Balance Sheets of Financial Intermediaries: Do They Forecast Economic Activity?

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Abstract

This paper conducts a *real-time*, out-of-sample analysis of the forecasting power of various aggregate financial intermediaries balance sheets to a wide range of economic activity measures in the U.S. I find evidence that the balance sheets of leveraged financial institutions do have predictive power for future economic activity, and this predictability arises mainly through the housing sector. Nevertheless, I show that these variables have very little predictive power during periods of economic expansions and that predictability comes mainly during the crisis period.

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1 Introduction

The extent of the recent turmoil in financial markets and its long-lasting spillover effects to the real economy has renewed the interest in studies of the interaction between credit conditions and the macroeconomy. More meaningfully, it has called attention to the role played by financial intermediaries in the fluctuations of risk premia and economic activity.

This paper conducts a careful examination of the predictive power of different financial intermediaries' balance sheets to future changes in a wide set of economic activity measures in the U.S. Unlike previous research, I conduct all my forecasting tests in an out-of-sample, *real-time* setting. I report evidence that the balance sheets of some financial intermediaries, namely security broker-dealers, and, to a smaller extent, shadow banks have out-of-sample power in *real-time* for future economic activity. Nevertheless, I also find that the informational content of the balance sheets are quite unstable, accruing more significantly in recessionary periods, and/or times of financial stress. I then show, using data-rich forecasting methods, that the information contained in these balance sheets is roughly equal to the ones of traditional macro-financial series in normal economic environments.[1] On the data front, I contribute to the real-time forecasting literature by constructing a real-time dataset of aggregate financial intermediaries balance sheets as released by the Flow of Funds of the Federal Reserve Board quarterly.

My results also point to the relevant channels through which fluctuations in financial intermediaries' balance sheets forecast economic growth. I find that the predictive power of these balance sheets for future GDP arises mainly through the housing sector. Fluctuations in broker-dealers leverage and equity are strong predictors of expected real housing investment growth. This predictability is to a good extent orthogonal to the information contained in traditional macro and financial indicators.

Several papers have recently called attention to the importance of financial intermediaries balance sheets for the economy. On the theoretical front, a large number of recent papers show how fluctuations in balance sheets of financial intermediaries impact economic activity and and amplify economic shocks. Meh and Moran (2010), Christensen et al. (2010) and

[1] I define normal economic environments as periods absent of recessions and financial crisis.

Sandri and Valencia (2011) develop dynamic stochastic general equilibrium (DSGE) models to study how financial intermediaries balance sheets amplify shocks to the economy, as well as be the source of fluctuations itself, following significant disturbances to financial intermediaries' capital. On the empirical side, Adrian and Shin (2010) is one of the first studies to show that the fluctuations of balance sheets of financial institutions, especially Broker-Dealers, contain in-sample forecasting power for future GDP growth. Additionally, Adrian and Shin (2009b) argue that the balance sheets of Broker-Dealers and shadow banks have information for expected returns in the bond and equity markets in the US.[2] Kollmann and Zeugner (2012) show that the leverage of various sectors of the economy (financial, non-financial firms, and households) have both in-sample and out-of-sample forecasting power for economic activity. I add to their results by considering a real-time setting with additional financial intermediaries, more measures of economic activity, and by conducting a more systematic evaluation of time-variation in the forecasting performance of the different models.

The outline of the paper is as follows: Section 2 discusses the data. Section 3 exhibits an initial exploration of the forecasting power of balance sheets of financial intermediaries in a simple setup. The next section explores how the forecasting power of financial intermediaries' balance sheets compare to traditional macroeconomic and financial predictors, as well as examines its time stability. Finally, Section 4 concludes.

2 Data

I use a series of financial intermediaries' balance sheets, macroeconomic and financial indicators, and study the predictability of a diverse group of economic activity variables, namely: gross domestic product, industrial production, nonfarm payroll, real private investment, real housing investment, and durable consumption. Below I detail how I constructed my financial intermediaries' balance sheets, as well as macro-financial dataset.

In assessing the marginal predictive content of financial variables for real activity using

[2] Additionally, Adrian and Shin (2009a) argue that fluctuations in aggregate balance sheets of broker-dealers forecast exchange rate returns for a large set of countries at weekly, monthly and quarterly horizons, both in and out-of-sample. Etula (2008) shows that broker-dealer asset growth forecasts a wide range of commodity prices at quarterly horizons, both in-sample and out-of-sample.

real-time data, an important issue that arises is the fact that the latter is constantly being revised. I follow Faust and Wright (2009) and use the data as recorded two quarters after the quarter to which the data refers to as the realized value. For the national income and product accounts data, this corresponds to the data as recorded in the second revision.

2.1 Financial Intermediaries Balance Sheets Data

I investigate the predictive power of aggregate balance sheet fluctuations of the following financial intermediaries: (i) *Commercial Banks* (CB), comprised of Commercial Banks, Credit Unions and Savings Institutions; (ii) *Securities Broker-Dealers* (BD); (iii) *Shaddow Banks* (SB), comprised of Issuers of Asset Backed Securities, Finance Corporations and Funding Corporations; and (iv) *Agency- and GSE-backed mortgage pools.* Table 1 details the composition of all balance sheet variables. For each financial intermediary, I collect data on total financial assets (A) and liabilities (L). Equity (E) is then calculated as assets minus liabilities (A-L). Leverage is defined as assets over equity (A/E).[3]

Contrary to most financial variables, which are not usually revised, but akin to standard macroeconomic data, the Flow of Funds data is subject to data revisions. Hence, in order to analyze the performance of the balance sheet variables in a real-time setting, as the data were available to the forecaster at each period of time, I recovered vintage data available at the Federal Reserve Board website back to June 1999, the first available real-time vintage available. This date is, then, the starting period of my out-of-sample exercise. There is a trade-off in forecasting exercises on how to split the sample between the in-sample period for initial parameter estimation, and the out-of-sample evaluation period.[4] My choice of the starting period for the out-of-sample forecasts is determined by data availability. The models are estimated with data starting in March 1985. It was during this period, which coincides with the "Great Moderation", that the market based financial system became more prominent in the provision of credit in the economy.

[3] All variables are available at the Federal Reserve Bank Flow of Funds data. See http://www.federalreserve.gov/releases/z1/default.htm.

[4] Rossi and Inoue (2011) propose a methodology for evaluating out-of-sample forecasting performance that is robust to window size.

Figure 1 plots the annual growth rate rate of all financial intermediaries balance sheets. Table 2 presents summary statistics. Broker-Dealers' balance sheet growth rates are orders of magnitude higher and more volatile than the ones for Commercial Banks, Shadow Banks and Mortgage Pools. Whereas the average annual growth rate of Commercial Banks assets is of 6.5% with a 3.5% standard deviation, the Broker-Dealers' one is of 14.9% and a standard deviation of approximately 21%.

2.2 Macroeconomic and Financial Series

In order to verify how the predictability provided by the aggregate financial intermediaries balance sheet variables compares to more traditional predictors, I construct a panel of commonly used macroeconomic and financial predictors of economic activity. As I estimate the models with only real-time data, the panel is composed of significantly more financial than macroeconomic series, as the number of potential financial predictors (which are not revised) is higher than the number of commonly available real-time macroeconomic series. All macro series were obtained with the Federal Reserve Bank of Philadelphia Real-Time Dataset for Macroeconomists. All the financial series refer to the last day of the second month of each quarter. Table 3 lists the data used, as well as the transformation applied to each series in order to ensure stationarity. In total, I use 15 macroeconomic series, 58 financial predictors and 8 different balance sheet measures from 4 different financial intermediaries' sectors.

3 Forecasting Models

I start by examining if simple predictive regressions augmented with balance sheet variables provide more accurate forecasts than the simple autoregressive model.

Let y_t be the annualized growth rate from *t-1* to t of the variable to be forecasted and, x_{it}, the $n \times 1$ predictor vector. y_{t+h} is the h-step ahead value of the cumulative growth rate to be forecasted, $y_{t+h} = \sum_{i=0}^{h} y_{t+i}/h$. I estimate the following model for each financial intermediaries balance sheet variable separately:

$$y_{t+h} = \alpha + \sum_{j=1}^{P} \beta_i y_{t-j} + \gamma x_{i,t} + \varepsilon_{t+h} \tag{1}$$

where y_t is the economic activity being forecasted; $x_{i,t}$ is the additional balance sheet variable in question. The horizon of the forecast is defined by h. I estimate the above models for $h =$ 0, 1, 2, 3 and 4-quarters ahead. The lag order P of the autoregressive term is defined by the BIC.

In order to evaluate the forecasts, I initially report the root mean squared prediction error (RMSPE) defined as

$$RMSE^h = \sqrt{\frac{1}{T}\sum_{t=1}^{T}(\hat{y}_{t+h} - y^*_{t+h})}$$

where $\hat{y}_{t+h}$ is the forecast and y^*_{t+h} is the variable as observed two quarters after the quarter to which the data refers to, and T is the number of out-of-sample forecasts.

In order to test if the ratio of the RMSPEs are different from unity when comparing the financial intermediaries balance sheet forecasts to the benchmark AR model, I use Diebold and Mariano (1995) equal predictive accuracy test. It is known that when forecasting models are nested, hence equal in population under the null hypothesis, the Diebold-Mariano test statistic has a nonstandard asymptotic distribution. Clark and McCracken (2001) and McCracken (2007) provide additional tests to compare nested models. Nevertheless, Clark and McCracken (2012) show that, in *finite samples*, the traditional Diebold-Marino test statistic provides a good-sized test, even in the case of nested models, when the correction suggested by Harvey et al. (1997) is used. This approach to inference is also followed by Faust and Wright (2012) when forecasting inflation.

Table 4 shows the results of these initial forecasts. Mixed results were found for the various balance sheet variables. I find evidence that balance sheet measures associated with Security Broker-Dealers have a significant forecasting power for some of the economic activity indicators. There is no evidence that Commercial Banks balance sheets provide any information for forecasting the economic indicators here examined. The inclusion of Commercial Banks and Mortgage Pools balance sheets most often lead to higher RMSPE than the ones obtained with the simple AR. This result is consistent with previous findings by Adrian and Shin (2009b, 2010), who find that the informational content of balance sheet variables for economic activity and risk premia in equity and bond markets is mainly concentrated in the highly leveraged Broker-Dealers financial intermediaries.

Among the different Broker-Dealer balance sheet variables (asset, leverage and equity growth), it is also noteworthy that measures of equity and leverage are significantly more informative for future economic activity than total financial assets. By contrast, there is no evidence that measures of Broker-Dealer asset growth lead to any gains in forecast accuracy.

Table 4 shows that Broker-Dealer equity and leverage growth improve upon the autoregressive benchmark by about 10% for the 4-quarter ahead forecasts for GDP growth. For the remaining variables forecasted, these gains are in the range of 5 to 9%, but these are rarely significant. The biggest forecasting gains are for housing investment, where Broker-Dealer equity leads to a significant 15% reduction on RMSPE. These results indicate that the predictability of Broker-Dealer's balance sheets for GDP growth comes mainly from its ability to predict the housing sector.

3.1 Balance Sheets and other Macro and Financial Predictors

The simple models proposed in the previous section analyze if the information contained in financial intermediaries balance sheets provide additional information over the benchmark AR model. Next, I examine how the information contained in these balance sheets compare to other traditional macroeconomic and financial variables commonly used as predictors of economic activity. I use factor analysis in other to summarize the information of the real-time macroeconomic and financial dataset. I then analyze if the financial intermediaries balance sheets provide information over and above these factors.

Consider the following forecasting model:

$$y_{t+h} = \alpha + \sum_{j=1}^{P} \beta_i y_{t-j} + \sum_{i=1}^{m} \theta_i \hat{f}_{i,t} + \varepsilon_{t+h} \tag{2}$$

where $\{f_{i,t}\}_{i=1}^{m}$ are the first m estimated principal components of the $r \times 1$ vector of unobserved factors F_t in the following factor model

$$X_{it} = \lambda_i F_t + \epsilon_{it} \tag{3}$$

The macroeconomic and financial panel data is denoted by X_{it},[5] λ_i are the factor loadings, and ϵ_{it} are idiosyncratic shocks. The model above is the traditional diffusion index forecasting framework of Stock and Watson (2002). In order to generate forecasts with diffusion indices, one needs to choose the number of factors to be included in the forecasting regression. For the sake of parsimony, I restrict myself to forecasting regressions with the first three factors $F_{1:3,t}$.[6]

I first study how forecasting regressions augmented with the macro-financial factors, as in equation (2), and estimated with my real-time dataset, compare with the benchmark AR model. Table 5 shows the results for this comparison. As in Bernanke and Boivin (2003) and Faust and Wright (2009), I find no gains in forecast accuracy over the benchmark AR model for the factor augmented forecasts. As shown by these papers, the real-time nature of the data is not responsible for the factor model's poor results. The fact that my panel is relatively small compared to the datasets traditionally used for factor analysis, as well as that it significantly over-represents financial data to the detriment of other macroeconomic indicators, might explain the factor forecasts general poor results.

Next, I examine how the forecasts generated by the financial intermediaries' balance sheet models as in equation (1) compare with the macro-financial factors in equation (2). Table 6 summarizes the results. I find similar improvements over the factor forecasts than for the benchmark AR models. Nevertheless, most of these improvements are not statistically significant. A notable exception is again the housing sector, where the gains from forecasting with Broker-Dealer and Shadow Banks' balance sheets at longer horizons are also large and significant. As in the previous subsection, I find that the forecasting power for financial intermediaries' balance sheets, as in the previous section, are concentrated in the sectors

[5] X_{it} does not include any financial intermediaries' balance sheet data.

[6] In a supplemental appendix, I check the robustness of my results to different number of factors included in the forecasting regressions.

most sensitive to credit conditions, as housing and durable goods consumption.

3.2 When do (not) financial intermediaries' balance sheets add information?

In the previous section, I showed that models augmented with Broker-Dealers leverage and equity growth, as well as Shadow Banks asset growth provide significant forecasting power beyond the one already contained in traditional macroeconomic and financial series for future economic activity. Nevertheless, forecasting regressions have been recently shown to suffer from significant instabilities, as highlighted by Giacomini and Rossi (2010). Hence, one could envision a situation where forecasting models augmented with financial intermediaries' balance sheet variables provide more forecasting power during certain times, as periods marked by financial volatility, than periods characterized by financial tranquility.

3.2.1 Evidence from Giacomini and Rossi (2010) Fluctuation Tests

In order to capture the time variation in the relative forecasting performance of these financial intermediaries' balance sheets, I apply Giacomini and Rossi (2010) fluctuation test for forecast comparisons in unstable environments. Rossi and Sekhposyan (2010) applied the Fluctuation test to a wide range of models for predicting U.S. GDP growth and inflation. They find that most of the predictors either completely lost, or saw their predictive ability strongly diminished after the mid-1970s.

Giacomini and Rossi (2010)'s focus is the statistical difference between the two forecasting models:

$$rMSFE_t = \frac{1}{m}\left(\sum_{j=t-m/2}^{t+m/2} \hat{\epsilon}_{t+h}^2 - \sum_{j=t-m/2}^{t+m/2} \hat{\eta}_{t+h}^2\right) \tag{4}$$

where $\hat{\epsilon}_t$ and $\hat{\eta}_t$ are the out-of-sample forecast error of first (balance sheet model) and second (AR) model, respectively. I construct rolling estimates of the relative mean square forecast errors (rMSFE) using a two-sided window (m) of 20 quarters to depict the time variation in the performance of the financial intermediaries' balance sheet models relative to the simple

AR model.[7]

The fluctuation test is based on the following re-scaled version of the rMSFE statistic

$$F_{t,m}^{OOS} = \hat{\sigma}^{-1} m^{-1/2} \left(\sum_{j=t-m/2}^{t+m/2} \hat{\epsilon}_{t+h}^2 - \sum_{j=t-m/2}^{t+m/2} \hat{\eta}_{t+h}^2 \right) \tag{5}$$

where $\hat{\sigma}^2$ is a Heterocedasticity and Autocorrelation Consistent estimator of the variance σ^2.

The test's null hypothesis is that the forecasting performance of both models is equal at each period,

$$H_0 : E(\hat{\epsilon}_t^2 - \hat{\eta}_t^2) = 0 \tag{6}$$

Giacomini and Rossi (2010) show how to approximate the distribution of the Fluctuation test by functionals of Brownian motions and provide critical values for different significance levels, window and sample sizes.

Figures 2 to 7 plot the results of the tests, as well as its 10% critical values. Each figure shows the results for tests conducted with regressions using one financial intermediaries's balance sheet at a time, as in equation (1). By plotting the time variation in the $F_{t,m}^{OOS}$ statistic together with the critical values, one can easily see the periods of time when the statistic crosses the critical values, signalling that the financial intermediaries' balance sheet models outperformed, or were outperformed by the simple AR benchmark.

It is clear from the figures that balance sheets from Commercial Banks and Mortgage Pools have no forecasting power throughout the whole forecasting sample. For many of the indicators, models including Commercial Banks Leverage and Equity produce forecasts that are actually statistically inferior to the benchmark AR from 2005 to early 2007.

The figures also show that there is a substantial time-variation in the forecasting performance of Broker-Dealers equity and leverage growth for economic activity. Whereas Fluctuation Tests indicate that their forecasting performance was no better than the benchmark AR model in the first part of the sample, they also show a significant increase in forecasting power during the last financial crisis and following great recession.

[7] In an appendix, I test the robustness of the results to different choices of window sizes.

It is also interesting to note that Broker-Dealer equity and leverage growth not only have a higher forecasting power for housing investment, but that this forecasting power also arises significantly earlier than for other predicted variables. The Fluctuation Test signals the superiority of the Broker-Dealer equity growth model over the benchmark AR as early as in the first semester of 2007.

3.3 Real-time vs. revised data

In order to clarify the importance of real-time data for the balance sheet of the financial intermediaries, this section contrasts the results obtained with real-time data and the ones estimated with the revised data of balance sheets and macroeconomic aggregates, as they were observed in the last quarter of 2010.

Results are shown in Table 7. There is little different in the RMSPE ratios estimated with fully revised data, as in Bernanke and Boivin (2003) and Faust and Wright (2009).[8] In most cases, the financial intermediaries' balance sheet models with revised data compare slightly worst with the benchmark AR models than in the fully real-time case. Nevertheless, the conclusion that Broker-Dealers equity and leverage growth are the most informative predictors about future economic activity is robust to the use of real-time or revised data.

[8] As for the level of RMSPE's, the latter are usually higher in real-time than in revised data.

4 Conclusion

This paper has conducted an out-of-sample, real-time analysis of the predictive power of aggregate financial intermediaries' balance sheets of various financial intermediaries for a range of economic activity indicators in the U.S. I find significant forecasting power is restricted to balance sheets from the more leveraged financial sector, broker-dealers. I also show that there are significant forecasting instabilities in the performance of balance sheet models. Through Giacomini and Rossi (2010) fluctuation tests, I find that the positive performance of Broker-Dealers balance sheets forecasting models arise mainly during the crisis period.

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Table 1: Composition of Balance Sheet Variables

Financial Intermediaries	Variables
Broker-Dealers (BD)	Broker-Dealers
Total Commercial Banks (CB)	Commercial Banks Savings Institutions Credit Unions
Shadow Banks (SB)	Asset Backed Securities Issuers Finance Corporations Funding Corporations
Mortgage Pools (MP)	Mortgage Pools

Note: This table shows the composition of all balance sheet indicators used in the analysis. All data was gathered from the Federal Reserve Board Flow of Funds data. Equity is defined as total financial assets minus total financial liabilities, $(A - L)$. Leverage is defined as total financial assets over equity, $A/E = A/(A - L)$.

Table 2: Summary Statistics of Balance Sheet Explanatory Variables

	BDA	BDL	BDE	CBA	CBL	CBE	SBA	MPA
Mean	14.86	7.91	11.26	6.58	-3.77	14.30	12.37	10.20
Median	15.29	8.61	8.68	7.29	-1.97	10.08	13.09	10.18
SD	20.93	29.02	23.35	3.54	16.04	22.90	9.18	17.87
Min	-40.65	-64.67	-37.30	-1.94	-46.74	-30.27	-21.42	-80.03
Max	97.45	100.04	94.31	14.14	46.00	107.83	37.20	45.83
AR(1)	0.75	0.72	0.71	0.91	0.73	0.74	0.99	0.99

Note: The balance sheet sample is from 1985Q1 to 2010Q4. All data refers to quarterly growth rates in percentage points. BDA: Broker-Dealer Asset, BDL: Broker-Dealer Leverage, BDE: Broker-Dealer Equity, CBA: Commercial Banks Asset, CBL: Commercial Banks Leverage, CBE: Commercial Banks Equity, SBA: Shadow Banks Asset, MPA: Mortgage Pools Asset.

Table 3: Variables and transformations in our Large Dataset

Variable	Transf	Variable	Transf
Macroeconomic Variables (15)			
Gross Domestic Product	5	S&P 500	5
Personal Consumption Expenditures	5	Moody's Aaa yield	1
PCE Durables	5	Moody's Baa yield	1
Private Investment	5	Moody's Baa-Aaa spread	1
Housing	5	1-Month Euro Dollar rate	1
Inventories	5	3-Month Euro Dollar rate	1
Federal Government Expenditure	5	6-Month Euro Dollar rate	1
State and Local Government Expenditure	5	Exchange Rate: Switzerland	5
Exports	5	Exchange Rate: UK	5
Imports	5	Exchange Rate: Canada	5
Industrial Production	5	Oil Price	5
Capacity Utilization	5		
Nonfarm Payroll	5	*Balance Sheets (8)*	
GDP Deflator	6		
M2	6	Broker-Dealers Asset Annual Growth rate	1
		Broker-Dealers Equity Annual Growth rate	1
Financial Variables (59)		Broker-Dealers Leverage Annual Growth rate	1
Fama-French Factor: RmRf	1	Commercial Banks Asset Annual Growth rate	1
Fama-French Factor: SMB	1	Commercial Banks Leverage Annual Growth rate	1
Fama-French Factor: HML	1	Commercial Banks Equity Annual Growth rate	1
Frama-French Stock Portfolios (25)	1	Shadow Banks Asset Annual Growth rate	1
Momentum Factor	1	Mortgage Pools Asset Annual Growth rate	1
Fed Funds Rate	1		
3-Month TBill rate	1		
6-Month constant maturity Treasury yield	1		
6-Month constant maturity Treasury Spread	1		
1-Year constant maturity Treasury yield	1		
1-Year constant maturity Treasury Spread	1		
2-Year constant maturity Treasury yield	1		
2-Year constant maturity Treasury Spread	1		
3-Year constant maturity Treasury yield	1		
3-Year constant maturity Treasury Spread	1		
5-Year constant maturity Treasury yield	1		
5-year constant maturity Treasury Spread	1		
7-year constant maturity Treasury yield	1		
7-Year constant maturity Treasury Spread	1		
10-Year constant maturity Treasury yield	1		
10-Year constant maturity Treasury Spread	1		
3-Month nonfinancial commercial paper Yield	1		
3-Month nonfinancial commercial paper Spread	1		
3-Month Euro Dollar Rate Spread	1		

Note: This table shows our dataset, as well as the transformation applied to each one of the series: 1-No change, 2-log, 3-1st difference, 4-2nd difference, 5-1st difference of log, 6-2nd difference of logs.

Table 4: Relative Root Mean Square Error of Alternative Balance Sheets Augmented Models *vs* Direct Autoregression

		BDA	BDL	BDE	CBA	CBL	CBE	SBA	MPA
GDP	h=0	1.00	0.99	0.97	1.02	1.03	1.02	0.98*	1.00
	h=1	1.00	0.99	0.96	1.03	1.05	1.02	0.98*	1.00
	h=2	1.00	0.92*	0.94	1.02	1.05	1.03	0.99	1.00
	h=3	1.00	0.90*	0.92	1.03	1.03	1.02	0.99	1.00
	h=4	1.00	0.89**	0.91	1.02	1.02	1.02	0.99	1.00
Investment	h=0	1.04*	0.99	0.99	1.00	1.02	1.01	1.02	1.01
	h=1	1.03	0.97	0.98	1.00	1.03	1.01	1.03*	1.00
	h=2	1.02	0.96	0.96	1.00	1.04	1.02	1.03	0.99
	h=3	1.01	0.93	0.95	1.00	1.03	1.02	1.03	0.99
	h=4	1.00	0.93	0.95	1.00	1.03	1.03	1.02	0.98
Housing	h=0	1.02	1.15	0.95***	1.01	1.20***	1.12***	1.00	1.00
	h=1	1.02	1.04	0.94	1.00	1.20**	1.13**	1.00	1.01
	h=2	1.01	0.93	0.91*	0.99	1.18**	1.13**	0.99	1.01
	h=3	0.99	0.91**	0.86*	0.98	1.13**	1.08*	0.99	1.01
	h=4	0.98	0.94**	0.85*	0.98	1.06*	1.02	0.98	1.01
Nonfarm Payroll	h=0	1.00	0.99	0.95*	1.03	1.02	1.01	0.99*	1.00
	h=1	1.01	0.96	0.94	1.05	1.03	1.01	0.99	1.00
	h=2	1.01	0.95	0.93	1.05	1.05	1.03	0.99*	1.00
	h=3	1.01	0.95	0.93	1.05	1.04	1.03	0.99	1.00
	h=4	1.01	0.95	0.94	1.05	1.02	1.02	0.99	1.00
Durables	h=0	0.99	1.01	1.00	1.03	1.12*	1.10*	0.97	0.99
	h=1	1.03	0.98	1.01	1.04	1.15	1.12	1.00	0.99
	h=2	1.01	0.96	0.95	1.03	1.11	1.09	0.98	0.98
	h=3	0.99	1.00	0.98	1.01	1.06	1.04	1.01	0.99
	h=4	1.00	0.93**	0.95	1.01	1.04	1.03	1.00	0.99
IP	h=0	1.00	1.02	0.98	1.00	1.01	1.02	1.00	1.01
	h=1	1.02	1.01	0.96	1.01	1.02	1.01	1.00	1.01
	h=2	1.03	0.98	0.96	1.01	1.00	1.01	1.00	1.01
	h=3	1.01	0.97	0.96	1.00	1.00	1.01	1.00	1.01
	h=4	1.01	0.95	0.95	1.00	0.99	1.00	1.00	1.01

Notes: Sample: 1985Q1 to 2010Q4. Entries in the table denotes the ratio of the RMSPE from each balance sheet augmented autoregression to the RMSPE from a direct autoregression. The out-of-sample forecasts start at 1999Q2 and are fully real-time. One, two and three asterisks are assigned to entries in which the relative root mean square prediction error is significantly different from one at the 10, 5 and 1 percent significance levels, respectively. These are based on the two-sided test of Diebold and Mariano (1995), implemented as described in the text. BDA: Broker-Dealer Asset, BDE: Broker-Dealer Equity, BDL: Broker-Dealer Leverage, CBA: Commercial Banks Asset, CBE: Commercial Banks Equity, CBL: Commercial Banks Leverage, SBA: Shadow Banking Assets, MPA: Mortgage Pools Assets.

Table 5: Relative RMSPE of Real-Time Out-of-Sample Macro-Financial Factors Forecasts *vs* Benchmark Autoregressive

Economic Indicator	h=0	h=1	h=2	h=3	h=4
Gross Domestic Product	1.05	1.04	1.01	0.99	0.95
Investment	1.06	1.01	1.04	1.03	1.01
Housing	1.06	1.02**	1.06*	1.03	1.06
Nonfarm Payroll	1.02	0.99	1.01	1.02	1.03
Durables	1.14	1.11	1.17	1.08	1.12
Industrial Production	0.99	1.08	1.05	1.09	1.09

Note: Sample: 1985Q1 to 2010Q4. Entries in the table denote the ratio of the RMSPE from the factors augmented autoregression to the RMSPE from a direct autoregression. The out-of-sample forecasts start at 1999Q2 and are fully real-time. Factor forecasts use the first three principal components from the macro-financial dataset. One, two and three asterisks are assigned to entries in which the relative root mean square prediction error is significantly different from one at the 10, 5 and 1 percent significance levels, respectively. These are based on the two-sided test of Diebold and Mariano (1995), implemented as described in the text.

Table 6: Relative RMSPE of Alternative Balance Sheets real-time Forecasts *vs* Macro-Financial Factors Forecasts

		BDA	BDL	BDE	CBA	CBL	CBE	SBA	MPA
GDP	h=0	0.96	0.94	0.93	0.98	0.99	0.97	0.94	0.96
	h=1	0.96	0.95	0.92	0.98	1.00	0.98	0.94	0.96
	h=2	1.00	0.91	0.93	1.02	1.04	1.02	0.98	0.99
	h=3	1.01	0.91	0.93	1.04	1.04	1.04	1.00	1.01
	h=4	1.04	0.94	0.96	1.07	1.06	1.07	1.04	1.05
Investment	h=0	0.98	0.93	0.93	0.95	0.96	0.95	0.96	0.95
	h=1	1.01	0.95	0.96	0.99	1.01	1.00	1.01	0.98
	h=2	0.98	0.92	0.92	0.96	0.99	0.98	0.98	0.95
	h=3	0.98	0.90	0.92	0.97	1.00	0.99	1.00	0.96
	h=4	0.99	0.91	0.94	0.99	1.01	1.01	1.01	0.97
Housing	h=0	0.96	1.08	0.89	0.94	1.12	1.05	0.94	0.94
	h=1	1.00*	1.02	0.92**	0.98**	1.17	1.11	0.98**	0.98**
	h=2	0.95	0.88*	0.86*	0.94	1.11	1.07	0.94*	0.95
	h=3	0.96	0.88**	0.83*	0.95	1.09	1.05	0.96	0.98
	h=4	0.93	0.89**	0.80*	0.93	1.00	0.97	0.93	0.96
Nonfarm Payroll	h=0	0.98	0.97	0.93**	1.00	1.00	0.98	0.97	0.98
	h=1	1.02	0.98	0.95	1.07	1.05	1.02	1.00	1.01
	h=2	1.00	0.94	0.91	1.04	1.04	1.02	0.98	0.99
	h=3	0.99	0.93	0.92	1.03	1.02	1.01	0.98	0.99
	h=4	0.97	0.92	0.91	1.02	0.99	0.99	0.96	0.97
Durables	h=0	0.88	0.89	0.88	0.91	0.99	0.97	0.85*	0.88*
	h=1	0.93	0.89	0.91	0.94	1.04	1.01	0.90	0.89
	h=2	0.86	0.82	0.81	0.88	0.95	0.93	0.84	0.84
	h=3	0.92	0.92	0.90	0.94	0.98	0.96	0.93	0.91
	h=4	0.89	0.83**	0.84	0.90	0.92	0.92	0.89	0.88
IP	h=0	1.01	1.03	0.99	1.01	1.02	1.03	1.01	1.00
	h=1	0.95	0.94	0.90	0.93	0.95	0.94	0.93	0.99
	h=2	0.98	0.93	0.92	0.96	0.95	0.96	0.95	1.01
	h=3	0.92	0.89	0.88	0.92	0.91	0.92	0.92	1.01
	h=4	0.93	0.87	0.88	0.92	0.91	0.92	0.92	1.00

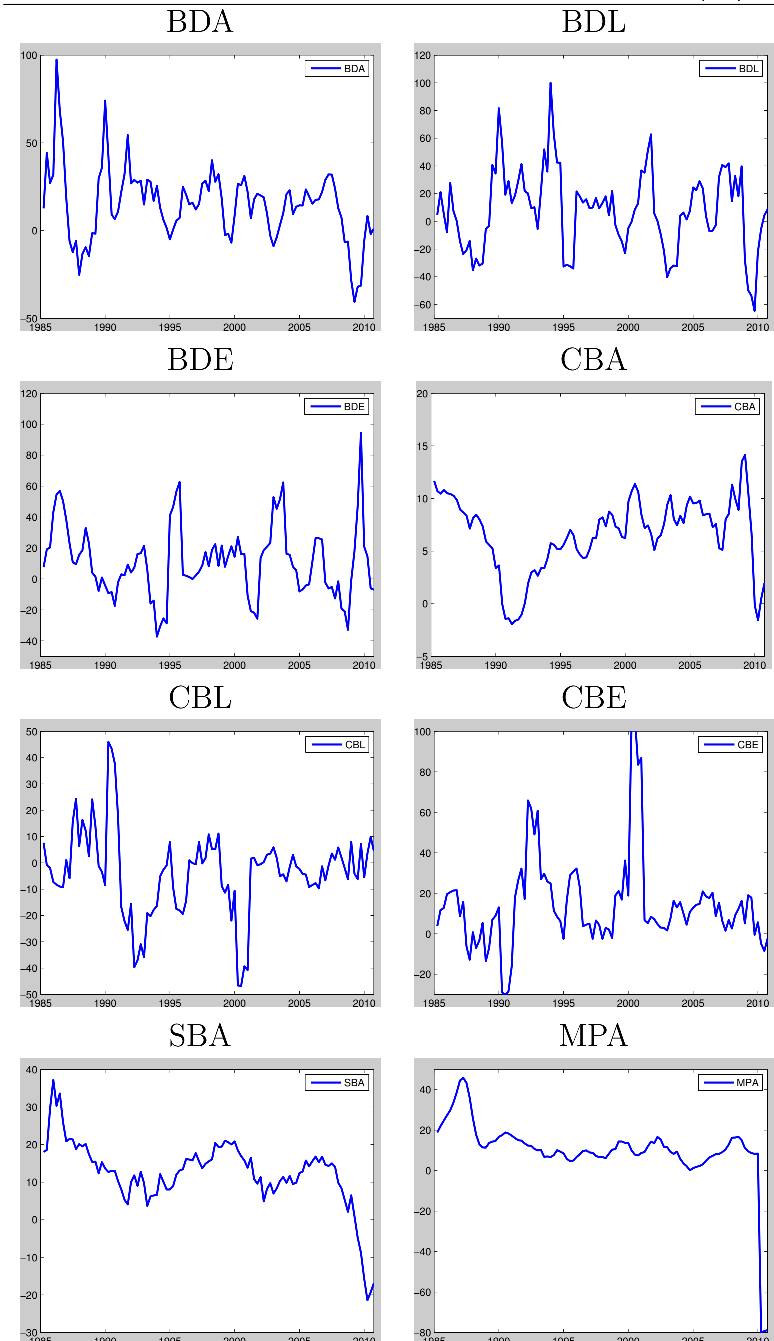
Note: As of Table 4, except that benchmark model is the factor augmented autoregression as in equation (2) with $m = 3$.

Table 7: Relative Root Mean Square Error of Alternative Balance Sheets over Benchmark Autoregressive - Final Revised Data

		BDA	BDL	BDE	CBA	CBL	CBE	SBA	MPA
GDP	h=0	1.00	1.00	0.98	1.02	1.02	1.03	0.98*	1.00
	h=1	1.00	0.99	0.97	1.04	1.04	1.05	0.98	1.00
	h=2	1.01	0.97	0.94	1.05	1.05	1.06	0.98	1.00
	h=3	1.00	0.95*	0.93	1.04	1.05	1.05	0.99	1.00
	h=4	1.00	0.94*	0.93*	1.03	1.04	1.04	0.99	1.00
Investment	h=0	1.04	1.00	1.01	1.00	1.01	1.02	1.02*	1.01
	h=1	1.03	0.98***	1.00	1.00	1.02	1.03	1.03*	1.00
	h=2	1.02	0.97**	0.98	1.00	1.03	1.04	1.03*	1.00
	h=3	1.01	0.96**	0.96	0.99	1.04	1.05	1.03	1.00
	h=4	1.01	0.95**	0.95	0.99	1.05	1.06	1.03	0.98
Housing	h=0	1.03	1.00	0.98	1.00	1.14***	1.16*	1.00	1.01
	h=1	1.02	0.98	0.97	1.00	1.12*	1.14	1.00	1.01
	h=2	1.01	0.96	0.96	1.00	1.11**	1.13	0.99	1.01
	h=3	0.99	0.93*	0.95	0.99	1.10***	1.11	0.99	1.01
	h=4	0.98	0.93*	0.97	0.99	1.07***	1.08	0.98	1.01
Nonfarm Payroll	h=0	1.00	1.00	0.96*	1.03	1.03	1.07	1.00	1.00
	h=1	1.01	0.98	0.94	1.05	1.07	1.11	0.99	1.00
	h=2	1.01	0.96	0.92*	1.04	1.07	1.11	0.99	1.00
	h=3	1.01	0.95	0.92*	1.04	1.08	1.11	0.99	1.00
	h=4	1.01	0.94	0.92*	1.04	1.07	1.11	0.99	1.00
Durables	h=0	0.98	1.01	0.99	1.03	1.05	1.07	0.96	1.00
	h=1	1.01	0.99	0.97	1.05	1.06	1.09	0.99	0.99
	h=2	1.00	0.98	0.96	1.03	1.06	1.09	0.97	0.99
	h=3	1.00	0.98	0.97	1.02	1.06	1.09	1.00	0.99
	h=4	1.00	0.97	0.95	1.01	1.03	1.06	1.00	1.00
IP	h=0	1.00	1.01	1.00	0.99	1.01	1.02	0.99	1.00
	h=1	1.02	1.01	0.98	1.00	1.04	1.05	1.00	1.00
	h=2	1.02	1.00	0.97	1.00	1.05	1.05	0.99	1.00
	h=3	1.01	0.99	0.98	1.00	1.05	1.05	1.00	1.00
	h=4	1.01	0.99	0.97	1.00	1.05	1.06	1.00	1.00

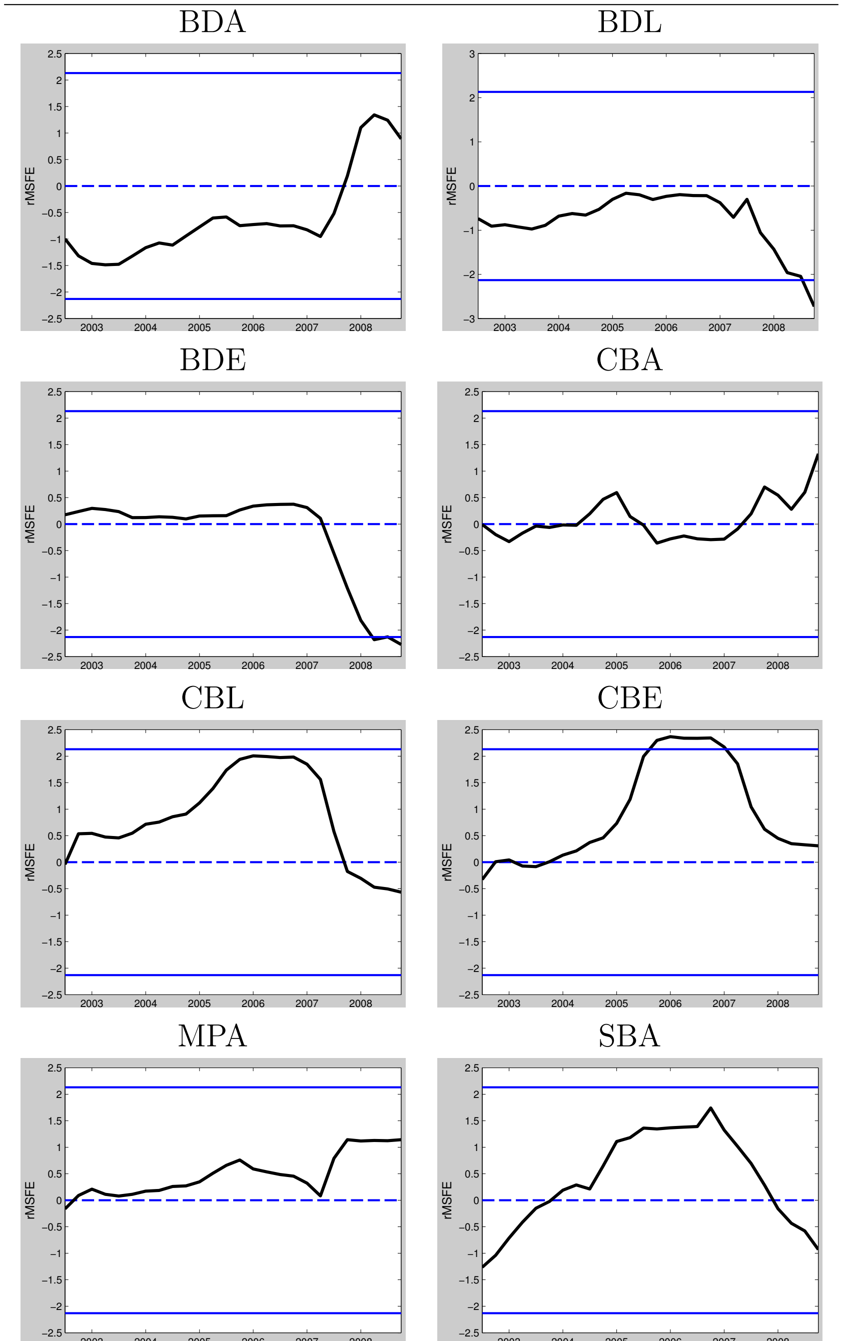
Note: As of Table 4, except that models used final revised data as of 2010Q4.

Figure 1: **Balance Sheets Annual Change (%)**



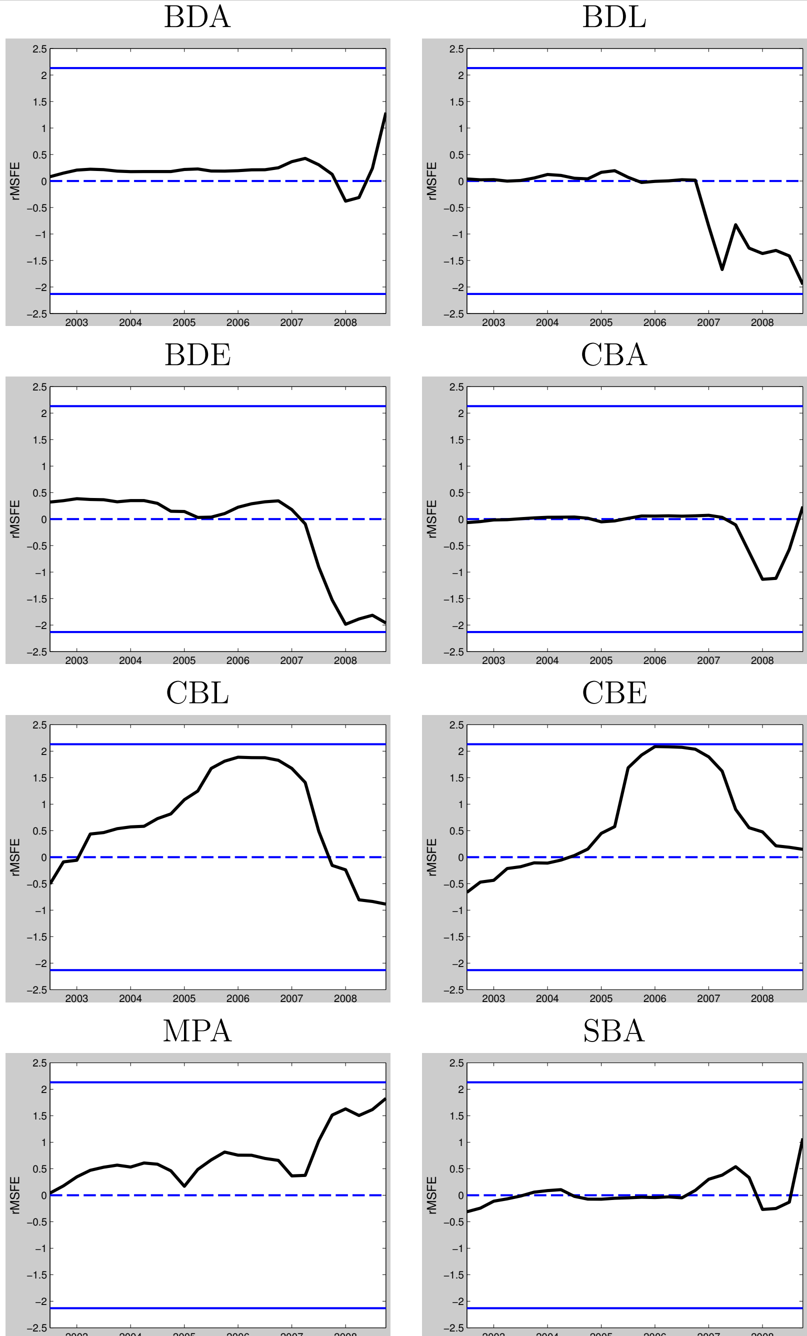
Notes: This figure shows the different balance sheet variables from 1985Q1 to 2010Q4. All data refers to anual growth rates in percentage points, as recorded in the 2010Q4 vintage. BDA: Broker-Dealer Asset, BDL: Broker-Dealer Leverage, BDE: Broker-Dealer Equity, CBA: Commercial Banks Asset, CBL: Commercial Banks Leverage, CBE: Commercial Banks Equity, SBA: Shadow Banks Asset, MPA: Mortgage Pools Asset.

Figure 2: Giacomini and Rossi (2010) Fluctuation Test for Equal Out-of-Sample Predictability for **GDP** at h = 4



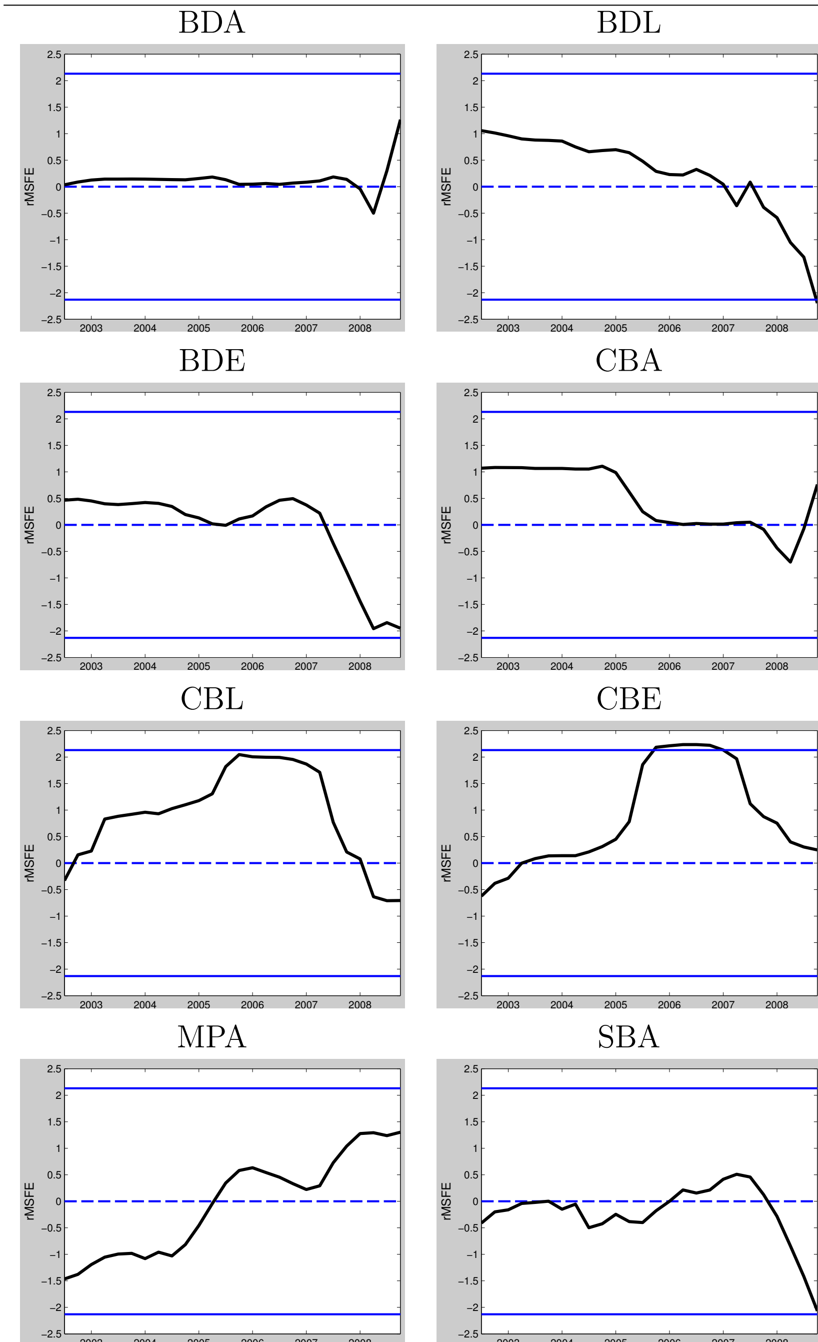
Notes: The figures show Giacomini and Rossi (2010) Fluctuation Test for Equal Out-of-Sample Predictability at h = 4, centered at time t with a two-sided window of 20 quarters for each of the balance sheets augmented forecasting models. Fluctuation test critical value at the 10% significance level (2.13 and -2.13) in blue; if the Fluctuation test statistic exceeds the critical value, the null that the benchmark model is the true model is rejected for the particular window. Benchmark model is direct autoregression.

Figure 3: Giacomini and Rossi (2010) Fluctuation Test for Equal Out-of-Sample Predictability for **Industrial Production** at h = 4



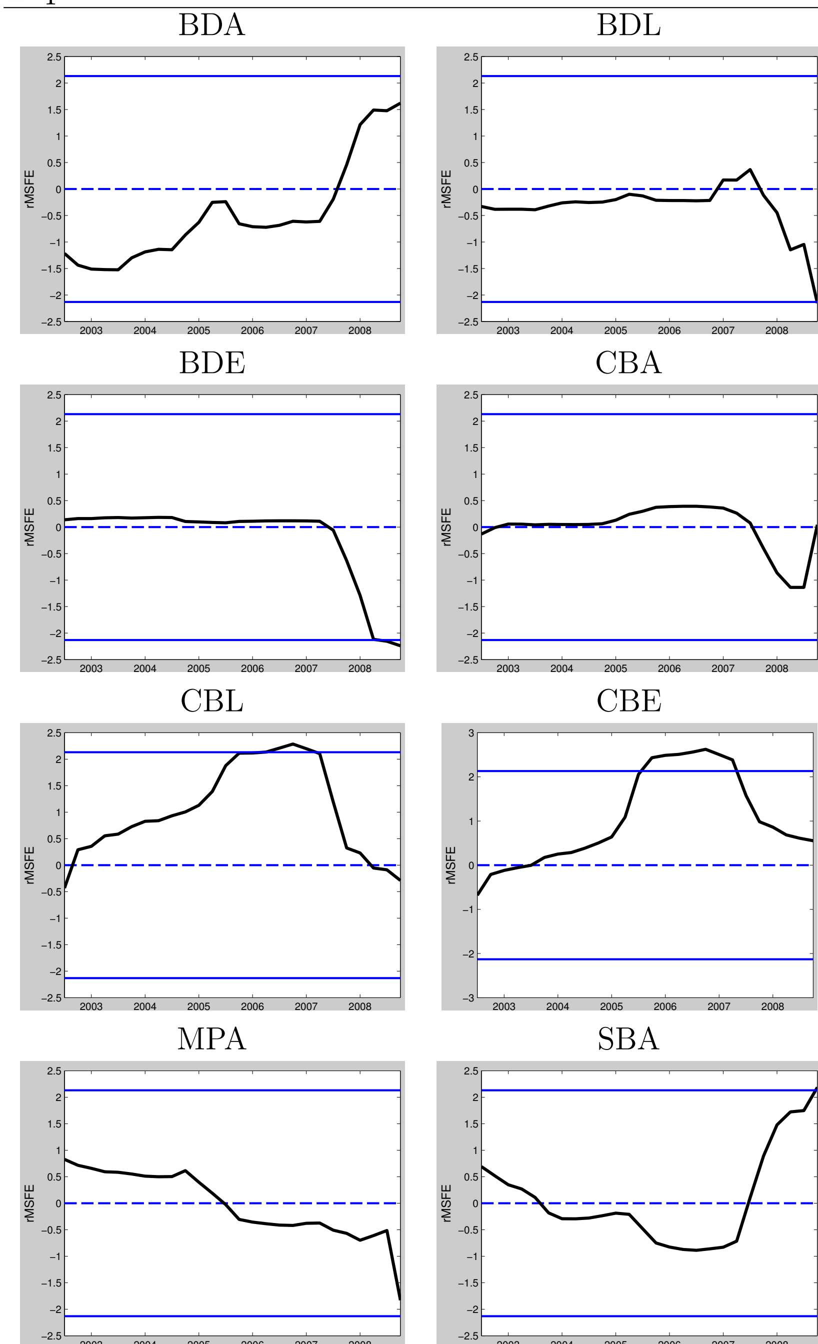
Notes: As of Figure 2.

Figure 4: Giacomini and Rossi (2010) Fluctuation Test for Equal Out-of-Sample Predictability for **Nonfarm Payroll** at h = 4



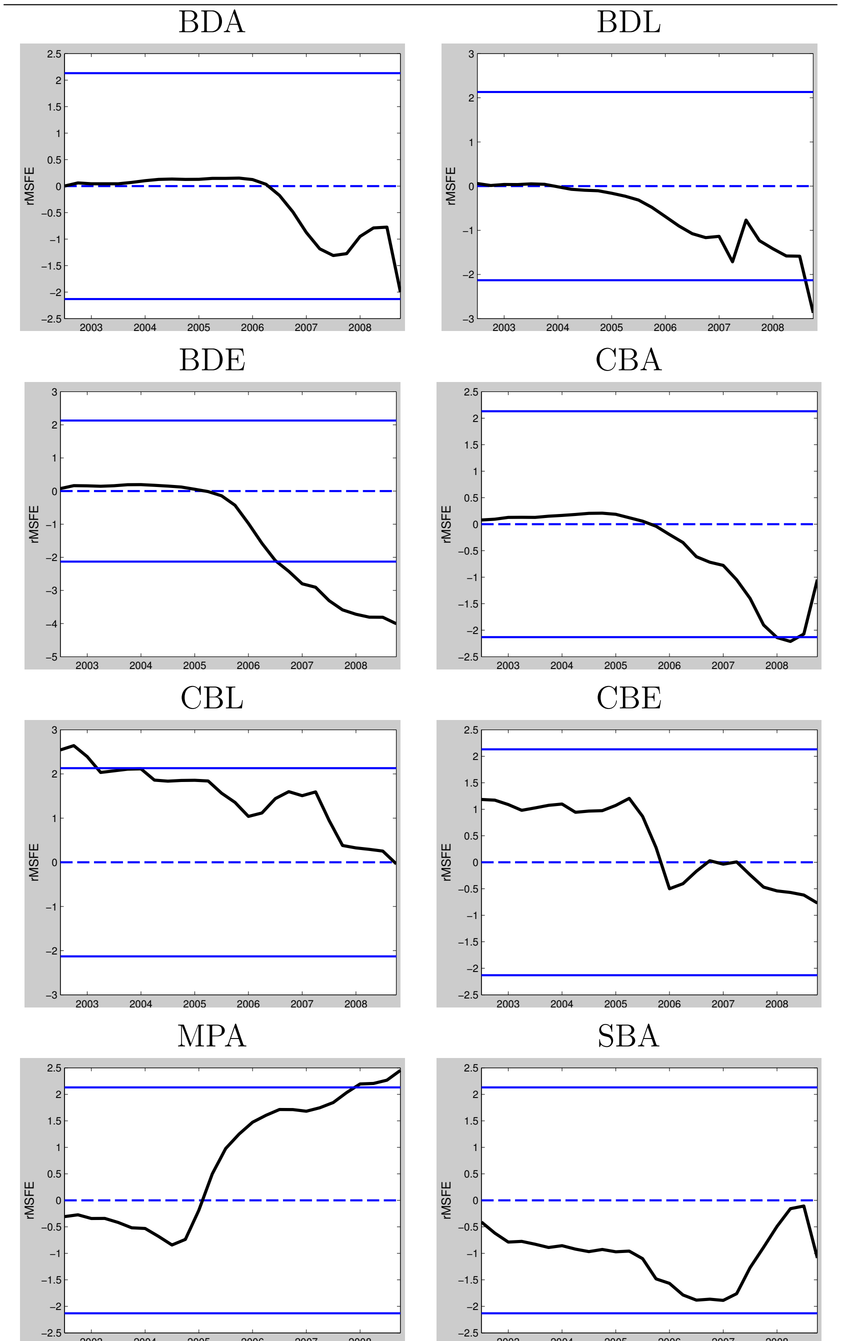
Notes: As of Figure 2.

Figure 5: Giacomini and Rossi (2010) Fluctuation Test for Equal Out-of-Sample Predictability for **Investment** at h = 4



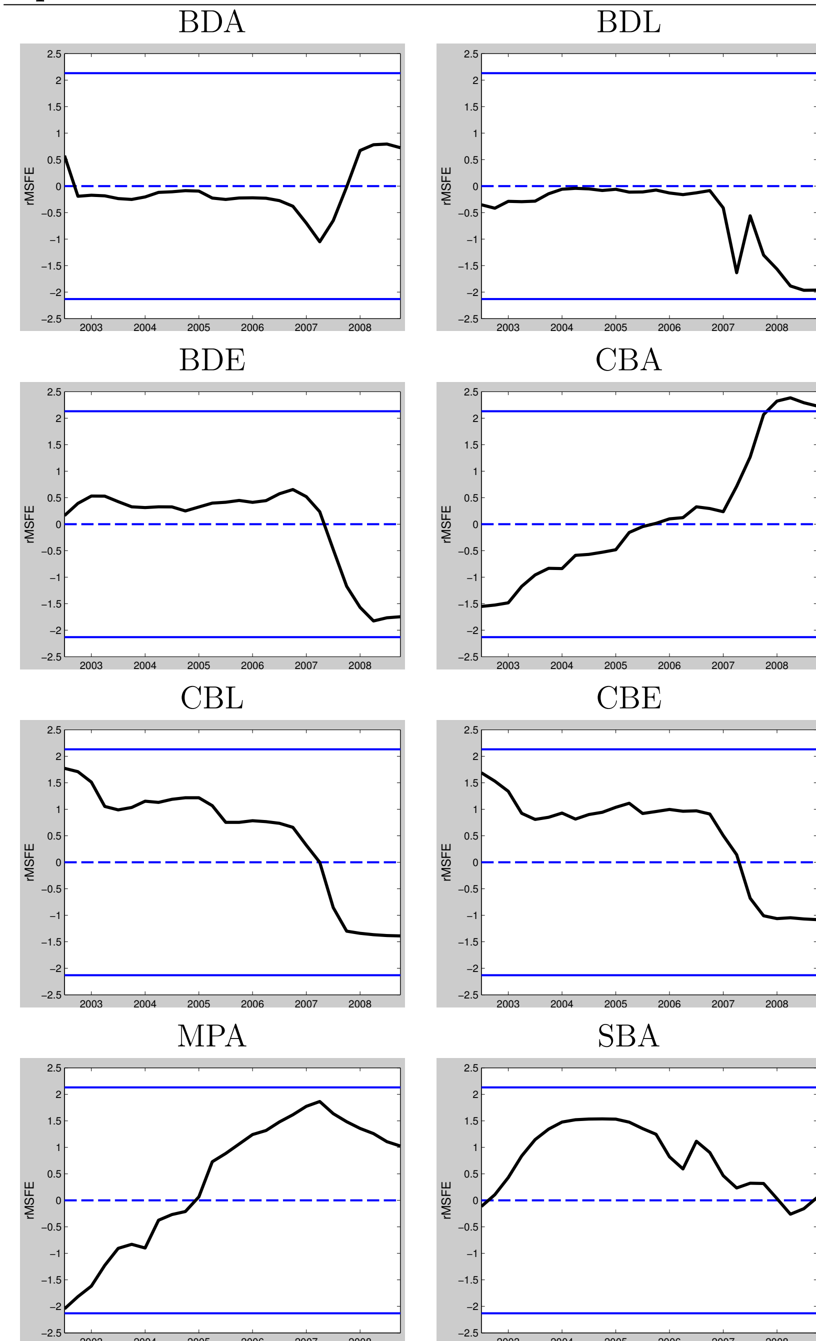
Notes: As of Figure 2.

Figure 6: Giacomini and Rossi (2010) Fluctuation Test for Equal Out-of-Sample Predictability for **Housing** at h = 4



Notes: As of Figure 2.

Figure 7: Giacomini and Rossi (2010) Fluctuation Test for Equal Out-of-Sample Predictability for **Durables Consumption** at h = 4



Notes: As of Figure 2.