Financial Intermediation, Asset Prices, and Macroeconomic Dynamics*

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Abstract

Fluctuations in the aggregate balance sheets of financial intermediaries provide a window on the joint determination of asset prices and macroeconomic aggregates. We document that financial intermediary balance sheets contain strong predictive power for future excess returns on a broad set of equity, corporate, and Treasury bond portfolios. We also show that the same intermediary variables that predict excess returns forecast real economic activity and various measures of inflation. Our findings point to the importance of financing frictions in macroeconomic dynamics, and provide quantitative guidance for preemptive macroprudential and monetary policies.

Keywords: Return Predictability, Financial Intermediation, Macroeconomic Dynamics, Macroprudential Policy.

JEL classification: G10, G12

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1. Introduction

Financial intermediaries often take the back seat in macroeconomic models that focus on the interaction of macroeconomic aggregates. However, financial intermediaries have been at the center of the global financial crisis of 2007–09. The credit losses borne by intermediaries as well as the erosion of their equity capital have figured prominently in the commentary on the decline in real activity, especially for sectors such as housing investment that are particularly sensitive to the credit cycle. These events have given renewed impetus for a deeper study of the interconnection between financial intermediaries, asset prices, and macroeconomic dynamics.

In this paper, we investigate the role of financial intermediaries in determining macroeconomic aggregates. We explore the extent to which banks and other intermediaries play the role of the engine of macroeconomic fluctuations through the determination of risk premia, thereby influencing the allocation of credit to real activities.

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 increased 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 intermediary balance sheets and real activity, as expanding balance sheets and higher real activity tend to be associated with lower risk premia.

The purpose of our paper is to document empirically this three-way association between intermediary balance sheets, asset prices, and real economic activity. We find strong evidence that the most informative balance sheet aggregates are those for the market-based intermediaries such as security broker dealers and the institutions in the shadow banking system associated with securitization. We document that balance sheet aggregates hold strong explanatory power for a broad range of financial asset prices, and in turn influence real activity through the components of GDP such as durable consumption and housing investment.

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 a large set of macroeconomic variables from the Bureau of Economic Analysis' National Accounts and a variety of price deflators of the Personal Consumption Expenditure survey (PCE). As for asset prices, we put together a large cross section of equity portfolio returns, credit returns, and Treasury returns. In addition, we control for commonly used predictor variables from the asset pricing literature.

The core of our paper consists of two sets of empirical results. First, we show that balance sheet variables hold useful information in forecasting returns for a wide range of financial assets. In order to select the intermediary balance sheet variables that are the best forecasters, we run univariate predictive regressions for quarterly excess returns of the three asset classes on lagged balance sheet variables of financial intermediaries. We then use subset selection methods to identify the best predictors. We find that lagged balance sheet variables hold useful information in forecasting asset returns, even when controlling for standard asset-pricing predictor variables. The close association between balance sheet variables and asset return forecastability is consistent with our hypothesis that balance sheets convey information on risk premia through fluctuations in the willingness to bear risk. These findings are consistent with models where the "risk appetite" of intermediaries enters the pricing kernel.

Having shown the connection between balance sheet variables and asset returns, we complete the circle by showing that the same balance sheet variables that predic texcess returns are also useful in explaining macroeconomic aggregates such as GDP and inflation and their components. These findings are consistent with the hypothesis that real activity is influenced by the supply of credit, which in turn is determined by the market risk premium. The market risk premium is influenced by the risk appetite of financial intermediaries.

The empirical regularities of our study can be used as foundation for preemptive monetary and macroprudential policies. Our results provide a quantitative assessment of the degree to which risky asset prices are determined by expansions and contractions of financial intermediary balance sheets. To the extent that such expansions and contractions of balance sheets are judged temporary, our results allow policy makers to tighten or loosen policy preemptively in order to offset the impact of excessively large or small risk taking behavior by intermediaries. In addition, all of our results rely on forecasting regressions, and thus provide "early warnings" to policy makers about the factors that are determining asset price movements.

Related Literature. We are certainly not the first to study frictions in the supply of credit. There has been an extensive discussion of financial frictions within monetary economics (see, for example, the overview by Bernanke and Gertler (1995) and Bernanke, Gertler and Gilchrist (1999)). However, it would be fair to say that financial frictions have received less emphasis within mainstream macroeconomics in the last decade or more. One reason for the lack of emphasis may be that the earlier literature that focused on commercial bank balance sheets or borrowers' balance sheets did not produce conclusive empirical results. Bernanke and Lown (1991) used a cross sectional study to argue that credit losses in the late 80's and early 90's did not have a significant impact on real economic growth across states.[1] In the same vein, Ashcraft (2006) finds small effects of variations in commercial bank loans on real activity when using accounting based loan data.[2] Morgan and Lown (2006) show that the senior loan officer survey provides significant explanatory power for real activity – a variable that is more likely to reflect underlying credit supply conditions and does not use commercial banks' balance sheet

[1] See Kashyap and Stein (1994) for an overview of the debate on whether there was a "credit crunch" in the recession in the early 1990s.

[2] However, Ashcraft (2005) finds large and persistent effects of commercial bank closures on real output (using FDIC induced failures as instruments).

data.

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. Adrian and Shin (2007) demonstrate 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. Piazzesi and Schneider (2009) link expected returns of Treasuries to the portfolio allocation of households.

The goal of this paper is to provide a benchmark for the dynamic interaction of macroeconomic variables, asset prices, and financial intermediary balance sheets in the spirit of Sims (1980). All of our empirical results rely on forecasting regressions, and thus reveal the dynamic correlations that are in the nexus of the Flow of Funds balance sheets, the National Accounts, and asset returns. Any structural modeling that incorporates the dynamics of financial intermediaries explicitly in the determination of asset prices and macroeconomic activity will have to 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 begin by setting the stage by describing the recent trends in financial intermediation in the United States toward a market-based, securitized system of financial intermediation. 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 our two sets of empirical results linking balance sheets, risk premia and real activity. We conclude with some general observations on the implications of our results, both for the asset pricing literature, but also for monetary economics.

2. The Changing Nature of Financial Intermediation

In preparation for our empirical investigations, we review briefly the structure of financial intermediation in the United States, in particular the increasing importance of market-based financial intermediaries and the shadow banking system.

2.1. Shadow Banking System

As recently as the early 1980s, traditional banks were the dominant institutions supplying credit to the real economy, but bank-based credit supply has been quickly overtaken by market supply of credit, particularly in the mortgage market. Figure 2.1 plots the size of different types of financial intermediaries for the United States from the 1985. We see that market-based financial intermediaries, such as security broker dealers, ABS issuers have become important components of the intermediary sector. The series marked "shadow banks" aggregates ABS issuers, finance companies and funding corporations.

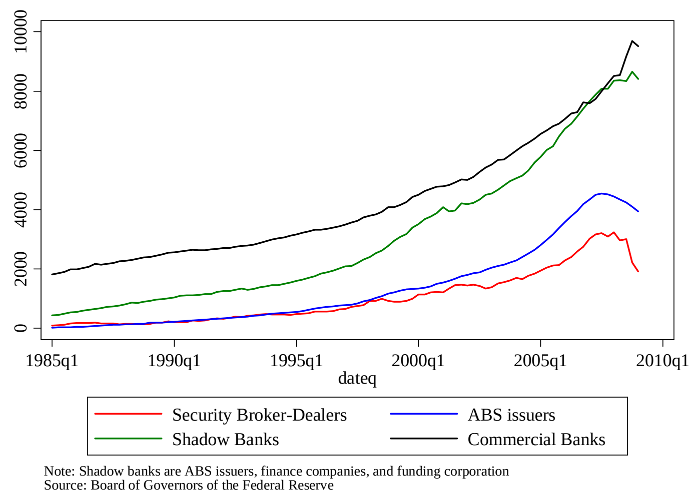

Figure 2.1: Total Assets of Commercial Banks, Shadow Banks, and Broker-Dealers.

In 1985, shadow banks were a tiny fraction of the commercial bank sector, but caught up with the commercial bank sector by the eve of the crisis. The increased importance of the market-based banking system has been mirrored by the growth of the broker-dealer sector of the economy. 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 had seen rapid growth in recent decades and is arguably a better barometer of overall funding conditions in a market-based financial system.

The growth of market-based financial intermediaries is also reflected in the aggregates on the liabilities side of the balance sheet. Figure 2.2 shows the relative size of the M1 money stock relative to the outstanding stock of repos of the primary dealers - the set of banks that bid at US Treasury security auctions, and hence for whom data are readily available due to their reporting obligations to the Federal Reserve. We also note the rapid growth of financial commercial paper as a funding vehicle for financial intermediaries.

Figure 2.3 charts the relative size of M2 (bank deposits plus money market fund balances) compared to the sum of primary dealer repos and financial commercial paper outstanding. As recently as the 1990s, the M2 stock was many times larger than the stock of repos and commercial paper. However, by the end of 2007, the gap had narrowed considerably, and M2 was only some 25% larger than the stock of repos and financial commercial paper. However, since the eruption of the financial crisis, the gap has opened up again.

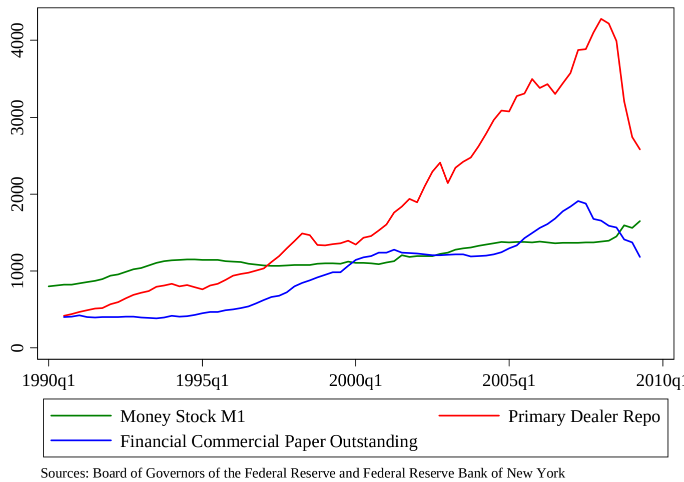

Figure 2.2: Liquid funding of financial institutions: Money (M1), Primary Dealer Repo, and Commercial Paper.

Not only have the market-based intermediaries seen the most rapid growth in the run-up to the financial crisis, they were also the institutions that saw the sharpest pull-back in the crisis itself. Figure 2.4 shows the comparative growth rate of the total assets of commercial banks (in red) and the shadow banks (in blue). Figure 2.5 shows the growth of commercial paper relative to shadow bank asset growth. We see that while the commercial banks have increased lending during the crisis, the shadow banks have contracted their lending substantially. Traditionally, banks have played the role of a buffer against fluctuations in capital market conditions, and we see that they have continued their role through the current crisis. Thus, just looking at aggregate commercial bank lending may give an overly rosy picture of the state of financial intermediation.

Finally, Figure 2.6 shows that the broker-dealer sector of the economy has contracted in step with the contraction in primary dealer repos, suggesting the sensitivity of the broker-dealer sector to overall capital market conditions. Therefore, in empirical studies of financial intermediary behavior, it would be important to bear in mind the distinctions between commercial banks and market-based intermediaries such as broker dealers. Market-based intermediaries who fund themselves through short term borrowing such as commercial paper or repurchase agreements will be sensitively affected by capital market conditions. But for a commercial bank, its large balance sheet masks the effects operating at the margin. Also, commercial banks provide relationship-based lending through credit lines. Broker-dealers, in contrast, give a much purer signal of marginal funding conditions, as their balance sheet consists almost exclusively of short-term market borrowing and are not bound as much by relationship-based lending.

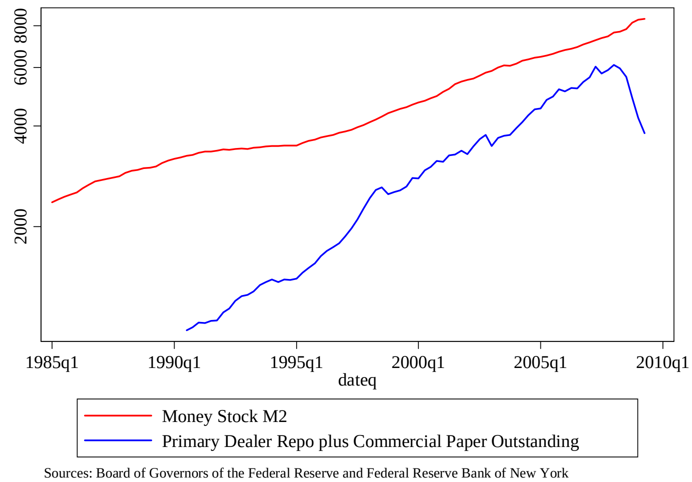

Figure 2.3: Short Term Funding: M2 versus Commercial Paper + Primary Dealer Repo.

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 – 2009Q2. 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 (2009)).

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 select 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 7.1 and 7.2, respectively. We consider a host of different types of financial intermediaries. We group them into five different categories: Banks (FINBANK), Pension Funds and Insurances (FINPI), Mutual Funds (FINMF), Shadow Banks (SHADBNK), 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 Insurances category comprises Property-casualty insurance companies (PCIC), Life insurance companies (LIC), Private pension funds (PPF), State & local government employee retirement funds (SLGERF), and Federal government retirement funds (FGRF). In the Mutual Fund category we include Money market mutual funds

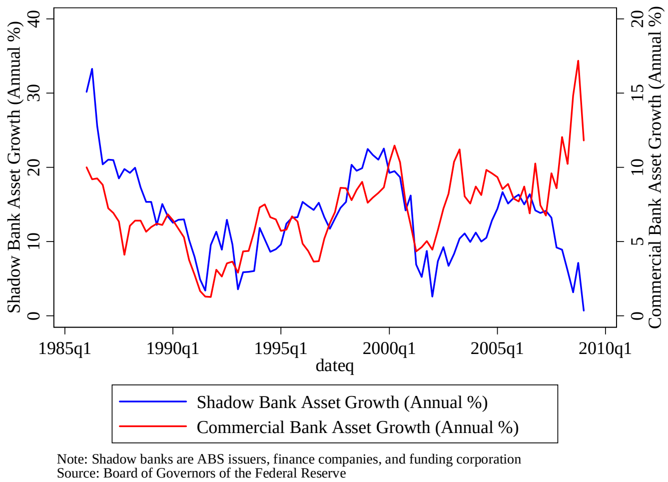

Figure 2.4: Total Asset Growth of Shadow Banks and of Commercial Banks.

(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: Agency- and GSE-backed mortgage pools (MORTPOOL), Issuers of asset-backed securities (ABS), Finance Companies (FINCO), and Funding corporations (FUNDCORP). These are financial intermediaries which perform bank-like business models (borrow short in order to lend long), but are not charted and regulated as banks. As discussed in Section 2, these institutions have become an important factor of the financial intermediation process with the rise of securitization markets that took off in the 1990s.

For the financial intermediaries that appear in Table 7.1 in the appendix, we calculate the quarterly and annual growth of total financial assets. Since some of the institutions have become important players in the financial intermediation process only later in the sample, we also calculate growth rates of total financial assets weighted by the lagged share 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 and "agw" for asset growth weighted by the lagged share of financial assets. 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, weighted by its share of assets in the total financial system is denoted "yMFagw". We also include for consideration quarterly and annual leverage growth for commercial banks, credit unions, and security broker dealers. Leverage growth series have the suffix "levg".

The macro series in Table 7.2 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

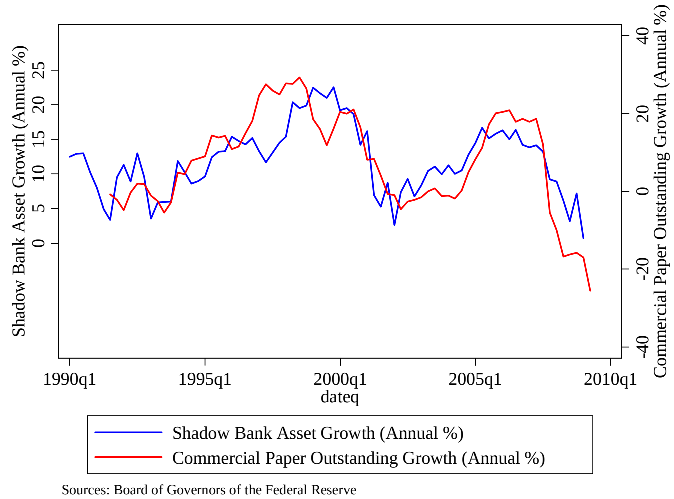

Figure 2.5: Marginal Funding of Shadow Banks is Commercial Paper.

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.

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) can be made in the most forceful way possible. We therefore also consider several return predicting variables that have been popularized in previous asset pricing studies. These are the Lettau-Ludvigson log consumption-wealth ratio (cay) which has been documented to be a successful predictor of stock returns, the Fama-French factors Mkt, HML, and SMB, the Market Dividend Price Ratio (obtained 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 TBill and its four quarter moving average (RREL). Finally, we include the bond return forecasting factor 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 these variables 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 7.3.

We now turn to a description of the return series that we will use as left-hand side vari-

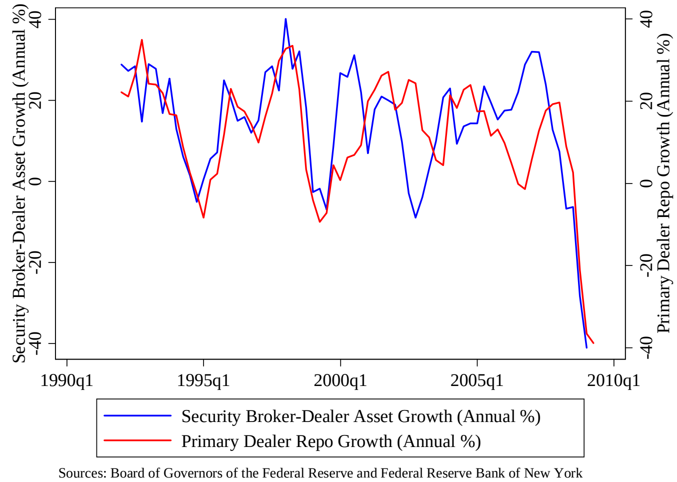

Figure 2.6: Marginal Funding of Broker-Dealers is Repo.

ables in our predictive return regressions. We examine three families of asset return series - stock portfolios, corporate bond portfolios and Treasury securities. As stock portfolios we consider the total Market, the Fama-French portfolios sorted by size and book-to-market, as well as portfolios sorted by momentum and dividend yield. We construct the latter using CRSP data which comprises all NYSE, NASDAQ, and AMEX stocks. The size and book-to-market portfolios are from the website maintained by Ken French. We consider only the "corner" portfolios of the size and book-to-market as well as momentum and dividend yield sorts. For example, "FF11" denotes the portfolio of stocks which fall in the smallest size quintile and the smallest book-to-market quintile. As another example, "D5M5" is the portfolio of stocks which fall in the highest dividend yield and momentum quintiles, respectively. Table 7.4 lists the equity portfolios considered in our study.

Table 7.5 lists the corporate bond portfolios and Treasury securities for which we have return series covering the full sample period 1986-2009. The data for corporate bonds are from Barclays (formerly Lehman Brothers). They include investment grade corporate bond portfolios for industrials, financials, and utilities as well as portfolios for corporate bonds rated "Aaa", "Aa", "A", and "Baa". As government securities we consider the constant maturity Treasury returns for seven different maturities ranging from 1 year to 30 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 TBill 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 market risk premia and real activity, 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 the risk premium on financial assets. The second is to show that intermediary balance sheets also contain useful information in forecasting macroeconomic activity.

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

$$Rx_{t+1}^{(n)} = \alpha + \beta Z_t + \epsilon_{t+1}^{(n)}$$

where $Rx_{t+1}^{(n)}$ is the excess return on a particular financial asset, Z_t is a set of return predictor variables whose forecasting power we seek to analyze.

Our strategy is to begin with few presumptions on 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 vector $Rx^{(n)}$, 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") 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 original paper by Efron et al. (2004). Alternatively, Hastie, Tibshirani, and Friedman (2009) contains an excellent 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. The process is continued by increasing the coefficients on the variables in the active set in their joint least squares direction, until some other predictor has as much correlation with the residual.

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 7.6, 7.7, 7.8 and 7.9 in the appendix present the results of the subset selection of predictive variables for stock portfolios, corporate bonds and Treasuries, in that order. We discuss each of the tables from the appendex in detail. 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, 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, lending weight to our main hypothesis that financial intermediary balance sheets convey useful information on risk premia ruling in the economy. Most importantly, we see that the annual leverage growth of the security broker dealers, *ySBRDLR:levg*, consistently enters as one of the top explanatory balance sheet variables for equity returns and corporate bond returns. More importantly, 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, the annual security broker and dealer leverage growth 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 cay, the term spread or the price dividend ratio.

Turning to the selection results for corporate bond and Treasury returns, we see that the asset-weighted quarterly shadow bank asset growth variable, *qSHADBNK:agw*, enters consistently as one of the top explanatory variables. In particular, it is the top predictor for all corporate bond returns, and is always selected before the broker dealer leverage growth and other common bond return predictor variables like the default spread, the term spread, and the Cochrane-Piazzesi factor. This finding suggests that balance sheet growth of market-based financial intermediaries such as ABS issuers, Finance companies or Funding corporations, all comprised in the shadow bank category, has strong predictive power for risk premia on fixed income instruments. We now turn to assessing the predictive power of the annual broker dealer leverage growth and the quarterly shadow bank asset growth in greater detail, explicitly controlling for the common return predictor variables.

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 nine 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). These are presented in Table 4.1. We see that the lagged annual growth of security broker dealers is the only variable which significantly predicts the excess return on the market portfolio for our sample period. Among the benchmark return predictors, only the log consumption wealth ratio shows marginal significance. More importantly, the broker dealer leverage growth variable remains significant in the presence of all benchmark return predictor variables. Indeed, its significance increases in the presence of the other explanatory variables.

It is important to note that the sign of the predictive relationship is negative. This means that an expansion (contraction) of broker dealer balance sheets predicts lower (higher) future equity returns. 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. Our results indicate that faster expansion of their balance sheets predict lower future excess returns.

Table 4.2 reports the predictive regression results for a particular 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 variables 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 significant predictor of the Fama-French FF55 among the set of benchmark return forecasting variables. 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.

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

Table 4.1: 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 lagged Market return (Mkt lagged), the difference of the 3-month Tbill rate and its four-quarter moving average (RREL), the term spread (TERM), the default spread (DEF), the dividend-price-ratio DPRATIO), 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 8 quarters. The bottom row shows the adjusted R-squared of each regression, respectively. The sample period is 1986Q1-2009Q2.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
MKT (lag)	-0.0402	-0.0206	-0.0445	-0.0176	-0.00891	-0.0549	-0.141
	(-0.501)	(-0.205)	(-0.490)	(-0.169)	(-0.0902)	(-0.596)	(-1.892)
RREL	1.308						-0.529
	(1.453)						(-0.520)
TERM		-0.131					-1.094
		(-0.211)					(-1.243)
DEF			-1.867				-5.628
			(-0.870)				(-1.792)
DPRATIO				-3.128			-5.075
				(-1.441)			(-1.341)
cay					68.64		31.71
					(1.890)		(0.542)
ySBRDLR:levg						**-0.0814**	**-0.116**
						(-2.721)	(-3.490)
$\bar{R}^2$	-0.001	-0.022	-0.015	-0.005	-0.000	0.055	0.088

ourselves to observing that the results are qualitatively very similar across all equity returns. 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) leverage growth of security brokers and dealers is an important predictor for lower (higher) future risk premia in the equity markets.

We now turn to the regression results for corporate bond returns. Informed by the results of the variable selection procedure discussed above, we now 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 term spread, the default spread, 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 4.3 and 4.4, respectively. The only two variables which appear significant individually in predicting the excess return

Table 4.2: 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 lagged Market return (Mkt lagged), the difference of the 3-month Tbill rate and its four-quarter moving average (RREL), the term spread (TERM), the default spread (DEF), the dividend-price-ratio DPRATIO), 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 8 quarters. The bottom row shows the adjusted R-squared of each regression, respectively. The sample period is 1986Q1-2009Q2.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
FF55 (lag)	0.0377	0.0706	0.0382	0.0717	0.0800	0.0804	-0.0508
	(0.562)	(0.912)	(0.523)	(0.845)	(0.984)	(0.987)	(-0.744)
RREL	1.961						0.136
	(1.816)						(0.137)
TERM		-0.260					-0.931
		(-0.330)					(-0.836)
DEF			-2.271				-6.464
			(-0.868)				(-1.610)
DPRATIO				**-3.967**			**-8.568**
				(-1.976)			(-2.458)
cay					45.30		-39.60
					(1.123)		(-0.662)
ySBRDLR:levg						**-0.0700**	**-0.0914**
						(-2.058)	(-3.084)
R^2	0.025	-0.016	-0.008	0.008	-0.008	0.037	0.079

on the IGF portfolio are the CP factor and the shadow bank asset growth variable. Both coefficients are highly statistically significant but have opposite signs. As expected, positive shadow bank balance sheet growth predicts lower future excess returns, whereas the CP factor predicts positive excess returns. While the broker dealer leverage growth variable is only marginally significant when considered as the only regressor, it does become strongly statistically significant when considered jointly with the shadow bank asset growth variable and all benchmark return predictors. The same holds true for the term spread. The default spread, not significant individually, also becomes slightly significant in the joint regression. Note that the R^2 of the joint return prediction regression is well in excess of 30% while the shadow bank asset growth variable alone explains about 20% of the one-quarter ahead variation of excess returns on investment grade corporate bonds. In comparison, the CP factor explains only about 10% of the return variation.

The results for the Baa rated bond portfolio are very similar. The lagged annual security broker dealer leverage growth variable now enters significantly both 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

Table 4.3: 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 lagged investment grade coporate bond return (IGF lag), 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 (ySBRDLR:levg) and the asset-weighted quarterly growth rate of shadow bank asset growth (qSHADBNKagw). All standard errors are Newey-West adjusted with a maximum lag length of 8 quarters. The bottom row shows the adjusted R-squared of each regression, respectively. The sample period is 1986Q1-2009Q2.

	(1)	(2)	(3)	(4)	(5)	(6)
IGF (lag)	-0.288	-0.277	-0.290	-0.325	-0.225	-0.249
	(-1.332)	(-1.280)	(-1.326)	(-1.319)	(-1.615)	(-1.712)
TERM	0.416					**-0.968**
	(1.803)					(-3.615)
DEF		0.515				**1.314**
		(0.584)				(2.097)
CP			**0.499**			**0.773**
			(4.470)			(5.183)
ySBRDLR:levg				-0.0265		**-0.0329**
				(-1.661)		(-3.037)
qSHADBNKagw					**-1.512**	**-1.848**
					(-4.644)	(-6.620)
$\bar{R}^2$	0.066	0.048	0.102	0.103	0.215	0.347

one-quarter ahead variation of the excess return. When the explanatory variables are considered jointly, they all become significant or more significant than individually and the R^2 jumps above 30%.

We interpret these results in the following way. Spread variables such as the term spread or the default spread are composed of at least two components. On the one hand, they contain information about the future expected path of short term interest rates or the future expected default frequency of corporate bonds. On the other hand, they also contain risk premia investors require for holding bonds with longer maturity or higher risk of default. Both components might have independent predictive power for excess returns which is disguised when we consider the aggregate spread variables alone. By adding balance sheet variables to the return regression, however, we directly enter a proxy for risk premia which helps us to disentangle the return predictability of the spread variables that is due to the expectations part and the risk premium part, respectively. As both components are independently important for predicting future excess returns, the fit of this regression improves and the significance of the coefficients increases.

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 pre-

Table 4.4: 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 coporate bond portfolio on one-quarter lagged observations of several explanatory variables. These are the lagged Baa bond return (BAA lag), 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 (ySBRDLR:levg) and the asset-weighted quarterly growth rate of shadow bank asset growth (qSHADBNKagw). All standard errors are Newey-West adjusted with a maximum lag length of 8 quarters. The bottom row shows the adjusted R-squared of each regression, respectively. The sample period is 1986Q1-2009Q2.

	(1)	(2)	(3)	(4)	(5)	(6)
BAA (lag)	0.116	0.154	0.115	0.0621	0.0950	0.0211
	(1.012)	(1.200)	(1.085)	(0.626)	(0.940)	(0.254)
TERM	**0.520**					**-0.615**
	(3.096)					(-4.060)
DEF		**1.679**				**1.765**
		(2.012)				(3.400)
CP			0.282			**0.471**
			(1.376)			(3.435)
ySBRDLR_levg				**-0.0333**		**-0.0377**
				(-2.464)		(-3.672)
qSHADBNKagw					**-1.325**	**-1.628**
					(-4.360)	(-6.843)
$\bar{R}^2$	0.037	0.048	0.017	0.116	0.170	0.368

dictor of excess bond returns, both when considered individually and in a joint regression with the benchmark return predictors. While less 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 risk premia 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 4.5 and 4.6, 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 expected, this variable enters significantly as a return predictor for both the two-year and ten-year Treasuries. The shadow bank asset growth variable alone explains 8% of the one-quarter ahead variation of the two year Treasury return and close to 12% of the variation

Table 4.5: 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 lagged two-year constant maturity Treasury return (CMT2 lag), the term spread (TERM), the default spread (DEF), the Cochrane-Piazzesi return forecasting factor, as well as the asset-weighted quarterly growth rate of shadow bank asset growth (qSHADBNKagw). All standard errors are Newey-West adjusted with a maximum lag length of 8 quarters. The bottom row shows the adjusted R-squared of each regression, respectively. The sample period is 1986Q1-2009Q2.

	(1)	(2)	(3)	(4)	(5)
CMT2 (lag)	0.0334	0.0325	0.0519	0.0315	0.0353
	(0.468)	(0.461)	(0.741)	(0.483)	(0.482)
TERM	0.0441				**-0.439**
	(0.437)				(-2.919)
DEF		0.0301			0.659
		(0.155)			(1.647)
CP			**0.184**		**0.353**
			(2.142)		(2.942)
qSHADBNKagw				**-0.469**	**-0.562**
				(-3.523)	(-3.853)
$\bar{R}^2$	-0.019	-0.021	0.031	0.081	0.173

of the ten year Treasury return. As for the corporate bond returns, the significance of the benchmark predictor variables increases in the multivariate regression, again supporting our interpretation that shadow bank asset growth is a useful proxy for risk premia.

In sum, the results of these predictive return regressions 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 particular, stronger balance sheet growth of these intermediaries is associated with lower risk premia on all three asset classes. Before discussing the potential implications of these findings for macroeconomic dynamics, we now study the robust of our results in two different dimensions. 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 give rise to similar findings.

4.3. Are the Results Due to the Financial Crisis?

Since our sample period covers the recent financial crisis, one potential issue in connection with our results reported so far is whether they are driven by the extreme realizations of variables during the crisis period. 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

Table 4.6: 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 lagged ten-year constant maturity Treasury return (CMT10 lag), the term spread (TERM), the default spread (DEF), the Cochrane-Piazzesi return forecasting factor, as well as the asset-weighted quarterly growth rate of shadow bank asset growth (qSHADBNKagw). All standard errors are Newey-West adjusted with a maximum lag length of 8 quarters. The bottom row shows the adjusted R-squared of each regression, respectively. The sample period is 1986Q1-2009Q2.

	(1)	(2)	(3)	(4)	(5)
CMT10 (lag)	-0.0202	-0.00268	0.0204	-0.0385	0.00451
	(-0.244)	(-0.0320)	(0.245)	(-0.505)	(0.0500)
TERM	0.467				-0.379
	(1.793)				(-0.799)
DEF		-1.029			-0.345
		(-1.596)			(-0.265)
CP			**0.556**		0.529
			(2.551)		(1.451)
qSHADBNKagw				**-1.678**	**-1.696**
				(-3.795)	(-3.799)
R^2	-0.003	-0.011	0.027	0.119	0.136

first problems in the subprime mortgage market materialized in August 2007.

Tables 7.10, 7.11 and 7.12 in the appendix report the results of the regressions for the shortened sample for equities, bonds and Treasuries, respectively. We see that our results remain robust to the exclusion of the crisis period. The message that emerges from this robustness check is that the informational value of 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 policy purposes if the intention is to use them for preemptive policy that tries to anticipate problems ahead. We return to this issue later in the paper.

4.4. Using Liability Aggregates

In our empirical investigations so far, we have used the quarterly asset series of the Federal Reserve's Flow of Funds data series. An alternative approach is to use the aggregates on 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 asset pricing studies of exchange rates and commodities (see Etula (2008) and Adrian, Etula and Shin (2009)).

As an additional robustness check on our results, we therefore use liabilities side aggregates as our balance sheet variables in the predictive return regressions. In particular, we use the series on the Financial Commercial Paper (FCP) series from the Federal Reserve Board's website and the stock of outstanding Primary Dealer repos from the Federal Reserve Bank of New York.[3] These series are available at the weekly frequency, but since we only have return data at the monthly frequency we estimate the predictive return regressions using monthly data.

For brevity, we only report the results for three different assets: the equity market portfolio, the investment grade financial bonds portfolio, and the ten year constant maturity Treasury return. These are provided in Tables 7.13, 7.14 and 7.15. The results are less strong for these regressions, and we lose the significance of the balance sheet variables in the regressions for the equity market portfolio, as we can see from Table 7.13. However, for corporate bonds and for Treasuries, the balance sheet variables continue to have predictive power. Indeed, both the growth of the repo and the FCP market are strongly significant predictors of excess returns on corporate and Treasury bonds. Altogether, these results support our earlier findings that variables which proxy for the balance sheet growth of financial intermediariesare significant predictors of future excess returns on various asset classes.

4.5. Taking Stock of the Results So Far

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. Our results confirm 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.

Our empirical results in this section point to considerable information value in the balance sheets of financial intermediaries, especially those that operate in the capital markets. The fact that our selection algorithm chooses broker dealers and the shadow banks as being most informative in the predictive regressions points to the growing importance of the market based financial system, and the greater informational immediacy of balance sheets that are continuously marked to market.

Having confirmed that balance sheet information is useful for predicting asset returns, we now turn to the second of our empirical exercises - that of showing that balance sheet

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

information also holds important implications for economic activity.

5. Forecasting Macroeconomic Aggregates

Do the balance sheet variables that have figured prominently in predictive regressions also predict macro variables? Our hypothesis is that the answer is "yes", due to the fact that balance sheets convey information on risk premia, and hence on the marginal project that receives funding from the financial system.

We conduct a series of predictive regressions for annual growth rates of macroeconomic aggregates, in particular, GDP and some of its key components such as consumption growth, durable goods consumption growth and residential investment growth. We also investigate the predictive value of balance sheet variables for total and core inflation.

To anticipate our main results, the predictive regressions show a consistent pattern in which faster growth of balance sheets predict higher real activity as measured in a variety of ways. Moreover, faster growth of balance sheets also predicts higher future inflation. To conserve space, we only report here the regression results for real GDP and total PCE inflation. We present additional regression results for the components of real GDP and for core inflation in the appendix. Table 5.1 shows the results for the predictive regressions of one quarter ahead GDP growth on our balance sheet variables as well as the Federal Funds rate, the term spread, and the default spread. These results show that while annual security broker dealer leverage growth is not a significant predictor of GDP growth, the coefficient on the quarterly shadow bank asset growth variable is small but statistically significant. This is true both when it is considered individually and in a joint regression. As we have seen for the predictive return regressions, the significance of the term and default spread becomes more pronounced when the balance sheet growth variable is added to the regression, suggesting a role for risk premia in predicting future output growth.

Tables 7.16 and 7.17 in the appendix show the regressions for consumption growth and durable consumption growth, respectively. In both cases, the lagged quarterly growth rate of shadow banks figures prominently and is statistically significant both individually and when we control for other predictor variables. Table 7.18 shows the predictive regression for investment growth. The lagged quarterly shadow bank asset growth is again significant whereas the lagged annual broker dealer leverage growth is not. Finally, we examine the predictive regression for residential investment growth in Table 7.19. Unlike the other components of aggregate demand so far examined, residential investment growth shows a role for the lagged annual leverage growth of the broker dealers, although the significance becomes marginal, and ceases to be significant at the 5% level in the final regression (column 6) which includes the corporate bond default spread (DEF). The fact that broker dealers show up for residential investment is consistent with the increased importance of the broker dealer sector as an intermediary in a market-based financial system based on marketable securities. The importance of the broker dealer sector balance sheets in forecasting macro aggregates was noted by Adrian and Shin (2008). In sum, our regression results show that faster expansion of financial intermediary balance sheets predicts higher

Table 5.1: Macro Forecasts: GDP growth

This table reports coefficient estimates and the corresponding t-statistics from a regression of the annual growth rate of real GDP (yGDP) on its own lag as well as on one-quarter lagged observations of several explanatory variables. These are the Effective Federal Funds Rate (FFR), the term spread (TERM), the default spread (DEF), the annual growth rate of security broker dealer leverage growth (ySBRDLR:levg), as well as the asset-weighted quarterly growth rate of shadow bank asset growth (qSHADBNK:agw). All standard errors are Newey-West adjusted with a maximum lag length of 8 quarters. The bottom row shows the adjusted R-squared of each regression, respectively. The sample period is 1986Q1-2009Q2.

	(1)	(2)	(3)	(4)	(5)	(6)
yGDP (lag)	**1.00**	**0.89**	**1.00**	**0.99**	**0.99**	**0.80**
	(13.05)	(15.97)	(12.86)	(12.60)	(14.27)	(14.67)
FFR	0.00	-0.00	-0.00	-0.00	0.00	0.00
	(0.18)	(-0.81)	(-0.63)	(-0.95)	(0.14)	(0.37)
TERM	0.00				**0.00**	**0.00**
	(1.57)				(2.12)	(3.84)
DEF		**-0.01**				**-0.01**
		(-2.98)				(-4.92)
ySBRDLR:levg			-0.00		0.00	-0.00
			(-0.29)		(0.26)	(-0.76)
qSHADBNK:agw				**0.00**	**0.00**	**0.00**
				(2.21)	(2.15)	(3.07)
$\bar{R}^2$	0.82	0.84	0.82	0.82	0.83	0.86

future real activity.

We now turn to examining the predictive power of our balance sheet variables for consumer prices. Table 5.2 has the results for total PCE inflation. The results for core PCE inflation, documented in Table 7.20 in the appendix are qualitatively very similar. We see that for both headline and core inflation the lagged quarterly shadow bank asset growth variable once again figures highly significantly. The results are somewhat stronger for the total PCE inflation regression, suggesting that the volatile elements in the inflation series may share some informational overlap with the balance sheet growth of intermediaries. The price of oil and other commodities come to mind as a possible connection, especially given the increased importance of some commodity price indices in the trading strategies of some market participants. It is also notable that the coefficient for the broker dealer leverage growth is negative but statistically insignificant. The overall lesson from the inflation regressions is that balance sheet growth of intermediaries, especially in the shadow banking sector, hold important information for the future evolution of inflation.

6. Implications for Policy

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

Table 5.2: Macro Forecasts: Total PCE Inflation

This table reports coefficient estimates and the corresponding t-statistics from a regression of the annual inflation rate for total Personal Consumption Expenditures (yJC) on its own lag as well as on one-quarter lagged observations of several explanatory variables. These are the Effective Federal Funds Rate (FFR), the term spread (TERM), the default spread (DEF), the annual growth rate of security broker dealer leverage growth (ySBRDLR:levg), as well as the asset-weighted quarterly growth rate of shadow bank asset growth (qSHADBNK:agw). All standard errors are Newey-West adjusted with a maximum lag length of 8 quarters. The bottom row shows the adjusted R-squared of each regression, respectively. The sample period is 1986Q1-2009Q2.

	(1)	(2)	(3)	(4)	(5)	(6)
yJC (lag)	**0.76**	**0.72**	**0.74**	**0.76**	**0.75**	**0.69**
	(13.94)	(11.22)	(10.85)	(16.77)	(14.11)	(12.67)
FFR	0.00	0.00	0.00	0.00	0.00	0.00
	(0.57)	(0.24)	(0.71)	(0.04)	(0.50)	(0.21)
TERM	0.00				0.00	0.00
	(0.10)				(0.78)	(1.37)
DEF		-0.00				**-0.01**
		(-1.62)				(-2.85)
ySBRDLR:levg			-0.00		-0.00	-0.00
			(-1.73)		(-1.33)	(-1.76)
qSHADBNK:agw				**0.00**	**0.00**	**0.00**
				(3.96)	(3.94)	(4.45)
$\bar{R}^2$	0.48	0.52	0.50	0.53	0.53	0.58

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 lagged annual security broker dealer leverage growth, and the second is the lagged quarterly shadow bank total 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 and government bond returns. When we examined the ability of balance sheet variables to predict future real activity, these same pair of balance sheet variables are significant in forecasting components of real economic activity and inflation.

We believe that our results hold important 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.[4]

Our empirical results also pose a challenge for any structural macro model that does

[4]See Danielsson, Shin and Zigrand (2008) for value at risk constraints, Adrian, Etula and Shin (2009) for the foreign exchange market and Etula (2009) for the commodities market.

not have a role for financial intermediaries as an integral part of the model. For policy makers - especially for central banks in conducting monetary policy - our results show how closely monetary policy (and the stabilization of macro aggregates) is tied to broader financial stability goals that have at its heart the role 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 preemptive monetary policy. However, the broader lesson is that the fluctuations in the real activity is part and parcel of the fluctuations in risk premia associated with financial intermediary balance sheet management. In this sense, macro-prudential 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 macro fluctuations will reveal the extent to which monetary policy and policies toward financial stability are linked.

Financial intermediaries lie at the heart of both monetary policy transmission as well as policies toward financial stability. The key thread to our discussion has been that the interaction of financial intermediaries' balance sheet management with changes in asset prices and measured risks represents an important component in the transmission mechanism of monetary policy.

The credit supply channel sketched so far differs from the financial amplification mechanisms of Bernanke and Gertler (1989), and Kiyotaki and Moore (1997, 2005). These papers focus on amplification due to financing frictions in the borrowing sector, while we focus on amplification due to financing frictions in the lending sector. Our approach raises the question of whether the failure of the Modigliani-Miller theorem may be more severe in the lending rather than the borrowing sector of the economy. The interaction of financial constraints in the lending and the borrowing sector is likely to give additional kick to financial frictions in the macro context that mutually reinforce each other. These interactions would be fertile ground for new research.

We have shown that financial intermediary balance sheet management matters for the real economy, as well as for the determination of risk premia. These findings have important implications for the conduct of macroprudential and monetary policies.

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7. Appendix

7.1. Data

Table 7.1: 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 instituion individually as well as for the five major groups (Banks, Pension Funds and Insurances, Mutual Funds, Shadow Bank, and Security Brokers and Dealers) . We also compute growth rates weighted by the share of total assets of the particular institution in the aggregate financial sector (the sum of all assets). This is in order to account for the changing decomposition of total financial assets across the different types of institutions over our sample. 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 and dealers. Leverage is defined as assets minus 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		Description
FINBANK		Banks
	CB	Commercial banks
	SI	Savings institutions
	CU	Credit unions
FINPI		Pension Funds and Insurances
	PCIC	Property-casualty insurance companies
	LIC	Life insurance companies
	PPF	Private pension funds
	SLGERF	State & local govt employee retirement funds
	FGRF	Federal government retirement funds
FINMF		Mutual Funds
	MMMF	Money market mutual funds
	MF	Mutual funds
	CEF	Closed-end funds and exchange-traded funds
SHADBNK		Shadow Banks
	MORTPOOL	Agency- and GSE-backed mortgage pools
	ABS	Issuers of asset-backed securities
	FINCO	Finance Companies
	FUNDCORP	Funding corporations
SBRDLR		Security brokers and dealers

Table 7.2: Macro 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
C	Real Personal Consumption Expenditures
CD	Real Personal Consumption Expenditures: Durable Goods
CN	Real Personal Consumption Expenditures: Nondurable Goods
CS	Real Personal Consumption Expenditures: Services
I	Real Gross Private Domestic Investment
F	Real Private Fixed Investment
FN	Real Private Nonresidential Fixed Investment
FR	Real Private Residential Investment
XNET	Real Net Exports of Goods & Services
G	Real Government Consumption Expenditures & Gross Investment
JC	Personal Consumption Expenditures
JCXFE	PCE less Food & Energy
JCXEG	PCE Excluding Energy Goods & Services
JCD	PCE Durable Goods
JCN	PCE Nondurable Goods
JCS	PCE Services

Table 7.3: 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
CAY	Log consumption wealth ratio
MKT	Fama French Excess Return on Equity Market Portfolio
SMB	Fama French Size Factor
HML	Fama French Value Factor
DPRATIO	Market Dividend Price Ratio
TERM	Term Spread (10year-3month)
DEF	Default Spread (Moody's Baa-Aaa)
RREL	3-month TBill minus its 4quarter moving average
CP	Cochrane Piazzesi Factor

Table 7.4: Equity Portfolios

This table summarizes the equity portfolios used in the predictive return regressions in Section 4.

Mnemonic	Description
MKT	Fama French Market Portfolio
D1M1	Low Dividend Low Momentum Portfolio
D1M5	Low Dividend High Momentum Portfolio
D5M1	High Dividend Low Momentum Portfolio
D5M5	High Dividend High Momentum Portfolio
FF11	Small Size Low Value Portfolio
FF15	Small Size High Value Portfolio
FF51	Large Size Low Value Portfolio
FF55	Large Size High Value Portfolio

Table 7.5: Bond Returns

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

Mnemonic	Description
	Corporate Bond Returns
IGI	Investment Grade Industrials
IGU	Investment Grade Utilities
IGF	Investment Grade Financials
Aaa	Aaa Rated
Aa	Aa Rated
A	A Rated
Baa	Baa Rated
	Treasury Returns
CMT1	1-year Constant Maturity Treasury Return
CMT2	2-year Constant Maturity Treasury Return
CMT5	5-year Constant Maturity Treasury Return
CMT7	7-year Constant Maturity Treasury Return
CMT10	10-year Constant Maturity Treasury Return
CMT20	20-year Constant Maturity Treasury Return
CMT30	30-year Constant Maturity Treasury Return

7.2. Additional Tables

Table 7.6: Best Return Predictors for Equity Portfolios

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 Relative Pricing Factors		
1st	qG	HML	qJCXEG	HML	qG
2nd	HML	qJCXEG	qCN	CAY	qCN
3rd	qCN	qG	yFR	SMB	RREL
4th	yFR	yJCS	qG	qCD	yJCN
5th	SMB	MKT	yJCS	yJCN	yFR
			Balance Sheet		
1st	ySBRDLR:levg	ySBRDLR:levg	ySBRDLR:levg	ySBRDLR:levg	yMMMF:agw
2nd	yMORTPOOL:agw	yFINMF:agw	yMMMF:agw	yFGRF:agw	yMORTPOOL:agw
3rd	yMMMF:agw	yPPF:agw	qCEF:agw	yCB:levg	qCEF:agw
4th	yFGRF:agw	yMORTPOOL:agw	ySHADBNK:agw	qFINCO:agw	ySBRDLR:levg
5th	qABS:agw	qSBRDLR:levg	qREIT:agw	qMMMF:agw	yCU:levg
			All		
1st	**ySBRDLR : levg**	HML	**ySBRDLR : levg**	HML	qG
2nd	qG	**ySBRDLR : levg**	qJCXEG	CAY	yMMMF:agw
3rd	HML	yFINMF:agw	yMMMF:agw	**ySBRDLR : levg**	yMORTPOOL:agw
4th	CAY	qJCXEG	qCEF:agw	SMB	qCEF:agw
5th	qCN	qPPF:agw	qG	qABS:agw	**ySBRDLR : levg**

Table 7.7: Best Return Predictors for Equity Portfolios

This table shows the results of the Least Angle Regression Procedure for the predictive return regressions of the four equity portfolios D1M1, D1M5, D5M1, and D5M5 as well as for the investment grade industrial corporate bond portfolio (IGI).

	D1M1	D1M5	D5M1	D5M5	IGI
			Macro and Relative Pricing Factors		
1st	qG	qGDP	qCN	yJCN	qCS
2nd	SMB	HML	SMB	qCN	TERM
3rd	CP	yCD	qG	CAY	MKT
4th	yJCS	yCN	DPRATIO	yJCS	CP
5th	qCD	yFR	qCD	DEF	yCD
			Balance Sheet		
1st	ySBRDLR:levg	yABS:agw	ySBRDLR:levg	qCB:levg	qSHADBNK:agw
2nd	qFINBANK:agw	ySLGERF:agw	qCEF:agw	qABS:agw	ySBRDLR:levg
3rd	qMMMF:agw	qFINMF:agw	qSI:agw	qCEF:agw	yFINMF:agw
4th	qPPF:agw	yFGRF:agw	qABS:agw	yREIT:agw	qPPF:agw
5th	yMORTPOOL:agw	ySBRDLR:levg	yFGRF:agw	ySHADBNK:agw	qSI:agw
			All		
1st	qG	yABS:agw	qCN	qCB:levg	**qSHADBNK : agw**
2nd	SMB	qGDP	SMB	qABS:agw	**ySBRDLR : levg**
3rd	**ySBRDLR : levg**	HML	**ySBRDLR : levg**	qCEF:agw	yFINMF:agw
4th	CP	ySLGERF:agw	qG	yREIT:agw	MKT
5th	qFINBANK:agw	yCD	DPRATIO	CAY	qCS

Table 7.8: Best Return Predictors for Corporate Bonds

This table shows the results of the Least Angle Regression Procedure for the predictive return regressions of the corporate bond portfolios for investment grade utiluities (IGU), investment grade financial (IGF), as well as "Aaa", "Aa", and "A" rated corporate bonds.

	IGU	IGF	Aaa	Aa	A
			Macro and Relative Pricing Factors		
1st	yCD	yFN	CP	CP	CP
2nd	qJCN	CP	HML	qCS	qCS
3rd	TERM	qFN	qCS	HML	HML
4th	CP	qCS	yJC	qJCD	yFN
5th	qCS	HML	qJCD	MKT	MKT
			Balance Sheet		
1st	qSHADBNK:agw	qSHADBNK:agw	qSHADBNK:agw	qSHADBNK:agw	qSHADBNK:agw
2nd	ySBRDLR:levg	ySBRDLR:levg	qCU:levg	qSI:agw	ySBRDLR:levg
3rd	qSBRDLR:levg	yFINMF:agw	qSI:agw	ySBRDLR:levg	yFINMF:agw
4th	qCB:levg	qSI:agw	qCB:levg	qFINMF:agw	qSI:agw
5th	qSI:agw	yMMMF:agw	ySBRDLR:levg	qPPF:agw	qFINMF:agw
			All		
1st	**qSHADBNK : agw**	**qSHADBNK : agw**	**qSHADBNK : agw**	**qSHADBNK : agw**	**qSHADBNK : agw**
2nd	**ySBRDLR : levg**	yFN	qCU:levg	CP	**ySBRDLR : levg**
3rd	qSBRDLR:levg	**ySBRDLR : levg**	CP	qSI:agw	CP
4th	qCB:levg	CP	qSI:agw	HML	yFINMF:agw
5th	yCD	qSI:agw	HML	**ySBRDLR : levg**	qSI:agw

Table 7.9: Best Return Predictors for Treasury Bonds

This table shows the results of the Least Angle Regression Procedure for the predictive return regressions of the "Baa" rated corporate bond portfolio as well as for Treasury returns for maturities one through seven years.

	Baa	CMT1	CMT2	CMT5	CMT7
			Macro and Relative Pricing Factors		
1st	yFN	qCS	qCS	HML	HML
2nd	qJCN	CP	CP	CP	CP
3rd	qCS	yXNET	HML	qCS	qCS
4th	TERM	qJCS	yFR	yJCN	yJCN
5th	CAY	yFR	qJCD	yFR	yFR
			Balance Sheet		
1st	qSHADBNK:agw	qSI:agw	qSI:agw	qSHADBNK:agw	qSHADBNK:agw
2nd	ySBRDLR:levg	qSHADBNK:agw	qSHADBNK:agw	qSI:agw	qSI:agw
3rd	yFINMF:agw	yMORTPOOL:agw	yMORTPOOL:agw	qCU:levg	qCU:levg
4th	qSBRDLR:levg	qMORTPOOL:agw	qREIT:agw	qCB:levg	qCEF:agw
5th	ySI:agw	qCB:levg	qCB:levg	yMORTPOOL:agw	qCB:levg
			All		
1st	**qSHADBNK : agw**	qSI:agw	qSI:agw	**qSHADBNK : agw**	**qSHADBNK : agw**
2nd	**ySBRDLR : levg**	qCS	**qSHADBNK : agw**	qSI:agw	qSI:agw
3rd	yFINMF:agw	**qSHADBNK : agw**	qCS	qCU:levg	qCU:levg
4th	qJCN	yMORTPOOL:agw	CP	HML	HML
5th	yFN	qMORTPOOL:agw	HML	CP	yJCN

Table 7.10: 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 lagged Market return (Mkt lagged), the difference of the 3-month Tbill rate and its four-quarter moving average (RREL), the term spread (TERM), the default spread (DEF), the dividend-price-ratio DPRATIO), 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 8 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)
MKT (lag)	-0.117	-0.117	-0.117	-0.122	-0.107	-0.139	-0.180
	(-1.715)	(-1.674)	(-1.732)	(-2.015)	(-1.593)	(-2.044)	(-2.719)
RREL	0.390						-1.337
	(0.494)						(-1.061)
TERM		-0.0964					-0.972
		(-0.135)					(-1.205)
DEF			-1.804				-9.613
			(-0.492)				(-1.367)
DPRATIO				-2.921			-6.632
				(-1.131)			(-1.190)
cay					58.94		-14.82
					(1.471)		(-0.189)
ySBRDLR:levg						-0.0494	-0.0933
						(-2.386)	(-3.221)
$\bar{R}^2$	-0.008	-0.010	-0.007	0.007	0.008	0.019	0.031

Table 7.11: 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 lagged Baa bond return (BAA lag), 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 (ySBRDLR:levg) and the asset-weighted quarterly growth rate of shadow bank asset growth (qSHADBNKagw). All standard errors are Newey-West adjusted with a maximum lag length of 8 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)
BAA (lag)	0.0588	0.0751	0.0873	0.0540	0.0413	0.0149
	(0.509)	(0.695)	(0.793)	(0.529)	(0.422)	(0.177)
TERM	0.511					-0.585
	(2.819)					(-2.782)
DEF		0.631				0.779
		(0.638)				(1.014)
CP			0.516			0.608
			(3.614)			(3.064)
ySBRDLR:levg				-0.0231		-0.0339
				(-1.843)		(-3.229)
qSHADBNKagw					-1.226	-1.579
					(-4.823)	(-5.624)
$\bar{R}^2$	0.038	-0.014	0.063	0.052	0.153	0.306

Table 7.12: 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 lagged ten-year constant maturity Treasury return (CMT10 lag), the term spread (TERM), the default spread (DEF), the Cochrane-Piazzesi return forecasting factor, as well as the asset-weighted quarterly growth rate of shadow bank asset growth (qSHADBNKagw). All standard errors are Newey-West adjusted with a maximum lag length of 8 quarters. The bottom row shows the adjusted R-squared of each regression, respectively. The sample period is 1986Q1-2007Q2.

	(1)	(2)	(3)	(4)	(5)
CMT10 (lag)	-0.0187	-0.0168	-0.00219	-0.0837	-0.0694
	(-0.200)	(-0.184)	(-0.0234)	(-1.031)	(-0.885)
TERM	0.618				-0.803
	(2.421)				(-2.178)
DEF		-0.894			0.867
		(-0.523)			(0.441)
CP			0.830		0.967
			(4.753)		(4.017)
qSHADBNKagw				-2.086	-2.193
				(-6.374)	(-5.933)
$\bar{R}^2$	0.013	-0.021	0.070	0.186	0.237

Table 7.13: 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 the difference of the 1-month Tbill rate and its one-year moving average (RREL), the term spread (TERM), the default spread (DEF), the dividend-price-ratio DPRATIO), as well as the monthly growth rate of total outstanding Financial Commercial Paper and the monthly growth rate of the stock of outstanding repos. All standard errors are Newey-West adjusted with a maximum lag length of 18 months. The bottom row shows the adjusted R-squared of each regression, respectively. The sample period is 1991:07-2009:06.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
MKT ()lag)	0.134	0.140	0.133	0.141	0.133	0.139	0.121
	(1.656)	(1.616)	(1.603)	(1.534)	(1.498)	(1.641)	(1.410)
RREL	0.422						0.333
	(1.661)						(1.060)
TERM		-0.0697					-0.182
		(-0.327)					(-0.699)
DEF			-0.580				-0.441
			(-0.855)				(-0.655)
DPRATIO				-1.346			-2.078
				(-1.781)			(-2.695)
FCP					0.0949		0.0629
					(0.840)		(0.518)
REPO						0.0306	0.0287
						(0.570)	(0.532)
$\bar{R}^2$	0.018	0.012	0.015	0.021	0.014	0.012	0.016

Table 7.14: Alternative Balance Sheet Measures: Investment Grade Financial Bonds

This table reports coefficient estimates and the corresponding t-statistics from a regression of the excess return of the investment grade financial corporate bond portfolio on its own lag as well as on one-month lagged observations of several explanatory variables. These are the the term spread (TERM), the default spread (DEF), the Cochrane-Piazzesi return forecasting factor, as well as the monthly growth rate of total outstanding Financial Commercial Paper and the monthly growth rate of the stock of outstanding repos. All standard errors are Newey-West adjusted with a maximum lag length of 18 months. The bottom row shows the adjusted R-squared of each regression, respectively. The sample period is 1991:07-2009:06.

	(1)	(2)	(3)	(4)	(5)	(6)
IGF (lag)	0.208	0.208	0.218	0.219	0.211	0.214
	(4.103)	(4.596)	(4.550)	(4.354)	(4.695)	(4.914)
TERM	0.174					0.0128
	(2.478)					(0.0949)
DEF		0.368				0.289
		(1.562)				(0.811)
CP			0.0825			0.125
			(1.058)			(1.294)
FCP				-0.0731		-0.0536
				(-2.984)		(-2.107)
REPO					-0.0546	-0.0550
					(-2.509)	(-2.864)
$\bar{R}^2$	0.052	0.047	0.044	0.047	0.059	0.069

Table 7.15: 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 the term spread (TERM), the default spread (DEF), the Cochrane-Piazzesi return forecasting factor, as well as the monthly growth rate of total ABCP and Financial Commercial Paper Issuance and the monthly growth rate of the stock of outstanding repos. All standard errors are Newey-West adjusted with a maximum lag length of 18 months. The bottom row shows the adjusted R-squared of each regression, respectively. The sample period is 1991:07-2009:06.

	(1)	(2)	(3)	(4)	(5)	(6)
CMT10 (lag)	0.0578	0.0588	0.0733	0.0872	0.0660	0.115
	(1.088)	(1.134)	(1.309)	(1.712)	(1.285)	(2.295)
TERM	0.191					0.0387
	(2.119)					(0.201)
DEF		0.0833				-0.432
		(0.359)				(-0.999)
CP			0.0920			0.0780
			(0.759)			(0.442)
FCP				-0.202		-0.228
				(-3.702)		(-4.167)
REPO					-0.0617	-0.0792
					(-2.558)	(-3.313)
$\bar{R}^2$	0.007	-0.005	0.000	0.047	0.013	0.066

Table 7.16: Macro Forecasts: Consumption Growth

This table reports coefficient estimates and the corresponding t-statistics from a regression of the annual growth rate of real Personal Consumption Expenditures (yC) on its own lag as well as on one-quarter lagged observations of several explanatory variables. These are the Effective Federal Funds Rate (FFR), the term spread (TERM), the default spread (DEF), the annual growth rate of security broker dealer leverage growth (ySBRDLR:levg), as well as the asset-weighted quarterly growth rate of shadow bank asset growth (qSHADBNK:agw). All standard errors are Newey-West adjusted with a maximum lag length of 8 quarters. The bottom row shows the adjusted R-squared of each regression, respectively. The sample period is 1986Q1-2009Q2.

	(1)	(2)	(3)	(4)	(5)	(6)
yC (lag)	1.00	0.90	1.00	0.98	0.97	0.76
	(10.58)	(13.02)	(10.09)	(10.88)	(10.48)	(10.53)
FFR	0.00	0.00	0.00	-0.00	0.00	0.00
	(0.54)	(0.21)	(0.04)	(-0.46)	(0.81)	(1.74)
TERM	0.00				0.00	0.00
	(1.49)				(2.08)	(5.00)
DEF		-0.01				-0.01
		(-2.23)				(-3.61)
ySBRDLR:levg			-0.00		-0.00	-0.00
			(-1.20)		(-0.76)	(-1.19)
qSHADBNK:agw				0.00	0.00	0.00
				(2.66)	(2.64)	(3.36)
$\bar{R}^2$	0.78	0.79	0.78	0.79	0.79	0.83

Table 7.17: Macro Forecasts: Durable Consumption Growth

This table reports coefficient estimates and the corresponding t-statistics from a regression of the annual growth rate of real Durable Consumption (yCD) on its own lag as well as on one-quarter lagged observations of several explanatory variables. These are the Effective Federal Funds Rate (FFR), the term spread (TERM), the default spread (DEF), the annual growth rate of security broker dealer leverage growth (ySBRDLR:levg), as well as the asset-weighted quarterly growth rate of shadow bank asset growth (qSHADBNK:agw). All standard errors are Newey-West adjusted with a maximum lag length of 8 quarters. The bottom row shows the adjusted R-squared of each regression, respectively. The sample period is 1986Q1-2009Q2.

	(1)	(2)	(3)	(4)	(5)	(6)
yCD (lag)	0.81	0.70	0.80	0.79	0.79	0.63
	(8.45)	(7.56)	(8.97)	(8.66)	(9.20)	(8.12)
FFR	0.00	-0.00	-0.00	-0.00	0.00	-0.00
	(0.10)	(-0.71)	(-0.06)	(-0.33)	(0.01)	(-0.83)
TERM	0.00				0.00	0.00
	(0.44)				(0.86)	(1.29)
DEF		-0.03				-0.03
		(-2.85)				(-3.54)
ySBRDLR:levg			-0.00		0.00	-0.00
			(-0.09)		(0.18)	(-0.58)
qSHADBNK:agw				0.00	0.01	0.01
				(1.31)	(1.39)	(2.38)
$\bar{R}^2$	0.59	0.61	0.59	0.59	0.58	0.62

Table 7.18: Macro Forecasts: Investment Growth

This table reports coefficient estimates and the corresponding t-statistics from a regression of the annual growth rate of real Investment growth (yI) on its own lag as well as on one-quarter lagged observations of several explanatory variables. These are the Effective Federal Funds Rate (FFR), the term spread (TERM), the default spread (DEF), the annual growth rate of security broker dealer leverage growth (ySBRDLR:levg), as well as the asset-weighted quarterly growth rate of shadow bank asset growth (qSHADBNK:agw). All standard errors are Newey-West adjusted with a maximum lag length of 8 quarters. The bottom row shows the adjusted R-squared of each regression, respectively. The sample period is 1986Q1-2009Q2.

	(1)	(2)	(3)	(4)	(5)	(6)
yI (lag)	0.96	0.74	0.97	0.97	0.96	0.65
	(9.29)	(12.33)	(8.90)	(9.36)	(10.26)	(9.05)
FFR	0.00	-0.00	-0.00	-0.00	0.00	-0.00
	(0.37)	(-1.55)	(-0.53)	(-0.70)	(0.31)	(-0.33)
TERM	0.01				0.01	0.02
	(2.34)				(3.03)	(7.01)
DEF		-0.07				-0.09
		(-3.40)				(-5.73)
ySBRDLR:levg			-0.00		0.00	-0.00
			(-0.13)		(0.66)	(-0.89)
qSHADBNK:agw				0.01	0.01	0.01
				(1.53)	(2.05)	(2.67)
$\bar{R}^2$	0.74	0.79	0.73	0.74	0.75	0.82

Table 7.19: Macro Forecasts: Residential Investment Growth

This table reports coefficient estimates and the corresponding t-statistics from a regression of the annual growth rate of real residential investment growth (yFR) on its own lag as well as on one-quarter lagged observations of several explanatory variables. These are the Effective Federal Funds Rate (FFR), the term spread (TERM), the default spread (DEF), the annual growth rate of security broker dealer leverage growth (ySBRDLR:levg), as well as the asset-weighted quarterly growth rate of shadow bank asset growth (qSHADBNK:agw). All standard errors are Newey-West adjusted with a maximum lag length of 8 quarters. The bottom row shows the adjusted R-squared of each regression, respectively. The sample period is 1986Q1-2009Q2.

	(1)	(2)	(3)	(4)	(5)	(6)
yFR (lag)	0.97	0.96	0.99	0.98	0.97	0.93
	(23.21)	(19.25)	(22.71)	(24.04)	(19.20)	(13.77)
FFR	0.00	-0.00	-0.00	-0.00	0.00	0.00
	(0.18)	(-1.37)	(-0.86)	(-0.74)	(0.23)	(0.06)
TERM	0.01				0.01	0.01
	(0.87)				(1.07)	(1.35)
DEF		-0.01				-0.02
		(-1.38)				(-1.40)
ySBRDLR:levg			0.00		0.00	0.00
			(2.17)		(2.08)	(1.81)
qSHADBNK:agw				-0.00	0.00	0.00
				(-0.22)	(0.64)	(0.86)
$\bar{R}^2$	0.90	0.90	0.90	0.90	0.90	0.90

Table 7.20: Macro Forecasts: Core PCE Inflation

This table reports coefficient estimates and the corresponding t-statistics from a regression of the annual inflation rate for personal consumption expenditures excluding food and energy (yJCXFE) on its own lag as well as on one-quarter lagged observations of several explanatory variables. These are the Effective Federal Funds Rate (FFR), the term spread (TERM), the default spread (DEF), the annual growth rate of security broker dealer leverage growth (ySBRDLR:levg), as well as the asset-weighted quarterly growth rate of shadow bank asset growth (qSHADBNK:agw). All standard errors are Newey-West adjusted with a maximum lag length of 8 quarters. The bottom row shows the adjusted R-squared of each regression, respectively. The sample period is 1986Q1-2009Q2.

	(1)	(2)	(3)	(4)	(5)	(6)
yJCXFE (lag)	0.76	0.76	0.74	0.75	0.75	0.75
	(12.54)	(12.48)	(11.54)	(13.81)	(12.21)	(11.99)
FFR	0.00	0.00	0.00	0.00	0.00	0.00
	(0.65)	(0.20)	(0.44)	(0.08)	(0.64)	(0.50)
TERM	0.00				0.00	0.00
	(0.39)				(0.78)	(0.87)
DEF		-0.00				-0.00
		(-0.93)				(-1.54)
ySBRDLR:levg			-0.00		-0.00	-0.00
			(-0.70)		(-0.21)	(-0.45)
qSHADBNK:agw				0.00	0.00	0.00
				(1.64)	(2.05)	(2.22)
$\bar{R}^2$	0.55	0.55	0.55	0.56	0.55	0.55