Asset returns and financial intermediary leverage

An emprical analysis

Erik Hapnes

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Abstract

In this paper the result of Adrian, Etula, and Muir (2014) is reexamined. They propose a model with financial intermediary leverage that is able to price a set of portfolios remarkably well. In this paper the model is estimated with different portfolios as test assets. This is done to account for recent critiques of the use of size and book-to-market sorted portfolios as test assets. This paper uses two new sets of portfolios, industry portfolios and portfolios sorted on size and pre-formation leverage beta. The proposed model with financial intermediaries is not able to explain the variation of cross-sectional average returns on the two new sets of portfolios.

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Preface

This thesis was written as the concluding part of my Master of Science in Economics and Business Administration at the Norwegian School of Economics(NHH). The thesis is written in conjunction with my major in Economic Analysis.

The idea for the topic and methods in this thesis builds on papers presented at a workshop in empirical asset pricing at NHH during the fall 2014. The work with the thesis has been very educational and left me with greater insight in how one can conduct economic research. Constructing portfolios to use as test assets have been the most challenging part of this thesis and it is not hard to understand why many researchers prefer to use readily available test portfolios.

I would like to thank my advisor, Jørgen Haug, for valuable input and suggestions during the writing process.

Bergen, June 2015

Erik Hapnes

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1 Introduction

In this paper I will reexamine the result from Adrian, Etula, and Muir (2014). They find that a simple one-factor model with shocks to financial intermediary leverage is able to explain the cross-sectional variation in average returns of a set of portfolios remarkably well. They use 25 size and book-to-market sorted portfolios, 10 momentum portfolios and 6 bond portfolios as test assets. In this paper, I redo their analysis with other portfolios as test assets. I use two new sets of portfolio compared to Adrian et al. (2014), industry sorted portfolios and portfolios sorted on size and their pre-formation leverage beta. Both new sets of test portfolios give results that are significantly different from the result from the aforementioned paper. I compare the results with the three-factor model of Fama and French (1993) as a benchmark. The model with intermediary leverage has similar performance as the benchmark for the original analysis. When I redo the analysis with new portfolios, I find little evidence for the proposed model with intermediary leverage in the industry and size and leverage portfolios.

Financial intermediaries are actors who are likely to be closer to the assumptions in asset pricing theory than individual consumers. Financial intermediaries are present in most markets and invest based on sophisticated models and analysis. One example is that banks can often take short positions with securities held in customer's margin accounts and therefore do not need to borrow the security to take a short position. In times of distress, such opportunities might disappear if the clients withdraw their funds. Security broker-dealers in the United States are subject to regulations from the Securities and Exchange Commission (SEC) that put constraints on their capital structure. The standard requirement in the "net capital rule"(SEC rule 15c3.1) is that its aggregate indebtedness should not exceed 1500% of their

capital (net capital must exceed $6\frac{2}{3}\%$ of their aggregate indebtedness). From 2004, security broker-dealers have under some circumstances been allowed to use internal risk models to determine if they fulfill the capital requirement.

The one-factor model is related to several recent theoretical papers where the discount factor of intermediaries can be tied to intermediary balance sheets. In the theoretical literature, the intermediaries are often modeled as risk-neutral actors who face risk related to funding constraints. Their leverage can be proxy for funding constraints. In the theoretical models, the marginal value of wealth for intermediaries is larger when their funding constraints are tighter. They do not need to be financially constrained today, but it might also be related to the risk of becoming financially constrained in the future.

In the empirical asset pricing literature there are a large amount of papers that tries to explain portfolio returns with linear factor models. A large amount of these papers use 25 size and book-to-market portfolios obtained from Kenneth French's website as test assets. Earlier research has found several combinations of factors that are able to explain the returns of these 25 portfolios. Recent papers have questioned these results and showed that the use of these portfolios can lead to wrong conclusion. Problems with these portfolios are both related to their factor structure and how they are constructed based on characteristics. One proposed solution to these problems is to use other, more appropriate test asset to evaluate a proposed asset-pricing model.

2 Literature review

2.1 Adrian, Etula, and Muir (2014)

Adrian et al. (2014) use information from financial intermediaries' balance sheets to explain the cross-sectional variation of asset returns. Their main result is that they are able to explain the cross-section of average returns for a set of portfolios remarkably well. They use a parsimonious model where the stochastic discount factor is given by:

$$m_t = 1 - bLevFac_t \tag{1}$$

where LevFac is a proposed factor of shocks to intermediary leverage[1]. They use the leverage factor to explain 25 portfolios sorted by size and book-to-market, 10 momentum portfolios and 6 bond portfolios. The model is compared to a benchmark model with the three factors from Fama and French (1993), the momentum factor and a principal component used to price the bond portfolios. The two models offer comparable performance with statistically insignificant estimated intercept close to 0, similar R^2 and similar mean absolute pricing errors of the portfolios. As robustness they construct a traded leverage-mimicking portfolio to be able to do time-series tests of their model. They are able to create the leverage-mimicking portfolio with monthly data over a longer time-period. The leverage-mimicking portfolio has comparable results from the time-series regressions as the model with the three Fama-French factors and the momentum factor. They compare the Sharpe-ratio of the leverage mimicking portfolio to the maximum Sharpe-ratio from the four factors and find that it has higher Sharpe-ratio than each of the four factors and almost as high as the maximum. They also create

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[1]A detailed description of the construction of the leverage factor can be found in the data description part of this paper.

portfolios sorted on their leverage factor. They find that average returns are monotonically increasing with increased leverage beta.

2.2 Adrian and Shin (2010)

Adrian and Shin (2010) examine the relationship between asset growth and leverage growth for different groups of actors. In the case of passive balance sheet management, we would expect to see a mechanical negative relationship between asset growth and leverage growth. This is what they observe for asset growth and leverage growth for households. For non-financial firms and commercial banks the correlation is close to 0. For financial brokers and dealers, there is a clear positive correlation between asset growth and leverage growth. This is evidence for active balance sheet management in financial brokers and dealers whereas households have more passive balance sheet management.

2.3 Shleifer and Vishny (1997)

An early theoretical paper that deals with funding constraints in asset pricing is "Limits to Arbitrage" by Shleifer and Vishny (1997). Their model consists of three time periods, t={1,2,3}. At time 1 there exists an arbitrage opportunity with an asset priced lower than the certain time 3 value. They abstract from problems concerning interest rate and risk at time 3. At the intermediate time period there is positive probability that the mispricing will become more severe. In their model, there are risk-neutral arbitrageurs who are financially constrained with funding based on previous performance. If the mispricing increases in time 2, the arbitrageurs' previous performance will deteriorate and their investors will withdraw funds. The implication in their model is that some arbitrageurs will be forced to reduce their holding of the mispriced asset when the mispricing is increased. The leverage factor in

Adrian et al. (2014) may be a proxy for the financial constraints of financial intermediaries. In Shleifer and Vishny (1997) the marginal value of wealth will be higher when the financial constraints are stronger.

2.4   Intermediary asset pricing
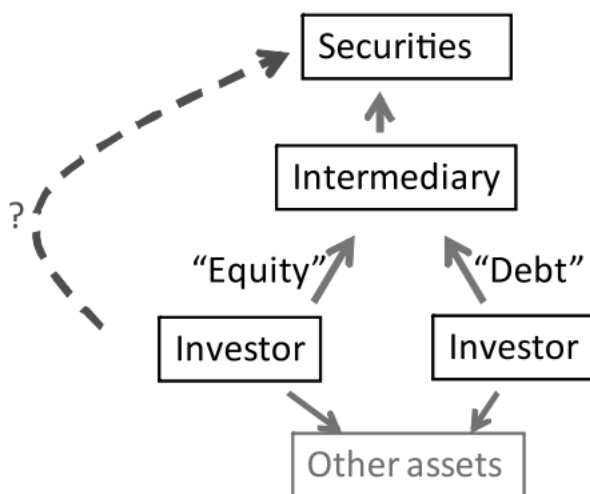
Figure 1: Intermediary Asset pricing:The

In his presidential address, Cochrane (2011) have a short discussion of intermediated markets as markets with frictions. Figure 1 is taken from his explanation of intermediated markets. Investors invest through intermediaries. Investors finance the intermediaries with different types of claims such as debt and equity. There may be problems with asymmetric information is these relationships that can affect asset prices. For instance, in times when the debt is high, the managers of intermediaries will try to avoid bankruptcy by selling risky assets. This is something that may be done by several managers at the same time. This can result in so called "fire sales" and "liquidity spirals". The dotted line is used to describe how large investors may enter in-

termediated markets if the prices deviate too far away from the fundamental value. Cochrane (2011) suggest that trying to tie prices or discount-rate variation to central items in models with financial intermediaries might be more productive than arguing over puzzling patterns. He mentions one possible way to do this can be to use balance sheet data from leveraged intermediaries.

There are several theoretical models where financial intermediaries influence asset prices. In Brunnermeier and Pedersen (2009), they model risk-neutral intermediaries subject to financing constraints. The model is concerned with market liquidity and funding liquidity of traders. Traders may experience initial losses that give funding problems. This requires them to reduce their positions. Under some circumstances, the result can be liquidity spirals where liquidity dries up when several traders have to reduce leverage. The resulting stochastic discount factor will be $m_{t+1} = \frac{\phi_{t+1}}{E_t[\phi_{t+1}]}$ where ϕ_{t+1} is the Lagrange multiplier on the funding constraint at time t+1. The Lagrange multiplier is monotonically decreasing in trader leverage. Leverage of financial intermediaries can be used as a proxy for funding conditions and Adrian et al. (2014) use this as a justification for their one-factor model with financial intermediary leverage. They propose that ϕ_t can be approximated by:

$$\phi_t \approx a - b \ln(Leverage_t) \qquad (2)$$

Another approach is Danielsson, Shin, and Zigrand (2010) who also consider risk-neutral intermediaries who are subject to VaR-constraints. In their model, traders risk appetite may be time varying because of the VaR-constraints even if preferences are constant. In equilibrium, the returns of assets depend on the risk appetite of the traders and through the VaR-constraints, the leverage of the traders enter the stochastic discount factor.

Examples of other theoretical approaches are Brunnermeier and Sannikov (2014) and He and Krishnamurthy (2008) where financial intermediary wealth, not leverage are driving asset prices. Brunnermeier and Sannikov (2014) develop a macroeconomic model with two types of agents, experts and households. In their model, physical capital can be traded in markets and the two types of agents wealth constraints determine equilibrium prices. Financial intermediaries exist due to problems of asymmetric information and the model predicts that financial intermediary wealth is a proxy for systematic risk. The model by He and Krishnamurthy (2008) has specialized intermediaries who invest in risky assets and riskless assets and households who invest through the intermediary or in the riskless asset similar to Figure 1. In their model, the intermediaries have constraints with raising equity funding. The result in their model is that when financial intermediary capital is low, losses for financial intermediaries have a strong effect on risk premia. If their capital is high, the effect of losses on risk premia is small. Thus the intermediary capital, not leverage, is the variable driving differences in the state prices. Empirically Adrian et al. (2014) do not find evidence that financial intermediary wealth is driving asset prices.

2.5 Lewellen, Nagel, and Shanken (2010)

Lewellen, Nagel, and Shanken (2010) observe that many recent asset pricing models are apparently successful at explaining the size and value premia. These models are often unrelated and therefore they cannot all be correct. Their suggestion is that the problem is related to the test assets. Many papers use the 25 portfolios sorted on size and book-to-market obtained from Ken French's website. These portfolios have desirable properties such as a large spread in the cross-sectional average returns. In addition to this, the portfolios are easily accessible to use for research. Their main argument is

that most of the variation in these 25 portfolios is explained by the three factors from Fama and French (1993). If you take a new factor model where the factors are correlated with the factors from Fama and French (1993), but not with the residuals, then the new model will also produce large R^2. They provide a simple proof of the problem. Assume the true model is:

$$R = BF + \epsilon \tag{3}$$

Where R is a vector of average excess returns, $B \equiv cov(R, F)var^{-1}(F)$ is a matrix of the loading of the risk factors, F is the cross-sectional risk premia and $E[\epsilon] = 0$. Since this is the true model it has $R^2 = 1$ if we do not consider the sampling variation. A proposed new model, P, with the same number of risk factor as the true model is estimated as:

$$\mu_R = z + C\lambda + \alpha \tag{4}$$

Their observation is that if $cov(F, P)$ is nonsingular and $cov(P, \epsilon) = 0$, the new model will also have $R^2 = 1$ and apparently be able to perfectly explain the cross-sectional variation regardless of how little correlation there is between the true model and the proposed model. A model that explains very little of the time-series variation in returns may look very good in the cross-sectional tests. We have cov(R,P)=Bcov(F,P). The factor loadings on P is then:

$$C = cov(R, P)var^{-1}(P) = Bcov(F, P)var^{-1}(P) \tag{5}$$

If Q is defined as $Q = cov(F, P)var^{-1}(P)$ we have $B = CQ^{-1}$ and $\mu = CQ^{-1}\mu_F = C\gamma$ where $\gamma = Q^{-1}\mu_F$. Thus we have a new model that also has $R^2 = 1$ and the proposed model is apparently successful at explaining the variation cross-sectional average returns. The risk premia in the proposed model γ is not necessarily equal to the risk premia of the factors P.

The crucial assumption here is that $cov(P, \epsilon) = 0$. In the 25 size and book-to-market portfolios, the 3 factors from Fama and French (1993) explain most of the variation and ϵ is small. Thus they argue that it is not surprising that many proposed factor models appear to explain these returns. Therefore it is not a large hurdle for a factor model to explain these portfolios. Any model where the factors are correlated with the SMB and HML[2] and not with ϵ will likely produce a high R^2.

They provide simulation-based tests of their argument and find that random simulated factors often provide strong test diagnostics. Figure 2 is from their Figure 1 and shows the R^2 from their random factors. The problem is not as severe for 1-factor models, but the 95th percentile still gives a very large R^2. They also simulate factors with mean 0 and thus the theoretical price of the risk factor should be 0 and the model should not have any explanation power. This still gives high R^2 for a large fraction of the simulated factors.

The conclusion from their analysis is that asset pricing tests can be misleading where models with good test diagnostics(high R^2 and small pricing errors) do not necessarily provide strong evidence for a model. They offer some suggestions to improve empirical test. Among them is the use of other portfolios than just size and book-to-market sorted portfolios such as portfolios sorted by industry or factor loading. Another suggestion is to take theoretical restrictions such as magnitude of price of risk and intercept into consideration. Other suggestions are to use GLS rather than OLS because it has more informative test diagnostics in their simulation studies or to create confidence intervals of the test diagnostics.

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[2]There is little variation in β_{mkt} among the 25 size and book-to-market portfolios and thus the variation in cross-sectional average returns is mainly explained by SMB and HML.
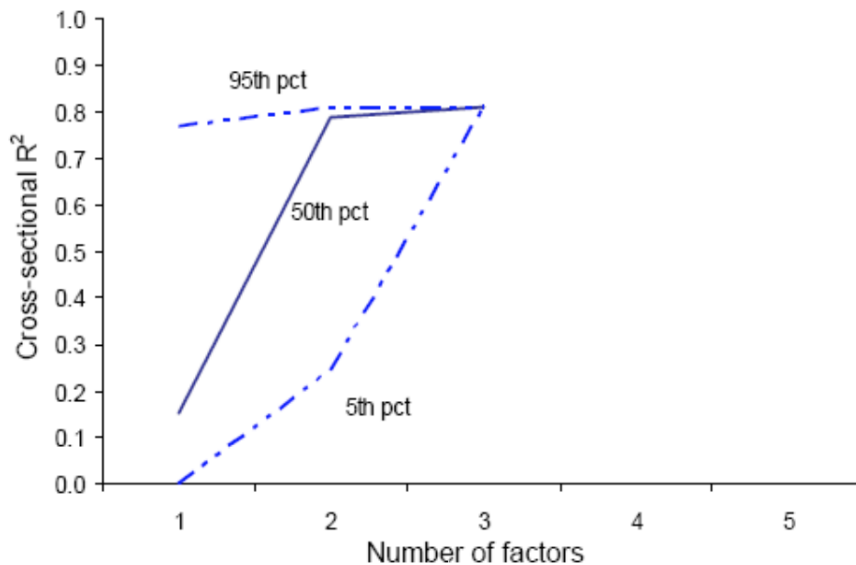
Figure 2: The figure shows R^2 with simulated factors from Lewellen et al. (2010) where the 25 size and book-to-market portfolios are used as test assets.

The paper is relevant because the original analysis use the 25 size and book-to-market portfolios in addition to 10 momentum portfolios and 6 bond portfolios. The model of Adrian et al. (2014) only has one factor and is thus less affected by the problems discussed in Lewellen et al. (2010) than models with more factors.

2.6   Daniel and Titman (2012)

Daniel and Titman (2012) also consider the problem that there are several factor models with economical motivated factors that are able to explain variation in average returns of portfolios. The factors in these models are only weakly correlated and as a result, they would give very different pricing kernels. They argue that the problem is related to how the portfolios are constructed.

When securities are sorted in portfolios based on characteristics, most of the variation in factor loadings that is independent of the characteristics is diversified away. The only variation in factor loadings that is left is the variation that is correlated with the characteristics. Since the characteristics are correlated with returns, the proposed factor loadings will be correlated with returns. The result will be that it appears as if the proposed factor loading is able to explain variation in average returns of the portfolios even when it is only correlated with returns through its correlation with the characteristics. They argue that with portfolios sorted on characteristics, asset-pricing tests have very little power to reject a proposed model if what they call the *characteristic* model is correct. In the case of portfolios sorted on size and book-to-market, the *characteristic* model would be that variation in average returns depends on size and book-to-market.

They simulate a simple model to explain the problems related to different ways of sorting portfolios. In their simulated model they have returns that vary with book-to-market value. In addition they have market betas that are correlated with book-to-market value. The market betas are only correlated with returns through their correlation with book-to-market value. As the null hypothesis they estimate CAPM on the simulated data with three different ways of sorting the portfolios. They use two ways of sorting based on a single variable. They sort on book-to-market and on market beta. Both approaches result in a clear linear trend with a statistically significant slope when they estimate the CAPM. The linear trend is only a result of the correlation between book-to-market values and market beta. The third way of sorting portfolios is to first sort on book-to-market values, then they sort on market beta within each group from the first stage. This creates variation in market beta that is almost independent of book-to-market value. When they

estimate CAPM on these portfolios, the results are close to the true model with a slope of 0.

They also reexamine two specific models with where they use more suitable portfolios. They use both portfolios created specifically to test the hypothesis in the earlier analysis and industry portfolios. When they create portfolios to test a hypothesis, they sort stocks based on size, book-to-market and pre-formation correlation with the factor. With this procedure, they are able to create variation in correlation with the proposed factor that is independent of size and book-to-market. When they use industry portfolios they are also able to get variation in both average returns of the portfolios and in the factor loadings. The results for both reexamined models is that the results look very different when they use different test portfolios.

They suggest to use test assets that span a higher dimensional subspace of the return space than the 25 size and book-to-market portfolios. The paper is related to Lewellen et al. (2010). Both articles argue that the low dimensionality of the 25 size and book-to-market portfolios cause problems. Lewellen et al. (2010) show that the result of the low dimensionality is that it will not be very difficult to price these portfolios with other factor models. Daniel and Titman (2012) argue that the way these portfolios are created diversifies away much variation and makes it difficult to distinguish between a proposed model and what they call the *characteristic* model. Daniel and Titman (2012) is relevant to this paper because it shows the importance of having independent variation in the correlation with the proposed factors.

3 Asset pricing theory

To test an asset pricing model we need to know what implications it has for the empirical observations. We can use the stochastic discount factor framework to do this.

3.1 Stochastic discount factor

The price of an asset is given by discounting all future dividends by the stochastic discount factor. The stochastic discount factor is not known and different asset pricing models will give different stochastic discount factors.

$$p_t^i = E_t[m_{t+1}(p_{t+1}^i + d_{t+1}^i)] \tag{6}$$

In the absence of arbitrage, the price of asset i at time t is given by (6) where m_{t+1} is the stochastic discount factor from time t to t+1. The price at time t is p_t and the dividend at time t is d_t. This can be rewritten in terms of returns by dividing by p_t^i and we get:

$$1 = E_t[m_{t+1}R_{t+1}^i] \tag{7}$$

This relationship also holds for the risk-free asset. From this property, we can rewrite (7) and get:

$$0 = E_t[m_{t+1}(R_{t+1}^i - R_{t+1}^f)] \tag{8}$$

This can be rewritten as:

$$E_t[R_{t+1}^{e,i}] = -\frac{Cov_t(m_{t+1}, R_{t+1}^{e,i})}{E_t[m_{t+1}]} \tag{9}$$

$R_{t+1}^{e,i}$ is excess return over the risk-free rate at time t+1 for asset i.

3.2 Linear factor models

The form of the stochastic discount factor is based on the asset-pricing model. For linear factor models, the stochastic discount factor is an affine function of the factors $m_{t+1} = a_t - b_t f_{t+1}$ where f_{t+1} is a vector of the factors at time t+1. For CAPM, f_{t+1} will be the return of the market portfolio at time t+1. Conditional factor models have a_t and b_t that may be time varying. If a_t and b_t are constant, we have an unconditional asset pricing model. Adrian et al. (2014) propose an unconditional factor model with their leverage factor. From (8) we observe that we can multiply m_{t+1} with any scalar without affecting the results. Thus we can normalize a to 1 to simplify the expression. When we have an unconditional one-factor model we can rewrite 9 and get:

$$E_t[R_{t+1}^{e,i}] = -\frac{Cov_t((1+bf_{t+1}), R_{t+1}^{e,i})}{E_t[1+bf_{t+1}]} = \frac{bCov_t(f_{t+1}, R_{t+1}^{e,i})}{bVar_t(f_{t+1})} \frac{-bVar_t(f_{t+1})}{E_t[1+bf_{t+1}]} \tag{10}$$

This can be rewritten as:

$$E_t[R_{t+1}^{e,i}] = \beta_t^i \lambda_t \tag{11}$$

Where we have the vectors $\beta_t^i = \frac{Cov_t(f_{t+1}, R_{t+1}^{e,i})}{Var_t(f_{t+1})}$ and $\lambda_t = \frac{-bVar_t(f_{t+1})}{E_t[1+bf_{t+1}]}$. When we have a multifactor model, the expressions for the loadings of the risk factor on the securities and the price of risk is not exactly as for one-factor models, but equation (11) still holds with β_t^i and λ_t as vectors rather than scalars. The empirical approach in the next section assumes that both the β_t^i and λ_t are constant over the time period. This means that it is assumed that the distribution of the factors and the covariance with excess return on the assets are constant over the time period. Ghysels (1998) consider the problems related to time-varying factor loadings. If we estimate a model with constant factor loadings when the factor loadings are time varying, the pricing errors will become larger.

4 Empirical strategy

4.1 Cross-sectional regressions

If the factor had been traded, it would have been possible to use either time-series regressions or a cross-sectional regression to evaluate the model performance. The leverage factor is not traded and therefore we cannot use time-series regressions to evaluate the model. When the factor is not a traded asset, we can use the two-stage method that gives the same results as using the procedure from Fama and MacBeth (1973) with constant betas. The first step is to estimate the factor loadings with time-series regressions for each portfolio:

$$R_t^{e,i} = \alpha + \beta^i f_t + \varepsilon_t^i, \ t = 1, \cdots, T \ \forall i \tag{12}$$

$R_t^{e,i}$ is the excess return of portfolio i at time t, f_t is the vector of proposed factors. Then we use the estimated betas to estimate the model from (11). The first step estimates the loading of the risk factors on the different test assets. The second step estimates the price of the different risk factors.

The theoretical model (11) for expected excess returns do not contain an intercept. When we estimate our model we could impose this structure when we estimate

$$E[R_{t+1}^{e,i}] = \lambda' \beta^i + \epsilon_i, \ i = 1, \cdots, N \tag{13}$$

and this would give more efficient estimates of λ. If we include an intercept, the intercept should be close to 0 and not statistically significant different from 0 if our model is correct and the market is efficient. Fama (1970) showed that we cannot distinguish between the two if we reject the null hypothesis. In the analysis, the model has been estimated with an inter-

cept to be able to test the theoretical restriction that it should be 0. If the factors are traded assets, λ should theoretically be the mean of traded factors.

The estimates from (13) is given by (14) where $\Sigma = Cov[\varepsilon_t \varepsilon'_t]$ and $\Sigma_f = Cov[f_t, f'_t]$ are the covariance matrices of the errors and the factors[3]. The standard errors of the estimated coefficients account for correlated errors in the cross-section, but do not account for time-series correlation or the fact that the factor loadings are estimated in the first stage regression. The lack of correction for time-series correlation is usually not a problem because there is little time-series correlation in stock returns. Shanken (1992) shows how to correct for estimated factor loadings. In Fama and MacBeth (1973) the model is estimated in a three-step procedure. The first step is the same as in the procedure used in this paper. The second step estimates the price of risk for each period based on the factor loadings from the first step. The third step averages the price of the risk factors over time and creates standard errors based on this average.

We can usually not say if the errors are too large if estimate a regression, but when we use the two-stage approach, the first stage gives information that enables us to do this. We can use the additional information from the first stage regression to test if the errors are statistically too large. We can calculate the statistic:

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[3]The estimates of the price of the risk factors are calculated by:

$$
\begin{aligned}
\hat{\lambda} &= (\beta'\beta)^{-1}\beta' E[R^e] \\
\sigma^2(\hat{\lambda}) &= \frac{1}{T}[(\beta'\beta)^{-1}\beta'\Sigma\beta(\beta'\beta)^{-1} + \Sigma_f]
\end{aligned}
\tag{14}
$$

The formulas for the price of risk and its variance are from Cochrane (2005). $\sigma^2(\hat{\lambda})$ has the variance of the coefficients along its diagonal.

$$\hat{\epsilon}' cov(\hat{\epsilon})^{-1} \hat{\epsilon} \sim \chi^2_{N-K} \qquad (15)$$

The statistic has a chi-square distribution with N-K degrees of freedom under the null hypothesis that our model is correct. N is the number of test asset and K is the number of estimated coefficients. If the statistic is sufficiently large, we can reject the null hypothesis that the pricing errors are not too large. $cov(\hat{\epsilon})$ is given by:

$$cov(\hat{\epsilon}) = \frac{1}{T}[I - \beta(\beta'\beta)^{-1}\beta']\Sigma[I - \beta(\beta'\beta)^{-1}\beta'] \qquad (16)$$

4.2 Economical vs. statistical rejection

The procedure used to test the model gives both economical and statistical ways to test whether it is a good model. Economically we would like to see an intercept close to 0, the price of risk with similar sign as predicted by theory or close to the mean if the factor is a traded asset, a large R^2 and small pricing errors. Statistically we can test if the intercept is statistically different from 0 and if the pricing errors are too large with the χ-statistic. In some situations, we might have opposite conclusion. One case is if we have a model that is close to the true model and also estimated precisely. Since it is estimated precisely, we may still reject the null hypothesis that the intercept is 0 when it deviates a little from 0. The other case is if we have a poor model, but also large standard errors of the coefficients. We may have an intercept that is not close to 0, but not statistically different from 0. The same may happen in the χ^2-test used to test if the pricing errors are too large.

In statistical hypotheses testing we may have type I or type II errors. A type I error is an incorrect rejection of a correct null hypothesis. A type II error is the opposite where we keep an incorrect null hypothesis. We can

usually calculate the distribution of a test statistic under the null hypothesis. This enables us to decide the maximum probability of a type I error we can accept. This is more difficult for type II errors because we can usually have infinitely many possible distributions other than the distribution under the null hypothesis and the probability for a type II error depends on which of these unknown distributions is the correct. There is a relationship between type I and type II errors where we can reduce the probability of one by increasing the probability for the other type of error. The power of a test is defined as 1 minus the probability of a type II error.

In the tests used in this paper, the null hypothesis in the statistical tests are that the model is correct. In the test with the intercept, the null hypothesis is that the intercept is 0 and the test of the pricing errors has a null hypothesis that all pricing errors are 0. Thus we might get results that look better in a statistical sense if our estimates have less power to reject our null hypothesis. To be able to be better able to test our model, we should use test assets that give more power to reject the null hypothesis in situations where it is incorrect. Daniel and Titman (2012) argue that many proposed models perform well because the empirical analyses lack power to distinguish between the null hypothesis and the *characteristic* model.

4.3   Choice of test assets

The test used in this paper assumes that both loadings of the risk factors to each test asset and the price of risk is constant. For many firms, the loadings of the risk factors will change over time. For instance, a firm may be a small firm in a new industry in the first part of the series and a large firm in a mature industry in the last part of the series. Such a firm is likely to have different exposures to risk in the early part of the series compared to the last

part of the series. One way to reduce such problems is to sort stocks into portfolios where the portfolios are less exposed to time-varying exposures to the risk factors. If we sort into portfolios, we might reduce such problems if the firms who change risk also moves to a new portfolio or if the changes within a portfolio cancels each other.

In the first stage of the regression, the loadings of the risk factors are estimated and therefore there are estimation errors. If the estimation errors of the different assets are independent, the estimation error of the portfolio will approach 0 as the number of assets approaches infinity(Huang and Litzenberger, 1988).

Ang, Liu, and Schwarz (2008) shows that grouping stocks into portfolios do not increase the efficiency in the cross-sectional analysis. They show analytically that more precise estimates of the loadings of the risk factors do not result in more precision in the estimates of the price of the risk factors. The grouping of stocks into portfolios reduce the variation in the loadings of the risk factors and causes less precise estimates of the price of risk factors.

There are different ways of sorting portfolios. One way is to sort portfolios based on observable characteristics such as size, book value divided by market value or industry. Another way is to sort them based on their beta with a proposed factor. When we sort securities into portfolios we want to create portfolios with variation in returns and loadings of the proposed risk factors to be able to estimate the price of risk with precision.

5 Data description

5.1 Leverage factor

The leverage factor is created from aggregate balance sheets of security broker-dealers. Security broker-dealers are agents who engage in trading securities, either for its own account or on behalf of its customers. Among the broker-dealers are subsidiaries of investment banks and commercial banks. Broker-dealers are required to file financial and operational reports(FOCUS-reports) to the SEC. The FOCUS-reports must be filled at least quarterly. The Federal Reserve *Flow of Funds* report contains the aggregate balance sheet of broker-dealers from the FOCUS-reports in Table L.129. Table 1 shows the aggregate balance sheet of broker-dealers at 2010Q4. It is similar to the balance sheet shown in Adrian et al. (2014), but it has been updated with both the asset and liability repurchase agreements(repos) rather than just net repos[4]. The Flow of Funds data series starts in 1952Q1, but the first period of the series have some properties that raise suspicions. In the first part of the series, the broker-dealer equity is negative and for most of the early part of the series, the leverage is very high. From the last part of the 1960s the leverage reaches more reasonable magnitudes and becomes more stable. Therefore Adrian et al. (2014) use the series between 1968Q1 and 2009Q4. The leverage time series is shown is Figure 3 where the blue line shows the leverage with full specification of repurchase agreements and the red line shows leverage with net repurchase agreement specification.

The leverage factor is constructed from the Federal Reserve *Flow of Funds* Table L.129. Leverage is calculated as:

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[4]The result of the cross-sectional regressions are not sensitive to the specification of repurchase agreements used to calculate leverage.
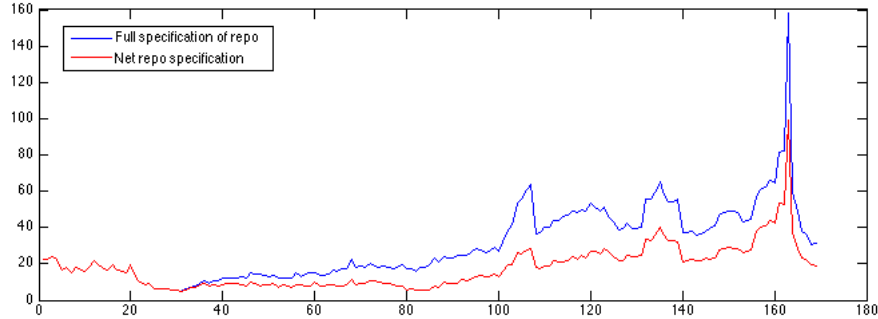
Figure 3: The plot shows the aggregate leverage of financial brokers-dealers from 1968Q1 to 2009Q4. The red line shows leverage with only net repo specification. The blue line use the more detailed specification with both the assets and liabilities that make up net repo and is therefore never smaller.

$$Leverage_t = \frac{Total\ Financial\ Assets_t}{Total\ Financial\ Assets_t - Total\ Liabilities_t} \quad (17)$$

The leverage factor is calculated as:

$$LevFac_t = [\Delta ln(Leverage_t)]^{SA} \quad (18)$$

The leverage factor has been seasonally adjusted using quarterly dummies and expanding window regressions. The reason to use expanding window regressions is to create the leverage factor with information available at time t. There is some evidence in the data that there are seasonal effects in the leverage factor if we do not adjust for seasonality. If one-way ANOVA is performed on the leverage factor without seasonal adjustment grouped by quarter, the p-value is 3.6% and we would reject a null hypothesis of no seasonal effects at a 5% significance level. Adrian et al. (2014) consider different ways to deseasonalize but prefer the expanding window regression because of its simplicity compared to for instance X11-filter approach. Their results are robust to the different procedures to deseasonalize the data that

Table 1: Assets and liabilities of Security Brokers and Dealers 2010Q4

This table presents the aggregate balance sheets of security broker-dealers at 2010Q4 from the *Flow of Funds*. The table gives the values in billions of USD. It is similar to the balance sheet presented in Adrian et al. (2014), but also includes the updated specification of repurchase agreements.(Source: U.S. *Flow of Funds* Table L.129.)

Assets		Liabilities	
Cash	$96.9	Repurchase agreements	$1833.2
Repurchase agreements	$1428.5	Corporate and foreign bonds	$129.7
Credit market instruments	$557.6	Trade payables	$18.1
Commercial paper	$36.2	Security credit	$936.6
Treasury securities	$94.5	Taxes payable	$3.6
Agencies	$149.8	Miscellaneous liabilities	$480.7
Municipal securities	$40.0		
Corporate and foreign bonds	$185.6		
Other	$51.4		
Corporate equities	$117.2		
Security credit	$278.2		
Miscellaneous assets	$1,025.3		
Totals	$3503.6		$3401.9
Totals (old specification)	$2,075.1		$1,973.4

they consider. When we use a dataset that is expanding over time as with expanding window regressions we do not ensure that there are no seasonal effects left in the deseasonalized data. When the same one-way ANOVA is performed on the deseasonalized leverage factor the p-value is 6.1% and there is almost as strong evidence for seasonality in the deseasonalized leverage factor. To initialize the data, Adrian et al. (2014) have used observations from 1965Q3. Seasonal adjustment at time t is done by running the regression on observations from 1965Q3:

$$Levfac_i = \sum_{j=1}^{4} \beta_j D_i^j \qquad (19)$$

Then the seasonal adjusted factor is calculated by:

$$LevFac_t^{SA} = Levfac_t - \sum_{j=1}^{4} \hat{\beta}_j D_t^j \qquad (20)$$

D_i is a dummy variable that takes the value 1 in quarter i and 0 otherwise. When I redo this procedure, I obtain a variable that has correlation of 0.96 with the leverage factor used by the authors. The main deviations are in the last couple of time periods and may be a result of adjustments of the dataset released after they obtained the data. If the two are compared without using the last 10 observations, the correlation is in excess of 0.99. This may indicate that the difference is mainly that the most recent observations have been updated in the Flow of Funds dataset after the initial release.

The leverage factor has several large spikes at times with economic crises. Notably we have large negative spikes in 2008Q4 during the financial crisis, during 1994Q4 during the Mexican peso crisis, 2002Q4 which is a time with high volatility[5] and 1987Q4 after the stock market crash. We can also note that there are no notable spikes during the crash after the Dot-Com bubble or during the crises in East Asia or Russia in 1997 and 1998. There are fewer notable spikes in the first part of the series. In 1974Q1-1974Q3 during the oil crisis the values are all negative and large, but smaller in magnitude compared to the later spikes. This indicates that the broker-dealer leverage is related to macroeconomic and financial events.

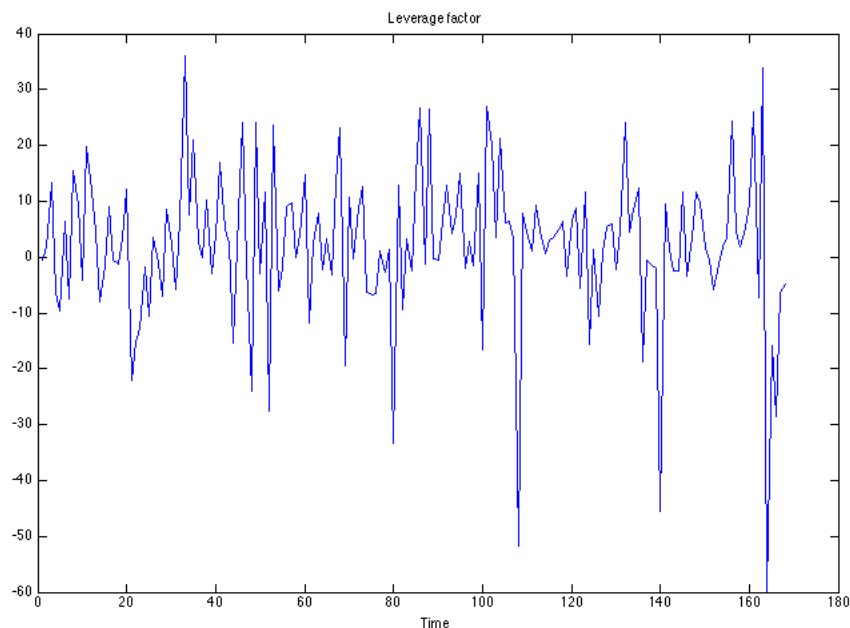[5]During the last half of 2002, the VIX index is large.

Figure 4: The plot shows the time-series of the leverage factor from 1968Q1 to 2009Q4.

The specification of the *Flow of funds* have recently been updated as described in Krishnamurthy and Nagel (2013). Before the change, the dataset only included *Net repo*, but now it is included for both asset and liabilities. This causes both assets and liabilities to be higher than in Adrian et al. (2014). To be comparable to the leverage factor in Adrian et al. (2014) you have to subtract security repurchase agreement in assets from both assets and liabilities when the leverage factor is created. The two measures of leverage are highly correlated. There largest deviations between the two measures are in the 1980s with smaller deviations before and after that period. Figure 5 shows the difference between the two specifications of the leverage factor where both have been normalized to have mean 0 and variance 1 and thus it shows the deviation in number of standard deviations.
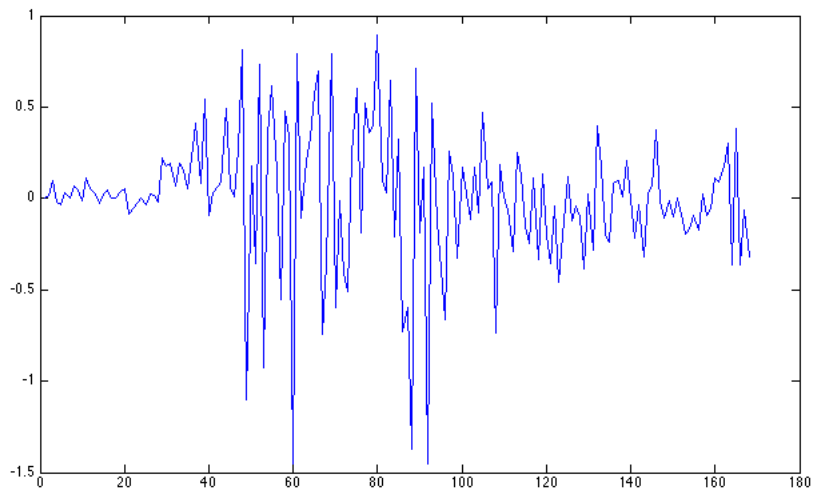
Figure 5: The plot show the difference between the leverage factor from the two specifications of repurchase agreements. Before calculating the difference, both time-series are normalized to mean zero and unit variance. The time-series is between 1968Q1 and 2009Q4.

I have used different specifications of the leverage factor to explain the variation in cross-sectional average returns of the 25 size and book-to-market portfolios as robustness check. The results are robust to inclusion of the updated specification of the security repurchase agreements with only minor differences in estimated coefficients and test diagnostics. The results are not robust to the use of seasonal adjustment. If seasonal adjustment with expanding window regressions is used, the cross-sectional adjusted R^2 is 74% when we use 25 size and book-to-market portfolios. If the factor is used without seasonal adjustment, the cross-sectional adjusted R^2 falls to 20% with the same test assets. The emphasis in this paper is not the specification of the factor, but its performance on explaining portfolio returns outside of the span of the 25 size and book-to-market portfolios. Therefore the results in section 6 are estimated with the deseasonalized factor obtained from the authors of Adrian et al. (2014).

Adrian et al. (2014) estimate the correlation between the leverage factor and other indicators. They find that it is positively correlated with broker-dealer asset growth and financial stock returns and it is negatively correlated with market volatility and credit spreads. This is consistent with Brunnermeier and Pedersen (2009) where both increase in volatility and reduction in asset value would cause funding conditions to worsen and thus give a higher marginal value of wealth.

Table 2: Leverage factor and other factors

Factor	Correlation with leverage factor
R_m^e	0.13
SMB	0.06
HML	0.26

Table 2 shows the correlation between the three factors in the Fama-French model. It shows that the leverage factor has low correlations with all three factors. The strongest correlation is with the HML factor and the SMB factor has the weakest correlation. The excess return on the market is in the middle of these two factors.

5.2 Portfolios

The Size/Book-to-market and industry portfolios are obtained from Kenneth French's web page. The Size/Book-to-Market consists of 25 portfolios sorted by 5 size groups and 5 groups of book-to-market ratios. The industry portfolios are sorted based on SIC codes of the firms. I have used the data sorted in 49 portfolios, but the *Healthcare* portfolio has been excluded from the analysis because it has missing values for part of the sample period. The results are robust to using other industry portfolios such as firms sorted in 10 or 30 portfolios based on industries.

The portfolios created specifically to test this model have been sorted on size and pre-formation beta with the leverage factor[6]. The data are monthly data on securities from the CRSP database, restricted to securities with share code 10 or 11. The data have been sorted in five groups based on market value of equity with the use of size breakpoints from NYSE stocks obtained from Kenneth French's website. The use of NYSE breakpoints makes sure that the results are not driven by the inclusion of many small stocks after 1982 when NASDAQ stocks were included in the CRSP dataset. The 10% smallest firms have not been included to not have results depend on very small firms. The resulting portfolios are sorted in (10-20), (20-40), (40-60),

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[6]It would be preferable to also sort on book-to-market values. The dataset used to create the portfolios did not contain information on book-to-market values.

(60-80) and (80-100) percentiles. The results are not significantly altered by using (0-20) instead of (10-20) for the portfolios of the smallest firms. The stocks in each portfolio are sorted based on pre-formation beta with the leverage factor[7]. To be included, I have required at least 4 quarters of observations to estimate the leverage beta of each stock. The results are robust to the use of 8 or 12 quarters as the minimum number of quarters. In each size group, the stocks are sorted in five groups with equal number of stocks sorted by beta with leverage factor. Value weighted portfolio returns are calculated by:

$$R_t^i = \frac{\sum_{j=1}^{N} R_t^{i,j} S_t^{i,j}}{\sum_{j=1}^{N} S_t^{i,j}} \tag{21}$$

Where $S_t^{i,j}$ is size of security j in portfolio i at time t. $R_t^{i,j}$ is the return of the same security. The returns take into account price changes, dividends and events such as mergers, liquidations and stock splits.

For the portfolios obtained from Kenneth French's website, the portfolios have monthly returns, whereas the leverage factor is constructed from data that is released every quarter. The annualized quarterly excess returns are calculated as:

$$R_t^{e,i} = 4(1 + R_{t,1}^i - R_{t,1}^f)(1 + R_{t,2}^i - R_{t,2}^f)(1 + R_{t,3}^i - R_{t,3}^f) \tag{22}$$

The return of portfolio i at month j of quarter t is $R_{t,j}^i$. The proxy for the risk-free interest rate is one-month Treasury bill rate.

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[7]For the time periods before 1968, I have sorted based on correlation with a leverage mimicking portfolio created as explained in Adrian et al. (2014) to be able to have the same time-span of the portfolios. The results are robust to starting later than 1968Q1 and not use the leverage mimicking portfolio.

6 Results

6.1 Cross-sectional regressions

Table 3 shows the results from the cross-sectional regressions of asset returns. The first two columns use the 25 size and book-to-market portfolios as test assets, the next two columns use industry portfolios as test assets and the last two columns use size and leverage sorted portfolios. Panel A shows the estimated coefficients from the second stage regression. Panel B shows the test diagnostics similar to those showed by Adrian et al. (2014). The MAPE is the mean absolute pricing error. Total MAPE is defined as the average absolute pricing error across all portfolios, plus the cross-sectional intercept. Max MAPE is the maximum absolute pricing error. The χ^2-statistic is the test statistic used to test if the pricing errors are statistically too large. The last row gives the p-value of this test.

The first two columns use the same factors on the same portfolios as Adrian et al. (2014) Table V and we should expect to see the same results. For the Fama-French factors, there are some small deviations in the estimated values, but qualitatively the results are the same. One reason for this might be difference in the portfolios or factors downloaded at different times. The estimate for the model with the leverage factor is almost exactly the same as Adrian et al. (2014) with one exception. The χ^2-statistic calculated in Adrian et al. (2014) is 34.98 with a p-value of 5.2%. When I calculate the same statistic the result is a χ^2-statistic of 71.48 with a corresponding p-value of 0.00%. It seems unreasonable that small variations in the dataset could result in such large deviations in this statistic. In Adrian et al. (2014) this statistic is consistently much lower for the model with the leverage factor compared to the other models over several choices of test portfolios. I am unable to replicate this result. As a robustness check, I have used my

Table 3: Cross-sectional regressions

This table presents the results of the cross-sectional regressions on the 25 size and book-to-market portfolios, 48 industry portfolios and 25 size and leverage portfolios. The models are estimated as $E[R_{t+1}^e] = \lambda_0 + \lambda_{fac}\beta_{fac}$. FF denotes the model with the three factors from Fama and French (1993). The LevFac is the one-factor model with the leverage factor. Panel A reports the risk-premia from the cross-sectional regression with Fama-Macbeth standard errors. Panel B reports the test diagnostics. All three sets of portfolios have data from 1968Q1 to 2009Q4.

|	25 Sz/B-M		48 Industry		25 Sz/Leverage	
	FF	LevFac	FF	LevFac	FF	LevFac
Panel A: Prices of Risk						
Intercept	13.08	1.16	6.03	6.63	7.49	7.86
t-FM	(3.20)	(0.30)	(1.53)	(2.17)	(2.27)	(2.82)
LevFac		55.30		-3.36		11.79
t-FM		(3.29)		(-0.28)		(0.77)
Market	-7.81		0.94		0.79	
t-FM	(-1.58)		(0.20)		(0.18)	
SMB	1.99		-2.85		2.29	
t-FM	(1.11)		(-1.29)		(1.06)	
HML	5.50		0.50		-0.97	
t-FM	(2.79)		(0.20)		(-0.24)	
Panel B: Test diagnostics						
MAPE						
Intercept	13.08	1.16	6.03	6.63	7.49	7.86
Total	14.10	2.22	7.51	8.31	8.25	8.96
MAX	4.12	3.58	6.07	6.75	1.85	2.40
AdjR2	0.71	0.74	0.15	-0.01	0.52	0.10
χ^2	60.82	71.48	61.38	61.30	18.71	21.76
p-value	0.0%	0.0%	4.25%	6.5%	60.3%	53.5%

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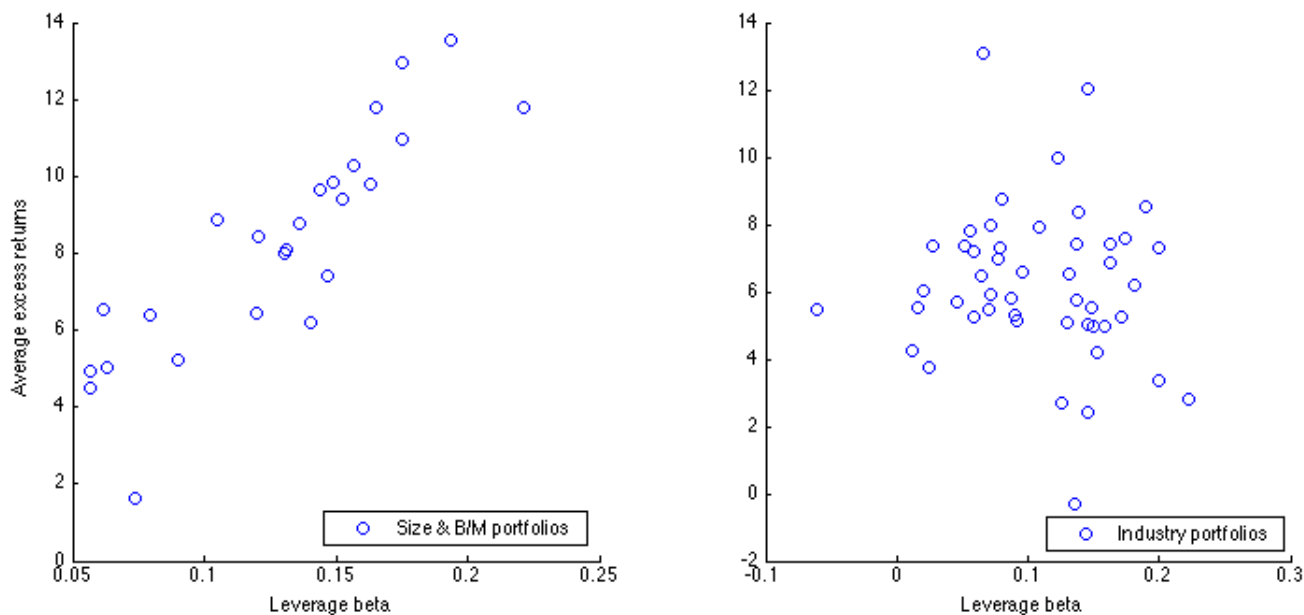
Figure 6: The plot shows the realized average excess return and estimated leverage beta. The left plot shows the 25 size and book-to-market portfolios. The right plot shows the 48 industry portfolios. The data used is quarterly, but returns have been annualized by multiplying with four.

program to replicate this statistic in other cases with success[8].

For the 25 size and book-to-market portfolios, the leverage factor does remarkably well at explaining the average cross-sectional returns of the portfolios. The intercept is close to 0 and not statistically significant. The coefficient for the leverage factor has a t-value of 3.30 and is statistically significant larger than 0. This coefficient has the interpretation as the price of the risk.

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[8]My program have been written in Matlab with formulas as explained in the empirical strategy section and are taken from Cochrane (2005). The program has been used to replicate the results from Martin Lettau's course in empirical asset pricing. The program is able to exactly replicate his results.

The leverage factor is not a traded asset and therefore there will be measurement error in the independent variable in the first step regression. This will bias the estimated betas from the first-stage regressions toward 0. As a result the estimated price of risk in the second stage regression will have bias in the opposite direction and the absolute value of the price of risk will be too large. The model with Fama-French factors on the other hand performs much worse in terms of intercept with an intercept of 13% per annum. If we compare the test diagnostics, they are of similar magnitude for both models. For the 25 size and book-to-market portfolios the leverage factor performs better than the Fama-French factors used as a benchmark.

The left part of Figure 6 shows the portfolios plotted with leverage betas on the X-axis and average returns on the Y-axis. The 25 size/book-to-market portfolios lines up nicely along a linear trend with respect to the leverage beta.

If we use industry portfolios, the conclusions are not the same. For the leverage factor, we get an intercept statistically different from 0 and a price of risk that has the opposite sign, but is not statistically different from 0. Both the MAPE and the maximum absolute pricing errors are larger. The adjusted R^2 becomes negative. The statistical test of the model on the other hand has a much larger p-value. A reason for this might be that if the model is estimated with lower accuracy, it is more difficult to reject an incorrect null hypothesis. The model with Fama-French factors performs better with respect to the intercept, but this may be due to sampling differences. The Fama-French factors has a higher adjusted R^2 of 15%, but still much lower compared when we compare it with the value from the 25 size and book-to-market portfolios. This is consistent with results in Lewellen et al. (2010) and Daniel and Titman (2012) who shows that being able to price the 25 size

and book-to-market portfolios is less demanding than pricing other portfolios such as industry portfolios. If we look at the variation in the estimated leverage betas and the variation in expected returns across the portfolios, we have fairly similar results for the variation in leverage betas and in expected returns.

The right part of Figure 6 plots average excess returns and estimated leverage beta of the 48 industry portfolios. The variation in leverage beta and average returns are similar for size/book-to-market and industry portfolios, but the trend we observed for size/book-to-market portfolios is not present for the industry portfolios.

The last two columns of Table 3 show the estimates from the second stage regression with the portfolios sorted on size and pre-formation leverage beta. For the model with the leverage factor, the estimated intercept is slightly larger than for the industry portfolios with a t-value of almost 3. We would reject the null hypothesis that the intercept is equal to 0 at conventional significance levels. The price of risk related to the leverage factor is 11.79, which is the same sign as for the size and book-to-market portfolio, but the magnitude is approximately one fifth. It has a t-value of less than 1 and we would not reject the null hypothesis that it is 0 at conventional significance levels. The R^2 is 10% and is thus better than for industry portfolios, but not nearly as high as for the size and book-to-market portfolios. The MAPE looks better than for size and book-to-market and industry portfolios. This may be a result of less variation in average excess returns in the size and leverage portfolios compared to the other two sets of portfolios. The χ^2-statistic is lower than for the other two sets of portfolio and we would not reject the null hypothesis that the errors are not too large with a p-value in excess of 50%. The benchmark model with the Fama-French factors has

an intercept of similar magnitude. The coefficients for excess return on the market and SMB have the right sign. The coefficient for HML is negative, but the average return on the HML portfolio is positive. This may be because there is little variation in loading with this factor and the market factor that makes the estimates imprecise. The price of risk for SMB is more precisely estimated than the other coefficients, something that is likely a result of the portfolios being sorted on size. The R^2 is 50% which is better than the leverage factor, but not as good as the model performed on the size and book-to-market portfolios. The three-factor model performs slightly better in terms of MAPE than the model with leverage factor.
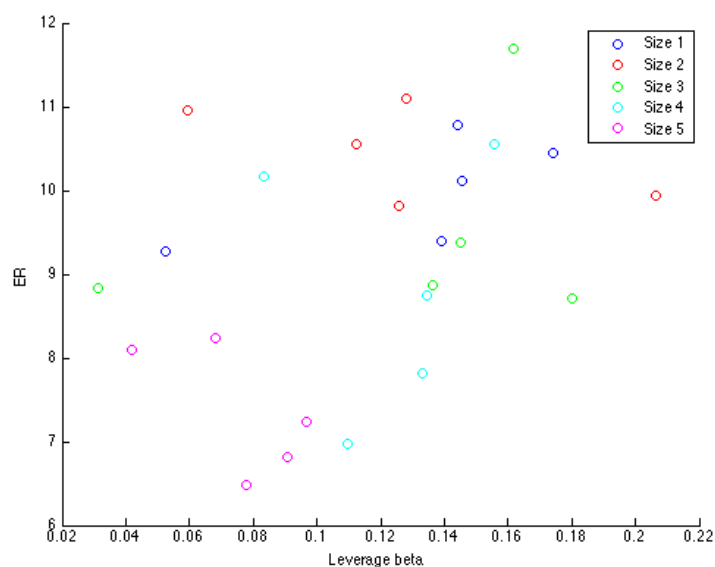

Figure 7: The plot shows the realized average excess return on the 25 size and leverage sorted portfolios and their estimated leverage beta. The different size groups have been plotted with different colors. The data used is quarterly, but returns have been annualized by multiplying with four.

Figure 7 shows the combination of leverage beta and average return of

the 25 portfolios sorted on size and leverage beta. The different size groups have different colored dots. There is slightly less variation in average returns compared to size and book-to-market and industry portfolios, but the variation in leverage beta is similar. There is a positive trend, but it is not as clear as for the size and book-to-market portfolios. We can observe that the portfolios with large firms(shown in magenta) are grouped in the bottom left corner with low excess returns and leverage beta. It looks like the portfolios within each size group has a less clear trend than if we consider all portfolios. We can estimate the model (13) with different intercept for each size group. This follows the approach from Daniel and Titman (2012) where they use the variation that is independent of characteristics. The reason to use different intercepts for each size group is to estimate how the leverage factor affects average returns within each size group.

$$E[R^{e,i}] = 1.96\beta_{LevFac} + 9.75I_{s=1} + 10.23I_{s=2} + 9.25I_{s=3} + 8.61I_{s=4} + 7.23I_{s=5}$$
$$\phantom{E[R^{e,i}] =}(0.13)\qquad(2.35)\qquad(2.78)\qquad(2.72)\qquad(2.77)\qquad(2.75)$$
$$\tag{23}$$

The estimated model is given by (23) where $I_{s=i}$ is an indicator function valued 1 for size group 1 and 0 otherwise. T-statistics are given in parenthesis. The price of risk of the leverage factor is closer to 0 with a point estimate of 1.96 instead of 11.79 when estimated with only a constant. The t-statistic of the estimate is almost 0 at 0.13. The conclusion from this this analysis is that the when we control for the different size groups, the estimated price of risk for the leverage factor is approximately 0.

6.2   Size-Leverage portfolios

Table 4 shows the return on the different size and leverage portfolios and the leverage beta estimated from the first-stage time series regressions. It also

Table 4: Time-series regressions

The table presents the average annualized returns of the 25 size and leverage sorted portfolios and their leverage beta. It also shows the same statistics for the 5-1 leverage portfolios in each size group. Panel A shows the average returns and the t-statistic for the null hypothesis that the average return is equal to 0. Panel B shows the estimated leverage betas and the t-statistics from the time-series regressions. Data are quarterly 1968Q1 to 2009Q4.

	Panel A: Average(Annualized) Returns											
Chr	r(%/yr)						t(r)					
SZ	1	2	3	4	5	5-1	1	2	3	4	5	5-1
1	9.27	9.40	10.11	10.46	10.77	1.50	(2.05)	(2.74)	(2.78)	(2.47)	(2.10)	(0.63)
2	10.96	9.82	10.55	9.93	10.10	0.15	(2.79)	(2.95)	(3.09)	(2.66)	(2.49)	(0.06)
3	8.84	8.72	9.38	8.86	11.69	2.85	(2.53)	(2.91)	(2.92)	(2.56)	(2.86)	(1.12)
4	10.16	6.97	7.82	8.75	10.56	0.40	(3.63)	(2.72)	(2.62)	(2.74)	(2.62)	(0.16)
5	8.10	8.24	6.48	7.24	6.81	-1.29	(3.12)	(3.67)	(2.71)	(2.63)	(2.06)	(-0.57)
	Panel B: Leverage betas											
b	leverage beta						t(leverage beta)					
SZ	1	2	3	4	5	5-1	1	2	3	4	5	5-1
1	0.05	0.14	0.15	0.17	0.14	0.09	(0.63)	(2.21)	(2.19)	(2.25)	(1.53)	(2.10)
2	0.06	0.13	0.11	0.21	0.13	0.07	(0.82)	(2.06)	(1.80)	(3.06)	(1.56)	(1.41)
3	0.03	0.18	0.15	0.14	0.16	0.13	(0.48)	(3.35)	(2.47)	(2.15)	(2.16)	(2.84)
4	0.08	0.11	0.13	0.14	0.16	0.07	(1.62)	(2.34)	(2.45)	(2.30)	(2.11)	(1.56)
5	0.04	0.07	0.08	0.10	0.09	0.05	(0.88)	(1.65)	(1.77)	(1.91)	(1.49)	(1.16)

includes the statistics for the portfolio created by the highest leverage beta minus the lowest leverage beta for each size. The upper part shows the returns and the lower part the leverage betas. The average returns and betas are as in Figure 7 and there are no clear pattern that the portfolios with higher leverage beta has a higher return within each size group. The bottom part shows the leverage beta of the different portfolios. There appears to be a positive trend within each size group that shows that pre-formation on leverage beta is able to create variation in the leverage beta. There is no monotonic increase in leverage beta within each size group, but all 5-1 portfolios have a positive estimated leverage beta.

If we look at the 5-1 portfolios, the differences in average returns all have low t-values and we would not reject a null hypothesis that the return on the portfolio with the smallest leverage betas are different from the portfolios with the largest leverage beta at conventional significance levels. The highest t-statistic is 1.12 within size 3. Except for size 5, the other size groups have higher average returns for the portfolio with largest preformation lever-

age beta than for the portfolio with lowest pre-formation leverage beta. If we look at the difference in leverage betas, they are closer to being statistical significant, but only 2 of 5 are higher than 2 and would be significant at a 5 % significance level.

7 Conclusion

In this paper I have reexamined the result from Adrian et al. (2014). Their proposed model has been tested on two new sets of portfolios, industry portfolios and portfolios sorted on size and pre-formation leverage beta. When industry portfolios are used, the model with intermediary leverage does not explain the variation in the cross-sectional average returns and the estimated coefficients are not similar to those from model estimated on the size and book-to-market portfolios. For the portfolio sorted on size and pre-formation leverage the model is somewhat better at explaining the differences in return, but when we control for each size group the price of risk for the leverage factor is very close to zero. The three-factor model from Fama and French is used as a benchmark. The proposed model with intermediary leverage has similar performance as the benchmark on the size and book-to-market portfolios, but when industry or size and leverage portfolios are used, the benchmark clearly outperforms the model with intermediary leverage.

If the proposed model was the correct asset pricing model it should have been able to price all assets and the resulting estimates should not differ to much with difference choices of test assets. I do not find evidence that the model is able to price the variation in returns that are outside of the return space spanned by the 25 size and book-to-market portfolios. Two possible topics for future research could be to use the model on other types

of securities or try to find another proxy for intermediary funding constraints. It could be interesting to estimate the model on securities where it is easier to assert the fundamental value. Shleifer and Vishny (1997) suggest that their model with limits to arbitrage is more relevant in situations where it is easier to assert the fundamental value of the security. Another possibility is that the aggregation of the factor may affect the results. The factor only has quarterly data and this could potentially reduce much of the variation in the factor. Consider a situation where financial intermediaries try to maintain a fairly constant leverage. If there is a shock to their leverage in the first part of a quarter they may try to offset this shock in the following months and the shock over the quarter will appear much smaller than the actual shock. In such a situation, aggregation over time will remove much of the shocks that occur in the early part of the quarter. The SEC Focus reports that is used to create the factor is filed quarterly by all security broker-dealers, but it is filed monthly for those who clear or carry customer securities. The use of this monthly data could potentially be better in a situation as the one described over.

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