Intermediary Asset Pricing and the Swedish Equity Market

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ABSTRACT

Increasingly, the focus of asset pricing research has shifted from the average household to the more sophisticated financial intermediaries. Our paper is the first to introduce this notion to the Swedish equity market by testing two intermediary asset pricing models, one based on shocks to broker-dealer leverage, and the other based on the return on aggregate wealth together with shocks to the primary dealer capital ratio. While both these models outperform standard benchmark models on US financial markets, applied to the Swedish equity market, only the model based on broker-dealer leverage outperforms the benchmarks, with a total mean absolute pricing error of 6.8% per annum. Our results do not prove the validity of the model, but rather bring into question the validity of the standard benchmarks.

Keywords: Financial intermediaries, Swedish equity market, asset pricing, leverage ratio

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I. Introduction

In finance theory, asset pricing models are based on the representative investor's marginal value of wealth as a driver of asset prices. This is since the expected payoff of assets tomorrow should be reflected in their prices today, and the payoffs will be discounted using a discount factor that accounts for the representative investor's marginal utility gained from the *uncertain* payoffs in the future. Thus, assets which are expected to pay off well in future bad states of the world, say in a recession (where the marginal value of wealth is high), should be expensive today, whereas assets expected to pay off well only when the economy is good (and the marginal value of wealth is low), should be cheap today. Historically, the representative investor has been assumed to be the average household, and measuring their marginal value of wealth should therefore provide us with the information to price any type of asset. However, households have been presumed to fulfill a number of assumptions, for instance that they do not face transaction costs, or that they are able to engage in complicated trading strategies. When examining the households, it cannot be said that they live up to these assumptions, and therefore, they may not prove to be the representative investor on which to base the discount factor.

Recently, financial research has suggested that, instead of regarding the average household as the representative investor, one should start looking at financial intermediaries and try to measure their marginal value of wealth instead, since the intermediaries live up to these assumptions. Financial intermediaries include banks, stock-brokers, and even hedge funds. We have decided to base our research on intermediary asset pricing in Sweden on two papers: one by Adrian et al. (2014a), who use broker-dealers registered at the Federal Reserve as the representative investor, and the other one is by He et al. (2016), who use primary dealers to the Federal Reserve as representative investors. These two models represent two different frameworks within intermediary asset pricing, the debt constraint and equity constraint frameworks, respectively. The debt constraint framework entails falling levels of leverage in bad times, whereas the equity constraint framework suggests the opposite.

Our analysis is performed by running full sample, two-pass regressions as suggested in traditional asset pricing literature. 21 portfolios are used as test assets, including portfolios sorted on size and book-to-market (6), momentum (10), and industry (5). The objective of including different portfolio sorts other than size and book-to-market is to increase power and to address contemporary critique of traditional empirical methods. The performance of the models are evaluated based on their total mean absolute pricing error (MAPE) on an annual basis compared with standard CAPM and Fama-French three-factor benchmarks. Benchmarks are matched in time with the two models for comparability. The total MAPE is used instead of adjusted R^2 as our main tool of evaluation in order to address the large *average* pricing errors across portfolio sorts. Our results suggest that an asset pricing model based on shocks to intermediary leverage performs better than the traditional benchmarks with a total annual MAPE of 6.8%, compared with 22.0% for the CAPM and 27.0% for the Fama-French three-factor model, on the Swedish equity market. Reversely, a model based on the return on aggregate wealth and shocks to the intermediary capital ratio performs in line with a total annual MAPE of 26.9%, compared with 26.9% for the CAPM and 31.9% for the Fama-French three-factor model. It should be emphasized that the performance of the two intermediary asset pricing models cannot be compared with each other, since the sample periods do not match. While statistically insignificant, our results seems to give credence to the debt constraint framework within intermediary asset pricing theory. Since we are, to the best of our knowledge, the first to test any intermediary asset pricing model on the Swedish market, we do not have any previous research to directly compare our findings with.

The rest of the paper is structured as follows: Section II outlines our research question, Section III provides an introduction to the field of intermediary asset pricing, Section IV gives a detailed overview of the data used in our analysis, including factor and portfolio construction, the sources used, and descriptions of potential bias in our data, Section V contains the empirical methods used and descriptions of the diagnostics, Section VI contains the results from the cross-sectional and time-series regressions, Section VII discusses the analysis and directions for further research, and finally, Section VIII concludes the paper.

II. Research question

The aim of this paper is to investigate the pricing power of two asset pricing models based on financial intermediaries on a cross-section of Swedish stock returns. The first model is based on shocks to intermediary leverage, and the second one on the return on aggregate wealth and shocks to the intermediary capital ratio. Both models are separately tested against the CAPM and the Fama-French three-factor model to measure their performance relative to these benchmarks.

III. Theory & Previous Literature

Asset pricing models, such as the CAPM and the Fama-French three-factor model (henceforth FF3), are based on the notion of investors' marginal value of wealth being able to correctly price assets. These investors are further assumed to fulfill a number of conditions, including that they do not face transaction costs, have the competence to implement complicated investment strategies, are continuously updating these strategies using estimations of the future, and that they are active in all markets. The typical representative investor used for the calculation of the marginal value of wealth has been the average household, imposing the aforementioned assumptions on them. This represents a problem, since the assumptions do not even remotely hold up to scrutiny in the case of households. They do certainly face transaction costs, in general do not have the competence to implement complicated trading strategies, that are updated continuously and based on forward-looking estimates, and they do not participate in all markets. This implies that the average household should not be the representative investor, and their marginal value of wealth should not be the driver of asset prices. Due to this mismatch between assumptions and reality, according to Adrian et al. (2014a), another representative set of investors has been proposed; the financial intermediary. Financial intermediaries are firms who serve as the middleman in financial transactions, taking orders from investors to buy or sell securities, then finding a counterpart to the trade, and finally executing the trade. The proposition of financial intermediaries as a more representative investor is based on the fact that financial intermediaries fulfill the assumptions of investors postulated by finance theory, and their marginal value of wealth should therefore possess greater pricing power than the average household's marginal value of wealth. If financial intermediaries do in fact possess this ability, the question arises; what aspect of the intermediary will capture the potential pricing power best? This question has given rise to two separate sets of theories: the debt constraint and the equity constraint frameworks.

The debt constraint framework is based on the assumption that leverage levels of intermediaries are constrained by either value-at-risk limits, which is proposed by Adrian & Shin (2014), or by endogenous haircuts, which is proposed by Brunnermeier & Pedersen (2009). For both of these suggested theories, in bad times, the leverage constraints tighten, and the leverage levels are brought down by the fire-sales of assets, selling assets at a lower equilibrium price. This indicates that leverage is pro-cyclical, and rises (falls) in good (bad) times, and if this framework holds, will correspond to a positive price of leverage risk, since assets that co-vary with intermediary leverage will pay off poorly in states where the marginal value of wealth is high. The equity constraint framework, which is formalized in He & Krishnamurthy (2012, 2013) and Brunnermeier & Sannikov (2014), works by taking into consideration two effects arising from financial intermediaries being hit by adverse shocks in their equity capital and reductions in their risk bearing capacity. The first effect is an increase in the intermediaries' leverage – when holding debt constant – due to a fall in asset value, and the second is a subsequent fall in leverage due to intermediaries endogenously reducing their debt. According to this framework, the first effect should outweigh the second one in equilibrium, yielding a net effect of increasing leverage ratios. Leverage should subsequently be counter-cyclical, increasing in times of financial distress, and the price of capital ratio risk positive, with a positive price of capital ratio risk being equivalent to a negative price of leverage risk, and as such, the two frameworks stand in stark contrast to each other. On one point, however, the two frameworks converge; the intermediaries should be engaging in active balance sheet management, actively reducing debt in bad times, and while this is the only effect on the intermediaries in the debt constraint framework, the equity constraint framework, as mentioned previously, allows for an even larger relative reduction in equity financing.

Intermediary asset pricing was first empirically tested by Adrian et al. (2014a). The authors derive a one-factor pricing model focusing on shocks to financial intermediaries' leverage ratio (see Section IV for details), with US broker-dealers included in the Federal Reserve *Flow of Funds* as intermediaries (the model will be denoted AEM henceforth, from the authors: Adrian, Etula and Muir). The test of the AEM model's pricing power is conducted on the cross-section of returns on 25 size and book-to-market, 10 momentum, and 6 Treasury bond portfolios over the sample period of 1968Q1 to 2009Q4. The results of the cross-sectional analysis shows an adjusted R^2 of 77% and a yearly total MAPE[1] of 1.3% across all portfolios, very much in line with four and five factor benchmarks. Moreover, the AEM model performs better than the FF3 model when solely tested on size and book-to-market portfolios. The price of risk is determined as positive, supporting the debt constraint framework and pro-cyclical leverage, as discussed earlier. The model is further tested across a wider range of asset classes in He et al. (2016). Additionally, this paper suggest an alternative two-factor pricing model using the return on aggregate wealth, (equivalent to the market excess return, as shown in He et al. (2016)), and shocks to the intermediary capital ratio (see Section IV for details) as explanatory factors (the model will be denoted HKM henceforth, from the authors: He, Kelly and Manela). These two factors should, together, capture the returns on intermediary wealth. The intermediaries used for testing the HKM model are US primary dealers, which are the trading counterparties of the New York Federal Reserve, over the sample period 1970Q1 to 2012Q4. The results show that the HKM model has an adjusted R^2 of 45% and quarterly total MAPE of 0.9% across asset classes, compared with an adjusted R^2 of 38% and quarterly total MAPE of 0.9% for the AEM model. However, the AEM model performs better than the HKM model when only equity portfolios are used as test assets. The paper also finds a positive price of capital ratio risk suggesting, contrary to Adrian et al. (2014a), that intermediary leverage

[1] MAPE is the mean absolute pricing error, see Section V for definition.

is counter-cyclical. The puzzling results regarding prices of risk are attributed to the different data sources and the different sets of financial intermediaries used in the analyses.

A clear distinction exists between the two studies in terms of intermediary data used. While Adrian et al. (2014a) rely on the balance sheet data of broker-dealers, which to a large extent are subsidiaries of international bank holding companies, He et al. (2016) rely on the balance sheet data of the entire holding companies as such. The decision to use the data of the holding companies is motived by the notion of internal capital markets from corporate finance literature. As suggested by Stein (1997) and Scharfstein & Stein (2000), financial shocks are supposed to be diversified and transmitted across divisions within a conglomerate. Since Swedish bank holding companies tend to be organized as one legal entity with several divisions, rather than with subsidiaries for the different business units as in the US, the theory is more likely to hold true in a Swedish setting. Even though de Haas & van Lelyveld (2010) show that the internal capital markets exist for multinational banking corporations across country borders, Cetorelli & Goldberg (2012) identifies a "home bias" in the activities of these companies, towards domestic operations of the head office, suggesting that the Swedish bank holding companies would provide a representative sample for factor construction in a Swedish study.

IV. Data

1. Broker-Dealer Leverage Factor

We define the leverage ratio of broker-dealers in accordance with Adrian et al. (2014a) as the aggregate book value of assets divided by the aggregate book value of assets minus the aggregate book value of liabilities:

$$Leverage\ Ratio_t = \frac{\sum_i Total\ Assets_{i,t}}{\sum_i (Total\ Assets_{i,t} - Total\ Liabilities_{i,t})}$$

Adrian et al. (2014a) defines the leverage ratio using financial assets and financial liabilities, however, the data they use include non-financial items on the asset side of the balance sheet. We will therefore be using the entire balance sheet data to construct our leverage ratio, with another reason for using the entire balance sheet values being that we do not have access to decomposed data over the entire sample period. We construct the variable by merging two quarterly datasets collected from Statistics Sweden (Swe: *Statistiska Centralbyrån*), which in turn receives its data from the Swedish Financial Supervisory Authority (Swe: *Finansinspektionen*). The full series is divided in two because the first series stopped being

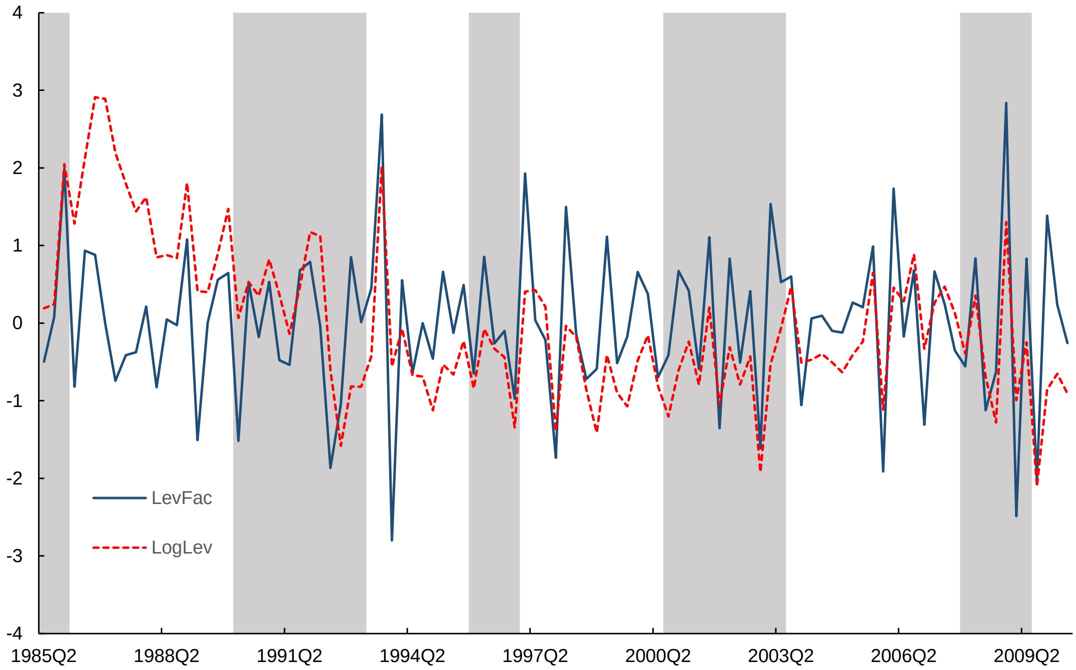

Figure 1. Leverage factor and log-leverage. We plot the leverage factor and the log-leverage of broker-dealers over the timespan 1985Q2 to 2010Q2. The series are standardized to have zero mean and unit variance. The shaded regions indicate OECD recessions in Sweden (downloaded from the St. Louis Federal Reserve's website).

published after 1996. One important thing to note is the translation of the concept broker-dealer to Swedish, where in the past, the translation would be *Fondkommissionär*, whereas today, there is a new legal term, *Värdepappersbolag*. This change of terms will, however, not create any problems for our leverage factor, since the new term was introduced in the early 1990s, and this change occurs within our first dataset. The first dataset covers the period 1985Q1 – 1995Q4 and is collected from the quarterly publication "*Statistiska Meddelanden – Serie K, Kapitalmarknad del II*" (published 1976-1997) from Statistics Sweden, whereas the second dataset covers the period 1996Q1 – 2010Q2, and was provided to us directly by Statistics Sweden due to confidentiality rules applying to the data[2]. This confidentiality imposes a problem in that we are unable to observe which companies are included in the sample. The dataset ends in 2010 due to the fact that after that point, there are no broker-dealers required to report to the Swedish Financial Supervisory Authority on a quarterly basis, and there are therefore no more quarterly observations. Another important aspect with our data in relation to the data used by Adrian et al. (2014a) is that our data do not contain any securities divisions of banks, but rather only independent securities broker-dealers, since in Sweden, the securities divisions of the banks are not separately identifiable entities.

[2] The data provided only contain "*Monetära Värdepappersbolag*". Another dataset containing "*Icke-Monetära Värdepappersbolag*" exists from 2003 and forward, however, these companies will not be included in our series due to them being very small and few in number.

Table I

Broker-Dealer Leverage Growth is Uncorrelated with Other Explanatory Factors

This table presents the cross-correlation between a number of variables, namely the broker-dealer leverage growth, the unadjusted leverage of broker-dealers, the excess market return (constructed using the return on the OMXSPI and the return on 1-month Swedish Treasury bills), the Fama-French SMB factor on the Swedish market (constructed from our size and book-to-market portfolios), and the Fama-French HML factor on the Swedish market (constructed from our size and book-to-market portfolios), see sub-section 4 for construction details. Data are from the period 1990Q3 to 2010Q2.

Cross-Correlation AEM					
	LevFac	Leverage	R_{Mkt}	SMB	HML
LevFac	1				
Leverage	0.62	1			
R_{Mkt}	0.06	0.00	1		
SMB	-0.07	0.10	0.04	1	
HML	0.01	-0.02	-0.28	0.25	1

We construct the leverage factor (LevFac) which will be used in the model as the log changes in the level of broker-dealer leverage:

$$LevFac_t = \Delta \ln(Leverage\ Ratio_t)$$

Note that we do not, as opposed to Adrian et al. (2014a), seasonally adjust the log changes in leverage, simply because we do not find any seasonal component in our data. Quarterly regression output and the seasonally adjusted leverage factor-series can be found in the appendix, Table AI and Figure A1, for reference.

In Figure 1, we show the time-series of broker-dealer leverage and the leverage factor, where the shaded areas are OECD recessions. We can see large swings in leverage during the 2008 financial crisis and following the recession in the early 1990s, but no such movements during the dot-com bubble of the late 1990s and early 2000s. We can also observe a large drop in leverage following the 1997 Asian financial crisis, which seems puzzling due to the limited overall effect of this crisis on the Swedish market, however, it could potentially be due to sector-specific contagion.

In Table I, we show the cross-correlation between the leverage factor and the other explanatory factors over the sample period used to evaluate the AEM model. We see that the leverage factor is not highly correlated with any of the other explanatory factors, indicating that the AEM model will explain different variation when we run our tests.

2. Primary Dealer Market Capital Factor

The pricing model presented in He et al. (2016) is a two-factor model with a market factor of excess market return and a market capital factor constructed from the market capital ratio of primary dealers. We define the market capital ratio similarly to He et al. (2016) as follows:

$$Market\ Capital\ Ratio_t = \frac{\sum Market\ Equity_{i,t}}{\sum(Book\ Liabilities_{i,t} +\ Market\ Equity_{i,t})}$$

The ratio is constructed for the primary dealer sector by summing the market value of equity and book value of liabilities (corresponding directly to the book value of debt used in He et al. (2016)) for each holding company in the sector on a quarterly basis from 1998Q1 to 2015Q4, with data collected from Compustat. Any missing values in the dataset are complemented with raw data from the holding companies' annual reports. All values are converted into Swedish Kronor using exchange rate series from Thomson Reuters Datastream. The usage of book value of liabilities is common in corporate finance as a proxy for the market value of liabilities, which is unobserved. All data used are the most recent data available, thus book values are collected at the end of each quarter and market values based on the share prices at the last trading day in the quarter. The time series of market equity and book liabilities used in the factor construction can be seen in the appendix, Figure A2. The set of primary dealers used for the construction of the capital ratio are based on a list provided by the Swedish National Debt Office (Swe: *Riksgälden*), which does not correspond to the publicly available list published by the Swedish Riksbank. This second public list suffers heavily from inclusion bias, since it classifies both primary and secondary dealers as "primary dealers". Holding companies are included based on a set of criteria including if the company has ever been listed, and if the book and market values are available in the Compustat data. Moreover, the holding companies' country of domicile are taken into consideration to account for the "home bias" of internal capital markets. Given these restrictions, we end up with a set of primary dealers including the "Big 5" of Scandinavian banks: Danske Bank[3], Nordea Bank, SEB, Svenska Handelsbanken, and Swedbank. For the unadjusted list of primary dealers provided by the Swedish National Debt Office, see the appendix, Table AII.

[3] Danske Bank is not a Swedish bank, however, it is included due to the company's very high exposure to, and systemic importance in, the Swedish market.

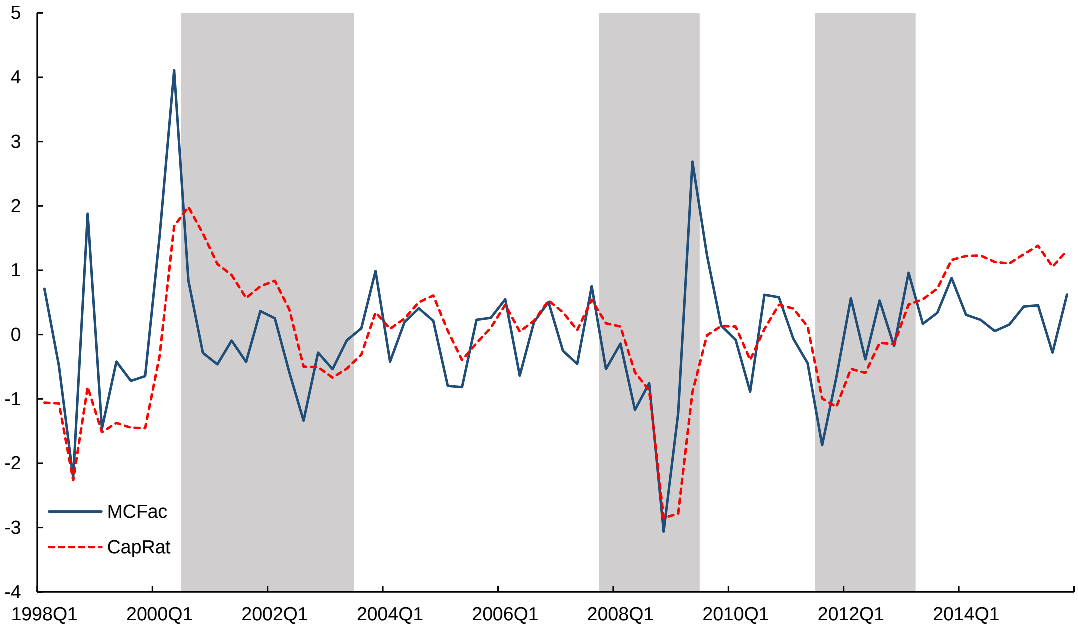

Figure 2. Market capital factor and capital ratio. We plot the market capital factor and the capital ratio of primary dealers over the timespan 1998Q1 to 2015Q4. The series are standardized to have zero mean and unit variance. The shaded regions indicate OECD recessions in Sweden (taken from the St. Louis Federal Reserve's website).

Using the market capital ratio previously defined, we construct the market capital factor (MCFac), equivalent to the market capital ratio growth rate, which is used in our main regressions. An AR (1) model is run to estimate the shock to the market capital ratio (u):

$$Market\ Capital\ Ratio_t = \rho_0 + \rho Market\ Capital\ Ratio_{t-1} + u_t$$

The estimated error term is then divided by the lagged market capital ratio to obtain the market capital factor:

$$MCFac_t = \frac{u_t}{Market\ Capital\ Ratio_{t-1}}$$

As theorized in Adrian et al. (2014a), this type of growth measure is more or less equivalent to the log changes in market capital ratio, due to high persistence. This is supported by the 95% correlation between the market capital factor and the log change in market capital ratio, which we find in our data.

The capital ratio and the market capital factor are plotted for the entire time period from 1998Q1 to 2015Q4 in Figure 2, with OECD recessions as the shaded regions, and what we observe is that the factor effectively captures the stock market boom and bust periods of the

Table II

Primary Dealer Market Capital Factor is Correlated with Excess Market Return

This table presents the cross-correlation between a number of variables, namely the primary dealer market capital factor, the unadjusted capital ratio of primary dealers, the excess market return (constructed using the return on the OMXSPI and the return on 1-month Swedish Treasury bills), the Fama-French SMB factor on the Swedish market (constructed from our size and book-to-market portfolios), and the Fama-French HML factor on the Swedish market (constructed from our size and book-to-market portfolios), see sub-section 4 for construction details. Data are from the period 1998Q1 to 2015Q4.

Cross-Correlation HKM					
	MCFac	Capital Ratio	R_{Mkt}	SMB	HML
MCFac	1				
Capital Ratio	0.50	1			
R_{Mkt}	0.47	-0.03	1		
SMB	0.19	0.31	-0.09	1	
HML	-0.08	0.37	-0.51	0.08	1

dot-com bubble of the late 1990s, the 2008 financial crisis, and the European banking crisis in 2009-2012. However, this may be due to pure mechanics since the capital ratio is constructed using the market value of equity.

A cross-correlation analysis can be seen in Table II, which shows that the market capital factor has a low correlation with the SMB and HML factors from the FF3 model, however, we observe a relatively high correlation of 47% between the market factor and the market capital factor. This may prove problematic since both variables are included as independent variables in our main regression, following the model configuration suggested in He et al. (2016). Specifically, the high correlation may result in multicollinearity in the time series regression. While multicollinearity does not affect the consistency of the estimates per se, it increases the standard errors and decreases the precision of the estimates, making them more sensitive to the realization of error terms in the sample. The driving force behind this is the weight of the market equity of the Swedish banks in the Swedish stock market index OMXSPI used in our market factor construction. We can also observe a strong negative correlation of -51% between the market factor and the HML factor. Similarly, a high correlation between these factors is found in Fama & French (1993).

3. Comparison of the Two Types of Intermediaries

Both Adrian et al. (2014a) and He et al. (2016) discuss the cyclical nature of the leverage and capital ratios of the different intermediaries, as in Section III. In Table III we present the correlation between leverage growth and asset growth for broker-dealers, and the correlation between capital ratio growth and asset growth for primary dealers. For the debt constraint framework to be supported, the intermediaries should display a positive and significant

Table III

Broker-Dealer Leverage is Pro-Cyclical, Primary Dealer Capital Ratio is not

This table presents the correlation between the broker-dealer leverage growth and broker-dealer asset growth, as well as the correlation between the primary dealer market capital ratio growth and the primary dealer market asset growth. Data are from the period 1985Q1 to 2010Q2 (broker-dealer) and 1998Q1 to 2015Q3 (primary dealer).

	Correlation	
	Broker-Dealer Leverage Growth with Asset Growth	Primary Dealer Capital Ratio Growth with Asset Growth
ρ	0.83	0.20
p-value	0.00	0.45

correlation between leverage growth and asset growth, indicating reductions in debt levels in times of market contraction (implying a negative and significant value for the correlation between capital ratio growth and asset growth). For the broker-dealers, this is exactly what we observe, with a highly significant, positive correlation between leverage growth and asset growth of 0.83, which indicates that they act within a debt constraint framework. For the primary dealers, on the other hand, we observe a weak, positive correlation between capital ratio growth and asset growth, and their relationship is far from significant, thus not allowing us to draw any definite conclusions regarding the constraint framework in which the primary dealers act. Another thing to notice is the fact that the capital ratio for the primary dealers is calculated using the market value of equity, which is something that the companies have more limited control over. For the graphical representation of the correlations, see the appendix, Figure A3.

Table IV presents the correlations between our two intermediary factors. What we observe is that neither the two different intermediary factors, nor the unadjusted leverage and capital ratios, are correlated with each other, indicating that they will not explain the same variation.

4. Test Assets & Benchmark Factors

The assets used to test the models are 21 Swedish equity portfolios, of which 6 are size and book-to-market sorted portfolios following Fama & French (1992), 10 momentum sorted portfolios following Carhart (1997), and 5 industry sorted portfolios following Fama & French (1997). We use momentum and industry sorted portfolios in addition to the size and book-to-market portfolios to avoid the potential issues discussed in Lewellen et al. (2010). Further discussion regarding the choice of portfolios is found in Section V. Our use of portfolios rather than individual stocks are based on two aspects: first, we want to avoid the errors-in-variables

Table IV

AEM and HKM Factors are Uncorrelated

This table presents the correlation between the broker-dealer leverage factor and primary dealer market capital factor, as well as the correlation between broker-dealer leverage and primary dealer market capital ratio. Data are from the period 1998Q1 to 2010Q2.

	Correlation	
	Broker-Dealer Leverage Factor with Primary Dealer Market Capital Factor	Broker-Dealer Leverage with Primary Dealer Capital Ratio
ρ	-0.17	-0.04
p-value	0.35	0.80

problem, as suggested in Jagannathan et al. (2010), and second, we want to stay true to the original tests of intermediary asset pricing.

To construct our portfolios, we collect book and market data for all companies with Sweden as the country of incorporation between 1987Q1 and 2016Q1 from Compustat, and remove all financial companies following the approach of Fama & French (1992). We construct the portfolios ourselves since no portfolio returns are publicly accessible for the Swedish market. For all portfolios, any company with less than 24 months of consecutive trading data is removed, in order to avoid any false returns being included in the portfolios (we can observe several cases of clearly incorrect observations in the Compustat data). Furthermore, all companies with negative book equity are removed due to the lack of interpretive value of the book-to-market ratio if it is negative, and to avoid including observations that contain errors made by Compustat. Additionally, for a company to be included in a portfolio, we require it to have data observations for all values used to place the company in a portfolio. For the size and book-to-market portfolios, we combine the values of all different types of shares outstanding at all times, e.g. class A and B shares, in order to achieve the most correct market value for the companies[4]. At the end of June of year t, we form the portfolios by first dividing the companies into two equally large groups based on the market capitalization as of the end of December of year t – 1, and then for each of the two size groups, we divide the companies into three groups based on the ratio of the value of book equity as of the end of December of year t – 1, and the market capitalization as of the end of December of year t – 1. The three groups are formed of the 30% with the highest book-to-market ratio, the middle 40%, and the lowest 30%, respectively.

For the momentum portfolios, we follow the approach of Carhart (1997), ranking companies each month based on the total return over the period 12 months to 1 month before

[4] For the minor inclusion bias effects of preferred shares on market capitalization in the portfolio sorting, see the appendix, Table AIII.

portfolio construction, and the companies are then divided into 10 equal groups based on their return over the period. The industry portfolios are formed using the GICS classification downloaded from Compustat. The GICS classification system includes 10 industry as the topmost classification level, but we combine the different industries into 5 portfolios (Consumer, Manufacturing, High-Tech, Health, and Other) following Fama & French (1997), in order to ensure that there are return observations for each of the portfolios for every time period in which we run our tests. The returns for the portfolios are calculated quarterly as the sum of the market capitalization-weighted returns for the portfolio constituents. Only the return of the main listed share class is used, in the case of several listings for the same company. We adjust these into excess returns using the quarterly return on 1-month Swedish Treasury bills, downloaded from the Swedish Riksbank's website.

It should be acknowledged that the Compustat data suffer from biases, especially exclusion bias in the early periods of the sample, where the number of companies included is only around 28, and heavily skewed towards big companies. This is not the correct number of companies listed in Sweden, which we have confirmed with data from the Stockholm Stock Exchange. The full time series of number of companies in our sample can be found in the appendix, Figure A4. One thing to note, however, is the fact that the Compustat data do not discriminate between the different stock markets that exist in Sweden, and therefore provide complete data for the later part of our sample.

We construct the benchmark factors as follows: The excess market return is based on the quarterly return on the OMXSPI downloaded from the Nasdaq OMX Nordic website, which is then adjusted using the quarterly return on 1-month Swedish Treasury bills, downloaded from the Swedish Riksbank's website. The SMB and HML factors are constructed in accordance with Fama & French (1993) as follows:

$$SMB = \frac{R_{SH} + R_{SN} + R_{SL}}{3} - \frac{R_{BH} + R_{BN} + R_{BL}}{3}$$

$$HML = \frac{R_{SH} + R_{BH}}{2} - \frac{R_{SL} + R_{BL}}{2}$$

R_{SH}, R_{SN}, and R_{SL} are the returns of the small portfolios, R_{BH}, R_{BN}, and R_{BL} are the returns of the big portfolios, and R_{SH} and R_{BH} are the returns of the portfolios with high book-to-market ratio, and R_{SL} and R_{BL} are the returns of the portfolios with low book-to-market ratio.

V. Empirical Approach

Similar to the approach suggested in Cochrane (2005) section 12.2, we test the models proposed using a standard two-pass regression corresponding to formula 12.9 and 12.10, but allowing for a free intercept, with a full sample time-series regression of portfolio returns for each asset $i = 1, \ldots$, N on the vector of risk factors (**f**) as our first regression:

$$R^e_{i,t} = c_i + \beta'_{i,f}\mathbf{f}_t + \epsilon_{i,t}\,, \qquad i = 1, \ldots, N, t = 1, \ldots, T$$

For the second stage cross-sectional regression, we regress the average portfolio returns on the estimated factor betas from the time-series regression:

$$E\left[R^e_{i,t}\right] = a + \beta'_{i,f}\lambda_f + \xi_i, \qquad i = 1, \ldots, N$$

The cross-sectional regression yields the prices of risk (λ) and the zero beta excess returns (a) or equivalently the average pricing error. The individual pricing errors are the error terms (ξ_i) from the cross-sectional regression, corresponding to the residuals in the sample. While more dynamic approaches exist, such as dynamic asset pricing models (as proposed by Adrian et al. (2014b)), we follow the original approach employed by Adrian et al. (2014a) and He et al. (2016) for comparability.

According to Adrian et al. (2014a), "A good pricing model features an economically small and statistically insignificant intercept (a), statistically significant and stable prices of risk (λ) [...] and individual pricing errors (ξ_i) that are close to zero." The sizes of the pricing errors are captured by two measures, the total mean absolute pricing error (MAPE) across portfolios defined as ($|a| + \frac{1}{N}\Sigma|\xi|$) by Adrian et al. (2014a) and the adjusted R^2 from the cross-sectional regression. While the total MAPE focuses less on outliers than the adjusted R^2, it accounts for the constant, or equivalently, the *average* pricing error across all portfolios. This adjustment is economically important, since the intercept should, theoretically, be equal to zero. As we wish to account for the potentially high constants, which are seen for equity portfolios in Adrian et al. (2014a), we use the total MAPE as our main diagnostic of the models' pricing performances.[5] A potential way to circumvent this issue would be to run the cross-sectional regression with the restriction of no free intercept, i.e. formula 12.10 in Cochrane (2005). However, this approach is only reasonable to pursue when the intercept is small and

[5] The issue seems to be mitigated in US data by adding more asset classes. This is not pursued in our study since it would be a divergence from our research question and due to the lack of data. For further detail, see Section VII.

insignificant, as the constant is simply assumed away. Moreover, by forcing the regression to draw a line through the origin, we would mechanically force the prices of risk to be positive in most cases, which does not necessary have to hold true. For the analysis of the different sets of portfolio sorts, the constant is dropped, yielding a MAPE of ($\frac{1}{N}\Sigma|\xi|$). The evaluation of the MAPE constitutes a minimization problem and adjusted R^2 constitutes a maximization problem, as the second measure decreases with the increasing sum of squared residuals (SSR). To correct for cross-sectional correlation in the second stage regression we report the Fama-MacBeth t-statistics, as developed in Fama & MacBeth (1973), in addition to the standard t-statics, which are White-corrected for heteroscedasticity.

The cross-sectional regressions for the different set of risk factor are run using equity portfolios sorted on size and book-to-market (6), momentum (10) and industry (5) as test assets. The regressions are run on all 21 equity portfolio returns at the same time over the same time period, i.e. we are always dealing with balanced datasets. The more challenging momentum and industry portfolios are included both to address the otherwise small sample size and small variation in factor betas as well as to accommodate for the 1st prescription in Lewellen et al. (2010). The authors claim that there exists a rationale in expanding the set of test assets beyond size and book-to-market portfolios, in order to address the issue of mechanically pushing up the pricing power of proposed factors, if they are highly correlated with the Fama-French factors. Our different sets of risk factors for the AEM model ($\mathbf{f}$ = LevFac) and HKM model ($\mathbf{f}$ = [R_{Mkt}, MCFac]) are tested against the CAPM ($\mathbf{f}$ = R_{Mkt}) and the FF3 model ($\mathbf{f}$ = [R_{Mkt}, R_{SMB}, R_{HML}]) benchmarks. The time-series data used are quarterly from 1990Q3 to 2010Q2 for the AEM model and from 1998Q1 to 2015Q4 for the HKM model. Since both models are tested over the entire available time span, it should be emphasized that the performance of the models cannot be compared with each other, but only with benchmark models within the same sample periods.

VI. Empirical Results

In Table V, we present our main empirical results. For all of our models, we test them against all of the 21 equity portfolios *simultaneously*. Panel I presents the cross-sectional prices of risk, and Panel II presents test diagnostics for each of the models. We test the two models based on financial intermediaries against the CAPM and FF3 benchmarks, matching the sample periods for the regressions to ensure comparability with the benchmarks.

Starting by looking at the first time period, we can see that both of the benchmark models generate very large and statistically significant intercepts, with the CAPM at 18.9% per annum and the FF3 model at 24.7% per annum, which can be contrasted with the intercept for the AEM model, which is at 2.9% per annum. These large intercepts for the benchmark models are mainly due to the negative price of risk for the market factor in both cases, which in turn suggests that investors should receive less return the more risk that they bear, directly contradicting the theory behind the CAPM. Similar patterns with large intercepts and negative prices of risk can be observed on the US equity markets, as in Adrian et al. (2014a). The AEM model, on the other hand, generates a positive price of risk for the leverage factor, which gives credence to the theory of debt constraints in financial intermediaries, since the economic interpretation of this positive price of risk is that the assets that broker-dealers will sell off in fire-sales carry higher risk, and on average will generate higher returns. These results are found again in Panel II, where the total MAPE of the benchmark models are 22.0% and 27.0% per annum for the CAPM and FF3 model, respectively. Comparing these numbers with the total MAPE of the AEM model, which is at 6.8% per annum, we can see clearly that the AEM model outperforms the benchmark models by yielding an approximately 3 – 4 times lower absolute pricing error. Important to note is that while the AEM model outperforms the benchmark models by far, generating a total annual MAPE of 6.8% represents a large mispricing. Subsequently, we cannot infer that the AEM model performs well, but only that the benchmark models perform very poorly. The adjusted R^2 for the benchmark models are higher (52% and 66% for the CAPM and FF3 model, respectively) than the 32% achieved by the AEM model, however, as stated in Section V, in the case of large cross-sectional intercepts, the adjusted R^2 provides a less informative measure of model performance.

Moving to the second time period, we can see that all of the models, benchmarks and the intermediary asset pricing model alike, generate very large cross-sectional intercepts, with the CAPM and HKM at 23.9% per annum and the FF3 at 29.9% per annum. Once again, this is driven by the negative prices of risk for the market factor, which is present in all three of the models, indicating model misspecification. Furthermore, the price of risk for the market capital factor in the HKM model is negative as well, and while it is not significantly so from a statistical point of view, this still gives some further credence to the debt constraint framework within financial intermediaries. This is due to the fact that capital ratio factors and leverage factors should display opposite signs on the price of risk *within* this framework, as is what can be observed, since the two measures are simply the inverse of each other. In Panel II, we see that the total MAPEs of the three models are fairly equal, with the CAPM

Table V

Pricing the Equity Portfolios

This table presents the cross-sectional pricing results for the 6 size and book-to-market, 10 momentum and 5 industry portfolios. The models are all estimated as $E[R^e_{i,t}] = a + \beta'_{i,f}\lambda_f + \xi_i$. CAPM denotes the capital asset pricing model, FF3 denotes the Fama-French three-factor model, AEM the intermediary leverage pricing model from Adrian et al. (2014a) and HKM the intermediary capital pricing model from He et al. (2016). Panel I reports the prices of risks with heteroscedasticity adjusted t-statistics and Fama-MacBeth t-statistics from the estimations in both time samples. Panel II reports the test diagnostics, including mean absolute pricing error (MAPE) by portfolio group, the total MAPE, as well as the adjusted R^2 for each model in both samples. Data are quarterly from the periods 1990Q3 to 2010Q2 in the first sample (AEM) and 1998Q1 to 2015Q4 in the second sample (HKM). Returns and risk premia are reported in percent per annum i.e. quarterly percentages multiplied by four.

Panel I: Prices of Risk

	1990-2010			1998-2015		
	CAPM	FF3	AEM	CAPM	FF3	HKM
Intercept	18.86	24.74	2.88	23.86	29.86	23.86
t-stat	7.79	10.02	2.67	12.23	11.50	11.96
t-FM	2.51	3.02	0.44	4.02	4.51	4.02
LevFac			95.15			
t-stat			4.52			
t-FM			1.54			
MCFac						-8.34
t-stat						-1.56
t-FM						-0.64
Market	-14.92	-20.16		-17.32	-23.25	-17.33
t-stat	-7.55	-10.75		-10.47	-9.22	-10.03
t-FM	-1.61	-2.05		-2.08	-2.64	-2.08
SMB		5.07			8.04	
t-stat		4.99			6.80	
t-FM		1.34			2.07	
HML		-1.29			4.94	
t-stat		-0.77			2.95	
t-FM		-0.21			0.87	

Panel II: Test Diagnostics

	1990-2010			1998-2015		
MAPE	CAPM	FF3	AEM	CAPM	FF3	HKM
Size B/M	4.74	0.89	4.05	3.78	1.19	3.76
Mom	6.10	3.26	3.81	3.29	2.68	3.28
Industry	4.84	1.78	3.81	1.64	1.89	1.68
Intercept	18.86	24.74	2.88	23.86	29.86	23.86
Total	22.01	26.97	6.76	26.90	31.92	26.89
R^2	0.52	0.66	0.32	0.68	0.85	0.67

and HKM model generating a total MAPE of 26.9% per annum in both cases, and the FF3 model producing a total MAPE of 31.9% per annum. The adjusted R^2 for the CAPM and HKM model are very similar as well, with the CAPM at 68% and the HKM model at 67%, and the FF3 model achieving an adjusted R^2 of 85%. Despite the high adjusted R^2 of the models, the remarkably high total MAPEs will only allow us to conclude that none of the three models in the second time period, benchmarks and the intermediary model alike, have little explanatory power.[6]

Looking at the individual MAPEs for the different types of portfolios in Panel II, we can see that the FF3 model performs better than the AEM model, with the momentum portfolios being the ones where the two models are most similar, only differing around 0.5% per annum, and the size and book-to-market portfolios being the ones where the FF3 model performs the best with a MAPE of only 0.9% compared with the leverage factor pricing model's 4.1% per annum. For the second time period, the FF3 model generates lower MAPEs for the size and book-to-market portfolios as well as the momentum portfolios (1.2% and 2.7%, respectively), than the CAPM and the HKM model do (3.8% and 3.3% for the size and book-to-market portfolios and the momentum portfolios, respectively), with the CAPM and HKM model producing almost identical average individual pricing errors for all portfolio sorts. For the industry portfolios, on the other hand, the CAPM and HKM model produce slightly lower MAPEs than the FF3 model (1.6% for the CAPM and HKM compared to 1.9% for the FF3 model).

In Figures 3 and 4, we plot the realized mean returns versus the predicted expected returns for the AEM and HKM models, and compare them with the FF3 benchmark. What we can see in Figure 3 is that the AEM model is not able to capture the returns of the test portfolios, with deviations from the 45-degree line. We can further see that FF3 model performs much better, however, it has a hard time pricing some of the momentum portfolios, especially Mom 8, just as the AEM has. Interestingly, this portfolio is a past relative winner, however, the mean realized return is negative, going against the concept of momentum. Looking at Figure 4, we see that the FF3 model generates a better fit around the 45-degree line than does the HKM model, essentially corresponding to the difference in R^2. No particular portfolio stands out as hard to price for the FF3 model, whereas the HKM model seems to have a hard time pricing Mom 4 & 8, as well as the small size and book-to-market portfolios.

[6] Out of curiosity, we also create our own model using the two intermediary factors, and test it during the overlapping period against the FF3 model. The results can be found in the appendix, Table AIV.

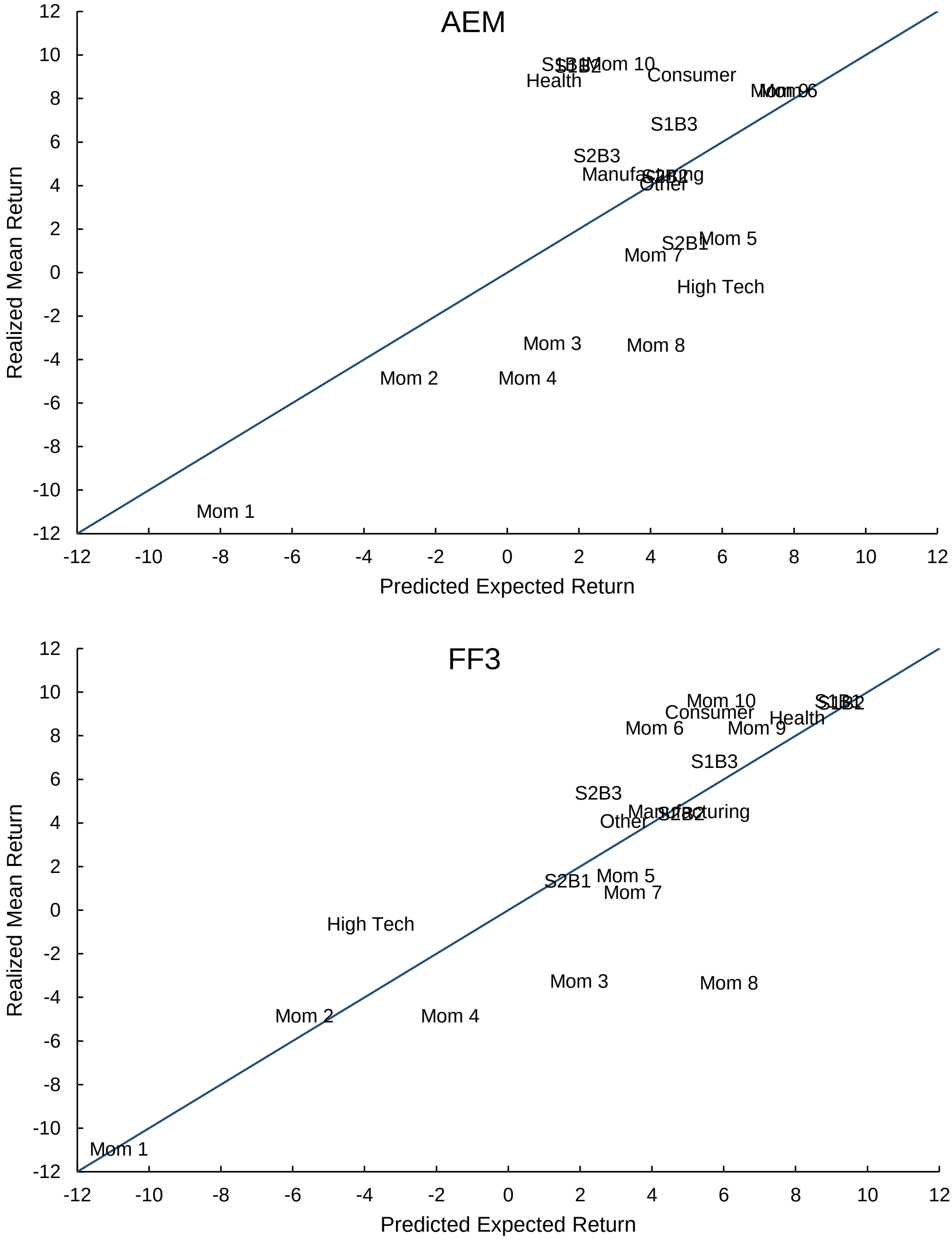

Figure 3. Realized and predicted mean returns: AEM model vs Fama-French three-factor benchmark. We plot the realized mean return for our 21 equity portfolios (6 size and book-to-market portfolios, 10 momentum sorted portfolios, and 6 industry portfolios) against the mean predicted expected returns from the estimation ($E[R^e_{i,t}] = a + \beta'_{i,f}\lambda_f + \xi_i$), using the AEM model ($\mathbf{f}$ = LevFac) and the Fama-French three-factor model ($\mathbf{f} = [R_{Mkt}, R_{SMB}, R_{HML}]$), as well as a 45-degree reference line. Data are quarterly, but the returns are expressed in percent per year (quarterly returns multiplied by four). The sample period is 1990Q3 to 2010Q2.

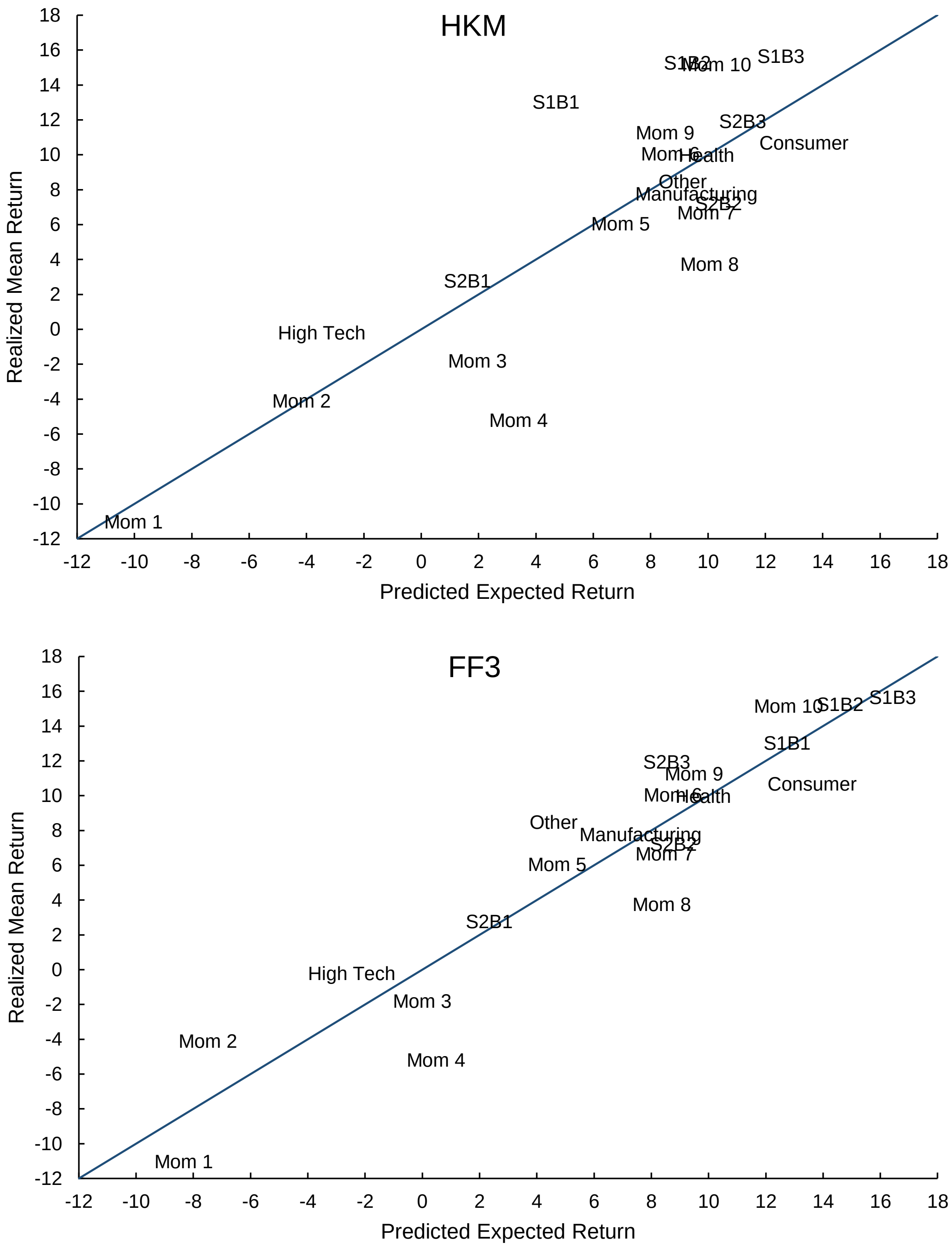

Figure 4. Realized and predicted mean returns: HKM model vs Fama-French three-factor benchmark. We plot the realized mean return for our 21 equity portfolios (6 size and book-to-market portfolios, 10 momentum sorted portfolios, and 6 industry portfolios) against the mean predicted expected returns from the estimation ($E[R^e_{i,t}] = a + \beta'_{i,f}\lambda_f + \xi_i$), using the HKM model ($\mathbf{f} = [R_{Mkt}, MCFac]$) and the Fama-French three-factor model ($\mathbf{f} = [R_{Mkt}, R_{SMB}, R_{HML}]$) , as well as a 45-degree reference line. Data are quarterly, but the returns are expressed in percent per year (quarterly returns multiplied by four). The sample period is 1998Q1 to 2015Q4.

In Table VI, we present the pricing errors for each of our test portfolios for the AEM, HKM, and FF3 models. First of all, we can see that all of the models have a hard time pricing the high tech and consumer portfolios, with no model having an absolute pricing error of less than 2% per annum. Despite this, all models (except the AEM) perform remarkably well on the industry portfolios, with low individual MAPEs, which is interesting considering the statement made by Lewellen et al. (2010), claiming that asset pricing models generally perform poorly on industry sorted portfolios. The HKM model especially stands out on the industry portfolios, with the lowest average MAPE of 1.7%, compared with the FF3 model's 1.9%. It is important to note, however, that the size of the intercepts are not taken into account here, indicating that these pricing errors do not capture the entire mispricing the models produce.

Table VII presents the results of the time-series regressions of the AEM and HKM models in their respective time samples on individual portfolios. We would like to emphasize that the time-series results provide little relevant information. What may seem puzzling in terms of low R^2 in the range of 0% – 2% for the AEM model is actually expected, since the factor used in our regression is not a return on a tradable asset. The low R^2 is thus caused by noise, and should not be interpreted as the actual explanatory power of the model. Reversely, since the HKM model includes a return on a tradable asset, the market portfolio, its R^2 in the time-series regression lies in the range of 44% – 87%. The low significance of the estimated leverage factor and market capital factor betas could potentially be problematic (further reduced by multicollinearity in the case of the HKM model). Problems arise if the betas are wrongly estimated and the wrongly estimated betas due to realization align perfectly in the cross-sectional regression, thereby increasing the explanatory power of the model in the sample. While the possibility of such a unique case exist, it is far from likely and should therefore not affect our analysis.

VII. Discussion & Further Research

While our investigation fails to provide strong evidence in favor of intermediary asset pricing, the results yields some empirical support for the debt constraint framework within the realm of intermediary asset pricing. This calls for further investigations into alternative sets of intermediaries. Interestingly, it is theorized in He et al. (2016) that the best set of intermediaries within the debt framework, in terms of fitting the descriptions, is hedge funds. However, constructing a testable factor of hedge fund leverage is associated with a major difficulty in a Swedish setting, since no public data are accessible regarding the sector's level of leverage.

Table VI
Pricing Errors: Pricing the Equity Portfolios

This table presents the average realized excess returns and the sample version of cross-sectional pricing errors, i.e. $\xi_i = E[R^e_{i,t}] - a - \beta'_{i,f}\lambda_f$, across portfolios in percent per annum for the Fama-French three-factor benchmark and the AEM and HKM models in their respective samples. The table also includes the mean absolute pricing error (MAPE) for the models in the different portfolio sorts. The information corresponds directly with Table V. Returns and risk premia are reported in percent per annum i.e. quarterly percentages multiplied by four.

Size and Book-to-Market Portfolios

	1990-2010			1998-2015		
	$E[R_e]$	FF3	AEM	$E[R_e]$	FF3	HKM
S1B3	6.86	1.12	2.20	15.67	-0.75	3.13
S1B2	9.52	0.26	7.55	15.28	0.69	6.00
S1B1	9.61	0.43	8.00	13.05	0.31	8.35
S2B3	5.39	2.89	2.89	11.95	3.41	0.75
S2B2	4.45	-0.36	0.05	7.24	-1.53	-3.13
S2B1	1.37	-0.29	-3.59	2.79	0.46	1.18
MAPE		0.89	4.05		1.19	3.76

Momentum Portfolios

	1990-2010			1998-2015		
	$E[R_e]$	FF3	AEM	$E[R_e]$	FF3	HKM
Mom 10	9.62	3.69	6.46	15.18	2.38	4.88
Mom 9	8.38	1.46	0.78	11.29	1.79	2.78
Mom 8	-3.31	-9.45	-7.46	3.77	-4.60	-6.29
Mom 7	0.84	-2.63	-3.25	6.69	-1.78	-3.26
Mom 6	8.38	4.30	0.53	10.08	1.32	1.39
Mom 5	1.61	-1.66	-4.55	6.08	1.37	-0.87
Mom 4	-4.82	-3.21	-5.40	-5.18	-5.66	-8.57
Mom 3	-3.22	-5.20	-4.48	-1.77	-1.78	-3.74
Mom 2	-4.83	0.85	-2.09	-4.07	3.41	0.10
Mom 1	-10.94	-0.10	-3.09	-11.00	-2.67	-0.97
MAPE		3.26	3.81		2.68	3.28

Industry Portfolios

	1990-2010			1998-2015		
	$E[R_e]$	FF3	AEM	$E[R_e]$	FF3	HKM
Consumer	9.11	3.50	3.96	10.71	-2.91	-2.64
Manufacturing	4.54	-0.49	0.75	7.79	0.15	-1.82
High Tech	-0.61	3.21	-6.57	-0.18	2.28	3.29
Health	8.85	0.80	7.54	9.99	0.18	0.05
Other	4.11	0.89	-0.25	8.50	3.92	-0.61
MAPE		1.78	3.81		1.89	1.68

Table VII
Time Series Regression

This table presents the results from time-series regressions $R^e_{i,t}= c_i +\beta'_{i,f} f_t + \epsilon_{i,t}$ of excess return on the leverage factor, **f** = [LevFac] for the AEM model as well as excess return on the excess market return and market capital factor, **f** = [R_{Mkt}, MCFac] for the HKM model. The t-stats are adjusted for heteroscedasticity and the R^2 for the two models unadjusted for degrees of freedom in both cases for consistency. Data are quarterly from the periods 1990Q3 to 2010Q2 in the first sample (AEM) and 1998Q1 to 2015Q4 in the second sample (HKM). For convenience leverage betas ($\beta_{i,\ LevFac}$) and market capital betas ($\beta_{i,\ MCFac}$) are multiplied by 100.

Size and Book-to-Market Portfolios								
	1990-2010			1998-2015				
	β_{LevFac}	*t*-stat	R^2	β_{MCFac}	*t*-stat	β_{Mkt}	*t*-stat	R^2
S1B3	1.86	0.33	0.20%	15.66	1.74	0.58	5.50	44.00%
S1B2	-0.96	-0.23	0.06%	12.62	1.64	0.78	8.71	63.11%
S1B1	-1.34	-0.30	0.10%	4.59	0.55	1.08	11.21	71.00%
S2B3	-0.40	-0.10	0.01%	4.66	0.68	0.71	8.80	60.83%
S2B2	1.60	0.46	0.26%	0.73	0.13	0.78	11.45	71.11%
S2B1	2.19	0.59	0.26%	-18.85	-3.22	1.37	20.16	86.87%

Momentum Portfolios								
	1990-2010			1998-2015				
	β_{LevFac}	*t*-stat	R^2	β_{MCFac}	*t*-stat	β_{Mkt}	*t*-stat	R^2
Mom 10	0.30	0.06	0.01%	3.10	0.03	0.78	6.52	44.25%
Mom 9	4.96	1.12	1.78%	1.98	-2.42	0.98	10.85	64.79%
Mom 8	1.33	0.40	0.13%	0.21	-1.37	0.84	10.42	64.35%
Mom 7	1.27	0.35	0.10%	0.94	-0.74	0.83	8.77	56.99%
Mom 6	5.22	1.25	2.07%	1.73	-0.89	0.90	13.82	77.01%
Mom 5	3.45	0.77	0.75%	0.64	-0.61	1.00	9.13	59.32%
Mom 4	-2.42	-0.41	0.25%	-2.31	0.92	1.13	7.99	57.08%
Mom 3	-1.70	-0.33	0.13%	-1.58	-0.50	1.29	10.48	66.14%
Mom 2	-5.90	-0.98	1.02%	-2.38	1.51	1.51	9.24	65.19%
Mom 1	-11.27	-1.26	1.99%	-4.44	0.59	1.90	7.84	55.16%

Industry Portfolios								
	1990-2010			1998-2015				
	β_{LevFac}	*t*-stat	R^2	β_{MCFac}	*t*-stat	β_{Mkt}	*t*-stat	R^2
Consumer	2.38	0.83	0.56%	2.10	-2.35	0.67	9.99	60.75%
Manufacturing	0.96	0.24	0.08%	1.24	1.53	0.78	11.86	74.83%
High Tech	3.23	0.58	0.31%	-1.53	-3.01	1.72	15.37	78.96%
Health	-1.66	-0.41	0.25%	1.86	2.91	0.69	7.67	62.11%
Other	1.55	0.28	0.17%	1.42	1.46	0.78	6.39	49.01%

Similar issues exist with the data of asset classes other than equity in Sweden. Since the asset pricing models tested are supposed to be able to price all assets, the models should ideally be tested across a wide range of asset classes similar to He et al. (2016). The lowest hanging fruit would subsequently be to include government bond portfolios sorted in accordance with Fama (1984), however, it has been indicated by the Swedish National Debt Office that such data are hard to collect. Moreover, the trading volume of more sophisticated financial instruments in Sweden has remained low until recent years. Another possible expansion of the test would be to look at cross-country evidence, with possible candidates of inclusion being the Eurozone and/or the United Kingdom. While the Eurozone lacks the agglomerated stock exchange needed for the test configuration, we want to acknowledge the fact that the UK remains a highly interesting setting for a similar test with its distinct stock market and country-specific implementation of monetary policy, but such an analysis lies beyond the scope of this paper.

Looking past the standard econometric approach used in our analysis, more sophisticated methods could be implemented both to address the potential weaknesses in the assumptions made as well as to address the critique of standard approaches in asset pricing stipulated in Lewellen et al. (2010). While we have taken the 1st prescription into consideration, we do not include other suggestions, such as confidence intervals for R^2, as suggested in the 5th prescription, since the R^2 fails to address the large *average* cross-sectional pricing errors. Similarly, a χ^2-test of the individual pricing errors, as proposed in section 12.2 of Cochrane (2005), will not add explanatory value for the performance of the models. Potential improvements of the analysis are adjusted standard errors in accordance with Shanken (1992) to address for the fact that factor betas from the times-series regression are estimated, or a horse race configuration, as suggested in section 13.3 of Cochrane (2005), to test the different sets of factors against each other. It should however be noted that the main objective of this paper is to provide, to the best of our knowledge, the first out-of-country sample test of intermediary asset pricing and not a well performed exercise in econometrics for its own sake.

VIII. Conclusion

The overall conclusion of our analysis is that the AEM model, with its low total MAPE of 6.8%, performs better than the standard benchmark models in the Swedish equity market, while the HKM model, with its high total MAPE of 26.9%, performs in line with the benchmarks. However, bearing in mind the eloquent remark of Cochrane (2005) that "many models are wrong, but still pretty darn good", the AEM model's outperformance does not suggest that the AEM model is correct in its configuration, but only that the CAPM and Fama-French three factor models are questionable benchmarks. Furthermore, our analysis contributes to the existing literature on intermediary asset pricing by adding new empirical evidence, suggesting that the debt constraint framework, and thereby pro-cyclical leverage, may hold true, as seen in the positive price of risk for the leverage factor and negative price of risk for the market capital factor. We hope our results will provide some guidance for future asset pricing research on the Swedish market, by shifting the focus from households to the more sophisticated financial intermediaries.

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Appendix

I. Seasonal Adjustment of the Intermediary Leverage Factor

Table AI presents the results from performing a quarterly seasonal dummy regression on the log changes in broker-dealer leverage, in accordance with the seasonal adjustment made by Adrian et al. (2014a). What we can see is that the seasonal components do not provide any explanatory value for the changes in leverage over our sample period, with the adjusted R^2 at 0%, and none of the seasonal dummies provide significant results at the 10% level. In Figure A1 we plot the leverage factor with and without seasonal adjustment. Here, we can see the low R^2 and non-significant estimates in action, where the seasonally adjusted series almost perfectly follows the unadjusted series. Note that we do not use an expanding window regression to estimate our regression coefficients, as in Adrian et al. (2014a), but since we do not receive significant results using the full sample period, running an expanding window regression will not change the interpretation of our results. Instead, it may even skew the leverage factor series due to the model falsely identifying a seasonal pattern in the early data simply due to realization of the error terms. Our results can be contrasted with the results found by Adrian et al. (2014a), where we find no seasonal component, and they find strong evidence for seasonal components in the data. While this may seem puzzling, there is no theoretical rationale for broker-dealers displaying seasonal patterns in their leverage.

II. Primary Dealers

Table AII presents a list of primary dealers provided to us by the Swedish National Debt Office. As opposed to the list of primary dealers that He et al. (2016) uses, our list contains quite a few non-listed companies, as well as a combination of Swedish, Nordic, and non-Nordic companies of very varying size, which led us to making the adjustments to the list for the factor construction outlined in Section IV. Figure A2 plots the market capitalization, book liabilities, and the sum of the two series for the time period 1997Q4 to 2015Q4, for the primary dealers included in our study. One interesting thing to note in the data is the development of libailities over the sample period; between 1997 and 2008, there seems to be almost constant growth, however, after the financial crisis, the growth stops, and liabilities stay more or less the same up until 2015. This effect is most probably due to regulatory changes for the financial sector following the financial crisis, and the companies included in our primary dealer sample will have been affected by these regulatory changes. On the other hand, this should not affect the viability of the pricing model, since this is the expected direction of causality.

III. Intermediary Leverage Cyclicalilty

In Figure A3, we show the cyclicality of broker-dealer leverage and primary dealer capital ratios. This is a graphical representation of Table III, and what we can see is that the broker-dealer leverage growth and asset growth are closely and positively correlated, lining up very neatly in an upward-sloping line. The primary dealers, however, do not display the same relationship, with the observations scattered, indicating that the net of the two effects within the equity constraint framework mentioned in Section III cannot be determined.

IV. Test Assets

Figure A4 compares the number of companies included in our sample from which we construct our test portfolios to the number of companies reported to be listed on the Stockholm Stock Exchange, as well as the World Bank's reported number of companies listed in Sweden in total. In the beginning of the sample, our data suffer from clear exlcusion bias, with only ~28 companies included. However, in the later parts of the sample, our data contain more companies than both of the other sources, which is due to our sample containing companies listed on all different exchanges, including smaller, independent exchanges such as Aktietorget and the Nordic Growth Market (NGM). Further, Table AIII shows the preferred shares listed on Swedish exchanges as of 2015-05-01. We can see that the vast majority of companies with preferred shares outstanding are real estate companies, which will be excluded from our test portfolios. Due to this very small number of preferred shares in our sample, the possibility of achieving skewed measures of market capitalization due to the relatively high market value of a preferred share compared with a common share will be minimal. Furthermore, there is no reliable way (except for manual adjustments) to remove the preferred shares from the Compustat data, since no differentiation is made between common and preferred shares.

V. Combining the AEM and HKM Models

Table AIV presents the results from combining the two intermediary factors in one model, denoted LevCap, over the overlapping period 1998Q1 to 2010Q2. Tests are run in exactly the same way as outlined in Section V, with the vector of risk factors being **f** = [LevFac, MCFac]. We run these tests to explore their combined exploratory value, since as we saw in Table IV, the two factors are uncorrelated, and should therefore explain different variation. However, since the method used is asymptotically valid in the time-series dimension, the short time-series data is far from optimal. Here, just as in Table V, the CAPM and Fama-French three-factor models generate extremely large intercepts in the cross-sectional regression, which in turn drives up the total MAPE (24.6% for the CAPM, and 29.7% for the Fama-French three-factor model). While the performance of the LevCap model in terms of MAPE is better compared to the two benchmark models, the total MAPE is still very large at 16.4% per annum, indicating poor model performance. The adjusted R^2 for the models also point in the direction of poor performance of the LevCap model, with the model only achieving a result of 45%, compared to 69% for the CAPM and 86% for the Fama-French three-factor model. Once again, just as in Table V, we can see that the price of risk is negative for the market capital factor, at -16.9%, which will drive up the intercept. In the case of further research on this topic, we would like to propose using the leverage ratio for the primary dealers, since our main results support the debt constraint framework, which implies that the change in leverage ratios is the correct measure of funding conditions, and thus what should correctly price financial assets. However, as is discussed in Section VII, the most interesting area for future research would be to identify the representative financial intermediary, rather than looking across the sector.

Table AI

Broker-Dealer Leverage Shows No Signs of Seasonality

This table presents the estimates, *p*-values, and R^2, of a quarterly seasonal dummy regression of the log changes in Broker-Dealer leverage. The model is estimated as $\Delta \ln(Leverage_t) = \beta_0 + \beta_{Q2}Q_2 + \beta_{Q3}Q_3 + \beta_{Q4}Q_4 + \varepsilon_t$. Data are quarterly over the period 1985Q1 to 2010Q2.

Quarterly Dummy Model					
	R^2	Constant	Q_2	Q_3	Q_4
Estimate		0.08	-0.15	-0.04	-0.14
p -value		0.38	0.13	0.74	0.31
R^2	0.00				

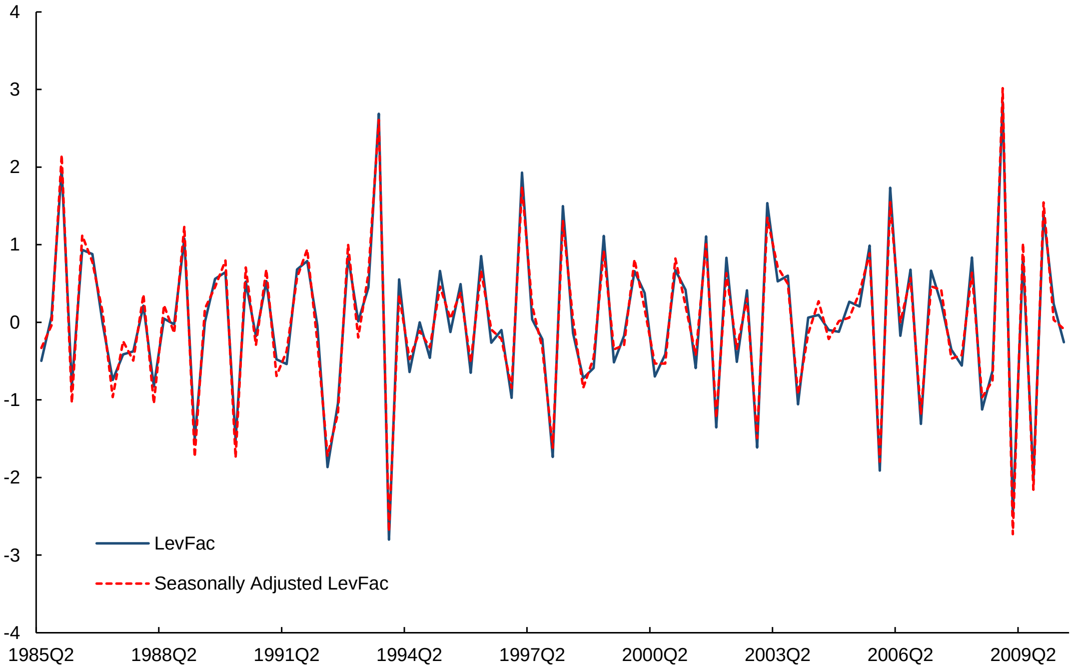


Figure A1. Broker-Dealers: leverage factor and seasonally adjusted leverage factor. We plot the leverage factor based on Adrian et al. (2014a), as well as the seasonally adjusted leverage factor. The seasonally adjusted leverage factor is the sample correspondent of the error term, $\varepsilon_t = Leverage_t - (\beta_0 + \beta_{Q2}Q_2 + \beta_{Q3}Q_3 + \beta_{Q4}Q_4)$. The series is standardized to display zero-mean and unit variance. Data cover the period 1985Q2 to 2010Q2.

Table AII

List of Primary Dealers

This table presents the primary dealers to the Swedish National Debt Office in the auctions of government bonds, the historical names as well as the current holding company. Furthermore, the current domicile, whether or not the primary dealer was listed, and the time span in which the company acted as a primary dealer is presented. The primary dealers listed in bold font are the ones used to construct the market capital factor.

Primary Dealers					
	Historical Name	Current Holding Company	Domicile	Listed	Years
Aragon	Aragon		SWE	No	1996
Barclays Capital	Barclays Capital		UK	Yes	2007-Current
Calyon	Bank Indosuez	Crédit Agricole	FR	Yes	1996-1997
Danske Bank Markets	Danske Bank Markets	Danske Bank	DK	Yes	1996-Current
Handelsbanken Markets	Handelsbanken Markets	SHB	SWE	Yes	1996-Current
JP Bank	JP Bank	Ålandsbanken	SWE	No	1996-1999
JP Morgan	JP Morgan		US	Yes	1998-2000
Midland	Midland	HSBC	UK/HK	Yes	1996-1998
Nordea	Nordea		SWE	Yes	1996-Current
	Nordbanken		SWE		
	Unibank		DK		
Nykredit Bank	Nykredit Bank		DK	No	2011-2015
Penser	Penser		SWE	No	1996-1998
Royal Bank of Scotland	Royal Bank of Scotland		UK	Yes	1996-Current
	ABN Amro		NL		
	Alfred Berg Transferator		SWE		
Salomon Smith Barney	Salomon Smith Barney	Citigroup	US	Yes	1999-2002
SEB	SEB		SWE	Yes	1996-Current
Swedbank	Swedbank		SWE	Yes	1996-Current
	Föreningssparbanken		SWE		
United Securities	United Securities	HQ AB	SWE	Yes	1996
Öhman	Öhman		SWE	No	1996-2008

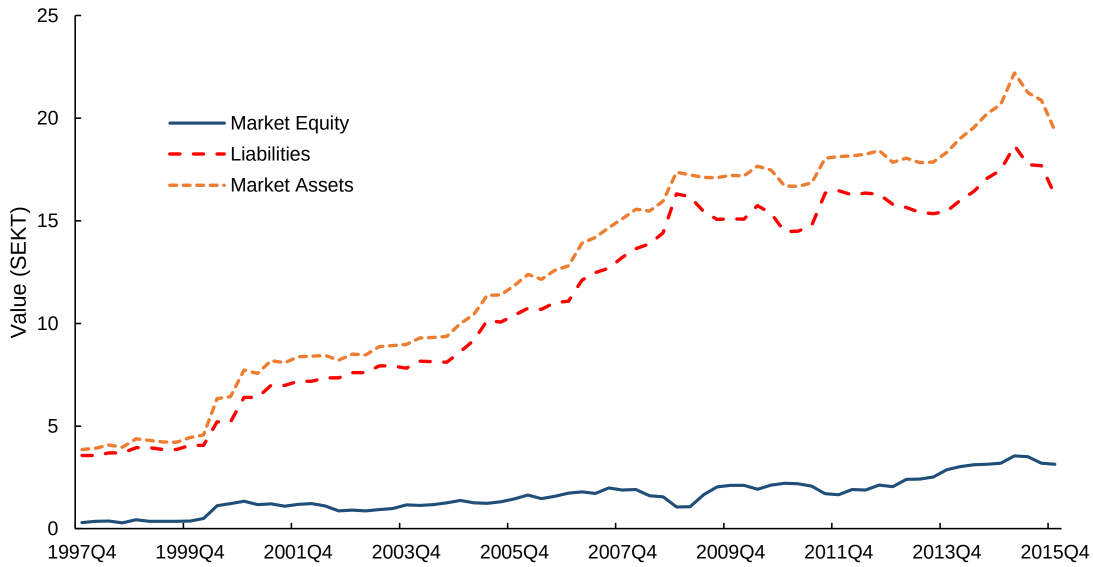
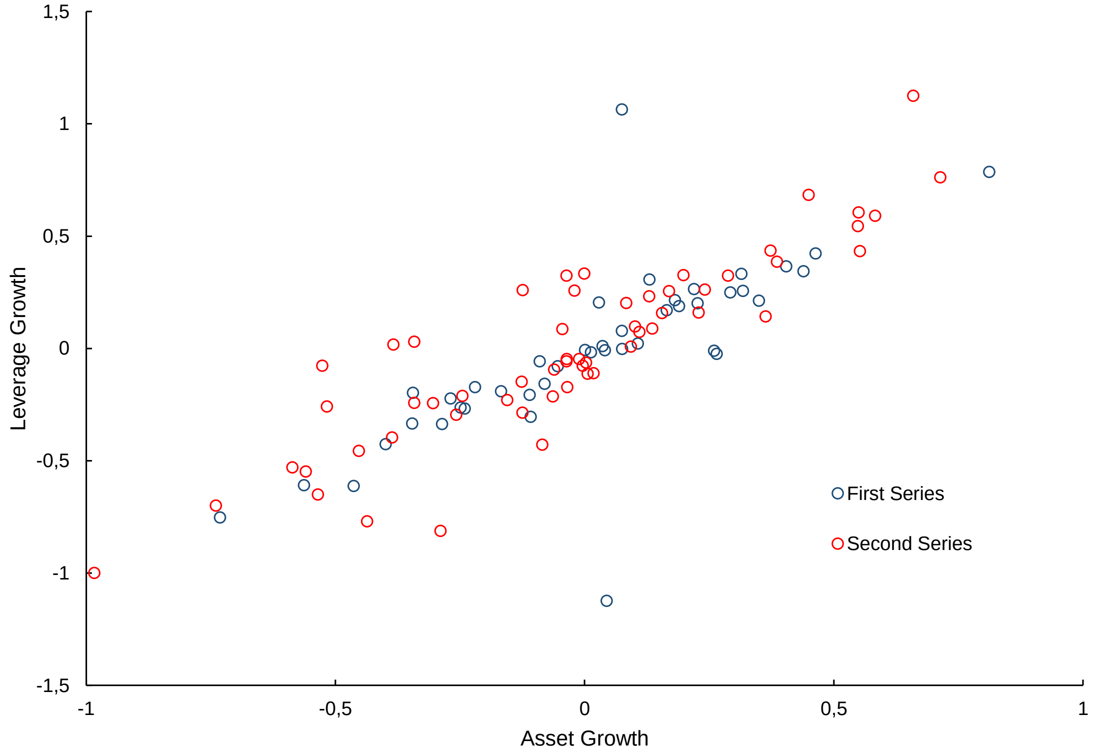
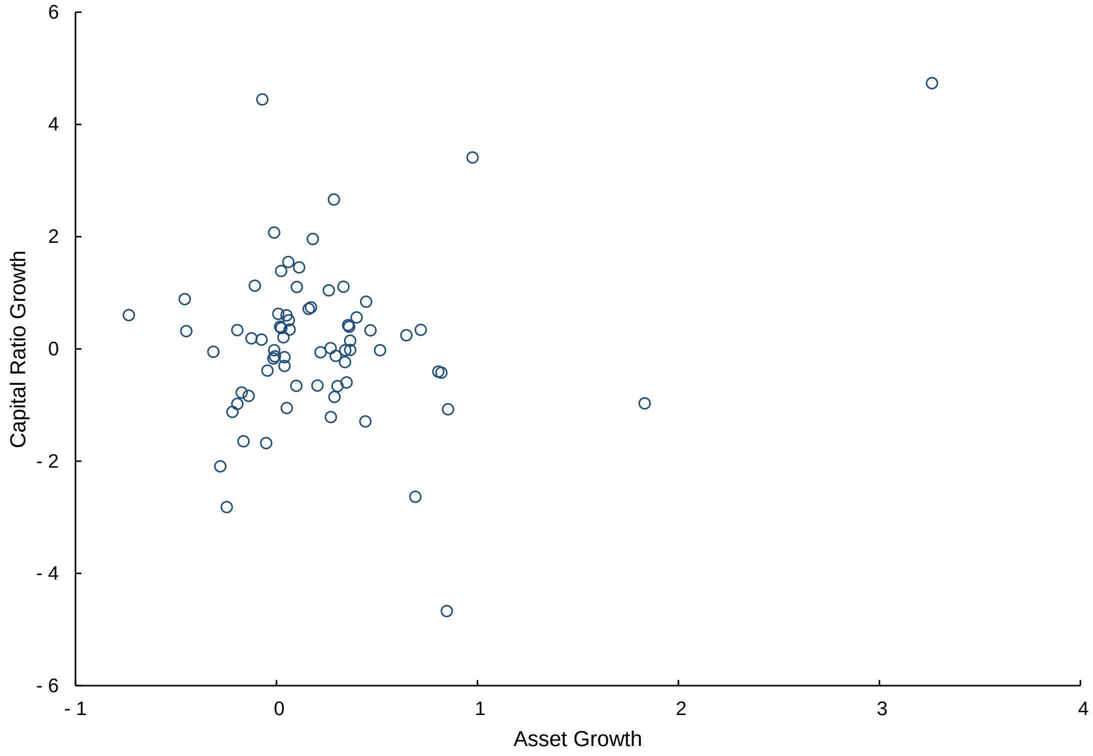


Figure A2. Market equity, book liabilities and market assets for primary dealers. We plot the market equity, book liabilities and market assets (defined as the sum of market equity and book liabilities) for the primary dealers used to construct our market capital factor. Data are quarterly and cover the period 1997Q4 to 2015Q4.



a) Broker-Dealer



b) Primary Dealer

Figure A3. Broker-dealer leverage and primary dealer capital ratio cyclicality. We plot the leverage growth versus the asset growth for broker-dealers, as well as the market capital ratio growth versus the market asset growth for primary dealers. Broker-dealer data cover the period 1985Q2 to 2010Q2 (the first series cover 1985Q2 to 1995Q4, and the second series cover 1996Q1 to 2010Q2), while primary dealer data cover the period 1998Q1 to 2015Q3. In b), both series are multiplied by 10 for convenience.

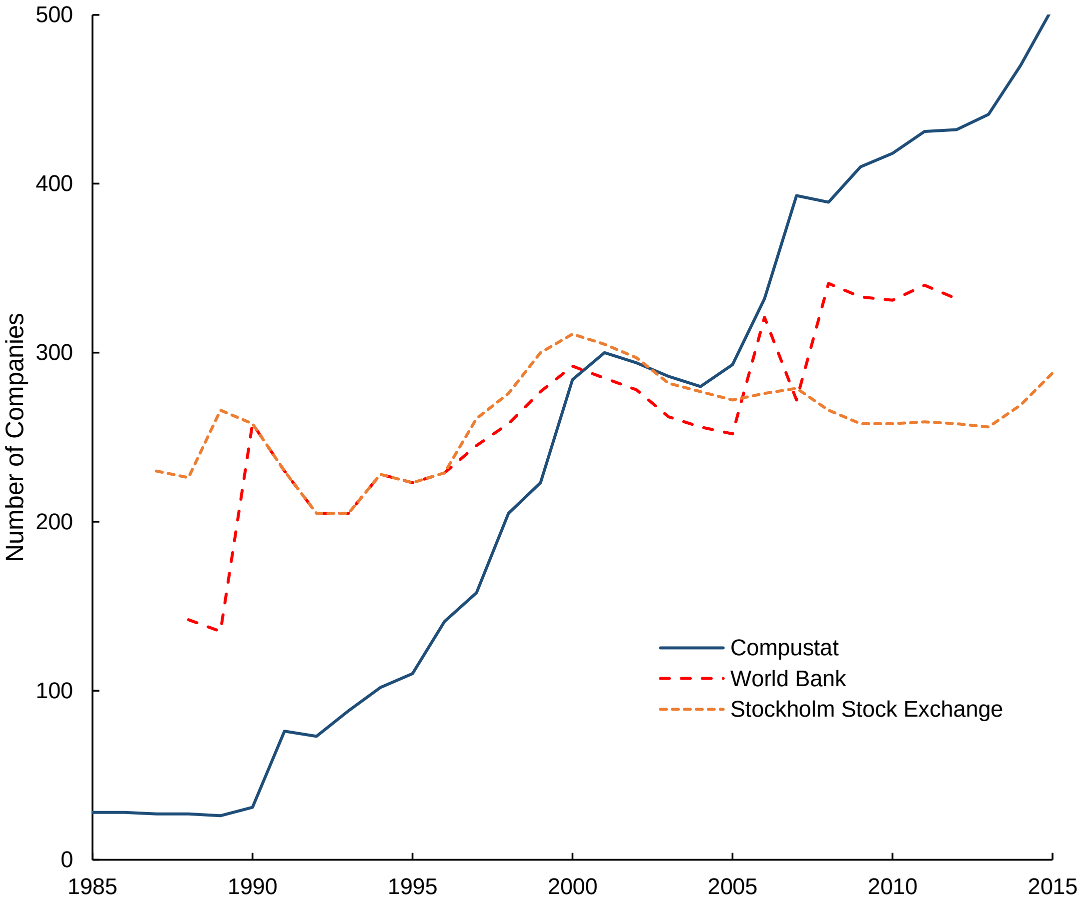


Figure A4. Number of companies in portfolios. We plot the number of companies listed in Sweden at year-end according to Compustat, World Bank, and the Stockholm Stock Exchange. Data are yearly over the period 1985-2015.

Table AIII

List of Companies with Preferred Shares Outstanding as of 2015

This table presents the companies listed in Sweden which have preferred shares outstanding as of 2015-05-01. Bolded firms represent the ones which will be included in our portfolios. Data have been collected from the Avanza Bank website.

Companies with Preferred Shares Outstanding as of 2015-05-01	
	Industry
Fastighets AB Balder	Real estate
Ratos	Investment
Corem Property Group	Real estate
Eniro	**Information**
FastPartners	Real estate
Hemfosa Fastigheter	Real estate
Klövern	Real estate
Sagax	Real estate
SAS	**Airline**
Victoria Park	Real estate
Akelius Residential	Real estate
ALM Equity	Real estate
Amasten Holding	Real estate
Ginger Oil	**Oil/Energy**
K2A Knaust & Andersson	Real estate
Prime Living	Real estate
Tobin Properties	Real estate

Table AIV

Pricing the Equity Portfolios: Combining Leverage and the Market Capital Ratio

This table presents the cross-sectional pricing results for the 6 size and book-to-market, 10 momentum and 5 industry portfolios. The models are all estimated as $E[R^e_{i,t}] = a + \beta'_{i,f}\lambda_f + \xi_i$. CAPM denotes the capital asset pricing model, FF3 denotes the Fama-French three-factor model, LevCap a model combining the intermediary leverage factor from Adrian et al. (2014a) and the intermediary market capital factor from He et al. (2016). Panel I reports the prices of risks with heteroscedasticity adjusted t-statistics and Fama-MacBeth t-statistics from the estimations in both time samples. Panel II reports the test diagnostics, including mean absolute pricing error (MAPE) by portfolio group, the total MAPE, as well as the adjusted R^2 for each model in both samples. Data are quarterly from the periods 1998Q1 to 2010Q2. Returns and risk premia are reported in percent per annum i.e. quarterly percentages multiplied by four.

Panel I: Prices of Risk

	CAPM	FF3	LevCap
Intercept	21.34	27.65	11.63
t-stat	12.72	19.30	3.43
t-FM	2.97	3.15	1.81
LevFac			86.54
t-stat			1.42
t-FM			1.07
MCFac			-16.90
t-stat			-1.34
t-FM			-1.03
Market	-17.61	-23.02	
t-stat	-10.97	-15.86	
t-FM	-1.68	-1.98	
SMB		8.21	
t-stat		5.37	
t-FM		1.75	
HML		5.06	
t-stat		2.53	
t-FM		0.63	

Panel II: Test Diagnostics

MAPE	CAPM	FF3	LevCap
Size B/M	3.07	1.34	6.03
Mom	4.20	2.64	4.38
Industry	1.58	1.87	3.81
Intercept	21.34	27.65	11.63
Total	24.59	29.74	16.35
R^2	0.69	0.86	0.45