary sector. Instead, we focus on all U.S.-based broker-dealers as captured by the Flow of Funds data. In addition to the largest banks included in the list of primary dealers, our intermediary universe thus also includes many medium-sized brokers and dealers which may not be publicly traded entities but could still arguably represent the marginal investor in some asset classes. As another important difference, the HKM factor is based on a ratio of *market* equity to the sum of market equity and book debt, while our broker-dealer factors are exclusively based on *book* equity and assets. As discussed in Section 2, we expect book values to provide the clearer pricing signal than market values, but ultimately this is an empirical question that our asset pricing tests may shed light on.

To assess whether the differences in cross-sectional asset pricing tests and predictive return regressions are due to our choice of book versus market equity, we also compute similar broker-dealer measures based on market equity values. We obtain broker-dealer market equity from Compustat-CRSP by aggregating individual firm data with SIC codes 6712 or 6211. Additionally, Merrill Lynch, Bear Stearns, Morgan Stanley, Lehman Brothers, and Goldman Sachs are hard-coded as broker-dealers. In each quarter, we sum the book value of the assets and the market equity of the resulting broker-dealers. We compute market leverage as the ratio of total assets and market equity and compute the equity ratio by dividing aggregate broker-dealer market equity by nominal U.S. GDP. A detailed discussion of the data construction is provided in Appendix A. Plots of the alternative equity ratio measures are provided in Figure 2.

Finally, we contrast the predictive power of the broker-dealer factors with benchmark return forecasting factors. These are the dividend yield (dy) for the S&P500, from Haver Analytics, the term spread ($TERM$), calculated as the difference between the ten-year constant maturity Treasury yield and the three-month Treasury bill rate, both from the Federal Reserve's H.15 release, the default spread (DEF), calculated as the difference between Moody's Aaa and Baa yields, also from the H.15 release, the equity share in new issues (ES) from Baker and Wurgler (2000), which we update with recent data, the book-to-market ratio (BM) for the aggregate value-weighted market portfolio from CRSP, the Markov-switching log consumption-wealth ratio from Martin Lettau's website (CAY_{MS}), as well as the Cochrane and Piazzesi (2005) Treasury return forecasting factor (CP), updated with recent data.

Our sample period is from 1968 through 2016 for a total of 196 quarters. Estimations involving the HKM factor start in 1970 when it becomes available. We study subsample robustness of our main results throughout.

4 Empirical Results

In this section, we empirically evaluate the ability of the broker-dealer factors to explain the cross-sectional and time-series variation of excess returns. This will allow us to assess the relative empirical plausibility of the different intermediary asset pricing theories discussed in Section 2. Before turning to the asset pricing tests, it is instructive to look at the informational overlap between the various pricing factors.

Table 1 provides the correlation coefficients between our two broker-dealer factors, the three Fama-French factors MKT, SMB, and HML, as well as the HKM and AEM factors, respectively.[8] The figures show that the two broker-dealer factors are largely orthogonal to the three Fama-French factors: none of the correlation coefficients exceeds 14% in absolute value. The same holds for the correlation with the HKM factor which is below 10% for

[8] As the HKM factor is only available from 1970 onwards, all correlations are computed over the sample 1970-2016.

Table 1: **Correlations between pricing factors**

This table reports correlations between different cross-sectional pricing factors. "BDblev factor" denotes the AR(1) innovations of the break-adjusted log U.S. broker-dealer book leverage ratio, "BDbe2gdp factor" denotes the AR(1) innovations of the detrended log U.S. broker-dealer book equity to GDP ratio, "MKT" is excess return on the CRSP market portfolio, "SMB" is the small minus big factor and "HML" is the high minus low factor (both from Ken French's website), "HKM" is the intermediary market equity factor of He, Kelly, and Manela (2017), and "AEM" is the leverage factor of Adrian, Etula, and Muir (2014). The sample period is 1970Q1 to 2016Q4.

	BDblev factor	BDbe2gdp factor	MKT	SMB	HML	HKM
BDbe2gdp factor	-0.7842					
MKT	-0.0526	0.0998				
SMB	-0.1215	0.0817	0.4445			
HML	0.0915	-0.1377	-0.3174	-0.1225		
HKM	-0.0705	0.0985	0.7635	0.3220	0.0314	
AEM	0.7263	-0.8451	0.0506	0.0430	0.2498	0.0153

both broker-dealer factors. Hence, the two broker-dealer factors capture information that is essentially unspanned by existing asset pricing factors or the HKM factor. In contrast, and not surprisingly, the correlations with the AEM factor are quite elevated, at 73% for the book leverage factor and negative 85% for the book equity ratio. The AEM factor, in turn, has a somewhat stronger correlation of about 25% with the HML factor. More importantly, the HKM factor features a sizable correlation of 32% with SMB and a strong correlation of 76% with MKT. This is not surprising, as the factor is constructed based on the market equity of primary dealers whose return one expects to be highly correlated with the return on the market portfolio. That said, it will be important to control for benchmark pricing factors when assessing the incremental ability of our broker-dealer factors or the HKM factor in pricing the cross-section of test assets.

4.1 Cross-sectional Asset Pricing Tests

We analyze the cross-sectional pricing power of the various pricing factors in explaining the cross-section of returns by estimating the model in equations (1 - 3) using the standard two-pass regression approach. For each model, we follow the prior literature and report as measures of model fit the cross-sectional R^2 and the mean absolute pricing error (MAPE) in percentage terms, see also HKM.

Table 2 provides estimates of the prices of risk associated with exposure to the various intermediary balance sheet indicators. GMM t-statistics are in brackets. The first column shows that the innovations to log broker-dealer book leverage are a strongly significant cross-sectional pricing factor even when controlling for the market return, in line with the findings in Adrian, Etula, and Muir (2014). Moreover, the positive sign of the estimated price of broker-dealer book leverage is consistent with theories based on risk-based leverage constraints. The estimated price of risk shows that a one unit higher exposure to broker-dealer book leverage innovations is associated with a twenty basis points higher average quarterly return. The standard deviation of beta estimates across the set of 40 test assets is about 3. Hence, a one standard deviation higher exposure to broker-dealer leverage risk translates into an economically significant additional 2.5% higher annual excess return. The estimated price of market risk is about 2% per quarter and thus about 8% per year, in line with common estimates of the equity risk premium.

The second column shows that innovations to the broker-dealer book equity ratio are also highly statistically significant, albeit with a negative coefficient. This is at odds with net worth based pricing models such as He and Krishnamurthy (2013) which imply a positive price of risk for exposure to intermediary equity shocks. Considering the innovations to the broker-dealer book leverage and equity ratio jointly (column 3), both retain their statistical significance, and the adjusted R^2 increases. This suggests that both factors have incremental explanatory power for our cross-section of test assets. Importantly, however, the estimated price of risk associated with the broker-dealer book equity ratio remains negative. This result

Table 2: **Cross-Sectional Asset Pricing Tests**

This table reports prices of risk for different intermediary pricing models. Each model is estimated using two-pass regressions as described in Section 2.2.1. The GMM t-statistics are in parentheses and adjust for cross-asset correlation in the residuals and for estimation error of the betas. "BDblev factor" is the broker-dealer book leverage factor, "BDbe2gdp factor" is the broker-dealer book equity to GDP ratio. The "HKM factor" is the pricing factor constructed by He, Kelly, and Manela (2017), and has been obtained from Asaf Manela's website. "MKT", "SMB', and "HML" are the three Fama-French pricing factors. The test assets are 25 size and value sorted portfolios, and ten momentum sorted decile portfolios (all from Ken French's website), as well as five constant maturity Treasury returns for maturities ranging from 1 through 10 years, obtained from Anh Le. Mean absolute pricing errors (MAPE) are in percentage terms. The sample period is 1968Q1 to 2016Q4 or 1970Q1 to 2016Q4 for the models involving the HKM factor. $***$ denotes significance at 1%, $**$ significance at 5%, and $*$ significance at the 10% level.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
			1968Q1 - 2016Q4				
BDblev factor	0.214***		0.233***	0.185***	0.211***	0.253***	0.228***
	[3.080]		[3.448]	[2.866]	[3.275]	[2.873]	[2.675]
BDbe2gdp factor		-0.228***	-0.206***		-0.192***	-0.185***	-0.176***
		[-3.414]	[-3.083]		[-3.411]	[-2.896]	[-2.607]
HKM factor				4.267**	3.581*		-1.035
				[2.139]	[1.702]		[-0.272]
MKT	2.006***	1.967***	2.009***	1.874***	1.888***	1.573**	1.626**
	[2.956]	[2.680]	[2.850]	[2.897]	[2.868]	[2.434]	[2.506]
SMB						0.572	0.547
						[1.465]	[1.413]
HML						1.231***	1.081**
						[2.757]	[2.467]
R^2	0.457	0.496	0.524	0.501	0.561	0.713	0.694
$MAPE, \%$	0.520	0.513	0.485	0.463	0.441	0.325	0.327
Assets	40	40	40	40	40	40	40
Quarters	196	196	196	196	196	196	196

is in contrast to the evidence in HKM who document a positive risk premium for their primary dealer market equity ratio.

Adding the HKM factor to the previous two regressions (columns 4 and 5) shows that it also carries a positive risk premium in our cross-section of test assets, albeit only statistically significant at the 10% level when considered jointly with both broker-dealer factors. The two broker-dealer factors also remain highly statistically significant when we include the Fama-French factors SMB and HML in the regression (column 6). In an encompassing regression of the three intermediary pricing factors and the three Fama-French factors (column 7), the two broker-dealer factors remain statistically strongly significant while the price of risk on the

HKM factor switches to a negative sign and loses its significance. Combined, these results suggest that both broker-dealer book leverage and net worth carry useful information for pricing the cross-section of equity and Treasury returns. While leverage innovations command a positive price of risk for these test assets, book equity ratio innovations are associated with a negative risk premium. This implies that broker-dealer leverage is procyclical while their equity is countercyclical.

What can explain the discrepancy between our results and those of HKM? As discussed in Section 3, there are a number of differences in the construction of the two intermediary equity-based pricing factors. While HKM use market values of primary dealers, some of which are large non-U.S. banks, we use the book equity of U.S.-based broker-dealers. Another discrepancy is our use of GDP as a denominator to scale the book equity of broker-dealers relative to all wealth in the economy.

To gauge whether our choice of using book equity or that of using GDP as denominator in the equity ratio drive our results, we construct two alternative equity ratio measures. First, we compute an equity ratio using market equity of all brokers and dealers with common stock traded on U.S. exchanges. We also relate this market equity to nominal GDP and detrend the resulting log equity ratio analogously to the book equity ratio. Second, we use total nonfinancial sector wealth, including the book equity of nonfinancial sector corporates, nonfinancial sector non-corporates as well as households from the FoF data, to scale the book equity of broker-dealers. Details on the factor construction are provided in Appendix A. Figure 2 provides plots of the raw and detrended alternative broker-dealer equity ratios. For comparison, the bottom left panel also provides the primary dealer equity ratio used in HKM, and the bottom right panel shows the inverse of the squared HKM ratio which will be used in predictive return regressions in Section 4.4.[9]

[9] To make our results comparable to those in HKM, we do not break-adjust the HKM ratio. That said, the Bai and Perron (1998) test indicates two structural breaks around the years 1992 and 2007 in this series.

Figure 2: **Alternative Intermediary Equity Ratios**

The top panel plots the log of broker-dealer book equity relative to total non-financial sector wealth (solid line) along with its linear-quadratic trend (dashed line) on the left, and the difference between the two series on the right. The middle panel plots the log of broker-dealer book equity relative to GDP (solid line) along with its linear-quadratic trend (dashed line) on the left, and the difference between the two series on the right. The bottom panel shows the primary dealer market equity ratio suggested by HKM on the left, and the squared reciprocal of the primary dealer market equity ratio on the right.

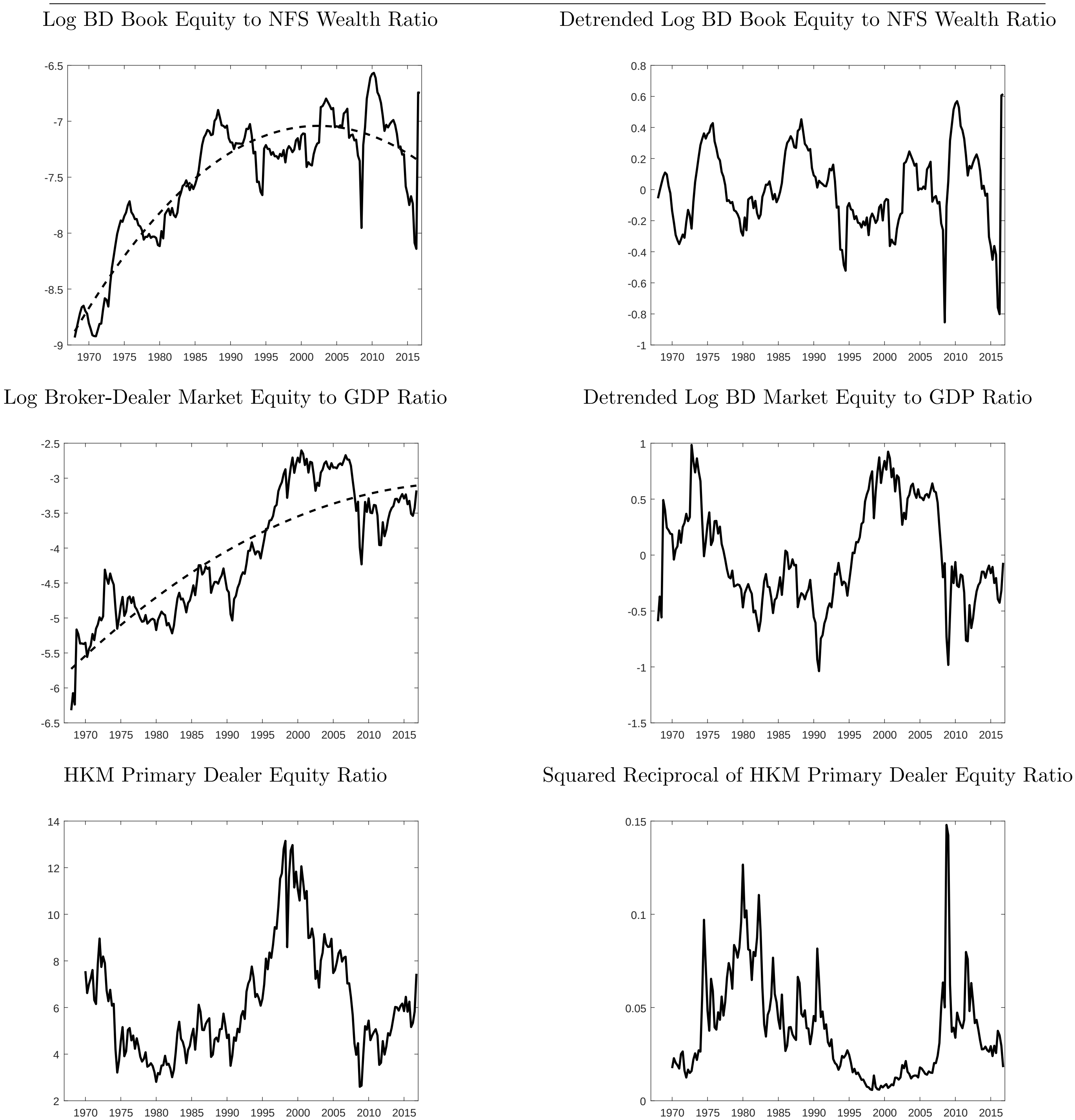


Table 3: **Cross-Sectional Asset Pricing Tests: Alternative Intermediary Equity Ratios**

This table reports prices of risk for different intermediary pricing models. Each model is estimated with GMM as $E[R^e] = \beta\lambda$. The GMM t-statistics are in parentheses and adjust for cross-asset correlation in the residuals and for estimation error of the betas. "BDblev factor" is the broker-dealer book leverage factor, "BDme2gdp factor" is the broker-dealer market equity to GDP ratio, and "BDbe2nfs" the broker-dealer book equity relative to total nonfinancial sector wealth. "MKT", "SMB', and "HML" are the three Fama-French pricing factors. The test assets are 25 size and value sorted portfolios, and ten momentum sorted decile portfolios (all from Ken French's website), as well as five constant maturity Treasury returns for maturities ranging from 1 through 10 years, obtained from Anh Le. Mean absolute pricing errors (MAPE) are in percentage terms. The sample period is 1968Q1 to 2016Q4 or 1970Q1 to 2016Q4 for the models involving the HKM factor. $***$ denotes significance at 1%, $**$ significance at 5%, and $*$ significance at the 10% level.

	(1)	(2)	(3)	(4)	(5)
			1968Q1 - 2016Q4		
BDblev factor	0.213***	0.226***	0.218***	0.232***	0.252***
	[3.066]	[3.413]	[2.816]	[3.366]	[2.817]
BDme2gdp factor	0.077*	0.070*	-0.018		
	[1.830]	[1.734]	[-0.325]		
BDbe2gdp factor		-0.184***	-0.167**		
		[-3.265]	[-2.536]		
BDbe2nfs factor				-0.205***	-0.187***
				[-3.137]	[-2.911]
MKT	1.848***	1.875***	1.607**	2.007***	1.574**
	[2.876]	[2.873]	[2.508]	[2.845]	[2.435]
SMB			0.587		0.565
			[1.505]		[1.449]
HML			1.085**		1.246***
			[2.516]		[2.809]
R^2	0.561	0.590	0.721	0.525	0.714
$MAPE, \%$	0.421	0.412	0.322	0.482	0.321
Assets	40	40	40	40	40
Quarters	196	196	196	196	196

Table 3 shows results for both broker-dealer equity ratios as alternative pricing factors. When considered jointly with broker-dealer book leverage innovations, the market equity ratio commands a positive risk premium which is statistically significant at the 10% level (column 1). This is still the case when we also add the book equity ratio series which itself remains highly statistically significant (column 2). Interestingly, however, and consistent with the results for the HKM factor, the risk premium on the broker-dealer market equity ratio switches to a negative sign and loses its statistical significance once we also control for SMB and HML (column 3). Using total nonfinancial sector wealth instead of GDP as denominator in the equity ratio does not affect the results. The coefficient remains negative with a similar magnitude as for the book equity to GDP ratio and remains highly statistically significant in a joint regression with the market factor and broker-dealer book leverage (column 4), but also when additionally controlling for SMB and HML (column 5).

Combined, these results show that intermediary equity ratios based on book values command statistically strongly significant negative risk premiums while intermediary equity ratios based on market values do not earn significant risk premiums once one controls for benchmark asset pricing factors. We interpret this as evidence against intermediary asset pricing models in which equity is the key state variable.

4.2 Predictive Return Regressions

The above results show that broker-dealer balance sheet indicators contain useful information for explaining the cross-section of asset returns, in line with some of the intermediary pricing models discussed in Section 2. These models also imply a role for intermediary balance sheets to explain time variation in risk premiums. Specifically, models such as Brunnermeier and Pedersen (2009), Danielsson, Shin, and Zigrand (2012), and Adrian and Boyarchenko (2013) imply that higher leverage forecasts lower future returns. In contrast, net-worth based intermediary asset pricing models imply that higher equity should predict lower future returns. In both types of models risk premiums are nonlinear functions of the respective intermediary balance sheet aggregates. In this section, we use linear approximations of these models to assess whether broker-dealer leverage and equity predict returns. Flexible nonlinear predictive regressions will be studied in Section 4.4.

We start by running simple time-series regressions of the excess return on the CRSP stock market portfolio on one-quarter lagged balance sheet indicators as in Equation (4). We use the (break and trend-adjusted) log levels of the two variables as predictors. We control for a host of benchmark return predictor variables including the log dividend yield (dy), the Markov-switching consumption-wealth ratio (CAY_{MS}) from Bianchi, Lettau, and Ludvigson (2018), the equity share in new issuance (ES) from Baker and Wurgler (2000), the market portfolio's book-to-market ratio ($B2M$), the term spread between the ten-year Treasury yield and the three-month Treasury bill yield ($TERM$), the default spread between the yields on Moody's benchmark BAA-rated and AAA-rated corporate bonds (DEF), the Cochrane and Piazzesi (2005) return forecasting factor (CP), and the quarterly sum of squared daily returns of a bank stock portfolio to proxy for financial sector volatility ($FinSecVol$).

Table 4 reports predictive coefficients and associated t-statistics based on the Newey-West adjustment with a maximum lag length of four quarters. The top panel shows the results for our baseline sample 1968-2016. Combined, the benchmark return predictors explain an impressive 12% of the variation in one quarter ahead excess returns on the market portfolio (top row). Individually, the broker-dealer book leverage factor explains 4% of the variation and is highly statistically significant at the 1% level (second row). The negative sign of the predictive coefficient is consistent with asset pricing theories based on risk based capital constraints: risk premiums are compressed when leverage is high. Importantly, broker-dealer book leverage remains highly statistically significant in a joint regression with *all* benchmark return predictors, and the adjusted R^2 increases to 15% (third row). Hence, broker-dealer leverage contains predictive information for future stock returns beyond that embedded in common risk factors.

In contrast to leverage, the broker-dealer book equity to GDP ratio does not predict the excess market return (fourth and fifth rows). Using leverage and the equity ratio in a joint regression, only leverage is strongly statistically significant (sixth row), even when adding all benchmark return predictors (last row). The sample standard deviation of the broker-dealer book leverage series is about 0.25. Hence, the predictive coefficient of about -10 implies that a one standard deviation increase in broker-dealer leverage is associated with an economically sizable 4 percentage points compression of excess returns on the aggregate stock market.

One might worry that the strong predictive power of the broker-dealer leverage factor is unduly influenced by the great financial crisis (GFC) of 2007-2009. During this period, prices of risky assets were declining rapidly which resulted in a sharp increase of broker-dealer leverage before these institutions could raise more equity and reduce the size of their balance sheets. Restricting the sample to the pre-crisis period ending in the second quarter of 2007 in the bottom panel of Table 4, we see that the predictive power of broker-dealer leverage is indeed reduced. That said, the coefficient on broker-dealer book leverage remains significant at the 5% level when considered in a joint regression with the equity ratio and significant at the 10% in the horse race with all benchmark return predictors included.

In sum, this section shows that broker-dealer book leverage is a strong predictor of excess stock returns. HKM also study the predictability of their primary dealer capital ratio measure. They show that a simplified version of He and Krishnamurthy (2013) implies that the risk premium is proportional to the squared inverse of the intermediary capital ratio and document that this measure predicts one-year ahead excess returns on various asset classes with the expected positive sign. In Section 4.4 below, we will assess the predictive power of broker-dealer book leverage relative to the HKM ratio, allowing for nonlinearities in risk premiums.

Table 4: **Predictive Return Regressions**

This table provides results for one quarter ahead predictive return regressions using the excess return on the CRSP market portfolio (MKT) as dependent variable. The predictor variables are the break-adjusted log U.S. broker-dealer leverage ratio (BDblev) and the detrended log U.S. broker-dealer equity to GDP ratio (BDe2gdp) as well as a variety of commonly used equity return forecasting factors. These are the log dividend yield (dy), the Markov-switching consumption-wealth ratio (CAY_{MS}) from Bianchi-Lettau-Ludvigson, the equity share in new issuance (ES) from Baker-Wurgler, the market portfolio's book-to-market ratio (B2M), the term spread between the ten-year Treasury yield and the three-month Treasury bill yield (TERM), the default spread between the yields on Moody's benchmark BAA-rated and AAA-rated corporate bonds (DEF), the Cochrane-Piazzesi forecasting factor (CP), and the quarterly sum of squared daily returns of a bank portfolio (taken from the 49 industry portfolios of Ken French's homepage) to proxy for financial sector volatility (FinSecVol). $***$ denotes significance at 1%, $**$ significance at 5%, and $*$ significance at the 10% level.

	BDblev	BDbe2gdp	dy	CAY_{MS}	ES	B2M	TERM	DEF	CP	FinSecVol	$\bar{R}^2$
					1968Q1 - 2016Q4						
Coeff			3.36**	105.27**	-18.18***	-8.00	2.20***	1.06	-1.51***	-21.17	0.12
t-stat			[2.35]	[2.39]	[-2.87]	[-1.17]	[3.32]	[0.56]	[-3.59]	[-0.68]	
Coeff	-8.12***										0.04
t-stat	[-2.69]										
Coeff	-7.31***		4.03***	89.53**	-17.24***	-11.41*	2.05***	0.78	-1.47***	-9.08	0.15
t-stat	[-3.04]		[2.88]	[2.00]	[-3.36]	[-1.76]	[3.00]	[0.40]	[-3.40]	[-0.36]	
Coeff		2.57									0.00
t-stat		[0.95]									
Coeff		0.58	3.42**	104.78**	-17.95***	-8.33	2.18***	1.01	-1.51***	-20.34	0.12
t-stat		[0.22]	[2.35]	[2.38]	[-2.85]	[-1.21]	[3.33]	[0.52]	[-3.59]	[-0.66]	
Coeff	-9.91***	-2.72									0.04
t-stat	[-3.08]	[-1.22]									
Coeff	-10.11***	-4.50*	3.81***	87.36**	-18.66***	-10.15	2.13***	1.07	-1.49***	-10.91	0.16
t-stat	[-3.80]	[-1.79]	[2.72]	[2.04]	[-3.37]	[-1.59]	[3.16]	[0.54]	[-3.46]	[-0.42]	
					1968Q1 - 2007Q2						
Coeff			3.37*	137.99*	-15.28***	-9.61	2.53***	1.74	-1.77***	148.38*	0.14
t-stat			[1.94]	[1.95]	[-2.87]	[-1.31]	[3.80]	[0.84]	[-4.68]	[1.74]	
Coeff	-4.98*										0.00
t-stat	[-1.65]										
Coeff	-3.14		3.54**	133.87*	-14.89***	-10.43	2.52***	1.54	-1.76***	143.52*	0.14
t-stat	[-1.07]		[2.09]	[1.86]	[-2.82]	[-1.46]	[3.74]	[0.73]	[-4.68]	[1.66]	
Coeff		-0.75									-0.01
t-stat		[-0.27]									
Coeff		-3.61	3.15*	135.02**	-17.85***	-8.22	2.54***	2.27	-1.79***	142.66*	0.14
t-stat		[-1.10]	[1.77]	[1.97]	[-3.12]	[-1.11]	[3.87]	[1.02]	[-4.63]	[1.70]	
Coeff	-6.16**	-2.52									0.00
t-stat	[-1.97]	[-0.99]									
Coeff	-5.21*	-5.04	3.36*	127.00*	-18.24***	-9.04	2.52***	2.15	-1.77***	132.34	0.15
t-stat	[-1.87]	[-1.59]	[1.96]	[1.82]	[-3.21]	[-1.27]	[3.80]	[0.96]	[-4.59]	[1.55]	

4.3 Dynamic Intermediary Asset Pricing

The previous two sections provide strong evidence that broker-dealer book leverage helps to explain the cross-sectional and time-series variation of asset returns, in line with theories based on risk based capital constraints. In this section, we combine the two by estimating reduced-form dynamic intermediary asset pricing models as in Equations (5) and (6). According to the respective theories discussed above, the innovations to both state variables should command a positive price of risk. The price of risk, in turn, should be decreasing in the level of intermediary leverage or equity relative to total wealth in the economy. First-order approximations of the nonlinear pricing kernels of both models would imply that the price of risk depends linearly on the respective intermediary ratio. We discuss nonlinear pricing in the next section.

Table 5 provides the estimates for four different models. The first column shows the intercept λ_0 of the prices of risk. The second and third column provide the coefficients of Λ_1. t-statistics are in brackets below. The fourth column shows the estimated average price of risk $\bar{\lambda}$, and the last column gives Wald statistics W_{Λ_1} with p-values below. The latter test for the null that the corresponding elements of Λ_1 are jointly zero, i.e. that there is no time variation in market prices of risk.

The top panel shows estimates for a linear dynamic "Leverage model" which uses the market return and innovations to broker-dealer book leverage as cross-sectional pricing factors and the level of break-adjusted log broker-dealer book leverage as the price of risk factor. The estimated coefficients are in line with those obtained in the cross-sectional and predictive regressions in Sections 4.1 and 4.2. Both the market return and the innovations to broker-dealer book leverage earn strongly statistically significant positive risk premiums. Moreover, the price of market risk is found to depend strongly negatively on the level of broker-dealer book leverage. These results are consistent with models with risk based capital constraints such as Adrian and Boyarchenko (2013). However, in contrast to this model's prediction we do not find evidence that the price of leverage risk is itself time varying as a function of leverage.

Table 5: **Dynamic Intermediary Asset Pricing**

This table provides estimated price of risk parameters for the two intermediary asset pricing models presented in Section 2.2.3, as well as for two combined models. The "Leverage Model" in the top panel has the market return and innovations to U.S. intermediary leverage as pricing factors and break-adjusted log broker-dealer leverage (BDblev) as price of risk factor. The "Net worth" model in the second panel has the market return and the innovations of the broker-dealer equity to GDP ratio as pricing factors and the detrended broker-dealer equity to GDP ratio (BDbe2gdp) as price of risk factor. The third panel shows the results for a combined model that includes the market return and the two broker-dealer innovations as cross-sectional pricing factors and BDblev and BDbe2gdp as price of risk factors. Finally, the bottom panel adds the Fama-French factors SMB and HML as cross-sectional pricing factors. The first column, λ_0, gives the estimated constant in the affine price of risk specification for each pricing factor. The second through third columns provide the estimated coefficients in the matrix Λ_1, which determine loadings of prices of risk on the forecasting factors. The column $\bar{\lambda}$ provides an estimate of the average price of risk for a given risk factor. The last column provides the Wald test statistic of the null hypothesis that the associated row is all zeros. This test can be seen as a test of time variation in the price of risk for a given risk factor. The sample period is 1968Q1 to 2016Q4. Standard errors are computed as in Adrian, Crump, and Moench (2015). $***$ denotes significance at 1%, $**$ significance at 5%, and $*$ significance at the 10% level.

	λ_0	BDblev	BDbe2gdp	$\bar{\lambda}$	W_{Λ_1}
			Leverage Model		
BDblev factor	0.224***	-0.165		0.223***	0.700
	[2.931]	[-0.837]		[2.955]	[0.403]
MKT	2.069***	-7.476***		2.051***	7.254***
	[3.130]	[-2.693]		[2.772]	[0.007]
			Net Worth Model		
BDbe2gdp factor	-0.234***		-0.178	-0.234***	1.176
	[-3.127]		[-1.085]	[-3.157]	[0.278]
MKT	2.025***		3.192	2.016***	1.551
	[2.836]		[1.246]	[2.654]	[0.213]
			Combined Model		
BDblev factor	0.249***	-0.130	0.031	0.249***	0.669
	[3.335]	[-0.529]	[0.143]	[3.366]	[0.716]
BDbe2gdp factor	-0.218***	-0.065	-0.175	-0.218***	1.079
	[-2.809]	[-0.339]	[-1.026]	[-2.825]	[0.583]
MKT	2.024***	-8.494**	-1.536	2.008***	7.599**
	[3.029]	[-2.468]	[-0.494]	[2.747]	[0.022]
			Combined Model 2 (adding SMB and HML)		
BDblev factor	0.253***	0.322	0.016	0.254***	1.369
	[3.018]	[1.026]	[0.074]	[2.925]	[0.504]
BDbe2gdp factor	-0.186***	-0.228	-0.096	-0.186***	1.359
	[-2.909]	[-1.165]	[-0.597]	[-2.884]	[0.507]
MKT	1.669**	-9.593***	-2.431	1.653**	8.910**
	[2.562]	[-2.798]	[-0.808]	[2.292]	[0.012]
SMB	0.584	1.455	0.829	0.585	0.438
	[1.412]	[0.660]	[0.424]	[1.420]	[0.804]
HML	1.226**	-0.101	3.275	1.217**	3.359
	[2.257]	[-0.039]	[1.498]	[2.131]	[0.186]

The second panel of 5 shows the results for the "Net worth model" which uses the market return and the innovations to the broker-dealer book equity to GDP ratio as cross-sectional pricing factors and the level of the detrended broker-dealer book equity to GDP ratio as price of risk factor. Again in line with the cross-sectional and predictive regressions, we find that the broker-dealer equity to GDP ratio earns a statistically strongly significant negative price of risk while a high broker-dealer book equity to GDP ratio is associated with a high price of market risk. As discussed before, both findings are inconsistent with the predictions of the net worth models a la He and Krishnamurthy (2013). As for broker-dealer leverage, we do not find evidence of time variation in the price of broker-dealer book equity ratio.

We empirically assess the relative importance of broker-dealer leverage versus the broker-dealer equity-ratio in explaining asset returns by estimating a nested linear dynamic model. In the nested model, the market return, (break-adjusted) log leverage as well as the (detrended) broker-dealer log book equity ratio are the state variables. The results are provided in the third panel of Table 5. In the combined model, MKT and broker-dealer leverage continue to command a highly significant positive risk premium while the broker-dealer equity ratio features a strongly significant negative average price of risk. Hence, also when taking into account time variation in risk premiums, broker-dealer book leverage is strongly procyclical while the broker-dealer equity ratio behaves countercyclically. Looking at the elements of Λ_1, we see that broker-dealer leverage remains a strong driver of time variation in the price of market risk: when leverage is high the price of market risk is low, consistent with the predictive regressions in Section 4.2. That said, neither the price of leverage nor the price of equity ratio risk are time varying, as shown by the insignificance of the corresponding Wald statistics in the last column. The bottom panel of Table 5 shows that this result is unchanged when we augment the model with the benchmark risk factors HML and SMB. All coefficients remain quantitatively very similar, and the corresponding t-statistics indicate no effect on the significance of the relevant coefficients.

To evaluate the usefulness of the nested intermediary model for pricing the test assets, it is instructive to compare the model-implied pricing errors with those of benchmark models such

Table 6: **Linear Dynamic Intermediary Pricing Models: Pricing Error Comparison**

This table provides average pricing errors (upper panel) and mean-squared one-step ahead forecast errors (lower power) for four different pricing models. CAPM is the standard Capital Asset Pricing Model with excess return on the market portfolio as the only pricing factor; FF denotes the Fama-French (1993) three factor model. Both models feature constant prices of risk. “Leverage Model” and “Net Worth Model” denote the intermediary asset pricing models described in the previous table, implemented using the break-adjusted broker-dealer U.S. book leverage (BDBlev) and detrended broker-dealer U.S. equity to GDP (BDbe2gdp). The two pricing factors and price of risk factors are considered jointly in the “Combined Model”. Finally, “Combined Model 2” adds SMB and HML (from Ken French’s website) as cross-sectional pricing factors, respectively. The upper panel reports the average pricing errors $\bar{e}^i = \frac{1}{T}\sum(R^i_t - \hat{R}^i_t)$ for a selected set of test assets as well as the cross-sectional average of the absolute values $|\bar{e}^i|$, “MAPE”. The lower panel reports mean squared one-quarter ahead prediction errors $\nu_i = \frac{1}{T}\sum(R^i_{t+1} - E_t[R^i_{t+1}])^2$ relative to those implied by the CAPM for selected test assets as well as the cross-sectional average of those ratios. The sample period is 1968Q1 to 2016Q4.

	CAPM	FF	Leverage Model	Net Worth Model	Combined Model	Combined Model 2
Average pricing errors						
S1B1	-2.25	-1.30	-0.94	-0.83	-0.91	-0.76
S1B5	1.24	0.67	1.56	1.07	1.20	0.62
S5B1	-0.29	0.28	-0.89	-0.53	-0.66	0.05
S5B5	0.52	-0.33	0.39	0.45	0.46	0.25
S2B3	0.62	0.43	0.28	0.27	0.13	-0.12
S3B2	0.38	0.51	0.26	-0.03	-0.01	0.14
MOM1	-3.23	-3.07	-0.98	-0.60	-0.33	-0.36
MOM5	-0.17	-0.36	-0.76	-0.65	-0.76	-0.60
MOM10	1.14	1.82	1.13	1.57	1.36	1.81
CMT1	0.25	0.24	0.05	0.14	0.08	0.09
CMT5	0.46	0.41	-0.26	0.41	0.11	-0.07
CMT10	0.69	0.71	-0.56	0.88	0.24	-0.10
MAPE	0.65	0.51	0.51	0.51	0.45	0.30
Mean squared one-step ahead forecast errors relative to CAPM						
S1B1		0.99	0.98	0.98	0.98	0.98
S1B5		0.99	0.98	0.99	0.98	0.97
S5B1		1.00	0.98	1.01	0.97	0.96
S5B5		1.00	0.96	0.99	0.96	0.96
S2B3		1.00	0.98	0.99	0.98	0.98
S3B2		1.00	0.97	0.99	0.97	0.97
MOM1		1.00	0.94	0.96	0.93	0.93
MOM5		1.00	0.97	0.99	0.97	0.97
MOM10		1.02	0.99	1.01	0.99	1.00
CMT1		1.00	0.99	0.99	0.98	0.98
CMT5		1.00	1.00	1.00	0.99	0.98
CMT10		1.00	1.01	1.01	1.00	0.98
Avg		1.00	0.97	0.99	0.97	0.96

as the CAPM and the Fama-French three-factor model. Table 6 provides average pricing errors for a subset as well as the cross-sectional mean asbolute pricing error for all test assets. The pricing errors show that the intermediary model prices most test assets more precisely than the CAPM or Fama-French model. The average absolute pricing error declines from a quarterly 0.65% for the CAPM to 0.51% for the Fama-French model to 0.45% for the nested broker-dealer model. The average absolute pricing errors decline even further to 0.3% when including HML and SMB, as this helps particularly in explaining the 25 size and book-to-market sorted stock portfolios.

In the dynamic model, we can also compare the mean squared one-quarter ahead return forecasting errors, shown in the lower panel of the table. Relative to the CAPM which features constant prices of risk, the nested dynamic broker-dealer model reduces mean squared return forecast errors by an average of 3% across all assets. The model augmented with HML and SMB further reduces return forecast errors slightly. Combined, the results from the dynamic model confirm the takeaways from the cross-sectional and predictive regressions: broker-dealer book leverage carries a strongly significant positive price of risk and predicts risk premiums with a strongly significant negative coefficient. The broker-dealer book equity ratio carries a negative price of risk but has little predictive power for excess returns.

4.4 Predictive Sieve Reduced Rank Regressions

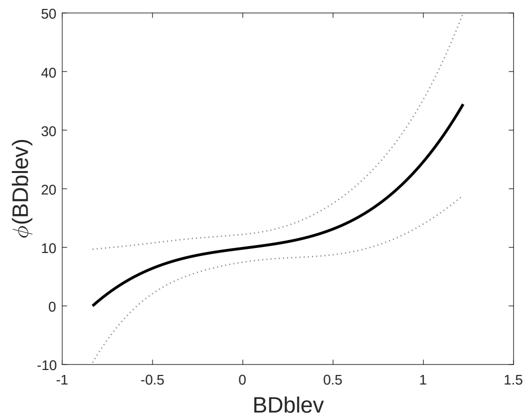
We now turn to an analysis of potential nonlinearities of risk premiums in the competing intermediary models. We use the approach of Adrian, Crump, and Vogt (2019) which allows us to estimate flexible nonlinear functions of the intermediary variables which best (in a mean squared error sense) predict excess returns on our cross-section of test assets. This will help us assess the degree of nonlinearity in the pricing of risk implied by the different intermediary ratios. Figure 3 plots the estimated pricing functions for broker-dealer book leverage and the equity to GDP ratio. As the signs of the functions $\phi(\hat{F}_t)$ are not separately identified from the signs in the predictive regression, we standardize them so that they are increasing functions.

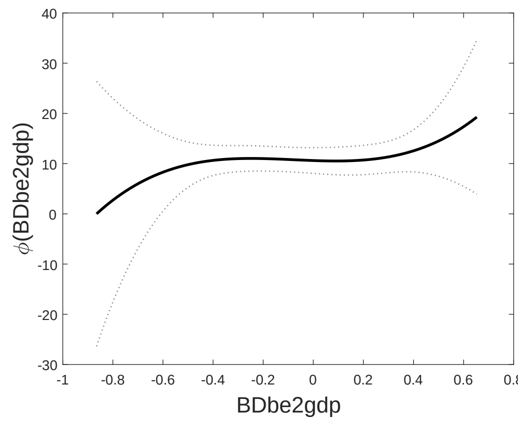
The estimated forecasting function for broker-dealer book leverage in the top left chart of Figure 3 shows that there is an approximately linear relationship between leverage and the

Figure 3: **Nonlinear Pricing Functions for Leverage and Net Worth Measures**

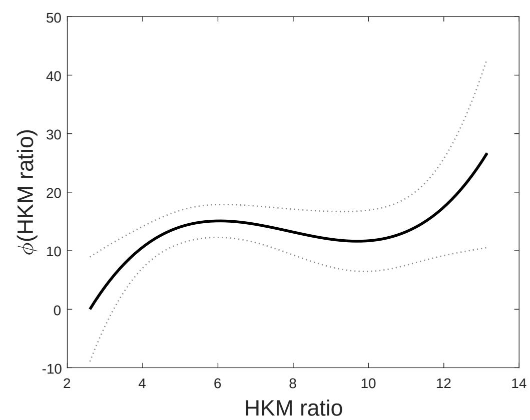
This figure shows the estimated nonlinear pricing functions $\phi(\cdot)$ for the different intermediary factors. These estimates are obtained from the sieve reduced rank regression $R^i_{t+1} = a_i + b_i \cdot \phi(X_t) + \varepsilon^i_{t+1}$ of Adrian, Crump, and Vogt (2019) as discussed in Section 2.2.4, where X is the break or trend-adjusted log level of the indicated broker-dealer balance sheet indicator or the HKM ratio, respectively. Dotted lines represent 95-percent confidence intervals. The sample consists of quarterly observations from 1968Q1-2016Q4 (1970Q1-2016Q4 for the HKM ratio).

I





HKM ratio



implied risk premium for small and intermediate values of leverage. However, especially at elevated levels of leverage (i.e. closer to the maximum of the support of the underlying break-adjusted book leverage series), the forecasting function increases more than proportionally. This suggests that in times of very high leverage risk premiums are particularly compressed.

The pricing function for the broker-dealer book equity to GDP ratio (top right chart) also has a linear functional form over much of its support. While there is some sign of non-linearities in the tails, these are imprecisely measured as shown by the wide confidence intervals. We find a bit more nonlinearity in the pricing function for the HKM ratio (bottom left chart). While risk premiums are relatively flat for intermediate values of the ratio, they strongly increase (fall) in the tails of its support. Of note, the functional form obtained via Sieve reduced rank regressions does not confirm the inverse squared relation implied by the He and Krishnamurthy (2013) model and used in HKM to predict excess returns. We evaluate the predictive power of both transformations below.

We now compare the predictive performance of the different nonlinear forecasting functions for the one quarter ahead excess market return. Table 7 provides the estimated predictive coefficients along with the corresponding t-statistics. The top panel shows the sample from 1970Q1 through 2016Q4 for which all variables are available. The first two rows document that the nonlinear forecasting function for broker-dealer book leverage is a highly statistically significant predictor of future market returns while that for the broker-dealer book equity to GDP ratio is not. Both coefficients have the sign predicted by models with risk based leverage constraints: high intermediary leverage (low equity) is associated with low expected returns. The nonlinear forecasting function of broker-dealer leverage alone explains 6% of the variation of quarterly excess market returns, a bit more than its linear counterpart. The third row instead uses the optimal nonlinear forecasting function of the HKM ratio as predictor. The coefficient is negative and statistically significant. This implies that higher intermediary market equity (lower intermediary market leverage) is associated with lower future market returns, consistent with models based on intermediary net worth. Combining the three nonlinear functions in one predictive regression the coefficient on broker-dealer equity switches sign (fourth row). However, when adding the benchmark return predictor variables only the nonlinear forecasting function based on broker-dealer leverage survives and remains strongly statistically significant.

Table 7: **Predicting Returns with Nonlinear Functions of Intermediary Variables**

This table provides results for one quarter ahead predictive return regressions using the excess return on the CRSP market portfolio (MKT) as dependent variable. The predictor variables are nonlinear pricing functions $\phi(\cdot)$ for the different intermediary pricing models. These are obtained from the sieve reduced rank regression $R^i_{t+1} = a_i + b_i \cdot \phi(X_t) + \varepsilon^i_{t+1}$ of Adrian, Crump, and Vogt (2019) as discussed in Section 2.2.4, using as inputs the break or trend-adjusted log levels of broker-dealer leverage and equity ratio and the HKM ratio, respectively. invsqHKM denotes the reciprocal of the squared HKM ratio. The control variables are the same as in Table 4. $***$ denotes significance at 1%, $**$ significance at 5%, and $*$ significance at the 10% level.

	ϕ(BDblev)	ϕ(BDbe2gdp)	ϕ(HKM)	invsqHKM	dy	CAY_{MS}	ES	B2M	TERM	DEF	CP	FinSecVol	$\bar{R}^2$
1970Q1 - 2016Q4													
Coeff	-0.99***												0.06
t-stat	[-6.74]												
Coeff		0.97											0.02
t-stat		[1.62]											
Coeff			-0.47***										0.03
t-stat			[-2.97]										
Coeff	-1.59***	-1.16**	-0.49***										0.09
t-stat	[-5.91]	[-2.49]	[-3.20]										
Coeff	-1.30***	-0.72	-0.11		3.55**	105.42*	-12.62**	-10.48	2.21***	0.20	-1.46***	7.65	0.16
t-stat	[-4.15]	[-1.50]	[-0.50]		[2.41]	[1.91]	[-2.19]	[-1.55]	[3.12]	[0.10]	[-3.02]	[0.33]	
Coeff				44.01*									0.01
t-stat				[1.91]									
Coeff	-1.61***	-1.18***		48.63**									0.08
t-stat	[-5.95]	[-2.58]		[2.26]									
Coeff	-1.21***	-0.37		-132.99***	5.83***	193.93***	-15.46**	-10.67*	2.57***	1.83	-1.98***	51.59*	0.18
t-stat	[-3.62]	[-0.63]		[-2.59]	[3.78]	[3.60]	[-2.55]	[-1.70]	[3.96]	[0.91]	[-4.61]	[1.80]	
1970Q1 - 2007Q2													
Coeff	-1.31**												0.01
t-stat	[-2.16]												
Coeff		1.49*											0.00
t-stat		[1.84]											
Coeff			-0.52***										0.03
t-stat			[-3.10]										
Coeff	-1.06	0.38	-0.49***										0.03
t-stat	[-1.26]	[0.35]	[-3.00]										
Coeff	-0.75	0.27	-0.03		3.11*	185.49**	-13.97**	-9.48	2.88***	1.67	-1.95***	145.70*	0.15
t-stat	[-1.20]	[0.20]	[-0.15]		[1.82]	[2.11]	[-2.42]	[-1.34]	[4.46]	[0.76]	[-5.01]	[1.68]	
Coeff				45.28*									0.01
t-stat				[1.81]									
Coeff	-1.11	0.35		42.20*									0.01
t-stat	[-1.34]	[0.31]		[1.69]									
Coeff	-0.49	0.60		-120.41*	5.38**	250.38***	-16.40***	-10.23	2.99***	2.73	-2.26***	190.45**	0.16
t-stat	[-0.73]	[0.48]		[-1.66]	[2.44]	[3.24]	[-2.72]	[-1.46]	[4.61]	[1.18]	[-5.67]	[2.07]	

Instead of specifying a flexible nonlinear function, HKM use the inverse squared intermediary equity ratio as a predictor of excess returns. This is the functional form implied by the He and Krishnamurthy (2013) model. We compare the predictive ability of the fully flexible nonlinear function with that of the inverse squared HKM ratio in the bottom three rows. Consistent with the above results as well as with those of HKM (Table 15), we find that a higher reciprocal of the squared HKM ratio (higher leverage) predicts higher future excess returns. However, in a joint regression with the nonlinear forecasting function of broker-dealer book leverage and the benchmark return predictors, the coefficient on the inverse squared HKM ratio switches sign. Hence, the time series evidence for the net worth model is sensitive to the inclusion of common predictor variables.

The bottom panel of Table 7 repeats these regressions for the sample excluding the financial crisis. While some of the nonlinear forecasting functions remain significant individually, they lose their significance when controlling for benchmark return predictors. We interpret this as evidence that nonlinearities in the pricing of risk via intermediaries are considerably more pronounced in times of market stress. Notably, the only intermediary variable that remains significant in this shorter sample is the inverse squared HKM ratio which again switches to a negative predictive coefficient when controlling for benchmark return predictor variables. In sum, the results in this section underscore our prior findings. High leverage is associated with a strongly negative risk premium, in line with models based on risk based capital constraints. In contrast, there is no systematic support for models with net worth constraints.

4.5 Robustness Analysis

In this section, we demonstrate the robustness of our main result along several dimensions. First, we show that the cross-sectional pricing ability of the break-adjusted broker-dealer book leverage factor does not depend on the number of identified structural breaks. Second, we show that the choice of considering U.S.-owned broker-dealer equity instead of total broker-dealer equity does not affect the cross-sectional pricing power of the resulting series. Finally, we also show that our finding that the HKM factor switches from a significant positive to a negative but insignificant price of risk once we control also for SMB and HML is not specific to our cross-section of test assets. Instead, we find the same result for almost all of the individual asset classes considered in HKM. Finally, we compare our cross-sectional results with those of Adrian, Etula, and Muir (2014) who construct their broker-dealer leverage factor in a slightly different way.

4.5.1 Adjusting broker-dealer book leverage for only one break

As discussed in Section 3, applying the Bai and Perron (1998) test for the number of structural breaks in the mean of a time-series to the log broker-dealer book leverage series, the BIC criterion and the modified Schwartz criterion suggested by Liu, Wu, and Zidek (1997) both suggest the total number of breaks to be equal to four. Hence, in our baseline results we have chosen to adjust the log broker-dealer leverage series by four breaks following the method suggested in Lettau and Van Nieuwerburgh (2007). However, applying the $sup-F$ test proposed by Bai and Perron (1998) to test for the number of l breaks against the alternative of $l+1$ breaks, we fail to reject the null of only one break (second panel of Table 8).

We therefore also consider an alternative specification where we adjust the log broker-dealer leverage series by only one break. The top panel of Figure 4 in Appendix B shows the original and break-adjusted time-series. Table 9 repeats the cross-sectional asset pricing test from Table 2 using the AR(1) innovations to this alternative break-adjusted broker-dealer book leverage series as the pricing factor. The results show that the ability of the factor to explain the cross-section of equity and Treasury returns is hardly affected by this change. Log broker-dealer book leverage adjusted for one break retains its strongly statistically significant positive price of risk and the adjusted R^2 and $MAPE$ indicate a similar model fit, both when considered only along with MKT, as well as when considered jointly with the broker-dealer book equity ratio, with the HKM factor, and with SMB and HML. Moreover, our earlier finding that the risk premium on the HKM factor switches sign and becomes insignificant when considered jointly with the Fama-French factors remains intact also in this specification.

Unreported results show that the log broker-dealer leverage series adjusted by only one break loses its time-series predictability for the market return over the full sample 1968-2016, but remains a highly statistically significant return predictor over the sample 1990-2016.

4.5.2 Considering also foreign-owned broker-dealer book equity

In our baseline specification, we compute the broker-dealer book leverage and equity ratio considering only broker-dealer equity that is not owned by foreign entities. In an alternative specification, we also include the equity of foreign institutions in U.S.-domiciled broker-dealer affiliates. We obtain this series by not subtracting the FDI portion of broker-dealer liabilities from their total liabilities. The resulting book leverage ($BDblev^{\mathrm{All}}$) and book equity ratio relative to nominal GDP ($BDbe2gdp^{\mathrm{All}}$) as well as their detrended versions are provided in the middle and bottom panels of Figure 4.

Table 10 in Appendix B repeats the cross-sectional exercise using the AR(1) innovations to these two measures as pricing factors. While the broker-dealer leverage factor remains significant controlling only for MKT (columns (1) and (2)), it loses its significance also adding the HKM factor (columns (3) and (4)). However, as above also adding SMB and HML as additional controls, the HKM factor loses its significance and switches to a negative price of risk, while both factors based on total broker-dealer book equity become statistically significant at the 5% level (10% level also controlling for HKM), with a price of risk indicating that leverage is procyclical.[10]

4.5.3 Using the HKM cross-section of assets

To cover a sample period of sufficient length and to facilitate comparison with other studies we focus on the sample period 1968-2016 in our baseline analysis. Over this long sample period, unfortunately we only have equity and Treasury returns available, as Adrian, Etula, and Muir (2014). In contrast, HKM study seven different asset classes available over shorter sample

[10]In unreported results we also considered a broker-dealer leverage measure that relates only the book equity of foreign institutions in U.S.-domiciled broker-dealer affiliates to total broker-dealer financial assets. We equally find that this leverage factor commands a positive price of risk in cross-sectional regressions.

periods. In this section, we study the pricing ability of our broker-dealer book leverage factors for the cross-sections of test assets used in HKM.

As discussed above, we do not include an intercept in our cross-sectional regressions as standard asset pricing theory implies that in correctly specified pricing models the exposure to risk factors should fully capture the cross-sectional variation of expected excess returns. Table 11 reports the results. The top panel replicates Table 18 in HKM, which provides estimation results using the HKM factor in cross-sectional asset pricing tests without an intercept.[11]

As in their analysis, the HKM factor is strongly significant at least at the 10% level with a positive price of risk in six out of seven considered asset classes. We have seen before that the HKM factor loses its significance on our cross-section of test assets once we also control for SMB and HML. We repeat this exercise in the middle panel of the table using the same test assets as HKM. The results show that this also occurs in the original HKM data, except for the cross-section of foreign exchange portfolios and the combination of all asset classes (shown in the last two columns). Given the relatively strong correlation of the HKM factor with SMB shown in Table 1, this may not be surprising. We conclude that the HKM result of a strongly significant positive price of risk of the primary dealer capital ratio is not robust to the inclusion of common risk factors.

HKM show that the AEM factor has a statistically insignificant price of risk in five of their seven asset classes while it commands a statistically significant negative price of risk on the cross-section of Credit Default Swap (CDS) returns. Using our broker-dealer book leverage factor we find broadly similar results: a statistically significant positive price of risk for the cross-section of 25 size and book to market sorted stock portfolios, a strongly significant positive price of risk for U.S. government and corporate bond portfolios, a statistically significant negative price of risk for CDS returns, and insignificant prices of risk for all remaining asset classes from HKM.

[11] The values for R^2 differ considerably. To the best of our understanding, this is because HKM estimate the coefficient of determination as $R^2 = \frac{var(\hat{\beta}_i \hat{\lambda})}{var(\bar{r}_i)}$, obtaining R^2 values above one in some specifications. We instead compute it as $R^2 = 1 - \frac{var(\hat{\alpha}_i)}{var(\bar{r}_i)}$. The formulas are only equivalent if $var(\bar{r}_i) = var(\hat{\alpha}_i) + var(\hat{\beta}_i \hat{\lambda})$ which need not generally be the case in GMM estimation.

In sum, the results in this section show that our main results are robust to variations in the measurement of broker-dealer book leverage and equity when considering U.S. equity portfolio and bond returns as test assets. However, our pricing factors do not explain well alternative asset classes. When controlling for benchmark pricing factors the same appears to be true for the HKM factor.

4.5.4 Comparison with AEM

As a final robustness check, we further compare the pricing ability of our broker-dealer factors with the book leverage factor by Adrian, Etula, and Muir (2014) (AEM factor). Though using the same underlying U.S.-owned broker-dealer book leverage series as input, this is constructed in a somewhat different way than our broker-dealer leverage factor. Adrian, Etula, and Muir (2014) build their factor as seasonally adjusted log changes in the level of broker-dealer leverage. Instead, we adjust the log book leverage series for breaks in the mean and then obtain our factor as the innovation to an autoregressive process of order one of this adjusted series. As shown in Table 1, the updated AEM factor is relatively strongly correlated with the BDblev and BDbe2gdp factors, reflecting the minor differences in factor construction. Table 12 provides cross-sectional regression results for the AEM factor, individually and jointly with our two broker-dealer factors. The first two columns confirm the finding by Adrian, Etula, and Muir (2014) that their broker-dealer factor earns a statistically significant positive price of risk in a cross-section of U.S. equity and Treasury portfolios, also when controlling for the three Fama-French factors. Adding the BDblev factor (column 3), both leverage factors are highly statistically significant, the cross-sectional R^2 increases and the MAPE declines relative to the model with only the AEM and MKT factors, showing that there is some incremental pricing information contained in the broker-dealer book leverage factor that we construct. When adding the broker-dealer equity to GDP ratio factor (column 4) this retains its negative coefficient while the overall pricing performance does not further increase. The risk premiums associated with all three broker-dealer factors are statistically significant in a joint regression that further controls for SMB and HML (column 5). In sum, these results show that different measures of broker-dealer book leverage are consistent with models based on risk based capital constraints.

5 Conclusion

Asset pricing theories in which financial intermediaries, not representative consumers, are the marginal investor, have attracted increasing attention since the financial crisis of 2007-2009. The theories differ along key dimensions. While some emphasize the role of intermediary equity as the key, procyclical variable, other theories emphasize intermediary leverage.

In this paper, we test the predictions from alternative intermediary asset pricing theories empirically. We find strong support for intermediary leverage-based theories. Innovations to broker-dealer book leverage are associated with a strongly significant positive price of risk, suggesting that investors command a premium for holding assets with exposure to intermediary leverage. Similarly, high intermediary leverage predicts low future excess returns, highlighting that intermediaries' balance sheet expansion may play a role in asset price booms when expected returns are compressed.

We find little support for equity-based intermediary asset pricing theories. In contrast to theoretical predictions, exposure to book equity of broker-dealers commands a highly significant negative risk premium. Moreover, high intermediary book equity predicts high excess returns. These findings are consistent for both linear and nonlinear specifications in the intermediary risk premium.

For macroeconomic modeling, our results imply that intermediary leverage should emerge endogenously as a procyclical variable, as is the case in theories with risk based leverage constraints, such as Fostel and Geanakoplos (2008), Brunnermeier and Pedersen (2009), Adrian and Boyarchenko (2013), and Danielsson, Shin, and Zigrand (2012). More generally, our findings highlight that intermediaries are central to the pricing of risk.

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Appendix - For Online Publication

A Data Construction

A.1 Financial Accounts (Flow of Funds) of the U.S.

We obtain book equity, total financial assets, and total liabilities for broker-dealers from Table L.130 of the Financial Accounts of the United States database. The three series are computed based on brokers and dealers' submissions of Form X-17A-5, the "Financial and Operational Combined Uniform Single" (FOCUS) Report, to the Securities and Exchange Commission (SEC) which all brokers and dealers registered with the SEC must complete. The SEC uses this information to assess broker-dealers' financial and operating conditions, and provides the data to the Federal Reserve Board of Governors who constructs the Flow of Funds (FoF).

Until 2016Q2, total liabilities of U.S. brokers and dealers in the FoF were computed as total liabilities from the FOCUS reports plus Foreign Direct Investment in U.S. Security Brokers and Dealers. The latter series is computed by the Bureau of Economic Analyses (BEA) as part of their "Quarterly Survey of Foreign Direct Investment in the United States" (FDIUS).[12] The FDIUS industry statistics are based on the industry of the consolidated U.S. enterprise. This means that the transactions, positions, and income statistics are published based on the industry with the largest revenues for the consolidated U.S. affiliate. For example, if a U.S. affiliate of a German bank derived more revenues from "securities and commodity contracts intermediation and brokerage" than from "bank branches or agencies" the BEA will classify that entity in the broker-dealer category.

If the U.S. affiliate and the foreign parent are both in the finance industry then the intercompany debt between the affiliate and the foreign parent group is not included in direct investment. The FDI series for securities brokers and dealers will include equity investment of the foreign parent in the U.S. affiliate and, if the foreign parent is not in the finance industry, any net debt (payables less receivables) owed by the U.S. affiliate to the foreign parent group. While debt and equity are not separately published for securities brokers and dealers, the finance and insurance sector (which includes brokers and dealers) typically has a small amount of net debt relative to equity.[13]

To account for the fact that the broker-dealer FDI series from the BEA largely contains equity and not debt, the Board of Governors has been subtracting FDI from total liabilities starting in 2016Q3.[14] Accordingly, total liabilities of brokers and dealers in the FoF data have been revised downwards. Total liabilities are now computed as

Total Liabilities = (Liabilities from FOCUS + FDI) - FDI,

whereas before they used to be calculated as

[12]The methodology is described here: `https://www.bea.gov/resources/methodologies/fdius-2012-benchmark`.

[13]These are available here: `https://apps.bea.gov/international/xls/fdius-current/fdius-position-by-account-selected-industries-2010-2017.xlsx` for the years 2010-2017. We thank Patricia Abaroa from the BEA for very helpful information on this issue.

[14]While there is no official document outlining this change, we thank Marco Cagetti from the Board of Governors of the Federal Reserve for confirming it in personal communication.

Total Liabilities = Liabilities from FOCUS + FDI.

The implicit argument behind this change is that if FDI was equity, it shouldn't be counted as part of liabilities. If instead it is debt, then it is already included in the liabilities stated in the FOCUS reports.

Given the available data, it is impossible to exactly single out the equity and liabilities portion of U.S. broker-dealer subsidiaries of foreign institutions. We therefore compute total broker-dealer book equity using two different approaches. In our baseline approach, we construct an augmented measure of total liabilities by adding the FDI series (FA663192003) to total liabilities (FL664190005), in line with the FoF definition until 2016Q2. We then obtain book equity by subtracting the augmented liabilities from total financial assets (FL664090005). We compute book leverage as the ratio of total financial assets and the FDI-adjusted book equity, see Section 3. This variable construction delivers broker-dealer book leverage consistent with that used in several previous studies (e.g. Adrian and Shin (2010), Adrian, Etula, and Muir (2014)), even using data published after 2016Q3. As an alternative, we use the current definition of total liabilities and equity and compute book leverage and the equity ratio as described in Section 3. We assess the robustness of our findings with respect to this alternative series in Section 4.5.

Finally, we use total nonfinancial sector wealth from the FoF as an alternative denominator in our construction of the broker-dealer equity ratio. This series is the sum of the total assets of households and nonprofit organizations, nonfinancial corporate business, nonfinancial noncorporate business (FL152000005+FL102000005+FL112000005), minus the sum of the total liabilities of these three types of entities (FL154190005+FL104190005+FL114190005).

A.2 Compustat-CRSP

We construct aggregate market equity for the broker-dealer sector using the monthly stock file from CRSP. In order to account for the changing ownership of institutions, a merger adjustment is performed. This entails using the new CRSP permno (nwperm), and assigning to each firm the ultimate acquirer, i.e. if firm A is acquired by B and B is acquired by C, a variable "acquirer" is created whose value is equal to the permno of C for the entire lives of A, B, and C. Before collapsing by acquirer, a quarterly dataset is generated by compounding end of month returns to the quarterly frequency. Then, the dataset is collapsed by acquirer-quarter, summing up total market equity and computing a value-weighted average return. This gives a historical time-series of effective market equity and returns of merger-adjusted entities. We then merge the permno-acquirer link generated by the CRSP data to the Compustat Fundamentals Quarterly File and apply the same merger adjustment — summing up total assets (atq) and liabilities (ltq) by acquirer-quarter. Finally, the merger adjusted CRSP and Compustat data are merged together by acquirer-quarter where acquirer is now taken to be "permno". We assign to the entire history of each merger-adjusted firm the most recently available SIC code from CRSP and the most recently available permco from Compustat. The universe of broker-dealers is defined to be firms with SIC codes 6712 or 6211. Additionally, Merrill Lynch, Bear Stearns, Morgan Stanley, Lehman Brothers, and Goldman Sachs are hard-coded as broker-dealers. Within each quarter, firms with growth rates less than the 1% and greater than the 99% percentiles are dropped to adjust for outliers. Aggregate broker-dealer market equity is then calculated by computing the average within the universe of firms already defined.

A.3 Structural Break Tests

This appendix summarizes the results of structural break tests applied to the various intermediary balance sheet factors. As in Lettau and Van Nieuwerburgh (2007), we rely on the test proposed by Bai and Perron (1998) to identify structural breaks in individual economic time series. A central input to the Bai-Perron procedure is the maximum number of allowed breaks. We follow Rapach, Strauss, and Zhou (2010) and set an upper limit of eight breaks.[15] The error terms are allowed to be heteroskedastic and autocorrelated. We follow the suggestion of Bai and Perron (2003) and first estimate the $UD\ max$ statistic to test if at least one break is present. Panel 4 of Table 8 shows that the null hypothesis of no break is strongly rejected against the alternative of one to eight breaks for both log broker-dealer book leverage for U.S.-owned ($lnBDblev$) and the log broker-dealer leverage for all U.S.-domiciled broker-dealers ($lnBDblev^{\text{All}}$). We further estimate the $supF(0, l)$ statistic to test the null of no breaks against the alternative of l breaks. For $lnBDblev$ we strongly reject the null of no break against any number of breaks between one to eight and for $lnBDblev^{\text{All}}$ we strongly reject the null for four to eight breaks, see Panel 1 in Table 9.[16] This is strong evidence for structural breaks. In order to determine the exact number of breaks, we follow the sequential test of Bai and Perron (1998, 2003). The $supF(k, k + 1)$ statistic tests the null of k breaks against the alternative of $k + 1$ breaks. We select the number of breaks m such that the test $supF(k, k+1)$ is insignificant for $k \geq m$. For $lnBDblev$ the sequential procedure is significant for $supF(3, 4)$ (see Panel 2) but insignificant for $k \geq 4$ (not shown). We therefore choose four breaks as our baseline. For $lnBDblev^{\text{All}}$ we select five breaks because the sequential approach is insignificant for $k \geq 5$ (not shown). Two alternative criterion-based approaches to determine the number of structural breaks are the BIC and Liu, Wu, and Zidek (1997) (LWZ henceforth) tests. For the U.S. leverage ratio the BIC and LWZ tests select four breaks, thus delivering identical results to the sequential approach. For the total broker-dealer leverage series the BIC and LWZ tests detect six breaks, one more than the sequential approach. Since Bai and Perron (2003) argue that the sequential procedure identifies breaks more precisely than BIC and LWZ in the presence of serial correlation or heterogenous segments, we adjust the series for five breaks. The last panel in Table 8 performs ADF tests on both the unadjusted and adjusted series and tests the null of a unit root. We cannot reject the null of a unit root for the unadjusted series of log U.S. book leverage and for log total book leverage. The break-adjusted series, however, strongly reject the null. This indicates that the break-adjustments generate stationary time series.

As discussed above, the choice of the maximum number of allowed breaks is central for the analysis. To show that results for log U.S. book leverage are robust to the exact choice of break-adjustments we repeat the Bai-Perron procedure with a maximum number of five breaks (trimming value of 0.15). For this specification (results are not shown) we only estimate one break in 1991Q1.

[15] This corresponds to a trimming value of 0.10. The sample horizon is 1967Q4 to 2016Q4 (T=197) such that the factors (which are AR(1) innovations) are available from 1968Q1 to 2016Q4.

[16] Results are only shown up to five breaks in order to conserve space.

Table 8: **Tests for Multiple Structural Breaks in the Mean**

This table reports Bai and Perron (1998) multiple structural break test results for log U.S. broker-dealer book leverage and log total broker-dealer book leverage. The sample length is 1967Q4 to 2016Q4. We allow for a maximum number of eight breaks and set a trimming value of 0.1. Residuals are allowed to be heteroscedastic and autocorrelated. The first panel reports $supF(0,l)$ statistics where l is the number of breaks under the alternative. The second panel reports $supF(k,l)$ statistics where k is the number of breaks under the null and l the number of breaks under the alternative. The third panel reports selected estimates of break dates from the Bai and Perron (1998) procedure. The fourth panel reports the UD_{max} test statistic of a one-sided test of the null hypothesis of zero breaks against the alternative of an unknown number of breaks up to a maximum of eight breaks; BIC and LWZ report the number of breaks chosen by the Bayesian Information Criterion (BIC) and the Liu, Wu, and Zidek (1997) (LWZ) criterion. $***$ denotes significance at 1%, $**$ significance at 5%, and $*$ significance at the 10% level. The bottom panel reports test statistics and p-values of an Augmented Dickey-Fuller test, testing the null of a unit root against the alternative of an AR(1) process.

	$supF(0,1)$	$supF(0,2)$	$supF(0,3)$	$supF(0,4)$	$supF(0,5)$
$lnBDblev$	22.4556$***$	33.2954$***$	38.7780$***$	58.7702$***$	54.6517$***$
$lnBDblev^{\mathrm{All}}$	4.0339	8.4870$*$	4.3099	12.1291$***$	26.137$***$
	$supF(0,1)$	$supF(1,2)$	$supF(2,3)$	$supF(3,4)$	$supF(4,5)$
$lnBDblev$		4.5244	1.9067	15.5400$***$	0.6490
$lnBDblev^{\mathrm{All}}$		3.6701	3.6701	66.1480$***$	66.1480$***$
			Date(s)		
$BDblev$	1991Q1			1972Q4, 1977Q4 1984Q1, 1992Q4	
$BDblev^{\mathrm{All}}$					1973Q1, 1978Q1 1984Q1, 1990Q3 2009Q1
	$\mathrm{UD}_{\max}$	BIC	LWZ		
$BDblev$	65.3391$***$	4	4		
$BDblev^{\mathrm{All}}$	76.5004$***$	6	6		
	ADF Test	p value			
$BDblev$	-0.4781	0.4758			
$BDblev$ (1 break)	-3.9729	<0.0010			
$BDblev$ (4 breaks)	-5.7491	<0.0010			
$BDblev^{\mathrm{All}}$	-0.4103	0.5006			
$BDblev^{\mathrm{All}}$ (5 breaks)	-5.8030	<0.0010			

B Robustness Analysis

Table 9: **Cross-Sectional Asset Pricing - Alternative Break Adjustment**

This table reports prices of risk for different intermediary pricing models. Each model is estimated using two-pass regressions as described in Section 2.2.1. The GMM t-statistics are in parentheses and adjust for cross-asset correlation in the residuals and for estimation error of the betas. "BDblev factor (1 break)" is the AR(1) innovation of the broker-dealer book leverage series adjusted for one break. "BDbe2gdp factor" is the broker-dealer book equity to GDP ratio. The "HKM factor" is the pricing factor constructed by He, Kelly, and Manela (2017), and has been obtained from Asaf Manela's website. "MKT", "SMB', and "HML" are the three Fama-French pricing factors. The test assets are 25 size and value sorted portfolios, and ten momentum sorted decile portfolios (all from Ken French's website), as well as five constant maturity Treasury returns for maturities ranging from 1 through 10 years, obtained from Anh Le. Mean absolute pricing errors (MAPE) are in percentage terms. The sample period is 1968Q1 to 2016Q4 or 1970Q1 to 2016Q4 for the models involving the HKM factor. $***$ denotes significance at 1%, $**$ significance at 5%, and $*$ significance at the 10% level.

	(1)	(2)	(3)	(4)	(5)	(6)
			1968Q1 - 2016Q4			
BDblev factor (1 break)	0.210***	0.245***	0.181***	0.225***	0.271***	0.243***
	[3.345]	[3.675]	[2.822]	[3.400]	[2.857]	[2.695]
BDbe2gdp factor		-0.207***		-0.197***	-0.185***	-0.175***
		[-3.015]		[-3.345]	[-2.970]	[-2.615]
HKM factor			3.914**	3.383		-1.447
			[2.004]	[1.544]		[-0.380]
MKT	1.991***	1.997***	1.865***	1.878***	1.530**	1.602**
	[2.905]	[2.801]	[2.838]	[2.831]	[2.308]	[2.432]
SMB					0.610	0.573
					[1.587]	[1.502]
HML					1.272***	1.102**
					[2.771]	[2.441]
R^2	0.435	0.512	0.466	0.550	0.700	0.686
$MAPE, \%$	0.538	0.503	0.486	0.454	0.345	0.343
Assets	40	40	40	40	40	40
Quarters	196	196	196	196	196	196

Table 10: **Cross-Sectional Asset Pricing – Including Foreign Owned Broker-Dealer Equity**

This table reports prices of risk for different intermediary pricing models. Each model is estimated using two-pass regressions as described in Section 2.2.1. The GMM t-statistics are in parentheses and adjust for cross-asset correlation in the residuals and for estimation error of the betas. "$BDblev^{\mathrm{All}}$" is the AR(1) innovation of the broker-dealer book leverage factor computed using the book equity of all U.S.-domiciled broker-dealers, see Section 4.5.2. "$BDbe2gdp^{\mathrm{All}}$" is the corresponding book equity to GDP ratio. The "HKM factor" is the pricing factor constructed by He, Kelly, and Manela (2017), and has been obtained from Asaf Manela's website. "MKT", "SMB', and "HML" are the three Fama-French pricing factors. The test assets are 25 size and value sorted portfolios, and ten momentum sorted decile portfolios (all from Ken French's website), as well as five constant maturity Treasury returns for maturities ranging from 1 through 10 years, obtained from Anh Le. Mean absolute pricing errors (MAPE) are in percentage terms. The sample period is 1968Q1 to 2016Q4 or 1970Q1 to 2016Q4 for the models involving the HKM factor. $***$ denotes significance at 1%, $**$ significance at 5%, and $*$ significance at the 10% level.

	(1)	(2)	(3)	(4)	(5)	(6)
			1968Q1 - 2016Q4			
$BDblev^{\mathrm{All}}$ factor	0.087**	0.088**	0.057	0.057	0.164**	0.106*
	[2.282]	[2.195]	[1.594]	[1.526]	[2.023]	[1.798]
$BDbe2gdp^{\mathrm{All}}$ factor		-0.001		-0.010	-0.045**	-0.029*
		[-0.077]		[-0.730]	[-2.113]	[-1.762]
HKM factor			4.175**	3.988**		-5.025
			[2.257]	[2.019]		[-1.173]
MKT	1.907***	1.931***	1.765***	1.851***	1.575**	1.670***
	[2.958]	[3.065]	[2.788]	[2.905]	[2.397]	[2.592]
SMB					0.588	0.509
					[1.290]	[1.223]
HML					1.152**	0.839*
					[2.237]	[1.654]
R^2	0.211	0.212	0.213	0.231	0.535	0.530
$MAPE, \%$	0.562	0.566	0.545	0.575	0.428	0.424
Assets	40	40	40	40	40	40
Quarters	196	196	196	196	196	196

Table 11: **Cross-Sectional Asset Pricing - HKM data**

This table reports prices of risk for several model specifications. In the top panel, the pricing factors are HKM factor and MKT, the excess return on the CRSP market portfolio. In the middle panel, the Fama-French factors SMB and HML are added as pricing factors. In the bottom panel, the pricing factors are the broker-dealer book leverage factor, the broker-dealer book equity to GDP ratio, and the excess return on the CRSP market portfolio. The prices of risk are estimated for the seven different asset classes of HKM, as well as for all portfolios together (*All*). The different portfolios are (1) 25 size and value sorted portfolios, (2) ten maturity-sorted government bond portfolios, (3) six sovereign bond portfolios, (4) 18 option portfolios, (5) 20 CDS portfolios, (6) 23 commodity portfolios, and (7) 12 foreign exchange portfolios. The GMM t-statistics are in parentheses and adjust for cross-asset correlation in the residuals and for estimation error of the betas. Mean absolute pricing errors (MAPE) are in percentage terms. The sample period is 1970Q1 to 2012Q4. $***$ denotes significance at 1%, $**$ significance at 5%, and $*$ significance at the 10% level.

	$FF25$	$USbonds$	$Sovbonds$	$Options$	CDS	$Commod$	FX	All
HKM Factor on HKM Asset Classes								
HKM factor	7.818***	6.997***	8.132***	24.690	6.568***	5.552*	23.747**	9.244***
	[3.812]	[3.208]	[3.492]	[1.392]	[2.580]	[1.742]	[2.570]	[2.833]
MKT	1.588**	4.890**	1.484	1.499	0.358	1.247	6.639	1.518
	[2.087]	[2.155]	[0.327]	[1.113]	[0.152]	[0.676]	[1.174]	[0.920]
R^2	0.526	0.548	0.788	0.984	0.549	0.133	0.484	0.589
$MAPE,\%$	0.344	0.247	0.344	0.157	0.260	1.350	0.496	0.624
Assets	25	20	6	18	20	23	12	124
Quarters	172	148	65	103	47	105	135	172
Additionally controlling for SMB and HML								
HKM factor	0.183	-1.159	1.926	15.997	5.067	3.666	16.422*	8.928**
	[0.069]	[-0.205]	[0.336]	[1.149]	[1.535]	[0.809]	[1.917]	[2.473]
MKT	1.505**	1.647	7.949	2.560	-0.110	0.645	6.942	1.358
	[2.137]	[0.446]	[0.622]	[1.583]	[-0.047]	[0.309]	[1.439]	[0.860]
SMB	0.502	0.628	-4.650	7.814	6.149**	-3.344	6.439**	0.348
	[1.194]	[0.188]	[-0.636]	[1.330]	[2.111]	[-1.253]	[1.962]	[0.360]
HML	1.332***	8.805	-16.475	5.588	-3.289	3.298	3.557	2.236
	[2.592]	[1.437]	[-1.081]	[0.463]	[-1.155]	[1.113]	[0.703]	[1.614]
R^2	0.652	0.925	0.967	0.992	0.747	0.409	0.577	0.582
$MAPE,\%$	0.303	0.080	0.165	0.118	0.251	1.122	0.377	0.637
Assets	25	20	6	18	20	23	12	124
Quarters	172	148	65	103	47	105	135	172
BD Book Leverage and Equity Factors on HKM Asset Classes								
BDblev factor	0.200*	0.122***	-0.047	-0.235	-0.270**	-0.047	-0.465	0.067
	[1.772]	[2.860]	[-0.135]	[-0.692]	[-2.056]	[-1.283]	[-1.068]	[0.987]
BDbe2gdp factor	-0.174**	-0.043	-0.150	0.301	0.243*	0.068	0.157	-0.029
	[-2.281]	[-1.025]	[-0.380]	[1.123]	[1.884]	[1.530]	[0.947]	[-0.394]
MKT	1.826**	4.435*	5.311	1.438	3.095	-0.098	-2.703	1.950
	[2.310]	[1.950]	[0.905]	[0.913]	[1.414]	[-0.031]	[-0.266]	[1.114]
R^2	0.334	0.836	0.761	0.956	0.869	0.167	0.289	0.260
$MAPE,\%$	0.458	0.119	0.368	0.258	0.134	1.209	0.527	0.873
Assets	25	20	6	18	20	23	12	124
Quarters	172	148	65	103	47	105	135	172

Table 12: **Cross-Sectional Asset Pricing - Comparison with AEM**

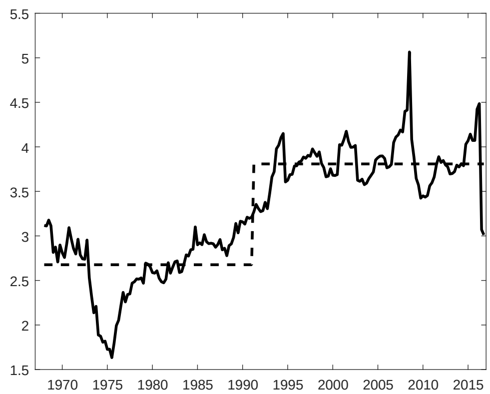
This table compares prices of risk for the two broker-dealer pricing factors with the Adrian, Etula, and Muir (2014) factor updated through 2016Q4 using the FDI-adjusted broker-dealer equity series as input. Each model is estimated using the two-stage regression approach described in Section 2.2.1. The GMM t-statistics are in parentheses and adjust for cross-asset correlation in the residuals and for estimation error of the betas. The test assets are 25 size and value sorted portfolios, and ten momentum sorted decile portfolios (all from Ken French's website), as well as five constant maturity Treasury returns for maturities ranging from 1 through 10 years, obtained from Anh Le. Mean absolute pricing errors (MAPE) are in percentage terms. The sample period is 1968Q1 to 2016Q4. $***$ denotes significance at 1%, $**$ significance at 5%, and $*$ significance at the 10% level.

	(1)	(2)	(3)	(4)	(5)
			1968Q1 - 2016Q4		
AEM factor	22.093***	31.841**	24.141***	23.769***	29.629***
	[3.060]	[2.487]	[3.354]	[3.653]	[2.790]
BDblev factor			0.221***	0.219***	0.250**
			[3.306]	[3.346]	[2.264]
BDbe2gdp factor				-0.175***	-0.201**
				[-2.945]	[-2.525]
MKT	1.500**	1.677***	1.685***	1.677***	1.626**
	[2.155]	[2.608]	[2.658]	[2.659]	[2.469]
SMB		0.489			0.520
		[1.226]			[1.348]
HML		1.401***			1.358***
		[2.588]			[2.713]
R^2	0.657	0.729	0.720	0.721	0.750
$MAPE, \%$	0.342	0.315	0.300	0.300	0.307
Assets	40	40	40	40	40
Quarters	196	196	196	196	196

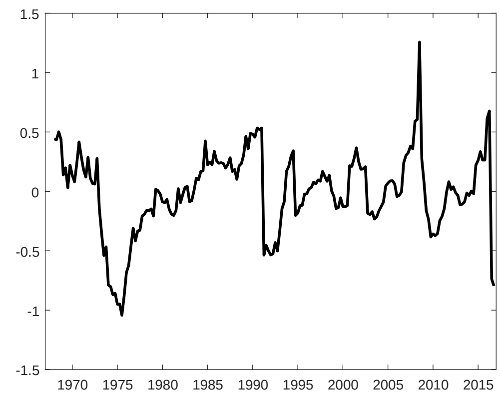
Figure 4: **Alternative BD Book Leverage and Equity Ratios**

The top panel plots the log U.S. broker-dealer book leverage ratio (solid line) along with its subsample means as identified by the Bai and Perron (1998) procedure with one break (dashed line) on the left, and the difference between the two series on the right. The middle panel plots the log total U.S. broker-dealer book leverage (including foreign-owned) (solid line) along with its subsample means as identified by the Bai and Perron (1998) procedure on the left, and the difference between the two series on the right. The bottom panel plots the log total U.S. broker-dealer book equity (including foreign-owned) to GDP ratio (solid line) along with its linear-quadratic trend (dashed line) on the left, and the difference between the two series on the right.

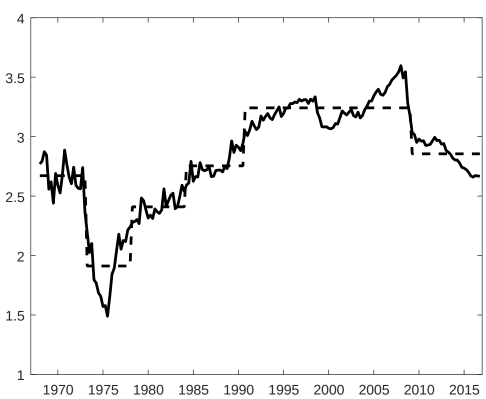
Log BD Book Leverage



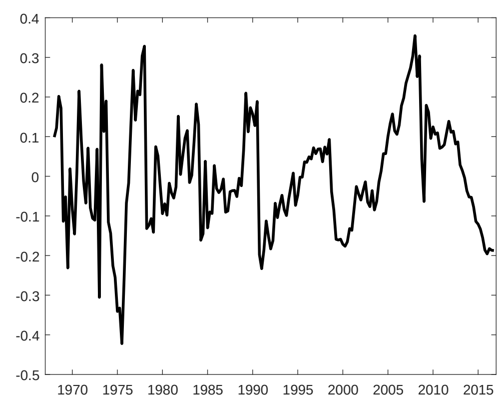
Log BD Book Leverage adjusted for one break



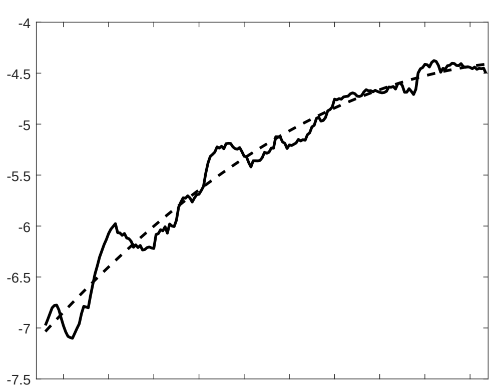
Log BD Book Leverage (incl. FDI)



Log BDblev (incl. FDI) adjusted for five breaks



Log BD Book Equity (incl. FDI) to GDP Ratio



Detrended Log BDbe (incl. FDI) to GDP Ratio