Federal Reserve Bank of New York
Staff Reports

Financial Intermediation, Asset Prices, and Macroeconomic Dynamics

Tobias Adrian
Emanuel Moench
Hyun Song Shin

Staff Report no. 422
January 2010
Revised September 2010

Financial Intermediation, Asset Prices, and Macroeconomic Dynamics
Tobias Adrian, Emanuel Moench, and Hyun Song Shin
Federal Reserve Bank of New York Staff Reports, no. 422
January 2010; revised September 2010
JEL classification: G10, G12

Abstract

We document that financial intermediary balance sheet aggregates contain strong predictive power for excess returns on a broad set of equity, corporate, and Treasury bond portfolios. Our results provide support to the hypothesis that financial intermediary balance sheet quantities matter in the determination of risk premia. We also explore the extent to which the intermediary variables that predict excess returns impact real economic activity. Our findings point to the importance of financing frictions in macroeconomic dynamics and asset pricing.

Key words: return predictability, financial intermediation, macro-finance

---

Adrian: Federal Reserve Bank of New York (e-mail: tobias.adrian@ny.frb.org). Moench: Federal Reserve Bank of New York (e-mail: emanuel.moench@ny.frb.org). Shin: Princeton University (e-mail: hsshin@princeton.edu). The authors thank Casidhe Horan, Nicholas Klagge, and Hoai-Luu Nguyen for outstanding research support. Sudipto Bhattacharya, John Campbell, Marco Del Negro, Erkko Etula, Dieter Hess, Nobuhiro Kiyotaki, Monika Piazzesi, Simon Potter, Thomas Sargent, Christopher Sims, Annette Vissing-Jorgensen, and Jonathan Wright provided helpful comments, as did seminar participants at the Federal Reserve Bank of New York, the Massachusetts Institute of Technology, Princeton University, the Bank of Italy, the Bank of France/Toulouse School of Economics Monetary Policy Workshop, Johns Hopkins University, the Federal Reserve Bank of Kansas City, the American Economic Association Annual Meeting, the London School of Economics, the Bank of Canada, the University of California (Davis), the European Central Bank, the Society for Economic Dynamics Annual Meeting, the NBER Asset Pricing Summer Institute, and the European Finance Association Annual Meeting.

1 Introduction

Financial intermediaries were at the center of the global financial crisis of 2007-09. The credit losses borne by intermediaries, the erosion of their equity capital, and the sharp deleveraging have figured prominently in the commentary on the decline in real activity. These events have given renewed impetus for a deeper study of the interconnection between financial intermediation, asset prices, and macroeconomic dynamics.

In this paper, we analyze the role of financial intermediaries in determining risk premia and macroeconomic aggregates. Recent events, as well as theories of financial amplification suggest that banks and other intermediaries impact macroeconomic fluctuations through the determination of asset prices. We investigate empirically the extent to which a three way association between intermediary balance sheet adjustments, asset prices, and real economic activity appear in the data. We find strong evidence that balance sheet aggregates of some financial intermediaries are informative for the evolution of asset prices. In particular, market-based intermediaries such as security broker-dealers and the institutions in the shadow banking system provide strong explanatory power for a broad range of financial asset returns.

The empirical approach of our study is driven by the data. We start with a comprehensive set of variables that capture intermediary balance sheet behavior from the U.S. Flow of Funds. We complement the balance sheet data by macroeconomic variables from the Bureau of Economic Analysis' National Accounts and a variety of price deflators of the Personal Consumption Expenditure survey. As for asset prices, we consider a broad cross section of equity portfolio returns, credit returns, and Treasury returns. In addition, we employ a variety of commonly used return predictor variables from the asset pricing literature.

The core empirical result of our paper consists in showing that balance sheets provide statistically significant information for future excess returns on a large corss section of financial assets. In order to select the intermediary balance sheet variables that are the best forecasters, we run predictive regressions of quarterly excess returns for various asset classes on lagged balance sheet variables of a large set of financial intermediaries. We then use subset selection methods to identify the best predictors among these balance sheet measures, a large number of macro variables, and a large set of common return predictor variables. We document that two balance sheet variables, the annual growth rate of security broker-dealer leverage and the quarterly growth rate of shadow bank total financial assets, are consistently selected among the best predictors for equities, corporate bonds, and Treasuries out of that large pool of potential regressors. We then show that these two balance sheet indicators significantly predict returns in multivariate regressions controlling for benchmark return predictor variables.

We complement these basic predictive return regressions with a number of robustness checks that also help us in the interpretation of the results. First, we show that the return forecastability is present prior to the global financial crisis of 2007-2009. Second, we document that the predictability is also present for alternative variables that proxy for financial intermediary balance sheet expansion and which are available at higher data frequencies. Third, for these latter variables we provide evidence suggesting that they carry predictive power for excess returns also out of sample. Finally, we conduct a simulation analysis to demonstrate that the significance of the forecasting results is not due to data mining in the form of the subset selection method that we use to identify the institutions with the highest predictive power.

In order to facilitate the interpretation of the results of our predictive return regressions, we run a set of complementary regressions. First, we repeat the predictive return regressions controlling for analysts' cash flow expectations and professional forecasters' expectations about future GDP growth and inflation. We show that the strong predictive power of the balance sheet variables prevails when controlling for these measures. We also run forecasting regressions for future earnings and dividend growth and do not find evidence that our balance sheet variables carry predictive information about these variables.

Together, these findings provide support for the interpretation that the expansion and contraction of intermediary balance sheets is proxying for time varying effective risk aversion of the financial sector. The close association between balance sheet variables and asset return forecastability is consistent with the hypothesis that balance sheets convey information on risk premia through fluctuations in the willingness to bear risk. In a final set of empirical exercises, we investigate the extent to which the balance sheet variables that predict excess returns are also useful in explaining macroeconomic dynamics. We document that the balance sheet aggregates of the market based-institutions that are most informative for asset returns also contain information for the future evolution of macroeconomic aggregates such as GDP and inflation. These findings, which are amplified by the recent financial crisis, are consistent with the hypothesis that real activity is influenced by the supply of credit, which in turn is determined by market risk premia.

Related Literature. The results in the paper are closely connected to an emerging literature on the role of balance sheets and credit aggregates in the determination of risk premia. Longstaff and Wang (2008) show that aggregate credit forecasts the equity premium, and the authors provide a theoretical framework with heterogenous agents to rationalize their findings. Piazzesi and Schneider (2009) link expected returns of Treasuries to the portfolio allocation of households. Krishnamurthy and Vissing-Jorgensen (2008) relate the AAA Treasury spread to the supply of Treasury securities, and argue that it represents a convenience yield. Gilchrist and Zakrajšek (2010) construct a credit spread index from micro-level corporate bond data and show that this index provides robust predictive power for real activity. They also document that the bulk of the predictability can be attributed to the risk premium component of the spread in the post-1985 period. Adrian and Shin (2010) show that expansions and contractions of repo and commercial paper funding forecast innovations in implied volatility, and Adrian, Etula, and Shin (2009) demonstrate that a similar forecastability holds for exchange rates. Etula (2009) further documents that expansions and contractions of security broker-dealer assets forecast changes in commodity prices. Adrian, Etula, and Muir (2010) show that broker-dealer leverage is a significant pricing factor for the cross section of equity returns. Equilibrium asset pricing models that give rise to equilibrium risk premia in which balance sheet intermediary variables contain forecasting power include Brunnermeier and Pedersen's (2009) model of market and funding liquidity in which fire sale externalities play a key role (see Shleifer and Vishny 1992 for an analysis of fire sale externalities in the context of non financial corporations), and He and Krishnamurthy (2007) who analyze equilibrium asset pricing dynamics in a general equilirbrium setting with levered financial intermediaries.

While our results point to the importance of the supply of credit for risk premia and macroeconomic dynamics through the balance sheet adjustments of financial intermediaries, some recent papers also highlight the role of credit supply shocks for the emergence of banking crises and the international transmission of shocks. Examples include Peek and Rosengren (2000), Schnabl (2010), as well as Puri, Rocholl, and Steffen (2010). A related recent paper by Rice ad Strahan (2010) studies the role of banking regulations for the transmission of credit supply shocks to other industries by exploiting cross-state variation in bank branching regulations. Paravisini (2008) documents a quick and persistent impact of government transfers to constrained banks on the supply of aggregate credit. Gatev and Strahan (2006) show that when funding in the CP market becomes more expensive, corporate borrowers turn to bank lending which is funded by a simultaneous increase in deposits—the latter partly being explained by government guarantees for these deposits. He, Kang, and Krishnamurthy (2010) also document the relevance of banks in the recent crisis, focusing on their purchases of mortgages and mortgage-backed securities.

The goal of this paper is to provide a non-structural benchmark for the dynamic interaction of macroeconomic variables, asset prices, and financial intermediary balance sheets in the spirit of Sims (1980). Our empirical results rely on predictive regressions, and thus reveal the dynamic correlations that are in the nexus of the Flow of Funds, the National Accounts, and asset returns. Structural modeling that incorporates the dynamics of financial intermediaries explicitly in the determination of asset prices and macroeconomic activity should match such dynamic correlations. Our paper can thus be viewed as a descriptive benchmark for structural dynamic macroeconomic models.

The outline of our paper is as follows. We set the stage by describing the recent trends in financial intermediation in the U.S. toward a market-based of financial intermediation in which securitization plays a central role. This discussion motivates the selection of the particular intermediary balance sheet data and the outline of our empirical strategy. We follow by presenting the results of the variable selection algorithm which we apply to identify the best return predictor variables and the results of predictive return regressions using individual balance sheet aggregates. We then present a number of robustness results that facilitate the interpretation of our findings. We continue by documenting empirical evidence that highlights the interconnections between financial intermediary balance sheets, asset prices, and macroeconomic aggregates. We conclude the paper with some general observations on the implications of our results, both for the asset pricing literature, but also for monetary economics.

2 Changing Nature of Financial Intermediation

In preparation of our empirical investigations, we review briefly the structure of financial intermediation in the United States, and in particular the increasing importance of market-based financial intermediaries and the shadow banking system. Financial intermediaries manage their balance sheets actively in response to changing economic conditions and the risks associated with new lending. Larger balance sheets and higher leverage are associated with a greater willingness to take on exposures and an increased provision of credit. To the extent that higher credit supply increases the range of real activities that receives funding, we may expect a close relationship between intermediary balance sheet size and the marginal real project that receives funding. Asset prices provide a window on the relationship between financial intermediaries and real activity, as expanding balance sheets and higher real activity tend to be associated with lower risk premia.

As recently as the early 1990s, traditional banks were the dominant institutions supplying credit to the real economy, but bank-based credit supply has been quickly overtaken by supply of credit from market based intermediaries, particularly in the mortgage market. Figures 1 and 2 document the rapid growth of market-based intermediaries in the US financial system over the past two decades.

There are two types of institutions that are particularly representative of developments in the market based financial system: security broker-dealers, and shadow banks. Broker-dealers have traditionally played market-making and underwriting roles in securities markets. However, their importance in the supply of credit has increased in step with securitization. Thus, although the size of total broker-dealer assets is small by comparison to the commercial banking sector (it was around one third of the commercial bank sector in 2007) it has seen rapid growth in recent decades and is arguably a better barometer of overall funding conditions in a market-based financial system.

We define shadow banks as consisting of an array of different types of financial institutions. The institutional details of the shadow banking system are reviewed by Pozsar, Adrian, Ashcraft, Boesky (2010). The growth of shadow banks is closely tied to the growth of securitized credit. We proxy overall shadow banking activity by summing over three types of intermediaries: asset-backed securities (ABS) issuers, finance companies, and funding corporations. ABS issuers are special purpose vehicles that hold pools of loans, mortgages, or receivables on the asset side of their balance sheet. These pools are then tranched, and the tranches receive credit ratings. The various tranches of ABS issuers are sold off to maturity transformation vehicles such as structured investment vehicles (SIVs) or credit hedge funds, or ultimate investors such as pension funds and insurance companies. Structured investment vehicles and credit hedge funds in turn obtain part of their funding in short term money markets. While structured investment vehicles are typically funded in the commercial paper market, credit hedge funds often use repurchase agreements (repos) to fund part of their balance sheet. Finance companies originate loans, not unlike commercial banks. In fact, some bank holding companies own finance companies which conduct loan and mortgage origination. More generally, however, finance companies tend to be specialized in different business areas than commercial banks, or tend to serve a different customer base such as subprime borrowers. Finance companies sell the majority of loans and mortgages that they underwrite to ABS issuers. Funding corporations are a collection of financial institutions that include four categories: subsidiaries of foreign banks that raise funds in the U.S. and transfer the proceeds to foreign bank offices in the U.S.; subsidiaries of foreign banks and nonbank financial firms that raise funds in the U.S. and transfer them to a parent company abroad; custodial accounts for reinvested collateral associated with securities-lending operations; and non-bank financial holding companies.

The market-based intermediaries (i.e. broker-dealers and shadow banks) fund part of their liabilities through short term borrowing such as commercial paper or repurchase agreements, and are thus sensitively affected by capital market conditions. For commercial banks, the greatest part of liabilities consist of deposits, and only a small fraction of liabilities are funded in capital markets. Commercial banks' large balance sheet masks these effects of operating at the margin. Also, commercial banks provide relationship-based lending through credit lines. Financial intermediaries of the market based financial system give a much purer signal of marginal funding conditions, as a larger fraction of their balance sheet is funded in capital markets.

3 Data

We use a broad range of aggregate macro and balance sheet data in our predictive regressions for asset returns. One set is the standard macro aggregates for the United States, obtained from the National Income Accounts (NIPA) of the Bureau of Economic Analysis. The second set is the aggregate balance sheet data for the United States obtained from the Federal Reserve's Flow of Funds accounts. We use quarterly data, with sample period

1986Q1 – 2009Q4. Our choice of sample period is intended to cover the time period of the "Great Moderation", which also coincides with the development of the market-based financial system in the United States (see Adrian and Shin (2010)).

For all of our variables, we compute growth rates, both at the quarterly and annual frequencies. Our strategy is to allow enough flexibility in the way that the variables enter into the analysis so that the pricing model will tell us whether movements at quarterly or at annual frequencies are the more important ones. We then use a subset selection method to identify the best predictors, as we will describe in greater detail below.

We list all the balance sheet aggregates and macro variables used in our predictive regressions in Tables 1 and 2, respectively. We consider a host of different types of financial intermediaries. We group them into six categories: banks (*FINBANK*), pension funds and insurance companies (*FINPI*), mutual funds (*FINMF*), shadow banks (*SHADBNK*), mortgage pools (*MORTPOOL*), and security brokers and dealers (*SBRDLR*). In the bank category, we include commercial banks (*CB*), credit unions (*CU*), and savings institutions (*SI*). The pension funds and insurance companies category comprises property-casualty insurance companies (*PCIC*), life insurance companies (*LIC*), private pension funds (*PPF*), state and local government employee retirement funds (*SLGERF*), and federal government retirement funds (*FGRF*). In the mutual fund category we include money market mutual funds (*MMMF*), mutual funds (*MF*), and closed-end funds and exchange-traded funds (*CEF*). In the shadow bank category we place the following types of institutions: issuers of asset-backed securities (*ABS*), finance companies (*FINCO*), and funding corporations (*FUNDCORP*). These are financial intermediaries which perform bank-like business activities (borrow short in order to lend long), but are not chartered and regulated as banks. As discussed in Section 2, these institutions have become an important feature of the financial intermediation process with the rise of securitization markets that took off in the 1990s.

For all financial intermediaries that appear in Table 1, we calculate the quarterly and annual growth of total financial assets. In terms of notation, we add a prefix "q" or "y" for quarterly and annual growth rates to the mnemonic of the particular institution considered, respectively. Further, we add the suffix "ag" for asset growth. As an example, the quarterly growth rate series of total financial assets for, say, commercial banks, is labeled *qCBag*. As another example, the annual growth rate of total financial assets for mutual funds, is denoted *yMFag*. We also include for consideration quarterly and annual equity and leverage growth for commercial banks, credit unions, and security broker-dealers. Equity is defined as the difference between total financial assets and total liabilities. Leverage, in turn, is defined as the ratio of total financial assets and equity. In terms of notation, we denote equity growth series with the suffix "eg" and leverage growth series with "levg".

The macro series in Table 2 cover all major categories of real GDP, including the components of personal consumption expenditures, real residential and nonresidential investment, and government spending. We also include PCE inflation for total consumption expenditures, excluding food and energy, excluding energy goods and services, as well as for durables, nondurables and services consumption. We use quarterly and annual growth rates of the components of GDP and PCE inflation as explanatory variables in the predictive regressions for asset returns and add the prefixes "q" and "y", respectively.

The long and comprehensive list of macro and balance sheet variables will serve as the proving ground from which informative pricing factors are allowed to emerge. In order to accommodate as wide a field of possible pricing factors, we supplement our list of macro and balance sheet variables by including other return predicting variables drawn from the asset pricing literature. The aim is to be inclusive, so that our main empirical results on the importance of balance sheet variables in determining asset returns can be made in the most forceful way possible. The benchmark return predictor variables that we consider are the Lettau-Ludvigson (2001) log consumption-wealth ratio, *cay,* the Fama-French (1993) factors *HML* and *SMB*, Carhart's (1997) momentum factor (MOM), as well as short-term ($STREV$) and long-term ($LTREV$) reversal factors. These last five factors have been obtained from Ken French's website. We further consider the log dividend price ratio *(d/p)* for the stock market (from Robert Shiller's website), the difference between the yields on a 10-year Treasury note and a 3-month Treasury bill ($TERM$), the difference between the yields on Moody's Baa and Aaa corporate bond portfolios (DEF), and the relative stance of monetary policy measured as the difference between the 3-month Treasury bill and its four quarter moving average ($RREL$). The Treasury data underlying these series are from the Federal Reserve Board's H.15 release. Finally, we include the bond return forecasting factor (CP) from Cochrane and Piazzesi (2005) which we updated using recent data. Numerous previous studies have documented the ability of these variables to predict excess returns on stocks and bonds. We therefore consider them as important benchmarks when it comes to assessing the ability of balance sheet variables to predict excess returns. The complete list of the benchmark return predictor variables that we consider is provided in Table 3.

We now turn to a description of the return series that we will use as left-hand side variables in our predictive return regressions. We examine three families of asset return series—stock portfolios, corporate bond portfolios and Treasury securities. Table 4 lists the return series that we consider. As stock portfolios we use the CRSP equity market portfolio (MKT) and the Fama-French portfolios sorted by size and book-to-market which we obtained from Ken French's website. We consider only the "corner" portfolios of the size and book-to-market sorts. For example, *FF11* denotes the portfolio of stocks which fall in the smallest size quintile and the smallest book-to-market quintile. The data for corporate bonds are from Barclays. They include investment grade corporate bond portfolios for industrials (IGI), financials (IGF), and utilities (IGU) as well as portfolios for corporate bonds with credit ratings A and *Baa*. As government securities we consider the constant maturity Treasury returns for maturities of 1, 2, 5, 7, and 10 years. These are obtained from CRSP. For all assets, we construct quarterly returns by compounding monthly returns and then obtain excess returns by subtracting the yield on the three-month Treasury bill as the risk-free rate.

4 Predictive Return Regressions

As mentioned at the outset, the central goal of our paper is to investigate the link between asset returns and macroeconomic variables, where the focus is on the role of financial intermediaries in connecting the two. As such, the core of our paper consists of two sets of empirical investigations. The first is to assess the role of intermediary balance sheets in determining asset prices. The second is to investigate the extent to which intermediary balance sheets interact with macroeconomic variables.

In this section, we tackle the first of our two empirical objectives by examining the extent to which financial intermediary balance sheet variables enter the forecasts of asset returns. We estimate univariate regressions of the form

$$Rx^i_{t+1} = \alpha_i + \beta_i' Z_t + \epsilon^i_{t+1} \tag{1}$$

where Rx^i_{t+1} is the excess return on a particular financial asset and where Z_t is a set of return predictor variables whose forecasting power we seek to analyze.

Our strategy is to begin with few presumptions about which variables belong on the right hand side, but then use an algorithm to select the explanatory variables that perform best. For each excess return Rx^i, we use a subset selection method to find the best predictors among

- all macro and benchmark return predictor variables;
- all balance sheet growth indicators;
- and then a combination of the two.

The particular subset selection mechanism that we apply is the Least Angle Regression ("LAR") approach which has recently been proposed by Efron, Hastie, Johnstone, and Tibshirani (2004). The LAR method is a regression algorithm for high-dimensional data that generalizes the Least Absolute Shrinkage Selection Operator ("LASSO") and

"Forward Stepwise Regression" methods. There are several desirable properties of the LAR method, which helps us in our investigation. Most importantly, it allows the selection of the best among a large set of potential predictors in linear regressions while being computationally as efficient as OLS. In the following, we provide a brief outline of the LAR procedure. For more details the reader is referred to the paper by Efron et al. (2004). Alternatively, Hastie, Tibshirani, and Friedman (2009) contains an account of the LAR procedure as well as its relation to other variable selection methods such as the LASSO.

The LAR algorithm is designed to find the optimal subset among a large set of predictors in univariate linear regressions. It starts with a zero active set. At the first step, LAR selects the variable most correlated with the dependent variable. It then increases the coefficient on that variable from zero towards its least squares value until some other predictor variable has as much correlation with the residual as the first selected variable has. Then, this second predictor variable joins the active set. Now, the coefficients on both predictors are simultaneously increased such that the residual remains equally correlated with both variables in the active set. Once the residual is equally correlated with both variables in the active set and a third variable from the pool of remaining regressors, this third variable enters the active set.

In principle, the process can be continued until all right-hand side variables are in the active set (in which case the solution would be the full least squares fit) or until a zero residual is encountered (in case the number of predictors is larger than the number of observations of the dependent variable). In practice, we restrict the number of variables in the active set to five, i.e. we use the LAR algorithm to identify the five best predictors among the three different sets of return forecasting variables for each of the left-hand side returns individually. We then investigate which of the predictor variables have been selected most often across the different returns. As we will see below there is a striking overlap across the optimal set of predictors selected from the host of balance sheet variables that we consider. Once the best predictors are identified, we use them as right-hand side variables in individual OLS regressions of each excess return, controlling for benchmark return predictors for the particular asset class.

4.1 Subset Selection of Return Predictors

Tables 5, 6, and 7 present the results of the subset selection of predictive variables for stock portfolios, corporate bonds and Treasuries, in that order. Each table contains three panels. The top panel lists those variables chosen by the selection algorithm as the best predictors among the macro and benchmark return predictor variables, the second panel reports the best predictors from the set of balance sheet variables alone, and the bottom panel reports the best predictive variables from the set that combines the macro, benchmark return predictors and balance sheet variables. The main purpose of presenting the results in this way is to demonstrate the relative importance of the balance sheet variables when they are considered together with the macro variables and common return predictors, the latter being more familiar from the asset pricing literature.

The results show that balance sheet variables figure prominently in the predictive regressions. Most importantly, we see that the annual leverage growth of the security broker-dealers, *ySBRDLRlevg*, consistently enters as one of the top explanatory balance sheet variables for equity returns. The broker-dealer leverage growth also remains among the top five predictors for most equity and corporate bond portfolios when we add the macro aggregates and benchmark return predictors to the set of potential explanatory variables. For example, *ySBRDLRlevg* is the best among all considered predictor variables for the equity market return. This is striking since we consider a host of return forecasting variables which have previously been suggested in the literature, including for example the log consumption-wealth ratio, the term spread or the dividend-price ratio.

We now turn to the selection results for corporate bond returns that are summarized in Table 6. We see that there is one variable in addition to *ySBRDLRlevg* which enters consistently as one of the top explanatory variables. This is the quarterly growth rate of shadow bank assets, *qSHADBNKag.* This variable is among the top two predictors for all corporate bond returns. While it is always selected before the broker-dealer leverage growth variable, both variables consistently enter among the top five predictors for all five corporate bond returns considered. This is true also when the subset selection method is applied ot the larger set of all macro, balance sheet, and benchmark return predictor variables which include the default spread, the term spread, and the Cochrane-Piazzesi factor.

Turning to the subset selection results for Treasury returns shown in Table 7, we see that *qSHADBNKag* continues to be identified among the top predictor variables for Treasury returns of all maturities while *ySBRDLRlevg* is not selected for this set of returns. Interestingly, while the Cochrane-Piazzesi bond return forecasting factor is among the top two predictors when only the macro variables and benchmark return predictor variables are considered, this is not true when the balance sheet quantity variables are included in the pool of potential regressors.

Finally, notice that two other balance sheet variables were found to be useful predictors for corporate and Treasury bond returns. First, the quarterly asset growth of funding corporations, *qFNDCORPag*, is selected among the best five predictors for three of the corporate bond returns. As was discussed in Section 3 above, funding corporations are one of the three types of institutions which we subsume in the shadow bank category. Hence, the variable *qSHADBNKag* to some extent nests the information in *qFNDCORPag* and we continue to consider only the former. Second, the quarterly asset growth of savings institutions, *qSIag*, is identified as the top predictor for some Treasury returns. However, a closer inspection of this series reveals that it features large spikes over the last few years of data. This leads us to believe that its strong correlation with future Treasury returns may be driven by a few outliers. We therefore do not consider this variable in our further analysis.

To summarize, the findings from this exercise suggest that balance sheet growth of market-based financial intermediaries such as security broker-dealers as well as ABS issuers, finance companies or funding corporations, the latter comprised in the shadow bank category, has strong predictive power for excess returns on equities and fixed income instruments. We now turn to assessing the predictive power of annual broker-dealer leverage growth and the quarterly shadow bank asset growth in greater detail, explicitly controlling for the common return predictor variables from the asset pricing and macro finance literature.

4.2 Predictive Value of Balance Sheet Variables

In order to investigate the incremental predictive value of lagged balance sheet variables, we conduct predictive return regressions for each asset return separately. We begin with the predictive return regression for the equity portfolios. Since we consider a total of five different equity portfolios, we only report a subset of the results in detail. We will, however, briefly discuss the commonalities among the results across the different returns. We start by documenting the regression results for the equity market portfolio (MKT) which are presented in Table 8. We see that the lagged annual growth of security broker-dealers, *ySBRDLRlevg*, is the only variable which has a strongly significant predictive coefficient for the excess return on the market portfolio. The Newey-West adjusted t-statistic equals -3.01 and the adjusted R^2 from the regression on just the lagged market return and broker-dealer leverage growth is an impressive 7%.[1] Moreover, while Among the benchmark return predictors, only the log consumption wealth ratio (*cay)* proves to be significant at common confidence levels. However, it loses its significance when considered jointly with the other predictors. In contrast, the significance of broker-dealer leverage growth increases in the joint regression. These results underscores our findings from the previous section which have pointed to *ySBRDLRlevg* as the single best predictor of the excess return on the equity market portfolio among all considered variables.[2]

[1] Note that we report t-statistics based on Newey-West adjusted standard errors with a maximum lag length of 4 quarters.

[2] In a recent paper, Chava, Gallmeyer, Park (2010) provide evidence that the tightness of lending standards by commercial banks provides predictive information about future excess returns on the equity market portfolio. Unreported results show that *ySBRLDRlevg* remains strongly significant when we use this variable as an additional control.

It is important to note that the sign of the predictive relationship between broker-dealer leverage growth and the excess return on the equity market portfolio is negative. This means that a faster expansion (contraction) of broker-dealer balance sheets predicts lower (higher) equity returns in the next quarter. According to our preferred interpretation of the results, this is consistent with the notion that balance sheet growth is a proxy for the effective risk aversion of market based financial institutions which varies with the tightness of the balance sheet constraints these institutions face. The looser these constraints, the greater the financial intermediaries' risk appetite which in turn will be reflected in a stronger expansion of their balance sheets and in smaller expected excess returns. We will provide a more thorough interpretation of our results further below.

Table 9 reports the predictive regression results for another equity portfolio - in this case, the Fama-French *FF55* portfolio of large firm high value stocks. Again, we see that the lagged annual broker-dealer leverage growth variable enters significantly as an explanatory variable, both individually and in the presence of other asset pricing variables. The dividend price ratio proves to be the only benchmark return forecasting variable which appears to have some predictive value for the return on the *FF55* portfolio. However, as for the case of the market portfolio, the significance of the broker-dealer leverage growth variable increases when we add the benchmark return forecasting variables to the regression, whereas the dividend price ratio becomes insignificant in the joint regression.

We conducted the same experiment with all other equity portfolios discussed above. We don't report the individual estimates here in order to conserve space, but restrict ourselves to observing that the results are qualitatively very similar across all equity returns.[3] In all cases, the broker-dealer leverage growth was found to be a statistically significant predictor of excess stock returns, both when considered individually and in a joint regression with the benchmark return predictors. Moreover, the coefficients of these regressions were always negative. This leads us to conclude that positive (negative)

[3]Table 21 in Section 5.4 provides the Newey-West adjusted t-statistics and the R^2s from univariate predictive regression of all returns onto the two balance sheet predictor variables. These regressions do not involve lagged dependent variables but are otherwise the same as the ones documented here.

leverage growth of security brokers and dealers is an important predictor for lower (higher) future returns in the equity markets.

Finally, note that the predictive value of broker-dealer leverage growth is also economically significant. Indeed, the coefficient on *ySBRDLRlevg* in the predictive regression for the market portfolio being -0.09 and the quarterly standard deviation of annual security broker-dealer leverage growth being 31 percent, a one standard deviation rise in the growth rate of leverage of these institutions is associated with a 2.7 percent decline in the equity market risk premium in the next quarter.

We now turn to the regression results for corporate bond returns. Informed by the results of the variable selection procedure discussed above, we consider quarterly asset growth of shadow banks as an additional predictor. Moreover, we follow the asset pricing literature and consider a slightly different set of benchmark return predictor variables. In particular, these are the federal funds rate (FFR), the term spread ($TERM$), the default spread (DEF), as well as the Cochrane-Piazzesi bond return forecasting factor (CP).

As examples, we report results for investment grade financial bonds (IGF) and Baa rated corporate bonds (Baa). These are provided in Tables 10 and 11, respectively. Four variables appear significant individually in predicting the excess return on the IGF portfolio: $TERM$, CP, *ySBRDLRlevg*, and *qSHADBNKag.* While the coefficients on $TERM$ and CP are positive, the coefficients on both *ySBRDLRlevg* and *qSHADBNKag* are negative and statistically significant. This implies that positive broker-dealer leverage growth and positive (negative) shadow bank balance sheet growth predict lower (higher) future excess returns on investment grade financial corporate bonds. As for the equity portfolios, the broker-dealer leverage growth variable becomes more strongly statistically significant when considered jointly with other variables. Note that the adjusted R^2 of the joint return prediction regression is 29% while the shadow bank asset growth variable alone explains a striking 16% of the one-quarter ahead variation of excess returns on investment grade corporate bonds. In comparison, the CP factor explains only about 3% of the return variation.

The results for the Baa rated bond portfolio are very similar. Both the annual security broker-dealer leverage growth and lagged shadow bank asset growth now enter significantly when considered individually and jointly with the other return predictors. The lagged quarterly shadow bank asset growth variable is again the strongest predictor, explaining about 17% of the one-quarter ahead variation of the excess return. When the explanatory variables are considered jointly, the adjusted R^2 jumps above 30%. This indicates that the balance sheet variables capture predictive information that is not spanned by the common return predictor variables.

We conducted the same experiment with all other corporate bond portfolios in our dataset. Again, the results were very similar across assets. In all cases, the quarterly growth rate of shadow bank assets was found to be a statistically highly significant predictor of excess bond returns, both when considered individually and in a joint regression with the benchmark return predictors. While a little less strongly significant, the annual growth rate of broker-dealer leverage growth provided additional explanatory power beyond the shadow bank asset growth variable. The coefficients on both variables were always negative. This leads us to conclude that positive (negative) leverage growth of security brokers and dealers and asset growth of shadow banks are an important predictor for lower (higher) future returns in the corporate bond market.

We finally turn to the predictive regressions for excess returns on Treasury securities. We report the regression results for the two year constant maturity Treasury return (CMT2) and ten year constant maturity Treasury return (CMT10) in Tables 12 and 13, respectively. The regression results for the other Treasury series are qualitatively very similar, and are not reported here. As the subset selection algorithm had not indicated a role for security broker-dealer leverage growth in predicting Treasury returns, we drop this variable here and restrict ourselves to the shadow bank asset growth indicator which was consistently selected among the top five predictors for all Treasury securities. As shown by the results in Tables 12 and 13, the shadow bank asset growth variable alone explains 8% of the one-quarter ahead variation of the two year Treasury return and the ten year Treasury return, respectively. Among the benchmark return predictor variables only the Cochrane-Piazzesi factor CP is individually significant in both regressions. However, it loses its significance in the joint regression for the 10-year Treasury return. The regressions for the other Treasury maturities provided very similar results.

To summarize this section, our results show that the annual growth rate of broker-dealer leverage and the quarterly growth rate of shadow bank assets are strong predictors for excess returns on equities, corporate bonds, and Treasuries even when we control for a host of benchmark return predictors variables. In all three asset classes, stronger intermediary balance sheet growth is associated with lower one-quarter ahead excess returns. We now document that this basic results prevails in a variety of robustness checks.

5 Robustness of the Results

The results of the predictive return regressions from the previous section suggest that the two balance sheet growth variables selected by the LAR procedure, annual security broker-dealer leverage growth and quarterly shadow bank asset growth, are strong predictors for future excess returns on equities, corporate bonds, and Treasuries.

In this section, we provide a number of extensions to the baseline results as a robustness check. First, we investigate whether the regression results are driven by the recent financial crisis period. Second, we analyze whether alternative measures of intermediary balance sheet expansion which are available at higher data frequencies give rise to similar findings. Third, we assess whether these alternative measures of balance sheet expansion have predictive power for excess returns out-of-sample. Fourth, we evaluate to what extent the results of strong predictive power of balance sheet variables selected from a larger pool might be explained by data-mining.

5.1 Are the Results Due to the Financial Crisis?

Figures 3 and 4 plot the annual security broker-dealer leverage growth and the quarterly shadow bank asset growth variables which we have found to contain strong predictive power for excess returns. A visual inspection of these two variables shows that both exhibited sharp declines during the recent financial crisis. A sceptical reader might therefore be inclined to think that the strong results in support of predictive power of these variables are driven by this recent episode. In order to dispel this concern, we conduct a robustness check on our results by running our regressions for a restricted sample period that excludes the data after 2007Q2. Our choice of this cutoff date is motivated by the fact that the first problems in the subprime mortgage market materialized in August 2007.

Tables 14, 15 and 16 report the results of the regressions for the shortened sample for the excess return on the equity market portfolio, the excess return on the portfolio of Baa rated corporate bonds, and for the ten year Treasury return, respectively. We see that our results remain robust to the exclusion of the crisis period. In particular, annual broker-dealer leverage growth remains a significant predictor for the excess return on the equity market even before the financial crisis. Unreported results show that this result carries over to the other equity portfolios that we consider. Moreover, both *ySBRDLRlevg* and *qSHADBNKag* remain strongly significant in predicting the excess return on *Baa* rated corporate bond portfolios, as shown in Table 15. Finally, shadow bank asset growth also remains a strongly statistically significant predictor of the ten year Treasury return in the subsample regression, see Table 16.

The message that emerges from this robustness check is that the informational value of market-based intermediary balance sheets were present even before the recent crisis, and hence should be seen as a feature of the financial system in normal times. This finding holds importance for the potential use of balance sheet variables for the purpose of preemptive policy that tries to anticipate problems ahead. We return to this issue later in the paper.

5.2 Do the Results Hold at Higher Frequencies?

In our empirical investigations so far, we have relied on data related to the total financial assets of different types of financial institutions from the Federal Reserve's Flow of Funds accounts. Unfortunately, these are only available at a quarterly frequency. An alternative approach is to use the aggregates which proxy for the other side of the balance sheet - the liabilities of the financial intermediaries. This has the advantage that important liability aggregates such as the outstanding stock of repurchase agreements (repos) or financial commercial paper are available at high frequencies. In addition, the short-term nature of these liability aggregates imply that the discrepancy between market values and book values are quite small, meaning that the balance sheet data may be a closer reflection of the underlying market conditions. Previous studies have shown that repos and financial commercial paper figure prominently in forecasting returns of equity implied volatility and exchange rates (see Adrian and Shin (2010) and Adrian, Etula and Shin (2009)).

As an additional robustness check on our results, we therefore employ intermediary liabilities as explanatory variables in the predictive return regressions. In particular, we use the series on the total Financial Commercial Paper ($FINCP$) outstanding from the Federal Reserve Board's website and the stock of outstanding Primary Dealer repos ($REPO$) from the Federal Reserve Bank of New York.[4] These series are available at the weekly frequency since August 1990. However, since we only have return data at the monthly frequency we estimate the predictive return regressions using monthly data. The sample period for these regressions is August 1990 - March 2010.

For brevity, we only report the results for three different assets: the equity market portfolio, the Baa rated corporate bond portfolio, and the ten year Treasury. These are provided in Tables 17, 18 and 19. The results show that none of the two alternative balance sheet variables predicts the equity market portfolio, as we can see from Table 17. However, for corporate bonds and for Treasuries, the balance sheet variables continue

[4]Financial commercial paper includes both unsecured commercial paper issued by financials and asset backed commercial paper.

to have strong predictive power. Indeed, as shown by Table 18, both the growth of the repo and the financial commercial paper market are strongly significant predictors of excess returns on the BAA bond portfolio. In addition, the monthly growth rate of Primary Dealer repos is highly significant in the predictive return regression for the ten year Treasury, see Table 19.

Altogether, these results support our earlier findings that variables which proxy for the balance sheet growth of financial intermediaries are significant predictors of future excess returns on various asset classes.

5.3 Do the Results Hold Out of Sample?

The data used in the previous section cover monthly observations from August 1990 through March 2010 or a total of 235 observations. We therefore have a sufficiently long sample to assess whether the two liability side balance sheet aggregates, $FINCP$ and $REPO$, also have predictive power for excess returns out-of-sample. We use the first seven years of data, from August 1990 through July 1997, as our training sample. From August 1997 onwards we then make iterative forecasts of one-month ahead excess returns using only data available up to the time at which the forecast is made. We employ an expanding sample window.

Following Goyal and Welch (2008), we evaluate the out-of-sample forecasting power of the two balance sheet variables for excess returns using two formal measures of predictive accuracy. These are the $ENC\text{-}NEW$ statistic suggested by Clark and McCracken (2001) and McCracken's (2007) F-statistic. While we use the former to test if a model with a predictor variable and a constant encompasses a model with just a constant, we employ the latter to test whether the mean squared forecast errors of the model with just a constant and the model with a predictor variable are equal. Both test statistics have non-standard distributions and we rely on the tabulated critical values from simulated distributions provided in Clark and McCracken (2001) and McCracken (2007), respectively, to assess significance.[5]

We compare the results of our out-of-sample tests with those obtained for the benchmark return forecasting variables discussed above. As in the previous section, we restrict ourselves to three excess returns as dependent variables: *MKT*, *BAA*, and *CMT10*. Table 20 documents the results from this exercise. As expected from the in-sample analysis in the previous section, none of the two balance sheet growth indicators predicts excess returns on the equity market portfolio. However, consistent with the evidence in Goyal and Welch, none of the other return predictor variables we consider for that period has significant predictive power for *MKT* beyond the constant only model. Indeed, all considered variables gives rise to larger out-of-sample forecast errors than the naive benchmark.

Turning to the results for the return on BAA rated corporate bonds, we see that both *FINCP* and *REPO* have smaller root mean squared forecast errors than the naive benchmark. Among the benchmark predictor variables, this is only true for the term spread. According to the *ENC-NEW* statistic, this superior predictive ability is statistically significant at the 5% level for *REPO* and at the 10% level for *FINCP*. In addition, the superior predictive ability of *REPO* is also highly statistically significant according to McCracken's F-statistic. Among the benchmark return forecasting variables only the term spread provides statistically significant improvement in forecasts of the BAA return out-of-sample.

We finally assess the out of sample predictive power of the two variables for the ten year Treasury return, *CMT10*. As indicated by their values of ΔRMSE, both give rise to smaller forecast errors than the naive benchmark model. Moreover, according to the values of the two test statistics, this difference is highly statistically significant for both variables. In contrast, none of the competitor predictor variables provides significant forecast improvement over the naive benchmark model.

[5] Since we study prediction models with one predictor variable in addition to a constant, we have $k_2 = 1$ in the notation of both Clark and McCracken (2001) and McCracken (2007). Further, since our forecast window covers about 14 years of data wheras our training sample comprises 7 years, the ratio π of the number of out-of-sample observations and the number of in-sample observations equals 2.

In sum, these results indicate that the strong in-sample predictive power of balance sheet growth indicators for excess returns that we have documented in the previous section is also present out-of-sample.

5.4 Are the Results Due to Data-Mining?

We approached our empirical analysis from an agnostic point of view regarding the question of which financial intermediary balance sheets provide predictive information about future excess returns. We then used a subset selection method to identify the best balance sheet predictor variables out of a larger pool of potentially useful variables. We found that the annual growth rate of security broker-dealers and the quarterly growth rate of shadow bank asset growth consistently were selected among the most useful predictors out of that larger group. We then showed regression results which underscore that these two variables indeed carry predictive power for excess returns on equities, corporate bonds, and Treasuries, strongly outperforming common benchmark return forecasting variables.

Given the agnostic approach of our analysis, a critical reader might worry that the predictive power of our variables is spurious or due to data-mining. In this subsection, we address this concern in two ways. First, we follow Foster, Smith, and Whaley (1997) and analyze the distribution of the maximum R^2 in univariate predictive regressions where the predictor variable is selected from a larger set of potential regressors. Second, we simulate random variables and mimic our variable selection algorithm and subsequent predictive regressions on the simulated variables. We then compare the resulting empirical distribution of t-statistics and R^2s with the values found in our actual regressions.

Turning to the first set of results, we compute the 90 percent and 95 percent cutoff values of the R^2 statistic according to two different formulas provided in Foster et al.

(1997). These are:

$$
\begin{aligned}
U^1_{R^2}(r) &= [Beta(r)]^N, && (2)\\
\text{and } U^2_{R^2}(r) &= F^{-1}\left[1+\frac{\ln(r)}{\ln(N)^{1.8N^{0.4}}}\right] && (3)
\end{aligned}
$$

where $Beta(\cdot)$ is the cumulative distribution function of the beta distribution with $k/2$ and $[T-(k+1)]/2$ degrees of freedom. F^{-1} denotes the inverse of that cumulative distribution function. $N=\binom{m}{k}$ is the total number of possible combinations of k variables selected from a pool of m potential regressors. While the first statistic assumes independence across regressions, the latter adjusts for the effect from using the same dependent variable and correlated predictor variables. This latter statistic is thus more relevant for our setup where - by construction - many of the considered predictor variables are mutually correlated.

In our application, we find the best predictor among $m=54$ balance sheet variables and use it in regressions with sample size $T=95$ quarters. For these parameters, the 90 percent cutoff values are $U^1_{R^2}(0.9)=9.9$ percent and $U^2_{R^2}(0.9)=7.9$ percent, respectively. The 95 percent cutoff values are $U^1_{R^2}(0.95)=11.1$ percent and $U^2_{R^2}(0.95)=9.2$ percent. Table 21 provides the Newey-West adjusted t-statistics and R^2s form univariate regressions of each of the 15 considered excess return series on either annual security broker-dealer leverage growth (equities), quarterly shadow bank asset growth (Treasuries) or both (corporate bonds). Comparing these cutoff values with the R^2s reported in Table 21, we can see that the R^2 obtained in a regression of the excess return on the equity market portfolio, *MKT*, on *ySBRDLRlevg* falls within the 90 percent and 95 percent cutoff values implied by $U^2_{R^2}(r)$. Hence, with almost 95 percent confidence, we can say that the R^2 from that regression could not have been obtained by data-mining random regressors. The same is true for the Fama-French small size high value portfolio, *FF15.* The R^2s for the remaining three equity portfolios are each about 5 percent. While high with respect to much of the previous literature on quarterly predictive return regressions, they are below the 90 percent cutoff values for the maximal R^2 from the two statistics in Foster et al. and hence one could in principle have obtained a similar regression fit from just randomly picking useless regressors from a large pool of variables in a small sample.

We next turn to the regressions of corporate bond returns on broker-dealer leverage and shadow bank assets. *ySBRDLRlevg* alone has an R^2 of at least 9 percent in two of the five univariate regressions whereas *qSHADBNKag* alone achieves R^2s that are consistently greater than 13 percent and hence far above the 95 percent cutoff value implied by the more conservative $U^1_{R^2}$ statistic. Finally, the R^2s from univariate regressions of the five Treasury returns on *qSHADBNKag* are all between 7 and 9 percent and hence fall between the 90 percent and 95 percent cutoff region for $U^2_{R^2}$. Together, these results give us confidence that even though we identified the two regressors by parsing through a larger number of potential right-hand side variables, they are much more informative about one-quarter ahead excess returns of most of the equity, corporate bond and Treasury returns we consider than what can be explained by pure chance.

In a related paper, Ferson, Sarkissian, and Simin (2003) argue that data-mining for predictor variables can interact with spurious regression bias, thereby potentially amplifying the problem associated with the former. Having first-order autocorrelation coefficients of 0.71 and 0.33, respectively, our two main predictor variables *ySBRDLRlevg* and *qSHADBNKag* are much less persistent than many return predictor variables that have previously been considered in the literature. Moreover, the regression results reported in Tables 8 - 19 control for lagged dependent variables and hence should be less prone to spurious regression bias. We therefore believe that the interaction of spurious regression bias and data-mining should not be a concern in our analysis.

Still, to be sure, we carry out the following simulation exercise. We randomly generate panels of time series with persistence levels observed in our set of financial intermediary balance sheet variables. Precisely, we draw a first-order autoregressive coefficient from the uniform distribution bounded by the minimal and maximal values of AR(1) coefficients observed in our sample of balance sheet indicators, i.e. -0.12 and 0.97. We then simulate a time series with $T = 95$ observations from an AR(1) process with that persistence level using standard normal shocks. We repeat these steps 54 times, hence generating a random sample of time series with time series properties very similar to the variables in our panel. We further randomly generate a pseudo return series from the standard log-normal distribution, also with $T = 95$ observations. This implements the null hypothesis of no predictability. As in Section 4.1., we then run the LAR procedure to identify the best predictor among the 54 randomly generated right-hand side variables for the randomly generated dependent variable. Given this best predictor variable, we run an OLS regression as in equation (1), and compute the R^2 and the Newey-West adjusted t-statistic with a maximum number of four lags, just as in our predictive return regressions. We repeat this exercise 10,000 times and build up the empirical distribution of R^2s and t-statistics. The 95th and 90th percentile of the empirical distribution of the R^2 statistic are 11.1 percent and 10.0 percent, respectively. This is slightly above the R^2 that we obtain in the regression of the equity market risk premium onto *ySBRDLRlevg*, but well below the R^2s that we see in the univariate regressions of the corporate bonds on both *ySBRDLRlevg* and *qSHADBNKag*. Finally, the R^2 from the regression of the ten-year Treasury note's excess return *CMT10* onto *qSHADBNKag* being 10 percent, we can be 90 percent confident that this result cannot be explained by a combination of spurious regression bias and data-mining. Finally, note that the 95th and 90th percentile of the simulated Newey-West adjusted t-statistics are 3.07 and 2.75, respectively. These values are well within the range of actual t-statistics that we obtain in the regressions of *MKT, BAA*, or *CMT10* onto either *ySBRDLRlevg* or *qSHADBNKag* reported in Table 21. This gives us additional confidence that our results cannot be explained by data-mining or spurious regression bias.

6 Financial Intermediation and Macro Dynamics

So far, we have examined the predictive properties of balance sheet variables when forecasting asset returns. The rationale for our approach has been to interpret balance sheet expansions of financial intermediaries as indicating greater willingness to take on risky exposures, and hence indicative of lower overall risk premia in the market. We interpret our results as suggesting that stronger balance sheet growth goes hand in hand with lower risk premia and tighter spreads. Conversely, slower balance sheet growth or outright contractions of intermediary balance sheets are seen as indications of increases in risk premia and increases in spreads. The concept of deleveraging for financial intermediaries which was not well known before the financial crisis has now entered the lexicon of public debate after the crisis.

In this section, we present two sets of results that allow us to refine this interpretation of the empirical results by linking them to aggregate macroeconomic variables. First, we provide further evidence suggesting that the forecasting power of the balance sheet variables is due to variation in discount rate news and not cash flow news. To do so, we control explicitly for expectations about future macroeconomic aggregates, using the four quarter ahead GDP and inflation expectations from the Survey of Professional Forecasters (SPF), as well as analysts' earnings expectations for the S&P500 index from I/B/E/S. In addition, we present regression results where we show directly that security broker-dealer leverage does not have forecasting power for aggregate real earnings or real dividends, again providing indirect evidence that the forecasting power is due to discount rate variations, and not due to information about future cash flows.[6]

Given this interpretation, we then explore the implications of the time variation of risk premia driven by balance sheet adjustments for macroeconomic dynamics. To do so, we estimate a vector autoregression (VAR) with standard macroeconomic variables (real GDP, core inflation, and the fed funds target rate) augmented by three intermediary bal-

[6] Instead of using a Campbell and Shiller (1988) decomposition, we thus directly show that balance sheets have no predictive power for future cash flows.

ance sheet variables (broker-dealer equity, broker-dealer assets, and shadow bank assets) as well as the BAA default spread. The results reported in that subsection suggest that the time variation of the credit spread that is due to the time variation in intermediary balance sheets impacts the dynamics of real GDP. These findings are consistent with the interpretation that stronger balance sheets are associated with tighter risk premia, which in turn lead to greater macroeconomic activity. We present the findings from this macro-finance VAR in a series of impulse response functions that illustrate the role of the financial intermediary variables for macroeconomic activity.

6.1 Discount Rate or Cash Flow News?

The forecasting power of the security broker-dealer leverage growth variable for the equity market return is not due to expectations about future macroeconomic activity, or expectations about future earnings growth. This can be seen in Table 22, where we report the forecasting regressions of the broker-dealer variable for the equity market return, augmented with expectations about future GDP growth and future inflation from the SPF, and also controlling for analyst earning forecasts from I/B/E/S. Table 22 is reproducing exactly the regressions from Table 8, but augmented with the three expectations variables. Column (1-3) and (5) of Table 22 show that the expectations variables alone do not have any significant predictive power for the future market return when entered into the forecasting regression together with the relative Treasury bill rate, the term spread, the default spread, or the log consumption-wealth ratio. However, when entered in conjunction with the log dividend price ratio (d/p), real earnings expectations and CPI expectations become significant. In particular, higher inflation expectations tend to predict lower stock market returns, while higher earnings growth tends to predict a higher stock market return. However, the expectations variables are only significant in conjunction with the dividend price ratio. Among the predictor variables, d/p is the most persistent predictor, suggesting that there is some low frequency movement in inflation expectations and real earnings growth that is picked up by the joint significance of these variables with the dividend-price ratio.

For our purposes, the most important columns of Table 22 are (6) and (7). Column (6) shows that the significance of the security broker-dealer leverage growth variable is unchanged when the expectations variables are included. In particular, none of the expectations variables are significant when they are entered jointly with the broker-dealer variable. Column (7) confirms the earlier finding that the broker-dealer variable becomes more significant when other forecasting variables are entered simultaneously into the regression. Comparison of columns (7) in Tables 8 and 22 shows that the adjusted R^2 doubles from 8% to 16% when the expectations variables are included in the predictive regression. In addition, the t-statistic for the broker-dealer leverage growth variable is higher when the expectations variables are added as controls (-3.81 versus -3.57), again suggesting that the expectations variables capture orthogonal information relative to the broker-dealer variables. In sum, the results presented in Table 22 suggest that the predictive power of the broker-dealer variable for the excess return on the equity market portfolio arises due to time variation in discount rates, and not due to the information content of the broker-dealer variable with respect to future earnings growth or macroeconomic activity.

The interpretation of the broker-dealer leverage growth variable as a proxy for the time variation in risk premia is further strengthened by the results reported in Table 23, where we predict future cash flows. In columns (1) and (2), the dependent variable is the quarterly growth rate of real earnings for the S&P500 index, and in columns (3) and (4) the quarterly growth rate of real dividends is on the left hand side. In the regressions reported in columns (1) and (3), the broker-dealer variable is the only right hand side variable, while in columns (2) and (4), the lagged dependent variable is added to the regression. Column (1) shows that the broker-dealer leverage variable is significant at the 10% level in forecasting future real earnings. However, the sign is negative, and the significance goes away once we control for the lagged real earnings growth in column (2). We do not find any predictability of the broker-dealer variable for future real dividend growth, whether we do or we do not control for the lagged real dividend growth, see columns (3) and (4) .

In summary, the results of Tables 22 and 23 provide further evidence that broker-dealer leverage growth predicts equity returns because of time variation in discount rates, and not because of the information content of broker-dealer leverage for future cash flows. The results confirm the considerable information value in the balance sheets of financial intermediaries. Having confirmed that balance sheet information is useful for predicting asset returns due to discount rate variation, we now turn to the second of our empirical exercises - that of documenting that balance sheet dynamics also hold important implications for economic activity.

6.2 Implications for Macroeconomic Dynamics

Do the balance sheet variables that have appeared significant in the asset return forecasting regressions also predict macro variables? Our hypothesis is that the answer is "yes", owing to the fact that balance sheets convey information on risk premia, which in turn influence consumption and investment decisions.

Our empirical approach to study the information content of balance sheet variables for macroeconomic variables is to estimate a vector autoregression (VAR) that includes variables such as GDP and inflation, as well as the balance sheet variables that we identified earlier as containing relevant information for asset returns. We estimate the VAR in log levels, i.e. we use the logarithm of real GDP, the logarithm of the core PCE deflator, the level of the federal funds target rate, and balance sheet variables from security broker-dealers and shadow banks. For the shadow banks, we use log assets which we found to be a highly significant asset price predictor variable. For the security broker-dealers, we include both log assets and log equity. Since leverage is defined as the ratio between assets and equity, these two variables span all the information contained in the leverage growth variable which we have found to be an important predictor for equity and corporate bond returns. This allows us to trace back the informational content of leverage growth to its two components. We use two lags in the VAR following standard lag length selection criteria. We make sure that the VAR is stationary by checking that all of the roots of the VAR are inside the unit circle.

We use a simple recursive scheme to identify shocks in the VAR. The ordering of the variables is as follows: log real GDP, log core PCE deflator, fed funds rate, log broker-dealer equity, log broker-dealer assets, log shadow bank assets, and the default spread. This identification scheme implies that GDP, inflation, and the fed funds rate do not react to balance sheet shocks within the same quarter. However, shocks to the balance sheets do have a contemporaneous effect on the default spread. Moreover, note that we order broker-dealer equity before broker-dealer assets, implying that a shock to assets does not move broker-dealer equity on impact. This suggests that we can readily interpret a shock to assets as a shock to broker-dealer leverage growth. To see this, recall that the growth rate of leverage is just the difference between the log of broker-dealer assets and the log of broker-dealer equity. A positive shock to assets which does not move equity on impact implies that leverage goes up on impact. Such a shock thus represents an expansion of security broker-dealer balance sheets which is fully funded by taking on more liabilities.

The results of the VAR are summarized in Figures 5 - 8, and in Table 24. Figure 5 shows the response of GDP to the balance sheet variables and the default spread. The upper left plot in Figure 5 shows that a shock to broker-dealer equity orthogonal to broker-dealer assets is followed by positive GDP growth. The GDP response reaches 0.4% in the 4th quarter after the shock, the cumulative effect of a one standard deviation broker-dealer equity shock for real GDP growth is more than 2% over five years. We interpret the broker-dealer equity shock orthogonal to the broker-dealer asset shock either as a shock to the funding cost of broker-dealers e.g. due to an exogenous decline of short-term borrowing rates, or as a financial intermediation shock that revalues broker-dealer equity e.g. due to writedowns. The magnitude of the impact on GDP growth clearly points to the importance of broker-dealer net worth in financial intermediation. Inspection of Table 24 shows that much of the effect of broker-dealer equity on GDP is indirect, via the impact of equity on the default spread: higher equity implies a lower default spread, which in turn results in higher GDP growth.

The upper right hand panel of Figure 5 plots the impulse response of GDP with respect to a broker-dealer asset shock. As discussed above, this shock can be interpreted as a shock to leverage since broker-dealer assets are ordered after broker-dealer equity in the VAR. The plot again shows a large positive association between the broker-dealer asset or leverage shock, and subsequent GDP growth. The cumulative effect of a one standard deviation shock to broker-dealer assets on GDP is larger than 2% over the five years following the shock.

The remaining two lower panels in Figure 5 show that shadow bank assets do not have a significant impact on GDP, while the default spread does have a significantly negative impact. Lower spreads are thus followed by larger GDP growth and vice versa. Note that the default spread is the last variable in the VAR, so that the default spread can contemporaneously respond to shocks to all other variables in the VAR.

Figure 6 shows the response of the core PCE deflator to a broker-dealer equity, a broker-dealer asset, a shadow bank asset, and a default spread shock (clock wise from the upper left hand corner). The plots reveal that the core PCE deflator reacts significantly to the broker-dealer equity and the shadow bank asset shocks. These impulse response functions again suggest that macroeconomic activity is impacted by the time variation of the risk premia associated with balance sheet expansions and contractions. A positive shock to risk appetite as proxied for by a faster expansion of financial intermediary balance sheets is therefore associated with lower spreads, higher real activity, and higher inflation.

Figure 7 plots the impulse response functions of broker-dealer equity and assets to broker-dealer equity and asset shocks. On the diagonal, the response of the two variables to own shocks is plotted, while the off diagonal plot the equity response to an asset shock (upper right hand panel) and the asset response to an equity shock (lower left hand panel).

A shock to broker-dealer equity induces strong expansions of total balance sheet size (lower left hand panel), while a shock to assets does not induce a significant long-run response of assets (upper right hand panel). In interpreting this finding, the ordering of the VAR is important: the shock to equity is, per construction, orthogonal to the shock to assets. These findings about the dynamic interaction of broker-dealer assets and equity are fully consistent with Adrian and Shin (2010), who show that equity is the forcing variable in the balance sheet adjustment of broker-dealers. Total asset size is adjusted so as to target return on equity. Finally, note that shocks to broker-dealer equity and assets both have significantly negative effects on the default spread (see Figure 8). This result is consistent with the predictive regressions reported earlier.

7 Conclusion

The cumulative body of evidence presented in our paper points to the informational value of balance sheet variables of financial intermediaries in predicting excess returns for a large cross-section of assets. In particular two variables appear prominently after selection for the best set of explanatory variables. One is the annual security broker-dealer leverage growth, and the second is the quarterly shadow bank asset growth. Having started with a very large set of potential explanatory variables, our selection algorithm narrows down to these two variables. We have seen that an increase in the broker-dealer leverage growth predicts lower future equity returns and lower future corporate bond returns. Meanwhile, an increase in shadow bank asset growth predicts lower future corporate bond and Treasury returns. We have also documented that the predictive power of these balance sheet indicators for future excess returns does not appear to be due to information about future cash flows. We therefore interpret our findings as suggesting that balance sheet adjustments of financial intermediaries provide a window on the determination of risk premia in the economy. When we examined the joint dynamics of macroeconomic aggregates, financial intermediary balance sheet variables, and credit spreads, we found the same pair of balance sheet variables to provide useful information about future real economic activity and inflation.

We believe that our results hold notable implications on several fronts. For asset pricing, our results suggest that credit supply frictions play an important role in setting risk premia, possibly through the operation of balance sheet constraints and associated risk appetite effects. Our results are consistent with the theoretical basis for how balance sheet constraints determine risk appetite, as well as empirical results in the foreign exchange and commodities markets that indicate a key role for balance sheet variables.

Our empirical results also pose a challenge for any structural macro model that does not have a role for financial intermediaries as an integral part of the model. For policy makers—especially for central banks and systemic risk regulators—our results suggest that the evolution of macroeconomic aggregates and risk premia are closely tied together via the functioning of financial intermediaries.

Looking forward, there are some potentially exciting avenues of future research on possible ways in which balance sheet information can be used for preemptive macroeconomic policy. To the extent that balance sheet aggregates forecast real activity and inflation, there are clear implications for macroprudential policy. However, the broader lesson is that the fluctuations in real activity is part and parcel of the fluctuations in risk premia associated with financial intermediary balance sheet management. In this sense, macroprudential policy that aims to achieve stability of the financial system is closely related to the more conventional demand management role of monetary policy that looks only at inflation and the output gap. More systematic investigation of the role of financial conditions in macroeconomic fluctuations will reveal the extent to which monetary policy and policies toward financial stability are linked.

References

[1] Adrian, Tobias, Erkko Etula and Hyun Song Shin (2009) "Risk Appetite and Exchange Rates," *Federal Reserve Bank of New York Staff Reports* 361.

[2] Adrian, Tobias, Erkko Etula and Tyler Muir (2010) "Broker-Dealer Leverage and the Cross-Section of Stock Returns," *Federal Reserve Bank of New York Staff Reports* 464.

[3] Adrian, Tobias and Hyun Song Shin (2010) "Liquidity and Leverage," *Journal of Financial Intermediation* 19(3), pp. 418-437.

[4] Brunnermeier, Markus and Lasse Pedersen (2009) "Market Liquidity and Funding Liquidity," *Review of Financial Studies* 22(6), pp. 2201-2238.

[5] Campbell, John and Robert Shiller (1988) "The Dividend-Price Ratio and Expectations of Future Dividends and Discount Factors," *Review of Financial Studies* 1, pp. 195–228.

[6] Chava, Sudheer, Michael Gallmeyer, and Heungju Park (2010) "Credit Conditions and Expected Stock Returns," Working Paper, Texas A&M University.

[7] Clark, Todd and Michael McCracken (2001) "Tests of Equal Forecast Accuracy and Encompassing for Nested Models," *Journal of Econometrics* 105, pp. 85-110.

[8] Cochrane, John and Monika Piazzesi (2005) "Bond Risk Premia," *American Economic Review* 95, pp. 138-160.

[9] Efron, Bradley, Trevor Hastie, Iain Johnstone, and Robert Tibshirani (2004) "Least Angle Regression," *Annals of Statistics* 32(2), pp. 407-451.

[10] Etula, Erkko (2009) "Broker-Dealer Risk Appetite and Commodity Returns," *Federal Reserve Bank of New York Staff Reports* 406.

[11] Fama, Eugene, Kenneth French (1993) "Common Risk Factors in the Returns on Stocks and Bonds" *Journal of Financial Economics* 33 (1), pp. 3–56.

[12] Ferson, Wayne, Sergei Sarkissian, and Timothy Simin (2003) "Spurious Regressions in Financial Economics?" *Journal of Finance* 58(4), pp. 1393-1413.

[13] Foster, Douglas, Tom Smith, and Robert Whaley (1997) "Assessing Goodness-of-Fit of Asset Pricing Models: The Distribution of the Maximal R^2," *Journal of Finance* 52(2), pp. 591-607.

[14] Carhart, Mark (1997) "On Persistence in Mutual Fund Performance," *Journal of Finance* 52(1), pp. 57-82.

[15] Gatev, Evan and Philip Strahan (2006) "Banks' Advantage in Hedging Liquidity Risk: Theory and Evidence from the Commercial Paper Market," *Journal of Finance* 61(2), pp. 867-892.

[16] Gilchrist, Simon and Egon Zakrajšek (2010) "Credit Risk and the Macroeconomy," Working Paper, Boston University.

[17] Goyal, Amit and Ivo Welch (2008) "A Comprehensive Look at The Empirical Performance of Equity Premium Prediction," *Review of Financial Studies* 21(4), pp. 1455-1508.

[18] Hastie, Trevor, Robert Tibshirani, and Jerome Friedman (2009) *The Elements of Statistical Learning*, Springer Press: New York.

[19] He, Zhiguo and Arvind Krishnamurthy (2007) "Intermediary Asset Pricing," Working Paper, Northwestern University.

[20] He, Zhiguo, In Gu Khang, and Arvind Krishnamurthy (2010) "Balance Sheet Adjustments During the 2008 Crisis," *IMF Economic Review*, forthcoming.

[21] Krishnamurthy, Arvind and Annette Vissing-Jorgensen (2008) "The Aggregate Demand for Treasury Debt," Working Paper, Northwestern University.

[22] Longstaff, Francis and Jiang Wang (2008) "Asset Pricing and the Credit Market," unpublished working paper, MIT and UCLA.

[23] McCracken, Michael (2007) "Asymptotics for Out of Sample Tests of Granger Causality," *Journal of Econometrics* 140, pp. 719-752.

[24] Daniel Paravisini (2008) "Local Bank Financial Constraints and Firm Access to External Finance," *Journal of Finance* 63(5), pp. 2161-2193.

[25] Lettau, Martin, and Sydney Ludvigson (2001) "Resurrecting the (C)CAPM: A Cross-Sectional Test When Risk Premia are Time-Varying," *Journal of Political Economy* 109(6), pp. 1238-1287.

[26] Peek, Joe and Eric Rosengren (2000) "Collateral Damage: Effects of the Japanese Bank Crisis on Real Activity in the United States," *American Economic Review*, 90 (1), pp. 30–45.

[27] Piazzesi, Monika, and Martin Schneider (2009) "Trend and Cycle in Bond Premia," Working Paper, Stanford University.

[28] Puri, Manju, Joerg Rocholl, and Sascha Steffen (2010) "The Impact of the US Financial Crisis on Global Retail Lending," *Journal of Financial Economics* forthcoming.

[29] Rice, Tara and Philip Strahan (2010) "Does Credit Competition Affect Small-Firm Finance?" *Journal of Finance* 65(3), pp. 861-889.

[30] Schnabl, Philipp (2010) "Financial Globalization and the Transmission of Credit Supply Shocks," Working Paper, New York University.

[31] Sims, Christopher (1980) "Macroeconomics and Reality," *Econometrica* 48, pp. 1-48.

[32] Shleifer, Andrei, and Robert Vishny (1992) "Liquidation Values and Debt Capacity: A Market Equilibrium Approach," *Journal of Finance*, 47(4), pp. 1343-1366.

Table 1: Balance Sheet Data Series

This table displays the types of financial institutions whose aggregate balance sheet growth we consider as explanatory variables in the return predicting regressions. We consider quarterly and annual growth rates of total financial assets for each type of institution individually as well as for the five major groups (banks, pension funds and insurances, mutual funds, shadow bank, and security brokers-dealers). In addition to growth rates of total financial assets, we also consider quarterly and annual leverage growth for commercial banks, credit unions, and security brokers-dealers. Leverage is defined as assets divided by equity where equity is the difference between assets and liabilities. All data are from the Flow of Funds Accounts provided by the Board of Governors of the Federal Reserve.

Mnemonic	Haver	Description (All Variables: Bil $, NSA)
FINBANK		
CB	OA76TAO5	Commercial Banking: Financial Assets
	OL76TAO5	Commercial Banking: Total Liabilities
SI	OA44TAO5	Savings Institutions: Total Financial Assets
	OL44TAO5	Savings Institutions: Total Liabilities
CU	OA47TAO5	Credit Unions: Financial Assets
	OL47TAO5	Credit Unions: Total Liabilities
FINPI		Pension Funds and Insurance Companies
PCIC	OA51TAO5	Insurance Cos excl Life: Financial Assets
	OL51TAO5	Insurance Companies -excl Life Ins: Liabilities: Total
LIC	OA54TAO5	Life Insurance Companies: Financial Assets
	OL54TAO5	Life Insurance Companies: Total Liabilities
PPF	OA57TAO5	Private Pension Funds: Assets: Financial
	OL57PFR5	Private Pension Funds: Liabs: Pvt Noninsured Pension Reserves
SLGERF	OA22TAO5	State & Local Govt Retirement Funds: Assets: Financial
	OL22PFR5	State&Local Govt Retirement Funds: Liabs; Pension Fund Reserves
FGRF	OA34TAO5	Federal Government Retirement Funds: Total Financial Assets
	OL34PFR5	Federal Government Retirement Funds: Miscellaneous Assets
FINMF		Mutual Funds
MMMF	OA63MMF5	Money Market Mutual Funds: Net Acquisition of Financial Assets
MF	OA65TAO5	Mutual Funds: Financial Assets
	OL65COE5	Investment Companies [Mutual Funds]: Liab: Net Issues
CEF	OA55TAO5	Closed-end Funds: Total Financial Assets
MORTPOOL	OA41MOR5	Mortgage Pools: Assets: Mortgages
SHADBNK		
ABS	OA67TAO5	ABS Issuers: Assets; Total Financial Assets
	OL67TAO5	Asset-Backed Security Issuers: Total Financial Liabilities
FINCO	OA61TAO5	Finance Companies: Financial Assets
	OL61TAO5	Finance Companies: Total Liabilities
FNDCORP	OA50TAO5	Funding Corporations: Total Financial Assets
	OL50TAO5	Funding Corporations: Total Financial Liabilities
SBRDLR	OA66TAO5	Security Brokers-Dealers: Financial Assets
	OL66TAO5	Security Brokers-Dealers: Liabilities: Total

Table 2: Macroeconomic Data Series

This table presents the macroeconomic aggregates which we use as return predictor variables in Section 4 and as left-hand side variables in Section 5. They cover real GDP and its major components as well as inflation rates for PCE and its major components. We compute quarterly and annual growth rates for the real variables and quarterly and annual inflation rates for the PCE series. All data are from the Bureau of Economic Analyses.

Mnemonic	Description
GDP	Real Gross Domestic Product (SAAR, Bil.Chn.2000$)
C	Personal Consumption Expenditures (SAAR, Bil.$)
CD	Real Personal Consumption Expenditures: Durable Goods (SAAR, Bil.Chn.2000$)
CN	Real Personal Consumption Expenditures: Nondurable Goods (SAAR, Bil.Chn.2000$)
CS	Real Personal Consumption Expenditures: Services (SAAR, Bil.Chn.2000$)
I	Gross Private Domestic Investment (SAAR, Bil.$)
F	Private Fixed Investment (SAAR, Bil.$)
FN	Real Private Nonresidential Fixed Investment (SAAR, Bil.Chn.2000$)
FR	Real Private Residential Investment (SAAR, Bil.Chn.2000$)
XNET	Real Net Exports of Goods & Services (SAAR, Bil.Chn.2000$)
G	Real Government Consumption Expenditures & Gross Investment(SAAR, Bil.Chn.2000$)
JC	Personal Consumption Expenditures: Chain Price Index (SA, 2005=100)
JCXFE	PCE less Food & Energy: Chain Price Index (SA, 2005=100)
JCXEG	PCE Excluding Energy Goods & Services: Chain Price Index (SA, 2005=100)
JCD	Personal Consumption Expenditures: Durable Goods: Chain Price Index(SA,2005=100)
JCN	Personal Consumption Expend: Nondurable Goods: Chain Price Index (SA,2005=100)
JCS	Personal Consumption Expenditures: Services: Chain Price Index (SA, 2005=100)

Table 3: Benchmark Return Forecasting Factors

This table presents the benchmark return forecasting factors that we consider in addition to the macroeconomic aggregates and balance sheet variables.

Mnemonic	Description	Source
CAY	Log consumption wealth ratio	Sydney Ludvigson's website
MKT	CRSP market portfolio	Kennneth French's website
SMB	Fama French size factor	Kennneth French's website
HML	Fama French value factor	Kennneth French's website
MOM	Fama French momentum factor	Kennneth French's website
STREV	Fama French short-term reversal factor	Kennneth French's website
STREV	Fama French long-term reversal factor	Kennneth French's website
d/p	Log Dividend price ratio of S&P500	Robert Shiller's website
TERM	Term spread (10year-3month)	Haver (FCM10, FTBS)
DEF	Default spread (Moody's Baa-Aaa)	Haver (FBAA, FAAA)
RREL	3-month Treasury rate minus its 4-quarter moving average	Haver (FTBS3)
CP	Cochrane Piazzesi factor	Monika Piazzesi's website & CRSP

Table 4: Asset Returns

This table lists the equity portfolio returns and the corporate and Treasury returns used in the predictive return regressions in Section 4.

Mnemonic	Description	Source
	Equity Portfolios	
MKT	Fama French Market Portfolio	Kenneth French's Website
FF11	Small Size Low Value Portfolio	
FF15	Small Size High Value Portfolio	
FF51	Large Size Low Value Portfolio	
FF55	Large Size High Value Portfolio	
	Corporate Bond Returns	
IGI	Investment Grade Industrials	Barclays Corporate Bonds
IGU	Investment Grade Utilities	
IGF	Investment Grade Financials	
A	A Rated	
Baa	Baa Rated	
	Treasury Returns	
CMT1	1-year Constant Maturity Treasury Return	CRSP Monthly Treasuries
CMT2	2-year	
CMT5	5-year	
CMT7	7-year	
CMT10	10-year	

Table 5: Best Return Predictors for Equity Returns

This table shows the results of the least angle regression procedure for the predictive return regressions of five equity portfolios: the total market and four Fama-French size and book-to-market sorted portfolios FF11, FF15, FF51, FF55. The table contains three panels. The top panel lists those variables chosen by the selection algorithm as the best predictors among the macro and benchmark return predictor variables, the second panel reports the best predictors from the set of balance sheet variables, and the bottom panel reports the best predictive variables from the set that combines the macro, benchmark return predictors and balance sheet variables.

	MKT	FF11	FF15	FF51	FF55
			Macro and Benchmark Return Predictor Variables		
1st	qJCN	HML	qJCN	SMB	LTREV
2nd	SMB	qCS	MOM	cay	qG
3rd	qG	SMB	LTREV	qJCN	qJCN
4th	LTREV	SPVXO	qCS	HML	RREL
5th	MOM	yCS	qG	CP	MOM
			Balance Sheet Variables Only		
1st	**ySBRDLRlevg**	**ySBRDLRlevg**	**ySBRDLRlevg**	**ySBRDLRlevg**	**ySBRDLRlevg**
2nd	qSBRDLRag	qSBRDLRag	qCBag	yFINBANKeg	yMMMFag
3rd	yCBeg	yPPFag	qSBRDLRag	ySIeg	qSBRDLRag
4th	qSIag	ySLGERFag	yFNDCORPag	qSBRDLReg	yMORTPOOLag
5th	qFINCOag	qSIag	yFINPIag	qSBRDLRag	yCUlevg
			All		
1st	**ySBRDLRlevg**	**ySBRDLRlevg**	**ySBRDLRlevg**	SMB	LTREV
2nd	SMB	HML	qCBag	**ySBRDLRlevg**	qG
3rd	qJCN	qSBRDLRag	qSBRDLRag	cay	**ySBRDLRlevg**
4th	qSBRDLRag	yPPFag	qJCN	yFINBANKeg	yMMMFag
5th	cay	SMB	qCS	ySIeg	qSBRDLRag

Table 6: Best Return Predictors for Corporate Bond Returns

This table shows the results of the least angle regression procedure for the predictive return regressions of the investment grade industrial (IGI), the investment grade utilities (IGU), investment grade financial (IGF), as well as "A" and "Baa" rated corporate bonds.

	IGI	IGU	IGF	A	BAA
			Macro and Benchmark Return Predictor Variables		
1st	qCS	yCD	MOM	qCS	yC
2nd	yC	yC	yFN	CP	yFN
3rd	CP	MOM	qCS	HML	qCS
4th	TERM	qCS	CP	MOM	SPVXO
5th	SPVXO	SPVXO	yC	yC	TERM
			Balance Sheet Variables Only		
1st	**qSHADBNKag**	**qSHADBNKag**	qFNDCORPag	qFNDCORPag	**qSHADBNKag**
2nd	**ySBRDLRlevg**	qSBRDLReg	**qSHADBNKag**	**qSHADBNKag**	**ySBRDLRlevg**
3rd	ySIag	**ySBRDLRlevg**	ySIag	ySIag	qSBRDLReg
4th	qFNDCORPag	ySIag	**ySBRDLRlevg**	**ySBRDLRlevg**	ySIag
5th	qSBRDLReg	qCBlevg	qSIag	qSIag	qFNDCORPag
			All		
1st	**qSHADBNKag**	**qSHADBNKag**	qFNDCORPag	qFNDCORPag	**qSHADBNKag**
2nd	**ySBRDLRlevg**	qSBRDLReg	**qSHADBNKag**	**qSHADBNKag**	**ySBRDLRlevg**
3rd	ySIag	**ySBRDLRlevg**	MOM	ySIag	yC
4th	qFNDCORPag	ySIag	ySIag	**ySBRDLRlevg**	qSBRDLReg
5th	qSBRDLReg	yCD	**ySBRDLRlevg**	qSIag	qCS

Table 7: Best Return Predictors for Treasury Returns

This table shows the results of the least angle regression procedure for the predictive return regressions of the constant maturity Treasury returns for maturities one through ten years.

	CMT1	CMT2	CMT5	CMT7	CMT10
Macro and Benchmark Return Predictor Variables					
1st	CP	CP	CP	HML	HML
2nd	qCS	qCS	HML	CP	CP
3rd	yFR	yFR	qCS	yJCN	qJCN
4th	qJCN	HML	yJCN	qJCN	yJCN
5th	TERM	MOM	yFR	qCS	qCS
Balance Sheet Variables Only					
1st	qSIag	qSIag	qSIag	qSIag	qSIag
2nd	qFNDCORPag	**qSHADBNKag**	qFNDCORPag	**qSHADBNKag**	**qSHADBNKag**
3rd	ySIeg	qFNDCORPag	qCUlevg	qFNDCORPag	qFNDCORPag
4th	qMORTPOOLag	ySIeg	**qSHADBNKag**	qCUlevg	qCUlevg
5th	**qSHADBNKag**	qCBlevg	ySIeg	ySIeg	qCBag
All					
1st	CP	qSIag	qSIag	qSIag	qSIag
2nd	qSIag	**qSHADBNKag**	qFNDCORPag	**qSHADBNKag**	**qSHADBNKag**
3rd	ySIeg	CP	CP	qFNDCORPag	qFNDCORPag
4th	qCS	ySIeg	qCUlevg	qCUlevg	qCUlevg
5th	**qSHADBNKag**	qFNDCORPag	**qSHADBNKag**	HML	yJCN

Table 8: Predictive Return Regression - Equity Market Portfolio (MKT)

This table reports coefficient estimates and the corresponding t-statistics from a regression of the excess return of the equity market portfolio on one-quarter lagged observations of several explanatory variables. These are the market return (Mkt), the difference of the 3-month Treasury bill rate and its four-quarter moving average (RREL), the term spread (TERM), the default spread (DEF), the log dividend-price-ratio (d/p), the log consumption-wealth ratio (cay), as well as the annual growth rate of security broker-dealer leverage (ySBRDLR:levg). All standard errors are Newey-West adjusted with a maximum lag length of 4 quarters. The bottom row shows the adjusted R-squared of each regression, respectively. The sample period is 1986Q1-2009Q4.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
cst	**1.75**	1.30	1.22	**6.60**	1.21	**2.48**	12.68
	(2.05)	(0.79)	(0.45)	(2.26)	(1.22)	(2.79)	(1.67)
MKT	0.01	0.03	0.03	0.03	0.04	-0.04	-0.06
	(0.11)	(0.23)	(0.23)	(0.29)	(0.37)	(-0.37)	(-0.61)
RREL	1.13						-0.10
	(1.26)						(-0.11)
TERM		0.12					-1.01
		(0.16)					(-1.12)
DEF			0.30				-2.90
			(0.11)				(-0.89)
d/p				3.73			4.04
				(1.61)			(1.12)
cay					**70.33**		51.79
					(2.04)		(1.01)
ySBRDLRlevg						**-0.09**	**-0.11**
						(-3.01)	(-3.57)
# Obs	95	95	95	95	95	95	95
adj.R^2	-0.01	-0.02	-0.02	0.00	0.00	0.07	0.08

Table 9: Predictive Return Regression - Large Size High Value Portfolio (FF55)

This table reports coefficient estimates and the corresponding t-statistics from a regression of the excess return of the Fama-French large firm high value portfolio on one-quarter lagged observations of several explanatory variables. These are the Fama-French large size high value portfolio, the difference of the 3-month Treasury bill rate and its four-quarter moving average (RREL), the term spread (TERM), the default spread (DEF), the log dividend-price-ratio (d/p), the log consumption-wealth ratio (cay), as well as the annual growth rate of security broker-dealer leverage (ySBRDLR:levg). All standard errors are Newey-West adjusted with a maximum lag length of 4 quarters. The bottom row shows the adjusted R-squared of each regression, respectively. The sample period is 1986Q1-2009Q4.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
cst	**2.03**	1.85	1.47	**7.94**	1.39	**2.35**	15.46
	(2.40)	(1.54)	(0.46)	(2.58)	(1.24)	(2.12)	(1.63)
FF55	0.08	0.11	0.11	0.11	0.12	0.09	0.05
	(0.93)	(1.07)	(1.03)	(1.07)	(1.16)	(0.88)	(0.53)
RREL	1.81						0.85
	(1.85)						(0.80)
TERM		-0.12					-0.95
		(-0.15)					(-0.88)
DEF			0.16				-2.34
			(0.05)				(-0.51)
d/p				4.61			6.44
				(1.91)			(1.60)
cay					54.05		10.70
					(1.33)		(0.19)
ySBRDLRlevg						**-0.07**	**-0.08**
						(-2.23)	(-2.70)
# Obs	95	95	95	95	95	95	95
adj.R^2	0.02	-0.01	-0.01	0.02	0.00	0.04	0.06

Table 10: Predictive Return Regression - Investment Grade Financial Bonds (IGF)

This table reports coefficient estimates and the corresponding t-statistics from a regression of the excess return of the investment grade coporate bond portfolio on one-quarter lagged observations of several explanatory variables. These are the investment grade coporate bond return (IGF), the term spread (TERM), the default spread (DEF), the Cochrane-Piazzesi return forecasting factor (CP), as well as the annual growth rate of security broker-dealer leverage (ySBRDLRlevg) and the quarterly growth rate of shadow bank asset growth (qSHADBNKag). All standard errors are Newey-West adjusted with a maximum lag length of 4 quarters. The bottom row shows the adjusted R-squared of each regression, respectively. The sample period is 1986Q1-2009Q4.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
cst	1.58	-0.04	-0.60	**0.95**	**1.26**	**2.70**	2.06	1.86	**3.16**	**4.57**
	(1.38)	(-0.09)	(-0.50)	(2.85)	(2.66)	(3.20)	(1.32)	(1.46)	(4.52)	(3.81)
IGF	-0.09	-0.10	-0.10	-0.09	-0.16	-0.13	-0.20	-0.15	-0.22	-0.25
	(-0.62)	(-0.71)	(-0.77)	(-0.63)	(-0.92)	(-1.13)	(-1.29)	(-1.34)	(-1.60)	(-1.92)
FFR	-0.15						-0.20	0.04		-0.04
	(-0.79)						(-1.01)	(0.31)		(-0.28)
TERM		**0.54**					-0.44	-0.15		-0.63
		(1.98)					(-1.00)	(-0.41)		(-1.68)
DEF			1.53				1.12	0.90		0.23
			(1.13)				(0.91)	(0.86)		(0.26)
CP				**1.00**			**1.66**	**0.99**		**1.57**
				(3.90)			(3.18)	(3.00)		(3.98)
ySBRDLRlevg					**-0.03**		**-0.03**		**-0.03**	**-0.04**
					(-2.01)		(-2.45)		(-2.86)	(-3.69)
qSHADBNKag						**-0.15**		**-0.14**	**-0.16**	**-0.17**
						(-2.85)		(-3.03)	(-3.72)	(-4.05)
# Obs	95	95	95	95	95	95	95	95	95	95
adj.R^2	-0.00	0.02	0.02	0.03	0.06	0.16	0.12	0.17	0.25	0.29

Table 11: Predictive Return Regression - Baa Corporate Bonds (Baa)

This table reports coefficient estimates and the corresponding t-statistics from a regression of the excess return of the Baa rated corporate bond portfolio on one-quarter lagged observations of several explanatory variables. These are the Baa bond return (BAA), the term spread (TERM), the default spread (DEF), the Cochrane-Piazzesi return forecasting factor (CP), as well as the annual growth rate of security broker-dealer leverage (ySBRDLRlevg) and the quarterly growth rate of shadow bank asset growth (qSHADBNKag). All standard errors are Newey-West adjusted with a maximum lag length of 4 quarters. The bottom row shows the adjusted R-squared of each regression, respectively. The sample period is 1986Q1-2009Q4.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
cst	1.42	-0.20	-1.17	**0.79**	**1.17**	**2.17**	0.60	-0.10	**2.78**	**2.61**
	(1.82)	(-0.58)	(-1.33)	(3.38)	(3.32)	(3.55)	(0.48)	(-0.09)	(5.55)	(2.38)
BAA	**0.22**	0.20	0.20	0.22	0.12	0.14	0.08	0.12	0.02	-0.01
	(2.07)	(1.75)	(1.88)	(1.74)	(1.33)	(1.46)	(0.91)	(1.12)	(0.23)	(-0.16)
FFR	-0.14						-0.10	0.09		0.01
	(-1.05)						(-0.66)	(0.76)		(0.11)
TERM		**0.55**					-0.19	0.12		-0.34
		(2.90)					(-0.53)	(0.40)		(-1.15)
DEF			**1.98**				1.52	1.51		0.86
			(2.20)				(1.46)	(1.64)		(0.93)
CP				0.65			**1.14**	0.54		**1.12**
				(1.68)			(3.06)	(1.74)		(3.55)
ySBRDLRlevg					**-0.03**		**-0.03**		**-0.04**	**-0.04**
					(-2.96)		(-3.34)		(-3.63)	(-4.42)
qSHADBNKag						**-0.12**		**-0.10**	**-0.13**	**-0.13**
						(-3.29)		(-3.46)	(-4.21)	(-4.33)
# Obs	95	95	95	95	95	95	95	95	95	95
adj.R^2	0.05	0.08	0.12	0.06	0.15	0.17	0.21	0.19	0.30	0.33

Table 12: Predictive Return Regression - 2-year Treasury (CMT2)

This table reports coefficient estimates and the corresponding t-statistics from a regression of the excess return of the two-year constant maturity Treasury return on one-quarter lagged observations of several explanatory variables. These are the two-year constant maturity Treasury return (CMT2), the term spread (TERM), the default spread (DEF), the Cochrane-Piazzesi return forecasting factor (CP), as well as the quarterly growth rate of shadow bank asset growth (qSHADBNKag). All standard errors are Newey-West adjusted with a maximum lag length of 4 quarters. The bottom row shows the adjusted R-squared of each regression, respectively. The sample period is 1986Q1-2009Q4.

	(1)	(2)	(3)	(4)	(5)	(6)
cst	0.25	0.35	0.37	**0.49**	**0.92**	**1.24**
	(0.87)	(1.56)	(1.48)	(3.72)	(3.22)	(2.67)
CMT2	0.03	0.03	0.03	-0.02	0.02	-0.05
	(0.38)	(0.38)	(0.36)	(-0.19)	(0.20)	(-0.53)
FFR	0.04					0.04
	(0.85)					(0.77)
TERM		0.04				-0.23
		(0.39)				(-1.71)
DEF			0.06			0.08
			(0.34)			(0.34)
CP				**0.54**		**0.64**
				(4.55)		(5.13)
qSHADBNKag					**-0.04**	**-0.05**
					(-2.51)	(-3.19)
# Obs	95	95	95	95	95	95
adj.R^2	-0.02	-0.02	-0.02	0.07	0.08	0.16

Table 13: Predictive Return Regression - 10-year Treasury (CMT10)

This table reports coefficient estimates and the corresponding t-statistics from a regression of the excess return of the ten-year constant maturity Treasury return on one-quarter lagged observations of several explanatory variables. These are the ten-year constant maturity Treasury return (CMT10), the term spread (TERM), the default spread (DEF), the Cochrane-Piazzesi return forecasting factor (CP), as well as the quarterly growth rate of shadow bank asset growth (qSHADBNKag). All standard errors are Newey-West adjusted with a maximum lag length of 4 quarters. The bottom row shows the adjusted R-squared of each regression, respectively. The sample period is 1986Q1-2009Q4.

	(1)	(2)	(3)	(4)	(5)	(6)
cst	0.73	0.02	**1.50**	**0.85**	**2.30**	2.95
	(0.96)	(0.03)	(2.15)	(2.35)	(2.62)	(1.95)
CMT10	-0.03	-0.03	-0.02	-0.03	-0.03	-0.02
	(-0.38)	(-0.40)	(-0.30)	(-0.36)	(-0.42)	(-0.21)
FFR	0.01					0.19
	(0.09)					(1.43)
TERM		0.43				0.19
		(1.42)				(0.44)
DEF			-0.74			**-1.56**
			(-1.22)			(-2.09)
CP				**1.22**		0.77
				(3.50)		(1.64)
qSHADBNKag					**-0.13**	**-0.16**
					(-2.22)	(-3.47)
# Obs	95	95	95	95	95	95
adj.R^2	-0.02	-0.00	-0.01	0.03	0.08	0.12

Table 14: Subsample Regression: Equity Market Portfolio

This table reports coefficient estimates and the corresponding t-statistics from a regression of the excess return of the equity market portfolio on one-quarter lagged observations of several explanatory variables. These are the market return (Mkt), the difference of the 3-month Treasury bill rate and its four-quarter moving average (RREL), the term spread (TERM), the default spread (DEF), the log dividend-price-ratio (d/p), the log consumption-wealth ratio (cay), as well as the annual growth rate of security broker-dealer leverage (ySBRDLRlevg). All standard errors are Newey-West adjusted with a maximum lag length of 4 quarters. The bottom row shows the adjusted R-squared of each regression, respectively. The sample period is 1986Q1-2007Q2.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
cst	**2.21**	2.35	3.80	6.06	1.89	**2.70**	22.65
	(2.41)	(1.18)	(0.98)	(1.91)	(1.87)	(2.70)	(1.77)
MKT	-0.12	-0.12	-0.12	-0.11	-0.11	-0.14	**-0.16**
	(-1.51)	(-1.49)	(-1.54)	(-1.51)	(-1.36)	(-1.71)	(-2.26)
RREL	0.39						-1.27
	(0.44)						(-1.10)
TERM		-0.10					-0.97
		(-0.11)					(-1.08)
DEF			-1.80				-9.56
			(-0.42)				(-1.49)
d/p				2.82			6.71
				(1.08)			(1.34)
cay					50.97		-18.85
					(1.42)		(-0.29)
ySBRDLRlevg						**-0.05**	**-0.09**
						(-2.05)	(-3.52)
# Obs	85	85	85	85	85	85	85
adj.R^2	-0.01	-0.01	-0.01	0.01	0.00	0.02	0.03

Table 15: Subsample Regression: Baa Rated Corporate Bonds

This table reports coefficient estimates and the corresponding t-statistics from a regression of the excess return of the Baa rated coporate bond portfolio on one-quarter lagged observations of several explanatory variables. These are the Baa bond return (BAA), the term spread (TERM), the default spread (DEF), the Cochrane-Piazzesi return forecasting factor, as well as the annual growth rate of security broker-dealer leverage (ySBRDLRlevg) and the asset-weighted quarterly growth rate of shadow bank asset growth (qSHADBNKag). All standard errors are Newey-West adjusted with a maximum lag length of 4 quarters. The bottom row shows the adjusted R-squared of each regression, respectively. The sample period is 1986Q1-2007Q2.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
cst	1.02	-0.06	0.24	**0.84**	**1.05**	**2.35**	2.07	1.27	**2.99**	**4.10**
	(1.44)	(-0.16)	(0.25)	(3.27)	(3.13)	(4.42)	(1.47)	(1.28)	(5.62)	(3.74)
BAA	0.08	0.06	0.08	0.05	0.05	0.07	0.02	0.05	0.03	0.01
	(0.74)	(0.52)	(0.70)	(0.43)	(0.53)	(0.66)	(0.17)	(0.41)	(0.33)	(0.07)
FFR	-0.04						0.04	0.10		0.07
	(-0.39)						(0.29)	(0.73)		(0.67)
TERM		**0.51**					0.12	0.23		-0.14
		(2.50)					(0.40)	(0.80)		(-0.53)
DEF			0.63				-1.48	0.02		-1.36
			(0.60)				(-1.40)	(0.01)		(-1.70)
CP				**1.02**			**1.21**	**0.57**		**1.13**
				(4.06)			(3.59)	(1.97)		(3.93)
ySBRDLRlevg					**-0.02**		**-0.03**		**-0.03**	**-0.04**
					(-2.09)		(-2.96)		(-3.20)	(-4.59)
qSHADBNKag						**-0.12**		**-0.10**	**-0.14**	**-0.13**
						(-3.66)		(-3.42)	(-4.13)	(-3.87)
# Obs	85	85	85	85	85	85	85	85	85	85
adj.R^2	-0.02	0.04	-0.01	0.06	0.05	0.12	0.13	0.13	0.23	0.28

Table 16: Subsample Regression: 10-year Treasury

This table reports coefficient estimates and the corresponding t-statistics from a regression of the excess return of the ten-year constant maturity Treasury return on one-quarter lagged observations of several explanatory variables. These are the ten-year constant maturity Treasury return (CMT10), the term spread (TERM), the default spread (DEF), the Cochrane-Piazzesi return forecasting factor, as well as the quarterly growth rate of shadow bank asset growth (qSHADBNKag). All standard errors are Newey-West adjusted with a maximum lag length of 4 quarters. The bottom row shows the adjusted R-squared of each regression, respectively. The sample period is 1986Q1-2007Q2.

	(1)	(2)	(3)	(4)	(5)	(6)
cst	0.72	-0.43	1.44	0.66	**3.21**	2.75
	(0.81)	(-0.70)	(0.90)	(1.81)	(4.21)	(1.46)
CMT10	-0.02	-0.02	-0.02	-0.04	-0.05	-0.06
	(-0.21)	(-0.22)	(-0.19)	(-0.44)	(-0.59)	(-0.67)
FFR	-0.02					0.24
	(-0.11)					(1.72)
TERM		0.62				0.38
		(1.95)				(0.95)
DEF			-0.89			-1.83
			(-0.49)			(-0.91)
CP				**1.31**		0.70
				(3.75)		(1.37)
qSHADBNKag					**-0.20**	**-0.18**
					(-3.87)	(-3.44)
# Obs	85	85	85	85	85	85
adj.R^2	-0.02	0.01	-0.02	0.04	0.14	0.15

Table 17: Alternative Balance Sheet Measures: Equity Market Portfolio

This table reports coefficient estimates and the corresponding t-statistics from a regression of the excess return of the equity market portfolio on its own lag as well as on one-month lagged observations of several explanatory variables. These are the difference of the 1-month Treasury bill rate and its one-year moving average (RREL), the term spread (TERM), the default spread (DEF), the log dividend-price-ratio (d/p), as well as the monthly growth rate of total outstanding financial commercial paper (FCP) and the monthly growth rate of the stock of outstanding primary dealer repos (REPO). All standard errors are Newey-West adjusted with a maximum lag length of 12 months. t-statistics are in parentheses. The bottom row shows the adjusted R-squared of each regression, respectively. The sample period is 1990:08-2010:03.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
cst	**0.58**	0.41	0.82	**2.71**	0.48	0.47	**4.22**	**4.14**	0.45	**4.09**
	(2.14)	(0.82)	(1.17)	(2.27)	(1.44)	(1.43)	(2.59)	(2.52)	(1.34)	(2.47)
MKT	0.13	0.14	0.13	0.13	0.13	0.14	0.12	0.12	0.13	0.12
	(1.67)	(1.63)	(1.66)	(1.53)	(1.59)	(1.66)	(1.51)	(1.56)	(1.61)	(1.52)
RREL	0.41						0.43	0.46		0.46
	(1.60)						(1.39)	(1.47)		(1.39)
TERM		0.04					-0.10	-0.10		-0.10
		(0.19)					(-0.38)	(-0.42)		(-0.37)
DEF			-0.34				-0.38	-0.31		-0.27
			(-0.40)				(-0.48)	(-0.37)		(-0.33)
d/p				1.52			**2.13**	**2.12**		**2.13**
				(1.93)			(2.53)	(2.52)		(2.53)
FINCP					0.04		0.02		0.04	0.03
					(0.34)		(0.22)		(0.34)	(0.26)
REPO						0.03		0.03	0.03	0.03
						(0.53)		(0.54)	(0.53)	(0.56)
# Obs	235	235	235	235	235	235	235	235	235	235
adj.R^2	0.02	0.01	0.01	0.02	0.01	0.01	0.02	0.02	0.01	0.02

Table 18: Alternative Balance Sheet Measures: Baa Rated Corporate Bonds

This table reports coefficient estimates and the corresponding t-statistics from a regression of the excess return of the Baa rated coporate bond portfolio on its own lag as well as on one-month lagged observations of several explanatory variables. These are the federal funds rate (FFR), the term spread (TERM), the default spread (DEF), the Cochrane-Piazzesi return forecasting factor (CP), as well as the monthly growth rate of total outstanding financial commercial paper (FCP) and the monthly growth rate of the stock of outstanding primary dealer repos (REPO). All standard errors are Newey-West adjusted with a maximum lag length of 12 months. t-statistics are in parentheses. The bottom row shows the adjusted R-squared of each regression, respectively. The sample period is 1990:08-2010:03.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
cst	0.58	-0.13	-0.39	**0.31**	**0.32**	**0.34**	-1.55	-1.39	**0.37**	-1.33
	(1.89)	(-0.88)	(-1.76)	(3.11)	(3.04)	(3.07)	(-1.84)	(-1.80)	(3.40)	(-1.74)
BAA	**0.20**	**0.19**	**0.19**	**0.21**	**0.22**	**0.21**	**0.19**	**0.19**	**0.22**	**0.20**
	(2.86)	(2.65)	(2.85)	(2.86)	(2.71)	(2.96)	(2.60)	(2.76)	(2.76)	(2.56)
FFR	-0.07						0.15	0.14		0.15
	(-1.16)						(1.34)	(1.38)		(1.38)
TERM		**0.23**					0.28	0.27		0.27
		(2.88)					(1.42)	(1.40)		(1.38)
DEF			**0.72**				**0.79**	**0.74**		**0.66**
			(2.83)				(3.16)	(2.95)		(2.51)
CP				0.23			0.04	0.11		0.08
				(1.20)			(0.17)	(0.47)		(0.31)
FINCP					**-0.09**		-0.04		**-0.09**	-0.04
					(-2.60)		(-1.19)		(-2.63)	(-1.31)
REPO						**-0.06**		**-0.05**	**-0.06**	**-0.05**
						(-2.55)		(-2.62)	(-2.61)	(-2.62)
# Obs	235	235	235	235	235	235	235	235	235	235
adj.R^2	0.04	0.06	0.07	0.04	0.05	0.06	0.08	0.10	0.07	0.10

Table 19: Alternative Balance Sheet Measures: 10-year Treasury

This table reports coefficient estimates and the corresponding t-statistics from a regression of the excess return of the 10-year constant maturity Treasury on its own lag as well as one-month lagged observations of several explanatory variables. These are the federal funds rate (FFR), the term spread (TERM), the default spread (DEF), the Cochrane-Piazzesi return forecasting factor (CP), as well as the monthly growth rate of total outstanding financial commercial paper (FCP) and the monthly growth rate of the stock of outstanding primary dealer repos (REPO). All standard errors are Newey-West adjusted with a maximum lag length of 12 months. t-statistics are in parentheses. The bottom row shows the adjusted R-squared of each regression, respectively. The sample period is 1990:08-2010:03.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
cst	0.17	-0.01	0.20	**0.33**	**0.35**	**0.35**	-1.60	-1.50	**0.40**	-1.28
	(0.74)	(-0.07)	(0.72)	(3.07)	(3.01)	(2.83)	(-1.81)	(-1.80)	(3.29)	(-1.61)
CMT10	0.04	0.04	0.04	0.05	0.06	0.05	0.05	0.04	0.07	0.06
	(0.83)	(0.79)	(0.82)	(1.05)	(1.13)	(0.94)	(0.92)	(0.76)	(1.27)	(1.12)
FFR	0.03						**0.27**	**0.24**		**0.26**
	(0.71)						(2.36)	(2.43)		(2.42)
TERM		0.17					0.41	0.39		0.38
		(1.82)					(1.61)	(1.56)		(1.54)
DEF			0.10				0.15	0.21		-0.03
			(0.38)				(0.54)	(0.77)		(-0.12)
CP				0.33			-0.06	0.08		-0.01
				(1.93)			(-0.18)	(0.27)		(-0.04)
FINCP					-0.13		-0.13		-0.13	-0.14
					(-1.78)		(-1.65)		(-1.83)	(-1.75)
REPO						**-0.06**		**-0.07**	**-0.06**	**-0.07**
						(-2.52)		(-3.02)	(-2.66)	(-3.26)
# Obs	235	235	235	235	235	235	235	235	235	235
adj.R^2	-0.01	0.00	-0.01	0.01	0.02	0.01	0.04	0.03	0.04	0.06

Table 20: Out of Sample Analysis

This table presents results from an out-of-sample forecast exercise for three different assets: the return on the equity market portfolio (MKT), the return on the Baa rated corporate bond portfolio (BAA), and the return on the ten year constant maturity Treasury (CMT10). All returns are in excess of the one month Treasury bill. We compare results of a model using a constant and one predictor variable with a naive (constant only) forecast. We recursively predict excess returns one month ahead using information only up to the date when the forecast is made. The training sample is 1990:08 - 1997:07. The forecast sample is 1997:08 - 2010:03. Δ RMSE denotes the difference in root mean squared forecast errors between the naive and the conditional model. $MSE-F$ denotes McCracken's (2007) F-statistic of equal predictive ability, $ENC-NEW$ denotes Clark and McCracken's (2001) encompassing statistic. Significance at the 1 percent, 5 percent, and 10 percent level is indicated by three, two, and one asterisks, respectively. The predictor variables are the same as in previous tables.

Return	Predictor	ΔRMSE	MSE-F	ENC-NEW
MKT				
	DEF	-0.0920	-5.4319	0.5117
	FFTR	-0.0552	-3.2957	-1.0478
	RREL	-0.0026	-0.1572	0.0411
	TERM	-0.0511	-3.0525	-1.1472
	d/p	-0.0117	-0.7065	-0.0293
	FINCP	-0.0597	-3.5591	-0.5806
	REPO	-0.0207	-1.2510	-0.5382
BAA				
	CP	-0.0503	-7.7858	0.3981
	DEF	-0.0014	-0.2233	1.3538
	FFTR	-0.0034	-0.5429	0.0443
	TERM	0.0304	5.1051***	3.6508**
	FINCP	0.0025	0.4021	1.5031*
	REPO	0.0238	3.9170***	2.4885**
CMT10				
	CP	-0.0391	-5.3909	0.4924
	DEF	-0.0716	-9.6583	-3.1534
	FFTR	-0.0235	-3.2802	-1.1435
	TERM	0.0036	0.5145	1.0200
	FINCP	0.0123	1.7565**	6.0901**
	REPO	0.0123	1.7593**	2.0387*

Table 21: Univariate Regression Results for All Returns

This table reports Newey-West (with a maximum lag length of 4 quarters) adjusted t-statistics and R^2 for univariate regressions of all equity portfolio, corporate bond portfolio, and Treasury returns on the two balance sheet variables ySBRDLRlevg and qSHADBNKag. The sample period is 1986Q1-2009Q4.

	t	R^2	t	R^2
MKT	-2.76	0.09		
FF11	-2.22	0.05		
FF15	-2.62	0.09		
FF51	-2.12	0.05		
FF55	-2.19	0.05		
IGI	-2.35	0.07	-4.64	0.17
IGU	-2.83	0.09	-3.95	0.13
IGF	-2.34	0.06	-3.15	0.16
A	-2.06	0.05	-4.27	0.16
BAA	-3.03	0.15	-3.38	0.16
CMT1			-2.12	0.07
CMT2			-2.52	0.10
CMT5			-2.25	0.09
CMT7			-2.23	0.09
CMT10			-2.25	0.10

Table 22: Controlling for Cash-Flow Expectations: Equity Market Portfolio

This table reports coefficient estimates and the corresponding t-statistics from a regression of the excess return of the equity market portfolio on its own lag and one-quarter lagged observations of several explanatory variables. These are the the average expected growth rate of GDP over the next four quarters from the Survey of Professional Forecasters (GDP4Qavg), the average expected CPI inflation rate over the next four quarters from the Survey of Professional Forecasters (GDP4Qavg), the quarterly growth rate of analysts earnings forecasts over the next year for the S&P500 index from I/B/E/S (expearn1qg), the difference of the 3-month Treasury bill rate and its four-quarter moving average (RREL), the term spread (TERM), the default spread (DEF), the log dividend-price-ratio (d/p), the log consumption-wealth ratio (cay), as well as the annual growth rate of security broker-dealer leverage (ySBRDLRlevg). All standard errors are Newey-West adjusted with a maximum lag length of 4 quarters. The bottom row shows the adjusted R-squared of each regression, respectively. The sample period is 1986Q1-2009Q4.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
cst	11.13	10.88	10.86	**28.30**	11.37	9.64	**59.84**
	(1.41)	(1.35)	(1.40)	(2.56)	(1.50)	(1.29)	(3.60)
MKT	0.01	0.00	0.00	-0.01	0.01	-0.05	-0.07
	(0.08)	(0.00)	(0.00)	(-0.06)	(0.10)	(-0.47)	(-0.84)
GDP4Qavg	-2.49	-2.88	-2.72	-2.34	-1.85	-2.35	-1.23
	(-1.24)	(-1.41)	(-1.44)	(-1.14)	(-0.90)	(-1.34)	(-0.51)
CPI4Qavg	-0.93	-0.89	-0.85	**-3.28**	-1.92	-0.38	**-5.87**
	(-0.82)	(-0.75)	(-0.76)	(-2.09)	(-1.66)	(-0.31)	(-3.27)
expearn1qg	0.02	0.07	0.07	**0.12**	0.09	0.04	-0.02
	(0.27)	(1.39)	(0.98)	(2.21)	(1.77)	(1.04)	(-0.23)
RREL	1.34						0.15
	(1.01)						(0.16)
TERM		0.37					-1.69
		(0.48)					(-1.23)
DEF			0.11				-9.60
			(0.03)				(-1.93)
d/p				**8.24**			**17.29**
				(2.75)			(3.22)
cay					97.72		31.03
					(1.86)		(0.36)
ySBRDLRlevg						**-0.09**	**-0.13**
						(-2.81)	(-3.81)
# Obs	95	95	95	95	95	95	95
adj.R^2	-0.01	-0.03	-0.03	0.02	-0.00	0.06	0.16

Table 23: Predicting Future Cash-Flows

This table reports coefficient estimates and the corresponding t-statistics from regressions of the quarterly growth rates of real earnings (columns 1 and 2) and the quarterly growth rates of real dividends (columns 3 and 4) on the S&P500 index on their own lag and the lagged annual growth rate of security broker-dealer leverage (ySBRDLRlevg). The earnings and dividends data have been obtained from Robert Shiller's website. All standard errors are Newey-West adjusted with a maximum lag length of 4 quarters. The bottom row shows the adjusted R-squared of

	(1)	(2)	(3)	(4)
cst	24.47	20.77	1.08	-0.20
	(1.46)	(1.10)	(0.65)	(-0.28)
realearnings		**1.31**		
		(3.32)		
realdividends				**0.85**
				(12.26)
ySBRDLRlevg	-1.45	-1.00	0.06	0.02
	(-1.79)	(-1.35)	(1.06)	(0.83)
# Obs	95	95	95	95
adj. R^2	0.15	0.43	0.05	0.63

Table 24: Vector Autoregression

This table reports coefficient estimates from a VAR that includes the following variables: log real GDP, the log core PCE deflator, the federal funds rate, log security broker-dealer leverage, log security broker-dealer equity, log shadow bank assets, and the default spread. The sample period is 1986Q1-2010:Q1.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Real GDP	Core PCE Deflator	Fed Funds Rate	SBRDLR Equity	SBRDLR Assets	SHADBNK Assets	DEF
Constant	0.43	0.36**	-38.91	-14.74	7.19	-3.01	14.50
GDP (lag 1)	1.05***	-0.01	14.69**	2.43	-1.18	-0.14	-7.38*
GDP (lag 2)	-0.09	-0.03	-10.06	-0.52	0.06	0.64	6.70*
Core PCE Defl. (lag 1)	-0.69*	1.29***	16.19	8.37	-12.80**	-0.37	16.19
Core PCE Defl. (lag 2)	0.68*	-0.31***	-14.34	-8.26	13.10**	0.23	-19.38
Fed Funds Rate (lag 1)	0.00	0.00	1.50***	0.02	-0.01	0.01*	-0.00
Fed Funds Rate (lag 2)	-0.00	-0.00	-0.57***	-0.04	0.02	-0.01	-0.01
SBRDLR Equity (lag 1)	0.01*	-0.00	0.91***	0.70***	0.17**	-0.01	-0.84***
SBRDLR Equity (lag 2)	-0.01	0.00	-0.63*	0.03	-0.05	0.03	0.38**
SBRDLR Assets (lag 1)	0.01	-0.00	-1.63***	0.31*	0.55***	0.06*	0.04
SBRDLR Assets (lag 2)	-0.00	0.00	1.32***	-0.42**	0.27**	-0.01	0.06
SHADBNK Assets (lag 1)	0.07**	0.00	1.77	1.52**	-0.09	0.89***	0.54
SHADBNK Assets (lag 2)	-0.06**	0.01	-3.16*	-1.75***	0.45	-0.06	0.40
DEF (lag 1)	-0.01***	-0.00	0.02	0.10	-0.14***	0.01	0.88***
DEF (lag 2)	0.01***	-0.00	0.02	0.05	0.01	-0.02	-0.23**

Figure 1: Bank-based and Market-based Financial System in 1990Q1

This figure shows total financial assets for various types of fincancial institutions from the US Flow of Funds as of 1990Q1.

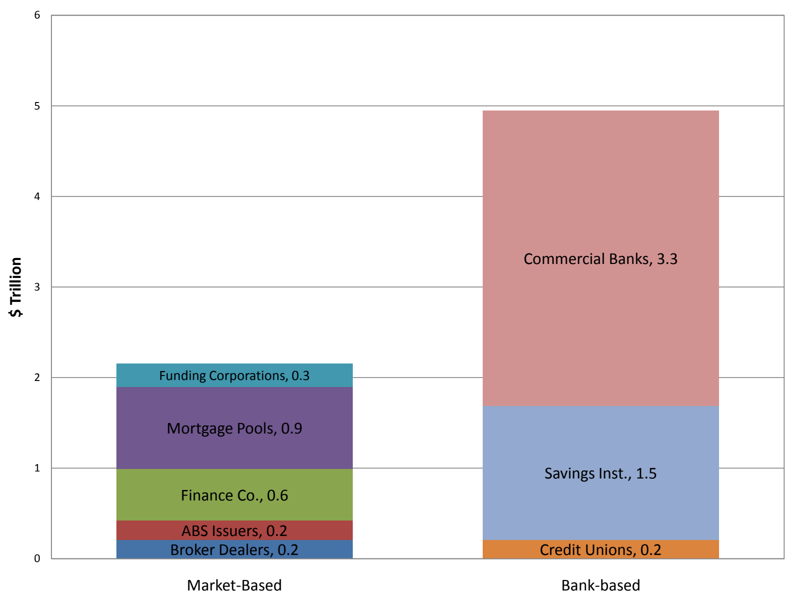

Figure 2: Bank-based and Market-based Financial System in 2007Q2

This figure shows total financial assets for various types of financial institutions from the US Flow of Funds as of 2007Q2.

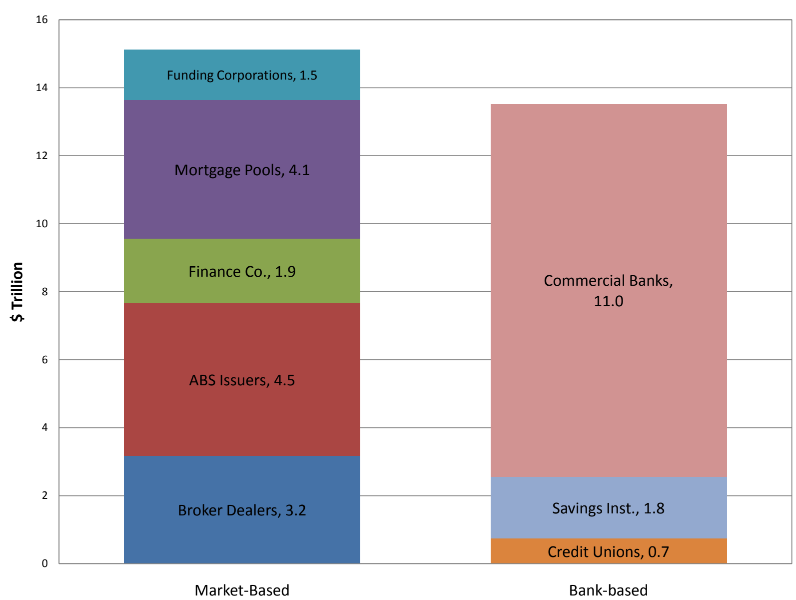

Figure 3: Annual Security Broker-Dealer Leverage Growth

This figure shows annual security broker-dealer leverage growth from 1986:Q1 - 2009:Q4.

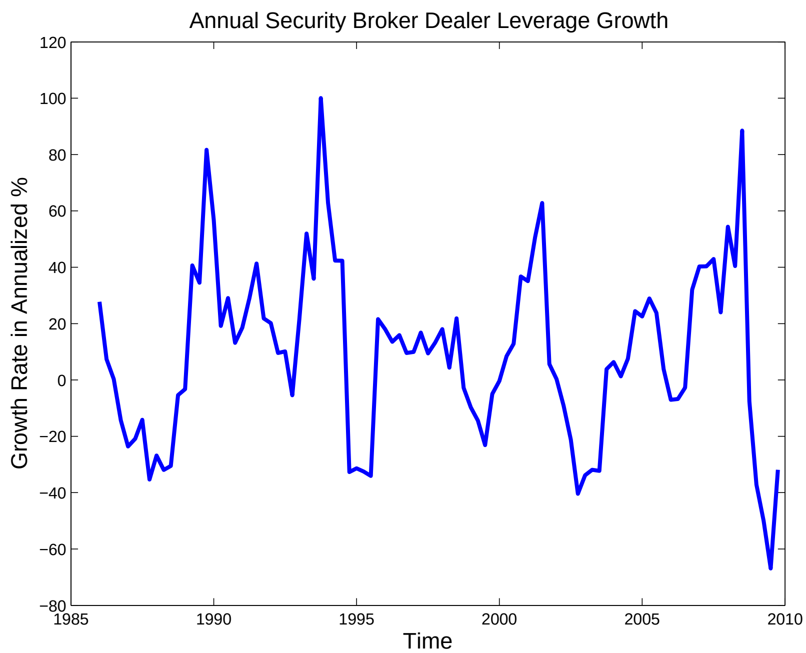

Figure 4: Quarterly Shadow Bank Asset Growth

This figure shows quarterly shadow bank asset growth from 1986:Q1 - 2009:Q4.

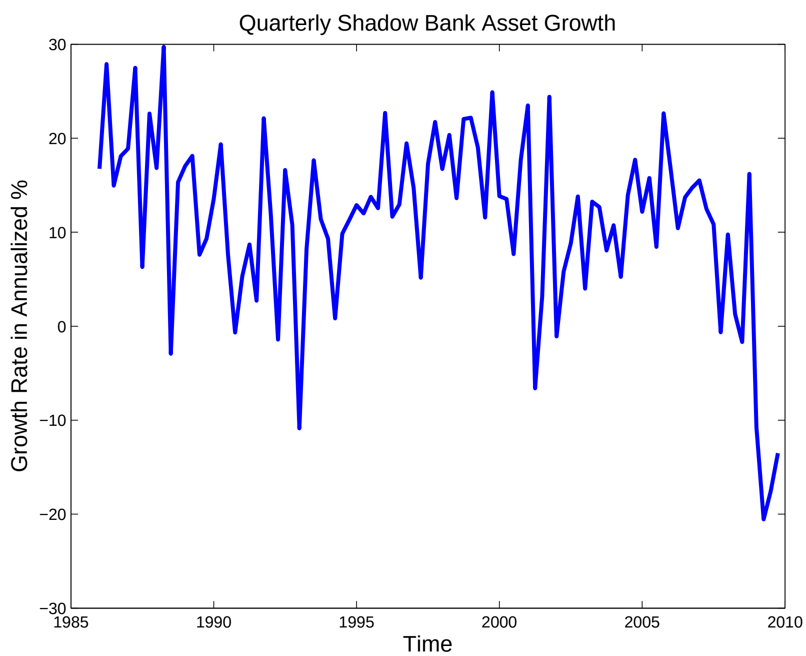

Figure 5: Impulse Response Functions: Real GDP

This figure shows impulse response functions for log real GDP from the VAR in Table 24. The VAR is identified using a recursive scheme with the

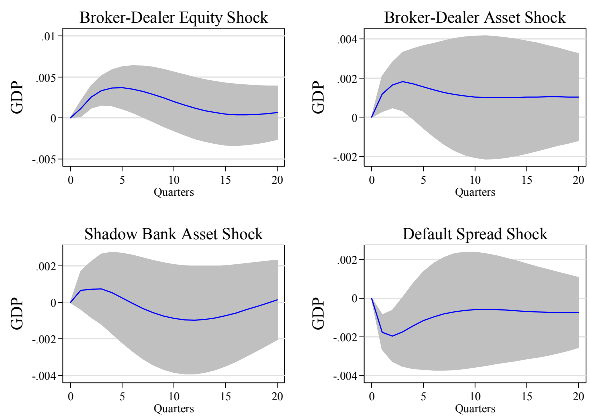

Figure 6: Impulse Response Functions: PCE

This figure shows impulse response functions for log PCE from the VAR in Table 24. The VAR is identified using a recursive scheme with the ordering of variables as reported in the table. The impulse is a one standard deviation shock, the response on the y-axis is in units of the response variable.

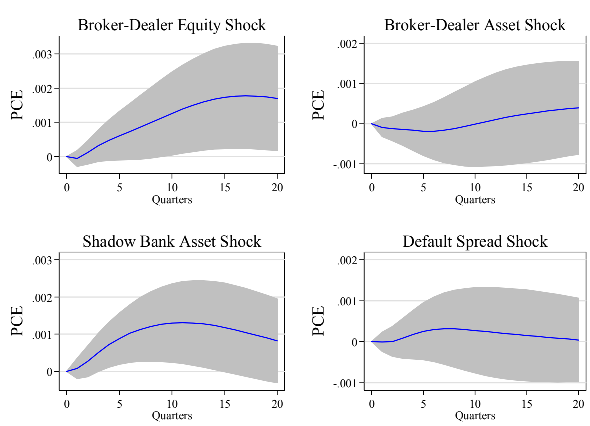

Figure 7: Impulse Response Functions: SBRDLR Equity and Assets

This figure shows impulse response functions for log security broker-dealer leverage and equity from the VAR in Table 24. The VAR is identified using a recursive scheme with the ordering of variables as reported in the table. The impulse is a one standard deviation shock, the response on the y-axis is in units of the response variable.

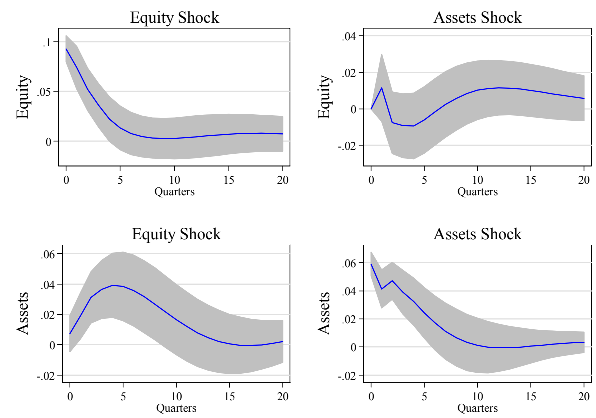

Figure 8: Impulse Response Functions: Default Spread

This figure shows impulse response functions for the default spread from the VAR in Table 24. The VAR is identified using a recursive scheme with the ordering of variables as reported in the table. The impulse is a one standard deviation shock, the response on the y-axis is in units of the response variable.