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ABSTRACT

Leverage as a Predictor for Real Activity and Volatility *

This paper explores the link between the leverage of the US financial sector, of households and of non-financial businesses, and real activity. We document that leverage is negatively correlated with the future growth of real activity, and positively linked to the conditional volatility of future real activity and of equity returns. The joint information in sectoral leverage series is more relevant for predicting future real activity than the information contained in any individual leverage series. Using in-sample regressions and out-of sample forecasts, we show that the predictive power of leverage is roughly comparable to that of macro and financial variables commonly used by forecasters. Leverage information would not have allowed to predict the 'Great Recession' of 2008-2009 any better than conventional macro/financial predictors.

JEL Classification: C53, E32, E37 and G20
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1. Introduction

In the years before the recent (2007-09) financial crisis, the leverage of many major financial institutions increased steadily, and reached unprecedented levels. The crisis revealed the fragility of the financial sector, and of many highly indebted non-financial firms and households, and it has triggered the sharpest global recession since the 1930s. Before the crisis, structural macro models largely abstracted from financial intermediaries, and macro forecasting models ignored balance sheet information. The recent dramatic events require a rethinking of the role of finance for real activity. In particular, understanding the link between balance sheet conditions and the real economy has become a key priority.

To explore that link, this paper analyzes the predictive power of leverage for GDP, industrial production, unemployment and physical investment (as well as for equity returns). Leverage is defined as the ratio of an agent/sector's assets to her net worth (assets minus debt). We use quarterly US data (1980-2010), and consider leverage information from the Flow of Funds, for three broad financial sectors (insurance companies, securities brokers-dealers, and commercial banks), as well as for households and for non-financial corporate businesses. We complement that information using the ratio of assets (at book-values) to the *market value* of equity, for financial corporations included in three Dow Jones stock price indices: 'US-Insurance', 'US-Banks' and 'US-Financial Services'. We estimate forecast equations for real activity and equity returns that use these 8 sectoral leverage ratios, and principal components of a set of 30 other macro-financial variables, as predictors. Predictive performance is evaluated using both in-sample fit and (rolling) out-of-sample forecast accuracy.

Our results show that *each* of our 8 leverage variables is negatively related to *future* real activity. This result is not driven by the recent financial crisis. The predictive power of leverage is roughly comparable to that of standard macro-financial forecast variables. Among the 8 leverage series, insurance sector leverage (from Flow of Funds), and the equity-market-value-based leverage measure for banks have the highest out-of-sample predictive ability for GDP. For forecasting real activity, it is advisable to combine the sectoral leverage information, using cross-sectional medians or principal components, instead of using the sectoral leverages series individually as predictors. Thus, the *joint* information in the sectoral leverage series is more relevant than the information contained in any individual sectoral leverage series. However, despite the high statistical significance of leverage (and of macro-financial factors) in the forecasting regressions, none of the variables considered here would helped in predicting the 'Great Recession' of 2008-2009.

We also document that higher leverage at a given date is associated with greater uncertainty about future economic conditions. In particular, leverage is strongly positively related to the absolute value of forecast errors for future real activity (generated by our forecast equations) and to the CBOE equity market volatility index VIX (a measure of expected *future* stock price volatility, derived from option prices). Furthermore, leverage is positively related to the cross-sectional dispersion (across forecasters) of predicted future real activity reported by the Philadelphia Fed's Survey of Professional Forecasters (SPF). The link between leverage and conditional future volatility seems consistent with recent theoretical models in which higher leverage amplifies the effect of unanticipated macroeconomic and financial shocks on real activity and asset prices—the idea is that higher leverage makes the economy more fragile. [1]

The work here contributes to key recent strands in the *macro-modeling* and *macro-policy* literatures. Since the crisis, much effort has been devoted to the development of dynamic general equilibrium models with financial intermediaries; e.g., In't Veld et al. (2011) and Kollmann et al. (2011);[2] in those models, leverage is a key state variables for real activity. Our goal here is to identify robust empirical regularities about the link between leverage and real activity that can be used to evaluate those models. In the policy arena, the development of a macroprudential supervision framework (to be implemented by new agencies, such as the European Systemic Risk Board and the US Office for Financial Research) has risen to top priority, since the crisis. The monitoring of leverage ratios, to issue early warning indicators of crises, is likely to be a key dimension of the new framework (see Galati and Moessner (2010)). However,

[1] See, e.g., Krugman (2008), Devereux and Yetman (2010) and Kollmann and Malherbe (2011) for discussions of these mechanisms (and for detailed references).

[2] Other contributions include Aikman and Paustian (2006), Van den Heuvel (2008), de Walque et al. (2009), Angeloni and Faia (2009), von Peter (2009), Cúrdia and Woodford (2009), Dib (2010), Gerali et al. (2010), Gertler and Kiyotaki (2010), and Meh and Moran (2010).

our results suggest that the use of *aggregate* leverage information is unlikely to be a panacea for predicting crises.

Our results on the predictive content of leverage for real activity complement a recent study by Adrian and Shin (2010) who argue, based on in-sample fit, that brokers-dealers (and shadow-banking) balance sheets explain future GDP.[3] We conduct a more systematic empirical exploration of the forecasting performance of leverage than these authors, by considering balance sheets for a larger number of sectors, using a broader set of controls, and evaluating both in-sample fit and *out-of-sample* forecast accuracy. Our approach thus seems better suited for evaluating which variables are robustly correlated with real activity. We document (inter alia) that the predictive ability of brokers-dealers is highly sample dependent, and that the joint information contained in sectoral leverage series is more relevant for future real activity than the information contained in any individual series. [4]

Section 2 describes the leverage data, and Section 3 discusses our econometric methodology. Sections 4 and 5 present the results, and Section 6 concludes.

2. Leverage data

We construct quarterly time series on the leverage ratios of five major sectors covered by the US Flow of Funds (FoF); specifically, we consider three financial sectors—property and life-insurance insurance companies (INS), securities brokers and dealers (SBD), commercial banks (CB)—as well as households (HH) and non-financial corporate businesses (BUS). For each of these sectors, the leverage ratio is defined as: total assets/(total assets – financial liabilities). Asset and liabilities reported in the FoF are partly measured at book values, and may thus differ from market values.[5] We thus complement the FoF leverage measures using the ratios of (book-value) assets to the *market value* of equity, for financial companies included in three Dow Jones stock price indices (as reported by Datastream): 'US-Insurance', 'US-Banks' and 'US-Financial

[3]Adrian, Moench and Shin (2010) also argue that brokers-dealers leverage predicts equity and bond returns.

[4] Also, as mentioned above, we show that balance sheet information would have failed to predict the crisis, and document that leverage is strongly related to the conditional *variability* of real activity.

[5] Deviations from market values are likely to be smallest when the balance sheets in a given sector are marked to market and/or when assets or liabilities are short term.

Services';[6] we refer to these sectors as INS-MV, BNK-MV and FIN-MV, respectively (where 'MV' stands for market value); the corresponding Datastream series are available from 1980q4. (See the Appendix for detailed information on the data.) We thus use data from 1980q4 in the subsequent analysis; our sample ends in 2010q3).

The forecast equations for real activity discussed below are estimated on rolling windows of 40 quarters; given the lag structure of the forecast regressions, the resulting (out-of-sample) forecast evaluation period is 1993q3-2010q3. Figure 1 plots the 8 sectoral leverage ratios over that period. The mean leverage ratios of households (1.2) and of non-financial corporations (2.0) are much lower than those of the financial sectors (INS: 7.7; CB: 8.9; SBD: 27.3). The sample averages of the three financial leverage measures based on the market value of equity (INS-MV, BNK-MV and FIN-MV) range between 5 and 8.3. Note also that these three leverage measures, and securities brokers-dealers (SBD) leverage (from FoF), undergo much bigger fluctuations than the other leverage series. SBD leverage grew very strongly until the crisis, reaching a peak of 55 in 2008q3, and then (after the Lehman bankruptcy) collapsed to about 20. INS-MV, BNK-MV and FIN-MV leverage likewise grew strongly, and peaked in 2009q2 (i.e. at the point in time when bank equity prices reached their lowest values, during the recent crisis), before falling noticeably.

Leverage also exhibits interesting correlations with GDP. The year-on-year (YoY) growth rate of securities brokers-dealers leverage is positively correlated with YoY GDP growth (correlation: 0.43), i.e. brokers-dealers leverage is pro-cylical (sample period: 1993q3-2010q3). INS and CB leverage is a-cylical (correlations with GDP close to zero, and statistically insignificant), while the remaining leverage variables are strongly counter-cylical (median leverage-GDP correlation: -0.50). However, the YoY growth of *all* eight leverage series is *negatively* correlated with *future* YoY GDP growth, at leads greater than 2 quarters. We show below that a significant negative link between leverage and *future* real activity can also be detected, when controlling for other macro/financial variables.

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[6] Datastream provides the aggregate market valuation of the firms included in each of these indices, as well as the corresponding (book-value) assets. The 'US-Banks' index includes major commercial banks; 'US-Financial Services' includes investment banks, credit card issuers, and institutions specializing in making consumer loans, and thus overlaps partially with the FoF 'securities brokers-dealers' (SBD) category.

3. Econometric methodology

We focus on one-year-ahead forecasts for real activity and equity returns.[7] Following Stock and Watson (2002), we fit forecasting equations of the following form (by OLS):

$$Y_{t+4} - Y_t = \beta_0 + \beta_1(Y_t - Y_{t-1}) + \beta_2\Phi_t + \beta_3\Lambda_t + \varepsilon_{t+4}\,, \qquad (1)$$

where Y_{t+4} is a measure of real activity in period t+4 (to be predicted given period t information). Λ_t is the change of an individual sector's log leverage between t-4 and t, or the median or first principal component of the (standardized) YoY changes of the 8 log sectoral leverage series. Φ_t is a vector of controls, discussed below. One period represents one quarter in calendar time. Note that, in equation (1), the quarterly first difference of real activity $(Y_t - Y_{t-1})$ is also included as a regressor.

We focus on the following measures of real activity: GDP, industrial production (IP), the unemployment rate (UE) and physical investment (I).[8] The future YoY changes of GDP, IP and I are expressed as annual log growth rates (in %). The forecast equations for unemployment use as a dependent variable the YoY change of the % unemployment rate. We also run the forecasting regression (1) for the % YoY excess equity return (Rx), defined as the difference between the stock market return and the T-bill return (see Appendix).

Due to the upward trends in several of the leverage series (see above), we use the YoY change in (log) leverage as a predictor, in equation (1). (We also estimated forecasting regressions that use the deviation of leverage from a moving average of lagged leverage as a predictor, or the deviation from a linear trend fitted to lagged leverage. The results are very similar to those discussed below.)

Note that log leverage equals the difference between log assets and log equity. We thus also considered forecast equations in which (YoY changes of) log assets and log equity are entered separately as predictors. These specifications yield lower out-of-

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[7] We also estimated forecasting equations with one- and two-quarter horizons, and found that the key results discussed below continue to holds for those horizons.

[8] It seems interesting to run the forecasting equation for investment, as investment might be especially sensitive to balance sheet conditions of financial intermediaries and of non-financial firms. Investment, IP, and UE growth rates are strongly correlated with GDP growth rates, but more volatile.

sample forecast accuracy than models in which log leverage is used as a predictor. We tested whether the coefficient of log equity equals the negative of the coefficient of log assets; for Flow of Funds data, we fail to reject that hypothesis—this suggests that the effect of equity and of assets on future real activity can be subsumed by leverage, consistent with regression equation (1). Hence, the subsequent analysis focuses on leverage as a predictor.

As controls (Φ_t), we use the four principal components extracted from a set of macro-financial variables other than leverage, following Stock and Watson (2002). We consider a set of 30 predictors (see list in Appendix) that are widely used in macroeconomic and financial forecasting: NIPA aggregates, employment, aggregate price indices, commodity prices, interest rates and the Fama-French (1993) asset pricing factors (all of these variables are properly stationarized).

We compute out-of-sample measures of forecast accuracy based on a rolling 40 quarter estimation window. As our data sets covers the period 1980q4-2010q3, the forecasts based on the rolling window pertain to 1993q3-2010q3 (taking into account the lags in (1)), as mentioned above. We also report the in-sample fit of model (1), based on a regression (non-rolling) for 1993q3-2010q3 (for dependent variable).

Tables 1-3 reports empirical results for different variants of regression (1). Specifically, the model variant referred to as 'Random Walk' only includes the intercept as a regressor, i.e. β_1, β_2 and β_3 are set at $\beta_1 = \beta_2 = \beta_3 = 0$. The 'Just ΔY' model variant also includes the first-difference of the predicted variable $(Y_t - Y_{t-1})$ as a regressor. (All other model variants also include the intercept and the first-difference of the dependent variable as regressors.) The forecast model labeled 'F' adds the four macro-financial factors. 'F, PC-LEV' adds the first principal component of the YoY change of the eight sectoral (standardized) log leverage series to the 'F' model. The 'MED-LEV' model variant uses the cross-sectional median of the eight standardized YoY changes of log leverage series as a predictor. The entries labeled 'INS', 'SBD' etc. pertain to forecast models that use the YoY difference of the corresponding individual sectoral leverage variable as regressors. The following Table summarizes these different model variants.

Forecast model variants

Model	**Restrictions**
Random Walk	$\beta_1 = \beta_2 = \beta_3 = 0$
Just ΔY	$\beta_2 = \beta_3 = 0$
F	$\beta_3 = 0$
F, PC-LEV	Λ_t=first principal component of YoY changes in 8 sectoral log leverages
PC-LEV	$\beta_2 = 0$, Λ_t=principal component of YoY changes in 8 sectoral log leverages
MED-LEV	$\beta_2 = 0$, Λ_t=median of standardized YoY changes in 8 sectoral log leverage variables
INS,SBD,CB,HH,BUS,INS-MV BNK-MV, FIN-MV	$\beta_2 = 0$, Λ_t is the YoY change of one of the eight sectoral log leverage variables

4. Results: leverage as a predictor for real activity and equity returns

Row 1 of Table 1 reports root mean squared forecast errors (RMSEs) for the 'Just ΔY' model variant. Henceforth, we take this model variant as a benchmark—in Table 1, we normalize the RMSEs for the other model variants by the RMSE of the 'Just ΔY' variant (see rows 2-14). The Table also reports the relative RMSE of the median forecasts (for GDP, IP, UE and I) reported by the Philadelphia Fed's Survey of Professional Forecasters (SPF). The left panel of Table 1 reports in-sample RMSEs, while the right panel reports RMSE's of out-of-sample forecasts, based on the rolling 40 quarter estimation windows. Throughout, the forecast evaluation period is 1993q3-2010q3.

In-sample results

In-sample, models with many regressors achieve the best fit (i.e. the lowest RMSEs). For GDP, industrial production (IP), the unemployment rate (UE), and investment (I), the in-sample forecast regressions with the *four* macro-financial factors (model variant labeled 'F') generate an RMSE that is about 25%-33% smaller than that of the benchmark 'Just ΔY' model; by contrast, the macro-financial factors do not help a great deal in predicting the excess equity return. In-sample, some individual sectoral leverages too perform well. In particular, FIN-MV leverage stands out, with relative RMSEs for GDP, IP, UE and I in the range 0.77-0.86. INS and SBD leverage yields relative RMSEs of 0.9 for the excess equity returns, and of 0.94-0.96 for GDP. Also, HH leverage is helpful in predicting the unemployment rate, while BNK-MV leverage helps predict GDP. The principal component and the median of the 8 YoY changes of sectoral log leverages likewise generate rather low relative RMSEs for all four real activity variables, and tend to outperform the individual leverage variables as predictors (see 'PC-LEV' and 'MED-LEV' models).

Table 2 (left panel) reports estimated slope coefficients for leverage (as well as R^2 coefficients of the corresponding regressions), based on the (non-rolling) regressions for 1993q3-2010q3. Note that almost all the leverage coefficients in the forecast equations for GDP, industrial production, investment and the excess equity return are negative, while the slope coefficients for unemployment are positive. *All* slope coefficients of the median and the principal component of leverage, and of Flow of Funds insurance leverage are highly statistically significant (for the other individual leverage variables, the slope coefficients in the GDP-regressions are likewise mostly highly significant). We also ran regressions in which the 8 sectoral leverage variables are included jointly (not reported in Table). Wald tests show that, for each dependent variable, the 8 leverages are overwhelmingly jointly significant (probability value in the range of 10^{-6}).

The in-sample evidence thus suggests that there exists a highly significant, negative link between leverage and future real activity.

Rolling forecast regressions

Out-of-sample forecasting performance based on the rolling regressions is worse than in-sample fit (see right panel of Table 1). This is especially the case for models with many regressors. The out-of-sample predictive content of the model variant with the four macro-financial factors for GDP is very close to that of the ('Just ΔY') benchmark model (relative RMSE: 0.97), although the four factors have non-negligible predictive content for unemployment (relative RMSE: 0.76).

The out-of-sample forecasts generated by the 'MED-LEV' model variant (that uses the cross-sectoral median of YoY sectoral leverage changes as a predictor) likewise outperform the benchmark model; 'MED-LEV' also outperforms the model with four macro-financial factors ('F'), in predicting GDP (relative RMSE: 0.90). When added to the four macro-financial factors, leverage achieves modest forecast improvements for GDP, as shown by the combined model 'F, PC-LEV'. Combining the median leverage predictor with the four macro-financial factors delivers an even more pronounced reduction in forecast errors (not displayed), which suggests that leverage contains information on top of established predictors. The model variants with the sectoral leverages for INS and SBD (insurance; securities brokers-dealers, from the Flow of Funds) perform marginally better than the benchmark model, but are outmatched by the four macro-financial factors in forecasting GDP. Finally, the efficacy of professional forecasts (SPF) is basically comparable to that of the benchmark model. None of the examined predictors help in forecasting excess stock returns out-of-sample, with the possible exception of the INS and SBD leverage measures.

As a further test of the out-of-sample forecasting capacity of leverage, we use the Clark and West (2007) 'MSPE-adjusted test' to test the null hypothesis that the RMSE of a given model is identical to that of the benchmark model ('Just ΔY'); see Table 3. For each dependent variable, the test is separately applied to the different alternative forecast models. For the model variants that include the principal component or the median of YoY changes in sectoral log leverages as a predictor, the p-values of the test are mostly below 0.05 (except for the excess equity return), which suggests that the predictive power of leverage is statistically significant – the same holds for the macro-financial factors.

We also use the Hubrich and West (2010) 'max-t-stat' test to test the *joint* null hypothesis that all of the eight models that include a single sectoral leverage variable ('INS', 'SBD', …,'FIN-MV') have the same predictive content as the 'Just ΔY' benchmark model. This test is separately applied for each of the predicted variables. The p-values for GDP, industrial production, the unemployment rate, investment and the excess equity return are 0.026, 0.019, 0.065, 0.035 and 0.068, respectively. These low p-values too suggest that the predictive power of the sectoral leverage information is statistically significant.

Estimated slope coefficients of leverage (rolling regressions)

The rolling regressions again show a negative link between leverage and future real activity. For each model that includes leverage as a regressor, Table 2 (right panel) reports the fraction of rolling 40 quarter estimation windows in which the estimated leverage coefficient is negative *and* statistically significant at the 10% level (as well as the fraction in which the slope coefficient is significant, irrespective of sign; see figures in parentheses). In the forecast equations for GDP, industrial production and investment, most slope coefficients of leverage are negative and statistically significant (consistent with this, most leverage coefficients in the forecast equations for unemployment are positive).

Figure 3 plots the standardized regression coefficients of leverage and their p-values, across the rolling estimation windows, for the GDP forecast equations.[9] For most of the sectoral leverage variables, the estimated slope coefficients are negative, across all windows. Hence, the empirical finding that leverage is negatively related to future real activity is not sample dependent—in particular, this result is *not* driven by the financial crisis. However, none of the sectoral leverage variables are highly significant across *all* estimation windows. Note, for example, that the slope coefficient of securities brokers-dealers (SBD) leverage was significant at the beginning and end of the sample, but insignificant (and close to zero) in the middle of the sample. However, jointly the eight sectoral leverage variables are highly significant predictors--and that in *each* of the estimation windows (this is shown by Wald tests not reported here). This again suggests that the *joint* information contained in the eight sectoral leverage series is more relevant for predicting future real activity than the information contained in any individual leverage series.

However, despite the strong (joint) significance of the leverage variables, these variables would not have allowed to predict the 2008-2009 'Great Recession' better than conventional predictors. This is shown in Figure 2 which plots the GDP forecasts (rolling window based) generated by the model with the four macro-financial factors ('F'), and by

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[9] The estimated slope coefficients are based on forecast equations that include these predictors: a constant, the quarterly first difference of GDP, and one leverage variable

the model with these four factors *and* the principal component of leverage ('F,PC-LEV'). Both models fail to predict the dramatic fall in GDP that during the recession—in fact, both models yield essentially the *same* predictions for GDP, for 2008-2009. Figure 2 reveals that the overall RMSE reduction produced by using leverage information mainly reflects smaller forecast errors made during the early 2000s (after the collapse of the dotcom bubble).

In summary, the in-sample and out-of-sample results suggest that leverage is a statistically significant predictor for real activity. However, *quantitatively,* the effect of using leverage as a predictor is modest—leverage information would not have generated an 'early warning' of the 2008-2009 recession.

Perhaps this finding should not entirely come as a surprise. Structural macro models with financial intermediaries suggest that the link between leverage and future expected real activity is ambiguous—in particular, it depends on the nature and relative importance of the shocks affecting the economy.[10] This suggests that it might be fruitful to condition on the underlying disturbances, when evaluating the empirical link between leverage and real activity--we leave an investigation of this issue for future research. However, intuition suggests that leverage might also matter for the conditional *volatility* of future real activity and returns: essentially, an increase in leverage today should amplify the effect of future shocks.[11] This would imply a positive link between leverage

[10] For example, in Kollmann et al.'s (2011) dynamic general equilibrium model with a banking sector, a transitory fall in total factor productivity (TFP) lowers bank leverage, on impact (as household savings and the supply of deposit fall, which leads banks to finance a larger share of their asset holdings by raising equity); the TFP shock lowers GDP, on impact, but GDP subsequently reverts to its pre-shock level. When TFP shocks are the dominant source of economic fluctuations, leverage is hence negatively correlated with *future* GDP growth. By contrast, the model predicts that an unexpected credit loss (a loan default shock) reduces the banks' capital (equity), on impact, and hence raises the leverage ratio; on impact the shock lowers GDP (as banks cut their lending), but subsequently GDP recovers. Hence, leverage is positively correlated with future GDP growth, when there are sizable credit losses.

[11] See, e.g., Krugman (2009), Devereux and Yetman (2010), and Kollmann and Malherbe (2011) for discussions of mechanisms through which leverage may amplify the effect of shocks.

and uncertainty about future economic conditions. The next Section documents that such a link does indeed exist in the data—and that it is powerful. [12]

5. Leverage and the conditional variability of real activity and equity returns

We evaluate the link between the date *t* YoY change in log leverage and the following three measures of uncertainty about future economic conditions:

(i) The absolute value of date *t*+4 forecast errors (in %) implied by the date *t* forecasts generated by the forecast models discussed in the previous Section.

(ii) The CBOE equity volatility index (VIX) at the end of period *t*--VIX is an estimate of the future volatility of stock prices (inferred from options prices).

(iii) The measure of dispersion (in %), across forecasters, of date *t* forecasts for real activity growth between *t* and *t*+4, reported by the Philadelphia Fed Survey of Professional Forecasters (SPF).[13]

Figure 4 presents scatter plots of the three measures of conditional future volatility/dispersion against the principal component of the changes in log sectoral leverage between t-4 and t (observed at t). (The sample period (t) is 1992q3-2009q3.) Figure 5 plots time series of these variables (using the same timing convention). The absolute forecast errors in Figures 4-5 pertain to GDP; these errors are rolling-window-based, and were generated using the forecast model referred to as 'F' in the previous Section (i.e. the four macro-financial factors are used as predictors). (Plots for errors generated by the other forecast models, and for the other predicted real activity measures are very similar.)

Figures 4-5 show a clear positive link between leverage information at *t* and the measures of future conditional variability (and the dispersion of forecasts made at *t*). The link is very pronounced during the crisis—but it is also clearly present in the pre-crisis period.

[12] Previous research has documented that the conditional volatility of real activity is time-varying (e.g. Giannone, Lenza and Reichlin (2008), and Frale and Veredas (2009)). Our results about the link between leverage and future conditional volatility of real activity are novel, to the best of our knowledge.

[13] The SPF dispersion measure is the % difference between the 75th and 25th percentiles of the cross-sections of forecasts.

Tables 4 and 5 provide regression evidence on the link between leverage and conditional future volatility/dispersion. Table 4 regresses absolute date t+4 forecast errors for each of our five dependent variables on (annual YoY changes of) our 8 sectoral log leverage variables observed at t (see first 8 rows of Table); we also regress absolute forecasts errors on all 8 sectoral leverage series *jointly*, and on the principal component and median value of (YoY changes of) sectoral log leverages. Table 4 furthermore shows results that obtain when the four macro-financial factors are added to these regressors. In Table 5, the cross-sectional dispersion of date t SPF forecasts (for GDP, industrial production, the unemployment rate and investment; see Columns (1)-(4)), as well as the VIX at t (Col. 5) are regressed on the regressors used in Table 4.

In almost all regressions, the slope coefficients of leverage are positive and highly statistically significant.[14] This result confirms the existence of a powerful positive link between leverage and conditional future variability/dispersion. That link is particularly strong for the leverage factor and median leverage. Each of these two leverage measures alone explains between 20% and 30% of the variances of the absolute GDP forecast errors, of SPF cross-sectional GDP forecast dispersion, and of VIX (see R^2 coefficients). The four macro-financial factors are likewise related to future conditional volatility—but less strongly than leverage (lower R^2s). Furthermore, the principal component and median of the sectoral leverage measures remain highly significant when the four macro-financial factors are added as predictors.

6. Conclusion

This paper documents statistically significant links between leverage and future real activity, and between leverage and the conditional volatility of future real activity. These links appear particularly clearly when information from sectoral leverage series is combined using cross-sectional medians or principal components. The results here show that the predictive power of leverage is roughly comparable to that of macro and financial predictors commonly used by forecasters. However, leverage information would *not* have

[14]There is only one *notable* exception: in about half of the regressions, securities brokers-dealers (SBD) leverage is negatively linked to the volatility/dispersion measures

allowed to predict the ‘Great Recession’ of 2008-2009 any better than conventional macro/financial predictors.

APPENDIX: Data sources and definitions of variables

(a) Predicted variables

Series label	*Variable*	*Source*
GDP	Real gross domestic product	Bureau of Economic Analysis
IP	Industrial production index	St. Louis Fed
UE	Civilian unemployment rate, percent	Bureau of Labor Statistics
I	Real gross private domestic investment	Bureau of Economic Analysis
Rx	Excess stock return (French-Fama stock return - T-bill return)	K. French website

(b) Leverage

Series label	*Variable*	*Source*
INS	Life and casualty insurance leverage ratio	Flow of Funds
SBD	Securities Brokers and Dealers leverage ratio	Flow of Funds
CB	Commercial Banks leverage ratio	Flow of Funds
HH	Households and nonprofit organizations leverage ratio	Flow of Funds
BUS	Non-farm non-financial corporate business leverage ratio	Flow of Funds
BNK-MV	US-Banks index : total assets / equity at market value	Datastream
INS-MV	US-Insurance index : total assets / equity at market value	Datastream
FIN-MV	US-Fin. Services index : total assets / equity at market value	Datastream

(c) Variables used to construct macro-financial factors

Variable	*Source*	*Transformation*
1) Real gross domestic product	Bureau of Econ. Analysis	Quarterly growth rate
2) Real government consumption and investment	Bureau of Econ. Analysis	Quarterly growth rate
3) GDP implicit price deflator	Bureau of Econ. Analysis	Quarterly growth rate
4) Real gross private domestic investment	Bureau of Econ. Analysis	Quarterly growth rate
5) Gross government saving, as share of GDP	Bureau of Econ. Analysis	Quarterly difference
6) Private housing starts of 1-family structures	Bureau of Econ. Analysis	Quarterly growth rate
7) Real personal consumption expenditures	Bureau of Econ. Analysis	Quarterly growth rate
8) Real personal consumption expenditures, durable goods	Bureau of Econ. Analysis	Quarterly growth rate
9) Real private non-residential fixed investment	Bureau of Econ. Analysis	Quarterly growth rate
10) Real private residential fixed investment	Bureau of Econ. Analysis	Quarterly growth rate
11) Real net exports of goods & services, as share of GDP	Bureau of Econ. Analysis	Quarterly difference
12) Total number of employees (non-farm)	Bureau of Labor Statistics	Quarterly growth rate
13) Commodities producer price index	Bureau of Labor Statistics	Quarterly growth rate
14) Civilian unemployment rate, percent	Bureau of Labor Statistics	Quarterly difference
15) Consumer price index, all urban consumers	Bureau of Labor Statistics	Quarterly growth rate
16) Oil price (spot WTI) USD/barrel	Dow Jones & Company	Quarterly growth rate
17) Return on 3-month U.S. T-bill	Federal Reserve Board	---
18) Return on 2-year U.S. Treasury bond	Federal Reserve Board	---
19) Return on 5-year U.S. Treasury bond	Federal Reserve Board	---
20) U.S. Treasury term spread: 10yr –3month par yield	Federal Reserve Board	---
21) ISM manufacturing inventories index	St. Louis Fed	Quarterly difference
22) ISM manufacturing new orders index	St. Louis Fed	Quarterly difference
23) Industrial production index	St. Louis Fed	Quarterly difference
24) Nominal M2 money stock	St. Louis Fed	Quarterly growth rate
25) Total industry capacity utilization	St. Louis Fed	Quarterly growth rate
26) French-Fama HML factor	St. Louis Fed	Quarterly growth rate
27) French-Fama Momentum factor	K. French website	---
28) French-Fama SMB factor	K. French website	---
29) French-Fama Short-term reversal factor	K. French website	---
30) French-Fama Long-term reversal factor	K. French website	---

(d) Other variables

Variable	*Description*	*Source*
VIX	Equity Volatility Index	Chicago Board Options Exchange
SPF median forecasts	Median forecasts for GDP, industrial production, unemployment rate and investment	Survey of Professional Forecasters, Philadelphia Fed
SPF cross-sectional dispersion of forecasts	% difference between the 75th and 25th percentiles of forecasts	Survey of Professional Forecasters, Philadelphia Fed

Notes: The Flow of Funds leverage ratio for commercial banks (CB) displays a break in 1999. We corrected for this break by projecting the CB leverage ratio on a time dummy and a linear and quadratic trend, and then adjusting the raw series for the dummy coefficient.

Section (c) lists the 30 variables from which the four macro-financial factors (used as predictors) are extracted (principal components). The right-most column lists the data transformations used in constructing the factors. Returns on Treasury bonds are derived from constant maturity yield curves (estimated using the methodology of Gürkaynak et al. (2007)), as published on the web page of the Federal Reserve Board.

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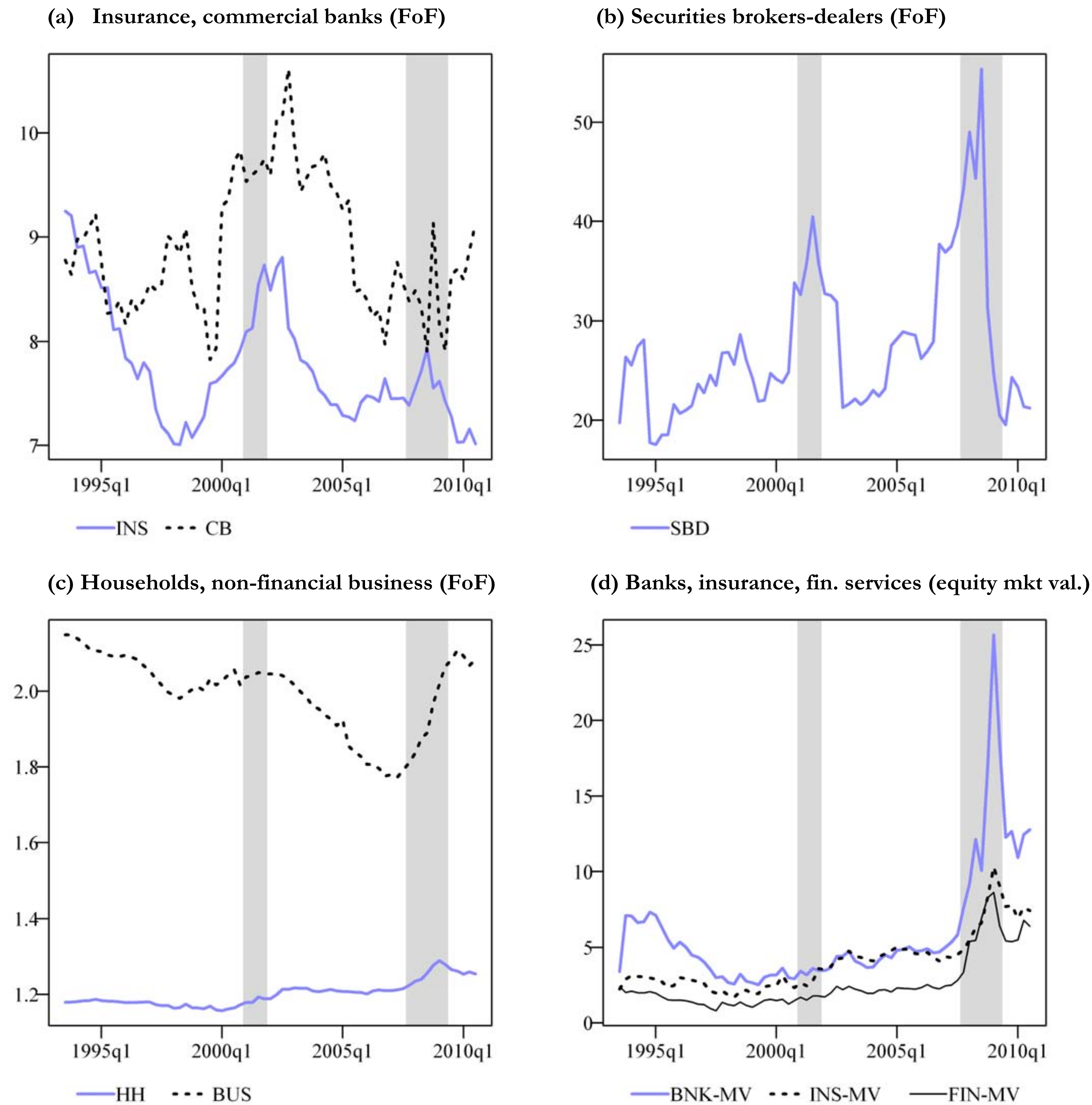
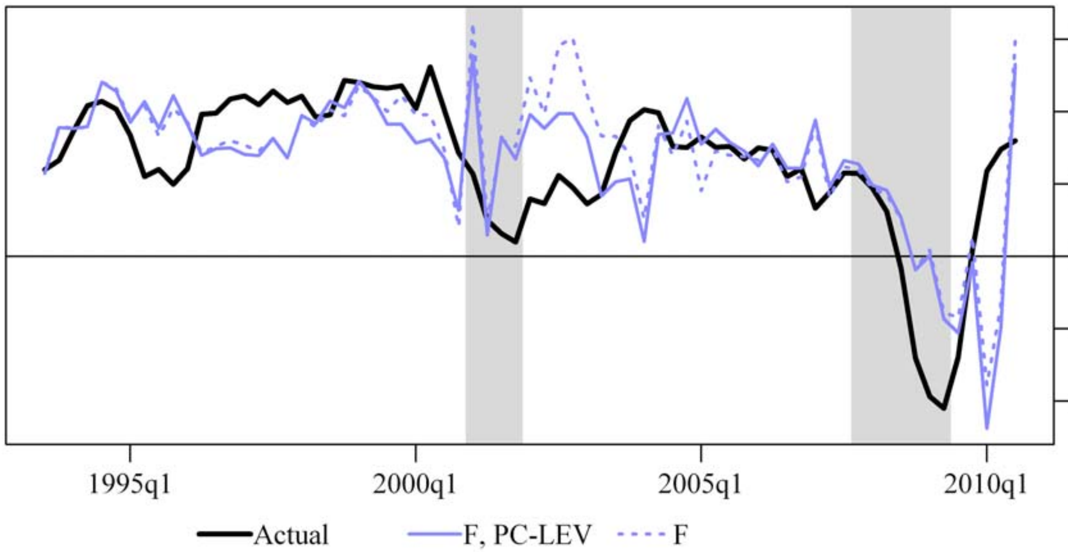
Figure 1: Leverage ratios



The Figure plots the time series of leverage ratios for the following sectors—INS: insurance (from Flow of Funds); CB: commercial banks (FoF); HH: households (FoF); BUS: non-financial corporate businesses (FoF); SBS: securities brokers and dealers (FoF); BNK-MV, INS-MV, FIN-MV: Banks, insurance and financial services, based on equity market values. Sample period: 1993q3-2010q3.
Shaded areas indicate NBER recessions.

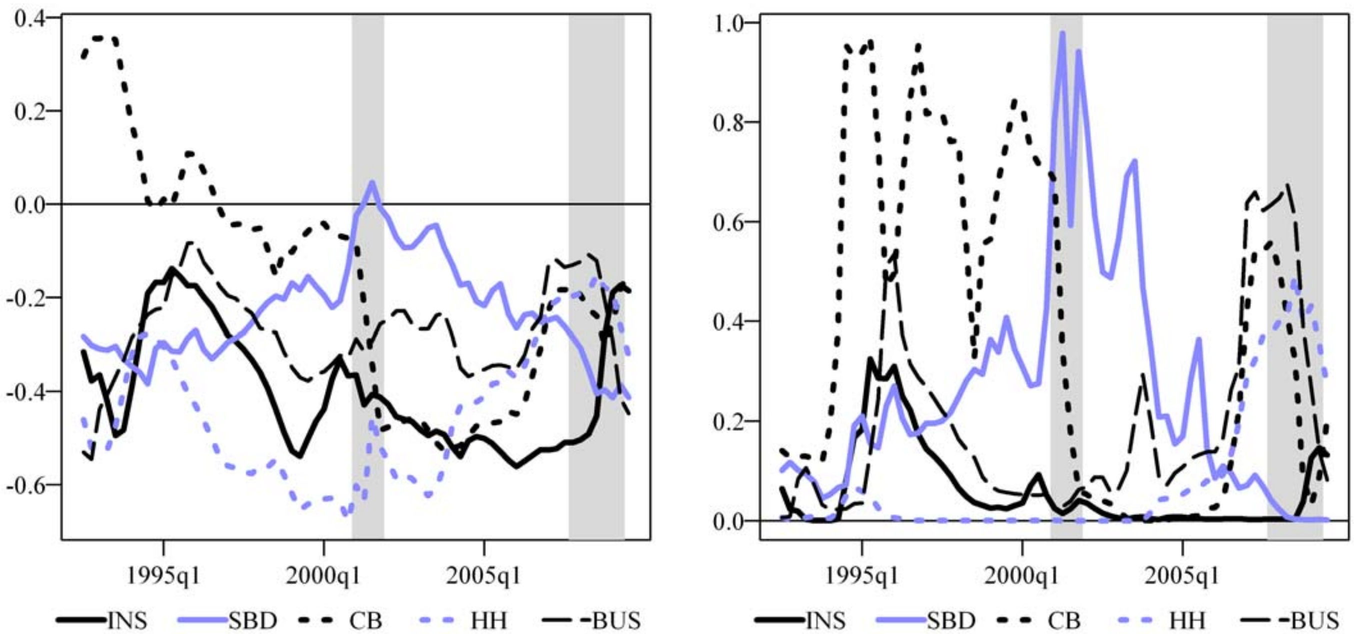
Figure 2: Year-on-year GDP growth rate (in %) – actual and predicted



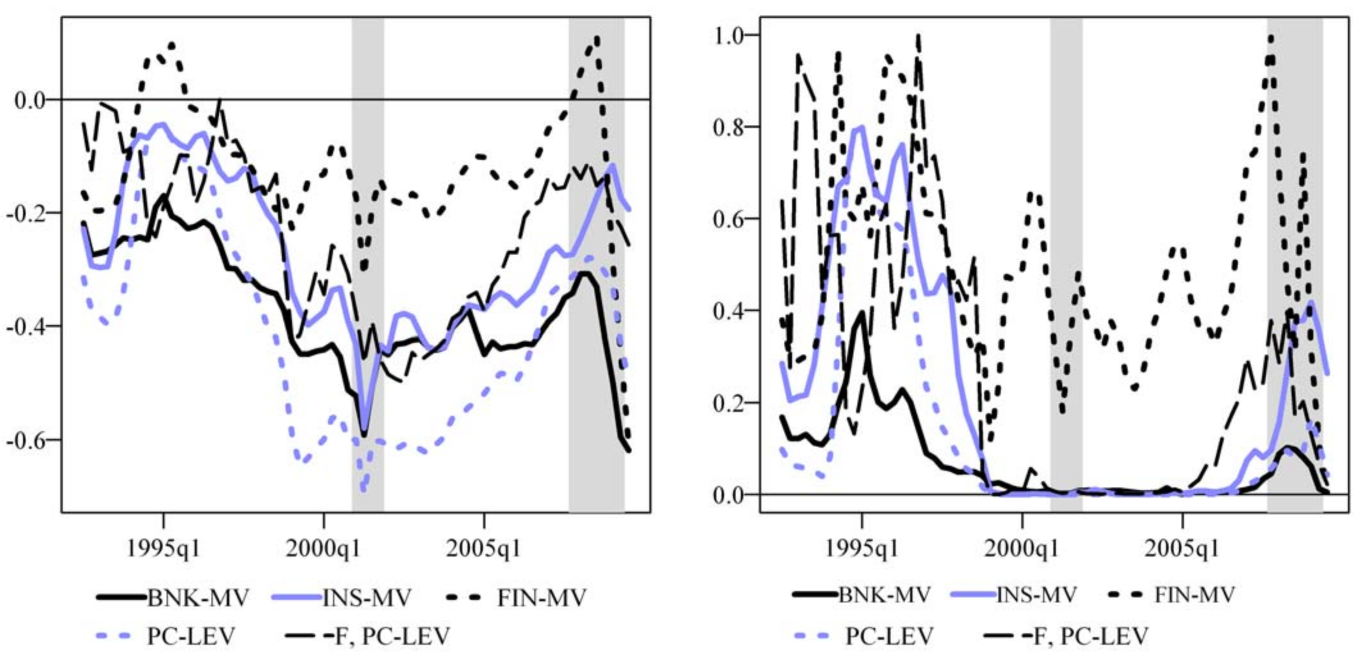
The Figure shows actual and predicted year-on-year GDP rates growth (in %), 1993q3-2010q3. The line labeled 'F' shows the prediction (based on 40 quarter rolling estimation window) generated by a forecast model that includes (as predictors) four factors extracted from a set of 30 macro-financial variables. The line labeled 'F, PC-LEV' shows the prediction obtained by adding the first principal component of the annual growth rates of the 8 sectoral leverage series, as a predictor. Shaded areas indicate NBER recessions.

Figure 3: Slope coefficients of leverage and p-values, from rolling forecast regressions for GDP

(a) Standardized coefficient: FoF leverage measures **(b) P-values: FoF leverage measures**



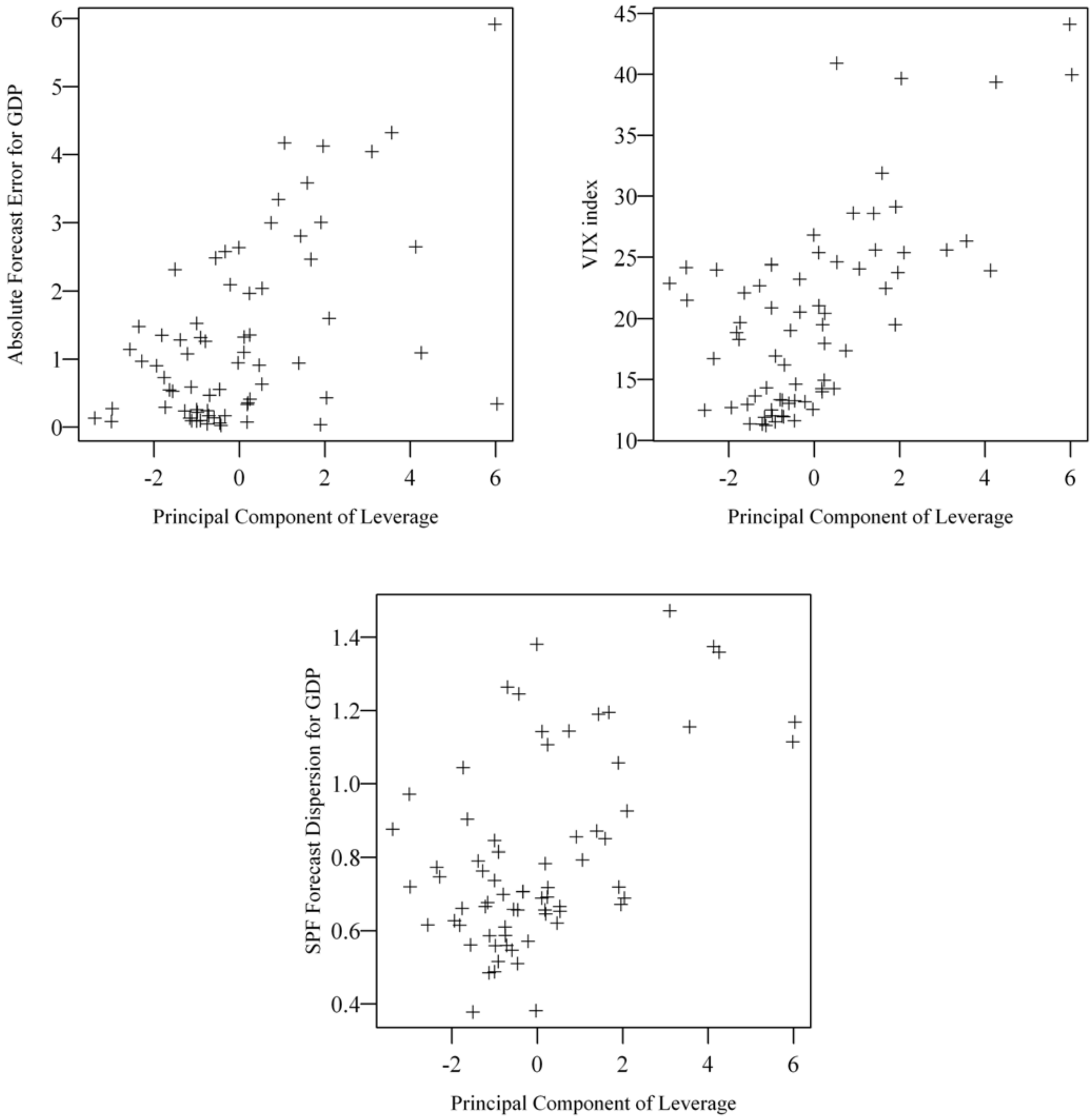
(c) Standardized coefficient: other leverage measures **(d) P-values: other leverage measures**



Panels (a) & (c): Standardized regression coefficients of leverage variables in forecast regression for GDP (based on 40 quarter rolling window). *Panels (b) & (d):* probability-values from Newey-West HAC t-statistics for slope coefficients of leverage (from GDP forecast regressions).

Each forecast regression includes the following predictors: a constant, the quarterly first difference of GDP, and one leverage variable. Date (abscissa) indicates final observation of the 40 quarter estimation window for the explanatory variables. Shaded areas indicate NBER recessions.

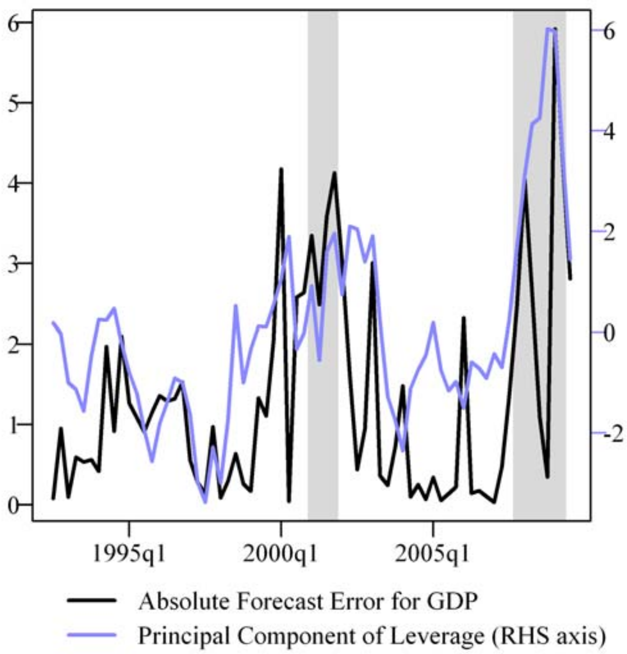
Figure 4: Scatter plots of future absolute forecast errors, VIX and forecast dispersion vs. leverage



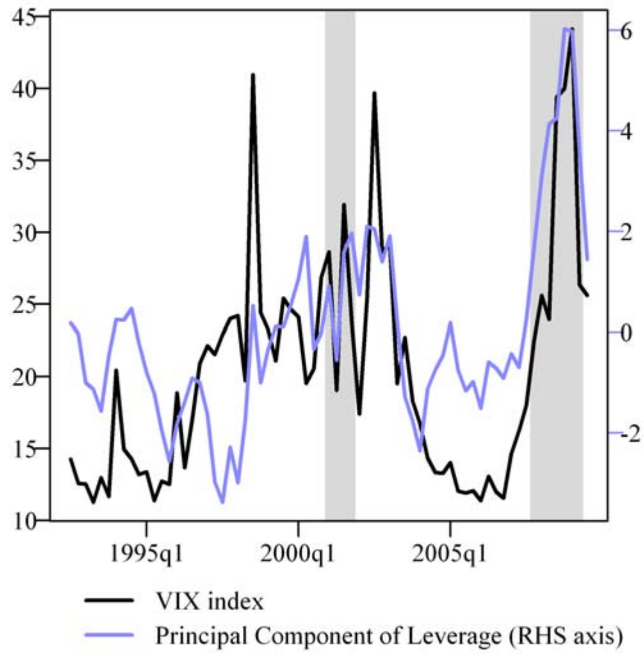
Scatter plots of absolute forecast error for GDP (in %) between t and t+4, of Equity Volatility Index (VIX) at end of period t, and of date t cross-sectional dispersion of SPF forecasts of GDP growth between t and t+4 vs. the first principal component (of the YoY change in sectoral log) leverage between t-4 and t are shown. The forecast error pertains to forecast model 'F' (four macro-financial factors used as predictors), and is based on rolling 40 quarter estimation window. The sample period (t) is 1992q3-2009q3.

Figure 5: Time series plots of absolute future forecast errors, VIX, forecast dispersion and leverage

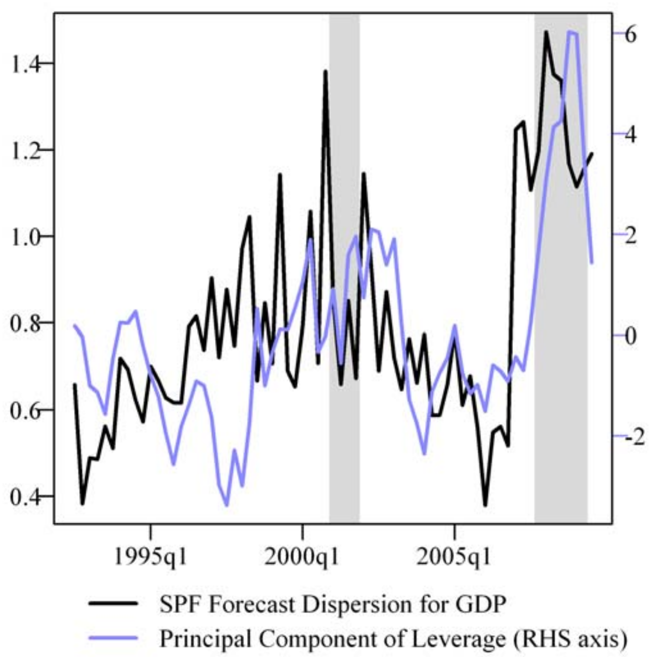
(a) Realized absolute GDP forecast error (in %)



(b) VIX



(c) Cross-sectional dispersion of SPF GDP forecasts



Each panel shows time series plots the first principal component of the YoY change in sectoral log leverages between t-4 and t, and another variable. Panel (a): absolute forecast error for GDP (in %) between t and t+4. Panel (b): Equity Volatility Index (VIX) at end of period t. Panel (c): SPF date t cross-sectional dispersion of forecasts of GDP growth between t and t+4. (Thus: same timing conventions as in Figure 4.) The forecast error pertains to forecast model 'F' (four macro-financial factors used as predictors), and is based on rolling 40 quarter estimation window. The sample period (t) is 1992q3-2009q3. Shaded areas indicate NBER recessions.

Table 1: RMSEs of 'Just ΔY' forecast model & relative RMSEs of other models and SPF

	In-sample RMSEs					*Out-of-sample RMSEs*				
Forecast model:	**GDP**	**IP**	**UE**	**I**	**Rx**	**GDP**	**IP**	**UE**	**I**	**Rx**
Just ΔY	1.77	3.90	0.87	10.16	19.63	1.91	4.27	0.95	10.93	20.96
Random Walk	1.09	1.11	1.22	1.04	1.00	1.05	1.04	1.10	1.00	0.98
F	0.74	0.78	0.67	0.69	0.92	0.97	0.87	0.76	0.85	1.10
F, PC-LEV	0.68	0.71	0.62	0.64	0.91	0.93	0.87	0.74	0.83	1.17
PC-LEV	0.89	0.93	0.88	0.93	0.99	0.96	1.03	0.91	1.00	1.12
MED-LEV	0.85	0.89	0.83	0.88	0.98	0.90	0.94	0.82	0.93	1.14
INS	0.94	0.95	0.95	0.93	0.90	0.95	0.97	0.97	0.95	0.94
SBD	0.96	0.96	0.94	0.91	0.90	0.99	0.94	0.95	0.89	0.93
CB	0.99	0.94	0.96	0.98	0.97	1.04	0.98	1.00	1.03	1.07
HH	0.95	0.98	0.89	0.97	1.00	1.00	1.00	0.92	1.00	1.18
BUS	0.99	1.00	0.99	1.00	1.00	1.19	1.22	1.17	1.30	1.28
BNK-MV	0.88	0.95	0.95	0.93	0.99	0.95	1.08	1.02	1.04	1.10
INS-MV	0.96	0.99	0.99	0.98	1.00	0.97	1.03	1.01	1.00	1.04
FIN-MV	0.86	0.79	0.77	0.81	0.97	1.02	0.93	0.93	0.98	1.06
SPF	NA	NA	NA	NA	NA	1.04	1.03	0.96	0.93	NA

Note: The first row shows absolute RMSEs of the 'Just ΔY' forecast model. Rows 2-14 show relative RMSEs, with respect to the 'Just ΔY' model, for the forecast model variants listed in the first Column (see main text for model descriptions). The last row ('SPF') shows relative RMSEs of median SPF forecasts (not available for equity returns).

'In-sample RMSEs' are based on regression (1) estimated for the sample 1993q3-2010q3 (for each dependent variable). 'Out-of-sample RMSEs' are based on (pseudo) out-of-sample forecasts one year ahead, from 40 quarter rolling estimation window (forecast evaluation period: 1993q3-2010q3).

Columns labeled 'GDP',...,'Rx' show RMSE's for the different forecasted variables (IP: industrial production; UE: unemployment rate; I: investment; Rx: excess equity return).

Table 2: Regression coefficients of leverage: whole sample and rolling windows

Forecast model	*Whole sample* GDP	IP	UE	I	Rx	*% Sign. negat. coeff. rolling windows* GDP	IP	UE	I	Rx
F, PC-LEV	-0.42***	-0.49***	0.37**	-0.38**	-0.24	0.46	0.68	0.14	0.52	0.19
	{0.62}	*{0.60}*	*{0.74}*	*{0.61}*	*{0.18}*	*{0.46}*	*{0.71}*	*{0.54}*	*{0.52}*	*{0.30}*
PC-LEV	-0.53***	-0.47**	0.60**	-0.44*	-0.15	0.75	1.00	0.00	0.81	0.30
	{0.34}	*{0.31}*	*{0.48}*	*{0.19}*	*{0.02}*	*{0.75}*	*{1.00}*	*{0.52}*	*{0.81}*	*{0.42}*
MED-LEV	-0.61***	-0.56***	0.63***	-0.57***	-0.25	0.87	0.97	0.00	1.00	0.43
	{0.40}	*{0.37}*	*{0.54}*	*{0.28}*	*{0.05}*	*{0.87}*	*{0.97}*	*{0.61}*	*{1.00}*	*{0.54}*
INS	-0.32***	-0.30**	0.26**	-0.38**	-0.46***	0.78	0.83	0.00	0.62	0.46
	{0.26}	*{0.27}*	*{0.39}*	*{0.20}*	*{0.19}*	*{0.78}*	*{0.83}*	*{0.45}*	*{0.62}*	*{0.57}*
SBD	-0.25*	-0.26	0.30	-0.40**	-0.44***	0.29	0.07	0.00	0.25	0.65
	{0.23}	*{0.26}*	*{0.40}*	*{0.22}*	*{0.19}*	*{0.29}*	*{0.09}*	*{0.26}*	*{0.26}*	*{0.65}*
CB	-0.13	-0.30***	0.22***	-0.20	-0.25	0.32	0.61	0.04	0.59	0.46
	{0.18}	*{0.29}*	*{0.38}*	*{0.11}*	*{0.06}*	*{0.32}*	*{0.71}*	*{0.88}*	*{0.68}*	*{0.59}*
HH	-0.43*	-0.29	0.62**	-0.35	0.05	0.81	0.48	0.00	0.70	0.00
	{0.25}	*{0.23}*	*{0.47}*	*{0.13}*	*{0.01}*	*{0.81}*	*{0.48}*	*{0.80}*	*{0.70}*	*{0.36}*
BUS	-0.15	-0.02	0.12	0.04	-0.10	0.46	0.29	0.03	0.17	0.55
	{0.18}	*{0.20}*	*{0.33}*	*{0.07}*	*{0.01}*	*{0.46}*	*{0.29}*	*{0.35}*	*{0.17}*	*{0.59}*
BNK-MV	-0.48**	-0.33	0.31	-0.41*	-0.14	0.72	0.41	0.00	0.75	0.03
	{0.35}	*{0.27}*	*{0.40}*	*{0.20}*	*{0.02}*	*{0.72}*	*{0.41}*	*{0.13}*	*{0.75}*	*{0.03}*
INS-MV	-0.28**	-0.16	0.14	-0.18	-0.04	0.54	0.26	0.00	0.54	0.00
	{0.23}	*{0.22}*	*{0.34}*	*{0.10}*	*{0.01}*	*{0.54}*	*{0.26}*	*{0.00}*	*{0.54}*	*{0.13}*
FIN-MV	-0.57**	-0.69***	0.62***	-0.67***	-0.30	0.01	0.86	0.00	0.48	0.01
	{0.39}	*{0.50}*	*{0.60}*	*{0.39}*	*{0.07}*	*{0.01}*	*{0.86}*	*{0.25}*	*{0.48}*	*{0.16}*

Note: The *Left panel* (labeled '*Whole sample*') shows standardized slope coefficients of leverage, from regressions of each dependent variable on lagged leverage and other predictors for the period 1993q3-2010q3 (for each dependent variable), not based on rolling window. Asterisks indicate significance levels (based on Newey-West HAC t-statistic): * 10%, ** 5%, *** 1%. Numbers in brackets are R^2 coefficients of corresponding regression equations.

The *Right panel* (labeled '*% Sign. negat. coeff. rolling windows*') shows shares of leverage coefficients that are significantly smaller than zero at a 10% level (two-sided Newey-West HAC t-test), among the rolling 40 quarter estimation windows; numbers in brackets pertain to the share of estimation windows with significant leverage coefficients at 10% level (i.e. sum of share for significant negative and positive coefficients).

Columns labeled 'GDP', …,'Rx' pertain to the different forecasted variables (IP: industrial production; UE: unemployment rate; I: investment; Rx: excess equity return).

Table 3: P-values of Clark-West (2007) test of equal predictive accuracy, relative to benchmark 'Just ΔY' model

Forecast model	GDP	IP	UE	I	Rx
Random Walk	0.61	0.35	0.35	0.33	0.03
F	0.06	0.04	0.02	0.02	0.59
F, PC-LEV	0.05	0.04	0.02	0.02	0.52
PC-LEV	0.04	0.31	0.04	0.21	0.62
MED-LEV	0.01	0.04	0.04	0.02	0.61
INS	0.00	0.00	0.11	0.01	0.01
SBD	0.07	0.15	0.13	0.12	0.05
CB	0.76	0.05	0.18	0.36	0.82
HH	0.01	0.03	0.01	0.02	0.97
BUS	0.45	0.69	0.64	0.89	0.64
BNK-MV	0.08	0.51	0.55	0.42	0.79
INS-MV	0.05	0.63	0.65	0.13	0.88
FIN-MV	0.61	0.00	0.11	0.08	0.94

Note: For each model listed in the first column (see main text), and for each of the forecasted variables, the Table reports the p-value of a test of the null hypothesis that that model has the same predictive accuracy (RMSE) as the benchmark 'Just ΔY' model. (The benchmark model is nested in each of the remaining models.) The MSPE-adjusted test statistic of Clark and West (2007) is used.

Columns labeled 'GDP', …,'Rx' show p-values for the different forecasted variables (IP: industrial production; UE: unemployment rate; I: investment; Rx: excess equity return). Out-of-sample forecasts (based on 40 quarter rolling estimation window) are used; the forecast evaluation period is 1993q2-2010q3.

Table 4: Regressions of absolute out-of-sample forecast errors on leverage and macro-financial factors

	GDP	IP	UE	I	Rx
Forecast model					
INS	0.26 {.08; .07}	0.21 {.12; .05}	0.25 {.06; .06}	0.36 {.01; .13}	0.29 {.04; .08}
SBD	-0.25 {.19; .06}	0.02 {.87; .00}	0.01 {.91; .00}	-0.07 {.64; .01}	-0.23 {.09; .05}
CB	0.22 {.01; .05}	0.38 {.04; .14}	0.24 {.01; .06}	0.25 {.05; .06}	0.42 {.00; .18}
HH	0.52 {.00; .27}	0.34 {.01; .12}	0.46 {.01; .22}	0.35 {.01; .12}	0.53 {.00; .28}
BUS	0.45 {.00; .20}	0.34 {.02; .12}	0.48 {.00; .23}	0.42 {.00; .18}	0.36 {.00; .13}
BNK-MV	0.39 {.00; .15}	0.29 {.10; .08}	0.40 {.08; .16}	0.26 {.05; .07}	0.42 {.00; .18}
INS-MV	0.44 {.00; .20}	0.28 {.04; .08}	0.24 {.23; .06}	0.28 {.04; .08}	0.48 {.00; .23}
FIN-MV	0.34 {.00; .11}	0.39 {.00; .15}	0.57 {.00; .32}	0.38 {.00; .14}	0.38 {.00; .14}
8 Leverages jointly	{.00; .37}	{.00; .33}	{.00; .55}	{.00; .31}	{.00; .50}
PC-LEV	0.57 {.00; .32}	0.42 {.00; .18}	0.52 {.01; .27}	0.45 {.00; .20}	0.61 {.00; .37}
MED-LEV	0.47 {.00; .22}	0.41 {.00; .17}	0.51 {.01; .26}	0.43 {.00; .18}	0.55 {.00; .31}
PC-LEV, *F*	{.00; .44}	{.01; .25}	{.01; .33}	{.00; .32}	{.00; .49}
MED-LEV, *F*	{.00; .37}	{.01; .25}	{.00; .32}	{.00; .29}	{.00; .49}
F	{.00; .19}	{.06; .13}	{.00; .15}	{.01; .15}	{.00; .20}

Note: This Table reports **standardized slope coefficients**, **p-values (1st figure in parentheses)** and **R^2 coefficients (2nd figure in parentheses)** of regressions of absolute forecast errors for GDP, industrial production (IP), the unemployment rate (UE), gross investment (I) and the equity excess return (Rx), on the variables shown in the first column (a constant is included in all regressions). Columns labeled 'GDP', …,'Rx' indicate the respective dependent variable. P-values are based on Newey-West HAC t-statistics.

Absolute forecast errors pertains to differences between realizations at t+4 and forecasts made at t; forecasts are generated using the forecast regression referred to as 'F' in the text (based on rolling 40 quarter estimation window), i.e. the four macro-financial factors are used as predictors. Absolute forecast errors are regressed on changes of log leverage between t-4 and t (observed at t). The sample period (t) is 1992q3-2009q3.

The first eight rows use each sectoral leverage variable (YoY changes) as an individual regressor. The row labeled '8 Leverages jointly' uses all 8 leverage series jointly as regressors (in parentheses: p-values of a joint significance test of all 8 leverage variables, based on Wald test, with HAC covariance matrix). The row labeled 'PC-LEV' pertains to a regression on the first principal component of YoY changes of the 8 sectoral leverage series. The row labeled 'MED-LEV' uses the median of the standardized YoY change of the 8 sectoral log leverage series as a regressor. The next two rows add the four principal macro-financial factors as regressors. The last row (labeled 'F') regresses absolute forecast errors on just the four macro-financial factors. All regressions include a constant.

Table 5: Regressions of cross-sectional *dispersion* of SPF forecasts for GDP, IP, UE and I (4 quarters ahead), and of equity price volatility index (VIX), on leverage and macro-financial factors

	Forecast dispersion				
	GDP	**IP**	**UE**	**I**	**VIX**
INS	0.26 {.04; .06}	-0.09 {.55; .01}	0.36 {.04; .13}	0.11 {.40; .01}	0.17 {.28; .03}
SBD	-0.45 {.01; .21}	-0.52 {.00; .27}	0.04 {.68; .00}	-0.39 {.09; .15}	-0.26 {.09; .07}
CB	0.01 {.92; .00}	0.05 {.70; .00}	0.01 {.92; .00}	-0.02 {.87; .00}	0.38 {.01; .15}
HH	0.54 {.00; .30}	0.48 {.00; .23}	0.16 {.30; .02}	0.51 {.00; .26}	0.59 {.00; .35}
BUS	0.62 {.00; .39}	0.42 {.09; .18}	0.11 {.48; .01}	0.67 {.00; .45}	0.42 {.02; .18}
BNK-MV	0.33 {.18; .11}	0.24 {.29; .06}	-0.04 {.80; .00}	0.56 {.00; .32}	0.33 {.08; .11}
INS-MV	0.43 {.02; .19}	0.40 {.03; .16}	0.02 {.91; .00}	0.52 {.00; .27}	0.49 {.01; .24}
FIN-MV	0.49 {.00; .24}	0.35 {.00; .12}	0.30 {.00; .09}	0.34 {.03; .12}	0.55 {.00; .30}
8 Leverages jointly	{.00; .55}	{.00; .50}	{.00; .22}	{.00; .59}	{.00; .57}
PC-LEV	0.54 {.00; .29}	0.36 {.05; .13}	0.20 {.19; .04}	0.54 {.00; .30}	0.59 {.00; .35}
MED-LEV	0.45 {.00; .20}	0.30 {.06; .10}	0.16 {.28; .02}	0.49 {.00; .24}	0.55 {.00; .30}
PC-LEV, *F*	{.00; .34}	{.01; .21}	{.01; .10}	{.00; .36}	{.00; .36}
MED-LEV, *F*	{.00; .28}	{.01; .18}	{.00; .08}	{.00; .31}	{.00; .32}
F	{.00; .14}	{.00; .13}	{.11: .04}	{.04; .15}	{.08; .06}

Note: This Table reports **standardized slope coefficients**, **p-values (1st figure in parentheses)** and **R^2 coefficients (2nd figure in parentheses)** of: (i) regressions of the cross-sectional dispersion of date t SPF forecasts for GDP, industrial production (IP), the unemployment rate (UE) and private investment (I) at t+4 on the change of log leverage between t-4 and t; (ii) regressions of the logged CBOE equity price volatility index (VIX) at the end of period t on leverage growth between t-4 and t. P-values are based on Newey-West HAC t-statistics. The sample period (t) is 1992q3-2009q3.

The first eight rows use each sectoral leverage variable (YoY changes) as an individual regressor. The row labeled '8 Leverages jointly' pertains to regressions on all 8 individual leverage series jointly (in parentheses: p-values of a joint significance test of all 8 leverage variables, and R^2). The row labeled 'PC-LEV' pertains to a regression of forecast dispersion/VIX on the first principal component of YoY changes of the 8 log leverage series. The row labeled 'MED-LEV' uses the median of the standardized YoY change of the log leverage series as a regressor. The next two rows add the four principal macro-financial factors as regressors. The last row (labeled 'F') regresses forecast dispersion/VIX on just the four macro-financial factors. All regressions include a constant.