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Leverage as a predictor for real activity and volatility ☆

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ABSTRACT

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 predictors 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.

1. Introduction

In the years before the recent (2007–2009) 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

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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 eight 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 eight 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 eight 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 have 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 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 variable 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, 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 – commercial banks (CB), property and life insurance companies (INS), securities brokers and dealers (SBD) – 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-Banks', 'US-Insurance' and 'US-Financial

[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. (2010), Angeloni and Faia (2009), von Peter (2009), Cúrdia and Woodford (2009), Antipa et al. (2010), Dib (2010), Gerali et al. (2010), Gertler and Kiyotaki (2010), and Meh and Moran (2010).

[3] Adrian et al. (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 when assets and liabilities are short-term.

Services[6]; we refer to these sectors as BNK-MV, INS-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. Fig. 1 plots the eight sectoral leverage ratios over that period. The mean FoF-based leverage ratios of households (1.2) and of non-financial corporations (2.0) in 1993q3–2010q3 are much lower than those of the financial sectors (CB: 8.9; INS: 7.7; SBD: 27.3). The sample averages of the financial sector leverage measures based on the market value of equity are lower than the FoF-based finance sector leverages (BNK-MV: 5.9; INS-MV: 4.0; FIN-MV: 2.6).[7]

Note also that securities brokers–dealers (SBD) leverage (from FoF) and the financial sector leverage measures based on the market value of equity 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. BNK-MV, INS-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.[8] By contrast, FoF-based commercial-bank leverage has had a flat trend since about 2005, and held up well during the crisis. This may partly reflect accounting discretion, which has allowed banks to overstate the value of their assets in the crisis (e.g., Huizinga and Laeven (2009)).

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 procylical (1993q3–2010q3). CB and INS 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.

3. Econometric methodology

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

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

where Y_{t+4} is a measure of real activity in period $t+4$ (to be predicted given period t information). One period represents one quarter in calendar time. 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 eight sectoral log leverage series.[9] Φ_t is a vector of controls, discussed below. Note that, in Eq. (1), the quarterly first difference of real activity (Y_t-Y_{t-1}) is also included as a regressor.[10]

We focus on the following measures of real activity: GDP, industrial production (IP), the unemployment rate (UE) and physical investment (I).[11] 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 Eq. (1).[12] (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

[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 commercial banks; 'US-Financial Services' includes investment banks, credit card issuers, and institutions specializing in consumer loans, and thus overlaps only partially with the FoF 'securities brokers–dealers' (SBD) category. These indices only include the major financial institutions, while Flow of Funds data cover all firms in a given sector.

[7] This partly reflects the fact that the *market* value of equity is generally greater than its *book* value. Leverage measures based on *book-value* equity (also available from Datastream) are much closer to FoF-based leverage measures: 13.8, 7.5 and 14.0, respectively, for 'US-Banks', 'US-Insurance' and 'US-Financial Services' (1993q3–2010q3).

[8] These movements of the BNK-MV, INS-MV, FIN-MV and SBD leverage measures are largely driven by the sizable fluctuations in these sectors' equity. BNK-MV, INS-MV, FIN-MV leverage are also highly negatively correlated with the overall stock market (the correlation of year-on-year growth of these three leverage measures and the annual Fama-French stock market return is about -0.7).

[9] We also estimated equations with forecast horizons of 1, 2, 6, 8, and 12 quarters, and found that the key results discussed below continue to hold for those horizons. The results are likewise robust to including leverage growth over more than four quarters as a predictor. See discussions below.

[10] Also considered were models in which up to eight lags of Y_t-Y_{t-1} and of Φ_t are included as regressors. The Bayesian information criterion (BIC) does not favor inclusion of these lags.

[11] 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.

[12] Unit root tests indicate that the eight individual log leverage series are integrated of order one.

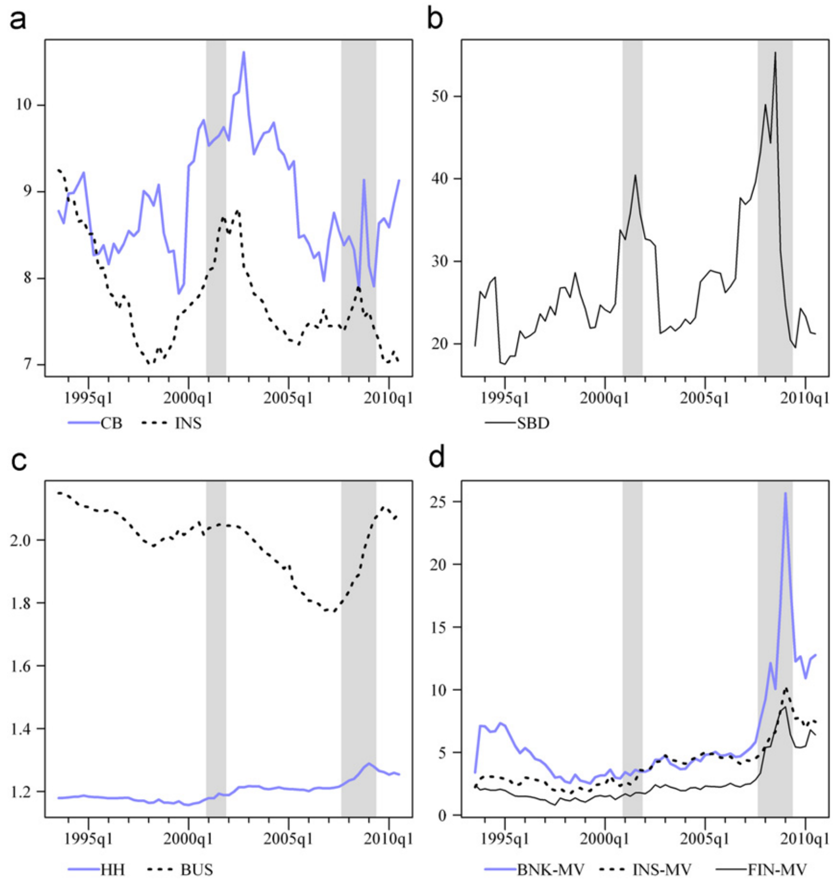

Fig. 1. Leverage ratios. The figure plots the time series of leverage ratios for the following sectors: *Panel (a)* CB: commercial banks (from Flow of Funds, FoF); INS: insurance (FoF). *Panel (b)* SBD: securities brokers and dealers (FoF). *Panel (c)* HH: households (FoF); BUS: non-financial corporate businesses (FoF). *Panel (d)* BNK-MV, INS-MV, FIN-MV: Banks, insurance and financial services, respectively, based on equity market values. Sample period: 1993q3-2010q3. Shaded areas indicate NBER recessions.

yield lower out-of-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 (1). Hence, the subsequent analysis focuses on leverage as a predictor.

As controls (Φ_t) we use the first four principal components (factors) extracted from a set of macro-financial variables other than leverage, following Stock and Watson (2002).[13] We consider a set of 30 predictors that are widely used in macroeconomic and financial forecasting: quarterly growth rates of NIPA aggregates and price indices, quarterly asset returns etc. (all variables are properly stationarized). See list in Appendix.[14]

We compute out-of-sample measures of forecast accuracy based on a rolling 40-quarter estimation window. As our data set 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 each dependent variable).

Tables 1–3 report 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

[13] We also considered specifications in which between one and eight factors are used as controls; see discussion below (and Web Appendix). The Akaike information criterion (AIC) and the Bayesian information criterion (BIC) favor the use of four factors. Models with four factors also have the best out-of-sample forecast performance; that performance decreases noticeably when more factors are included (due to overfitting). We thus use four macro-financial control factors in what follows. The fact that a small number of factors has best predictive power for macro variables has been widely documented; see, e.g., Giannone et al. (2005), and Stock and Watson (2008).

[14] The first four principal components of these 30 variables account for 57% of the total variance.

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

Forecast model	In-sample RMSEs					Out-of-sample RMSEs				
	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
F, MED-LEV	0.66	0.69	0.60	0.62	0.89	0.90	0.85	0.72	0.80	1.19
F, MED-FoF	0.62	0.70	0.61	0.63	0.80	0.84	0.90	0.83	0.87	1.00
F, MED-MV	0.68	0.71	0.63	0.63	0.90	0.96	0.87	0.76	0.85	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
CB	0.99	0.94	0.96	0.98	0.97	1.04	0.98	1.00	1.03	1.07
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
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 root mean squared forecast errors (RMSEs) of the 'Just ΔY' forecast model. Rows 2–18 show relative RMSEs, with respect to the 'Just ΔY' model. The model variants are listed in the first column (see main text for model descriptions). The last row ('SPF') pertains to 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 windows (forecast evaluation period: 1993q3–2010q3).
Columns labeled 'GDP',…,'Rx' show RMSEs for the different forecasted variables (IP: industrial production; UE: unemployment rate; I: investment; Rx: excess equity return).

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 'F, MED-LEV' model variant uses the cross-sectional median of standardized YoY changes of the eight log leverage series as the leverage predictor instead.

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 standardized YoY changes in eight sectoral log leverages
F, MED-LEV	Λ_t=median of standardized YoY changes in eight sectoral log leverage variables
F, MED-FoF	Λ_t=median of standardized YoY changes in five sectoral log leverages from Flow of Funds
F, MED-MV	Λ_t=median of standardized YoY changes in three sectoral log leverages based on equity market values
PC-LEV	$\beta_2=0$, Λ_t=principal component of YoY changes in eight sectoral log leverages
MED-LEV	$\beta_2=0$, Λ_t=median of standardized YoY changes in eight sectoral log leverage variables
CB, INS, SBD, HH, BUS, BNK-MV, INS-MV, FIN-MV	$\beta_2=0$, Λ_t is the YoY change of one of the eight sectoral log leverage variables

The leverage predictor in the model 'F, MED-FoF' is constructed as the median of YoY changes of log book-value-based leverage measures (from Flow of Funds data). In contrast, the model 'F, MED-MV' uses the median of YoY changes for the three market-value based leverage measures (based on Dow Jones/Datastream data). The entries labeled 'CB', 'INS', etc. pertain to forecast models that use the YoY difference of the corresponding individual sectoral leverage variable as regressors. The Table above summarizes these different model variants.

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

Tables 1–3 show results for forecasting Eq. (1). 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 2–18). The Table also presents the relative RMSE of the median forecasts (for GDP, IP, UE and I) reported by the Philadelphia Fed Survey of Professional Forecasters (SPF). The left panel

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

Forecast model	Whole sample					% Rolling windows with significant negative coefficients				
	GDP	**IP**	**UE**	***I***	**Rx**	**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}*
F, MED-LEV	−0.45***	−0.51***	0.40***	−0.45***	−0.39	0.74	0.70	0.07	0.77	0.45
	{0.63}	*{0.62}*	*{0.76}*	*{0.65}*	*{0.21}*	*{0.74}*	*{0.70}*	*{0.52}*	*{0.77}*	*{0.58}*
F, MED-FoF	−0.45***	−0.39***	0.31**	−0.33***	−0.65***	0.86	0.72	0.00	0.78	0.71
	{0.67}	*{0.60}*	*{0.75}*	*{0.63}*	*{0.36}*	*{0.86}*	*{0.72}*	*{0.49}*	*{0.78}*	*{0.81}*
F, MED-MV	−0.36**	−0.42***	0.29**	−0.39***	−0.24	0.36	0.29	0.33	0.29	0.09
	{0.61}	*{0.60}*	*{0.74}*	*{0.63}*	*{0.19}*	*{0.38}*	*{0.39}*	*{0.46}*	*{0.29}*	*{0.12}*
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}*
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}*
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}*
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). 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 '*% Rolling windows with significant negative coefficients*') 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 shares 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).

of Table 1 reports in-sample RMSEs, while the right panel reports RMSEs of out-of-sample forecasts, based on the rolling 40-quarter estimation windows. Throughout, the forecast evaluation period is 1993q3–2010q3.

4.1. In-sample results (forecasting Equation (1))

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 combined leverage indicators (principal component and median of standardized YoY changes of sectoral log leverages) tend to outperform the individual leverage variables, for all four real activity variables (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 ('MED-LEV' and 'PC-LEV'), 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 estimated regressions in which the eight sectoral leverage variables are included jointly (not reported in table). Wald tests show that, for each dependent variable, the eight leverages are overwhelmingly jointly significant (probability value in the range of 10^{-6}).

Table 3
The *p*-values of Clark and 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
F, MED-LEV	0.04	0.03	0.02	0.01	0.59
F, MED-FoF	0.03	0.03	0.02	0.01	0.06
F, MED-MV	0.06	0.06	0.02	0.02	0.67
PC-LEV	0.04	0.31	0.04	0.21	0.62
MED-LEV	0.01	0.04	0.04	0.02	0.61
CB	0.76	0.05	0.18	0.36	0.82
INS	0.00	0.00	0.11	0.01	0.01
SBD	0.07	0.15	0.13	0.12	0.05
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 nests the 'Random Walk' model and 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 1993q3–2010q3.

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

4.2. *Out-of-sample results — Rolling forecast regressions (Equation (1))*

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 for GDP of the model with the four macro-financial factors (model 'F') 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 continues to achieve forecast improvements for GDP, as shown by the combined models 'F, PC-LEV' and 'F, MED-LEV', which suggests that leverage contains information on top of established predictors.[15] The combined leverage models 'F, MED-FoF' and 'F, MED-MV' likewise perform well for all four real activity variables; their RMSEs are in the same range, i.e., the performance of book-value and market-value based predictions is roughly comparable. 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 *joint* leverage indicators is statistically significant — the same holds for the macro-financial factors.[16]

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 ('CB', 'INS', …,'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

[15] That result continues to hold when each of the *individual* macro-financial variables is used as a predictor (instead of principal components); use of individual macro-financial variables worsens RMSEs, but leverage remains a significantly negative predictor of future real activity growth.

[16] We also used the Clark and West (2007) test to compare models that use the four macro-financial factors *and* leverage as predictors, against the 'F' model. Tests of model 'F, MED-LEV' vs. 'F' yield *p*-values 0.08, 0.01, 0.09, 0.01 and 0.65, respectively, for GDP, IP, UE, I and Rx. Thus, *joint* leverage information has statistically significant predictive value added (for real activity), on top of the macro-financial factors. By contrast, *individual* sectoral leverage series generally yield no significant predictive improvement, when added to the macro-financial factors. (See Web Appendix for detailed results.)

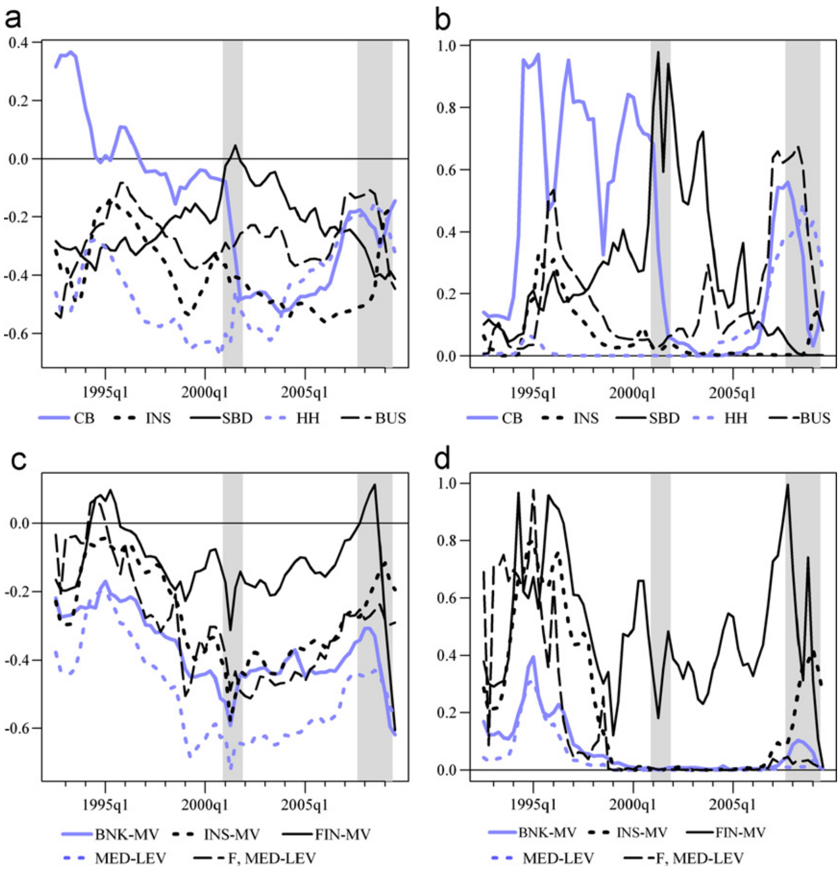

Fig. 2. Slope coefficients of leverage and p-values, from rolling forecast regressions for GDP. *Panels* (a) and (c): Standardized regression coefficients of leverage variables in forecast regressions for GDP (based on 40-quarter rolling windows). *Panels* (b) and (d): probability-values from Newey-West HAC t-statistics for slope coefficients of leverage (from GDP forecast regressions). The slope coefficients and p-values are shown for models 'CB', 'INS', 'SBD', 'HH', 'BUS', 'BNK-MV', 'INS-MV', 'FIN-MV', 'MED-LEV' and 'F,MED-LEV'. Date (abscissa) indicates final observation of the 40-quarter estimation window for the explanatory variables. Shaded areas indicate NBER recessions.

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.

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 of rolling samples 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). The median of YoY leverage growth rates (model 'MED-LEV') as well as their principal component (model 'PC-LEV') both feature a negatively significant coefficient (positive for unemployment) for the vast majority of samples.[17]

Fig. 2 plots standardized regression coefficients of leverage and their p-values, across the rolling estimation windows, for the GDP forecast equations. 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.

[17] When controlling for the macro-financial factors (models 'F, MED-LEV' and 'F, PC-LEV'), the leverage coefficient remains significantly negative for a majority of rolling samples (for each real activity variable).

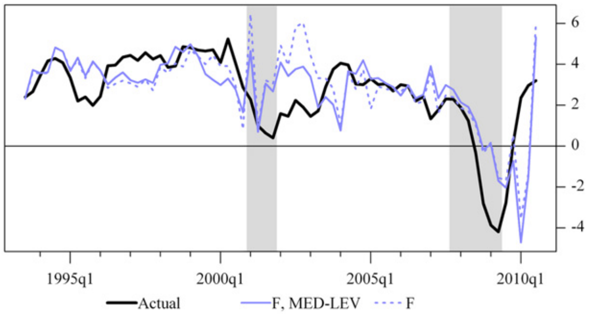

Fig. 3. The figure shows actual and predicted year-on-year GDP rates growth (in %), 1993q3–2010q3. The line labeled 'F' shows the prediction (based on 40-quarter rolling estimation windows) generated by a forecast model that includes (as predictors) four factors extracted from a set of 30 macro-financial variables. The line labeled 'F, MED-LEV' shows the prediction obtained by adding the median of the annual growth rates of the eight sectoral leverage series, as a predictor. Shaded areas indicate NBER recessions.

Table 4
RMSEs of models that include 8-quarter differences of leverage as predictors.

	In-sample RMSEs					Out-of-sample RMSEs				
Forecast model	**GDP**	**IP**	**UE**	***I***	**Rx**	**GDP**	**IP**	**UE**	***I***	**Rx**
Just ΔY	*1.80*	*3.99*	*0.88*	*10.32*	*20.17*	*1.95*	*4.39*	*0.97*	*11.16*	*21.53*
F	0.74	0.78	0.65	0.66	0.92	0.97	0.87	0.74	0.84	1.10
F, PC-LEV	0.69	0.71	0.61	0.65	0.90	0.94	0.89	0.76	0.86	1.16
F, MED-LEV	0.67	0.71	0.60	0.63	0.89	0.89	0.86	0.73	0.82	1.13
PC-LEV	0.96	0.98	0.96	0.99	1.00	1.01	1.06	1.02	1.07	1.16
MED-LEV	0.93	0.98	0.94	0.98	0.99	0.95	1.01	0.97	1.02	1.20

Note: The RMSEs reported in this table pertain to forecast models similar to Eq.(1), but with leverage indicators (Λ_t) based on 8-quarter differences of sectoral leverage series.
The first row shows absolute RMSEs of the 'Just ΔY' forecast model (RMSEs are different from those shown Table 1, as the forecast evaluation period here was shortened to 1994q3–2010q3 for data availability reasons). The remaining rows show relative RMSEs, with respect to the 'Just ΔY' model. The model variants are listed in the first column (see main text for model descriptions).
'In-sample RMSEs' are based on regressions estimated for the sample 1994q3–2010q3 (for each dependent variable). 'Out-of-sample RMSEs' are based on (pseudo) out-of-sample forecasts one year ahead, from 40-quarter rolling estimation windows.
Columns labeled 'GDP',…,'Rx' pertain to the different forecasted variables (IP: industrial production; UE: unemployment rate; *I*: investment; Rx: excess equity return).

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 Fig. 3, which plots the GDP forecasts (rolling-window based) generated by the model with the four macro-financial factors ('F'), and by the model with these four factors *and* the median of leverage growth rates ('F, MED-LEV'). Both models fail to predict the dramatic fall in GDP during the recession — in fact, both models yield essentially the *same* predictions for GDP, for 2008–2009. Fig. 3 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).

4.3. Robustness: Lag structure, non-linearities

The discussion so far has focused on forecast models that use past year-on-year changes of leverage as a predictor of real activity. Due to the sustained buildup of leverage before the crisis, it seems interesting to also consider (past) leverage growth over a period longer than one year, as a predictor of future real activity. We experimented with model variants in which leverage growth over 6, 8 and 12 quarters is used as a predictor — those variants have lower predictive accuracy than the baseline models (with YoY leverage growth). However, the link between past leverage growth and future real activity remains negative and highly significant. Tables 4 and 5 show results for a model variant in which 8-quarter leverage growth is used as a predictor.

We also considered forecast equations that use, as predictors, past changes of real activity over longer lags ($Y_t - Y_{t-s}$ for $s>1$) and macro-financial factors (Φ_t) based on changes of variables over more than one quarter.[18] These alternative specifications confirm our results about leverage; in fact, leverage emerges as a slightly more significant negative predictor

[18] Specifically, the quarterly growth rates and returns used in the construction of the factors (see right-most column in Panel (c) of Appendix) were replaced by growth rates and returns over $s>1$ quarters.

Table 5
Regression coefficients of leverage indicators (based on 8-quarter differences).

Forecast model	Whole sample					% Rolling windows with significant negative coefficients				
	GDP	**IP**	**UE**	***I***	**Rx**	**GDP**	**IP**	**UE**	***I***	**Rx**
F, PC-LEV	−0.43**	−0.52***	0.35**	−0.24	−0.29	0.49	0.71	0.00	0.40	0.37
	{0.61}	*{0.60}*	*{0.75}*	*{0.60}*	*{0.19}*	*{0.71}*	*{0.71}*	*{0.46}*	*{0.40}*	*{0.40}*
F, MED-LEV	−0.52***	−0.53***	0.38***	−0.37**	−0.40	0.66	0.85	0.00	0.60	0.58
	{0.64}	*{0.60}*	*{0.75}*	*{0.63}*	*{0.21}*	*{0.66}*	*{0.85}*	*{0.65}*	*{0.60}*	*{0.71}*
PC-LEV	−0.34*	−0.23	0.36**	−0.14	−0.10	0.62	1.00	0.00	0.68	0.18
	{0.24}	*{0.22}*	*{0.37}*	*{0.08}*	*{0.01}*	*{0.62}*	*{1.00}*	*{0.88}*	*{0.68}*	*{0.18}*
MED-LEV	−0.44**	−0.28	0.45***	−0.24	−0.13	0.83	1.00	0.00	0.89	0.42
	{0.29}	*{0.23}*	*{0.40}*	*{0.10}*	*{0.02}*	*{0.83}*	*{1.00}*	*{1.00}*	*{0.89}*	*{0.60}*

Note: The *Left panel* (labeled '*Whole sample*') shows standardized slope coefficients of leverage indicators, based on 8-quarter differences of sectoral leverage series, for the models considered in Table 4. The coefficients are from regressions of each dependent variable on these leverage indicators and other predictors for the period 1994q3–2010q3. Asterisks indicate significance levels (based on Newey-West HAC *t*-statistics): * 10%, ** 5%, *** 1%. Numbers in brackets are R^2 coefficients of corresponding regression equations.
The *Right panel* (labeled '*% Rolling windows with significant negative coefficients*') 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 shares for significant negative and positive coefficients). The left column lists model variants, as described in the main text. Columns labeled 'GDP',…,'Rx' pertain to the different forecasted variables (IP: industrial production; UE: unemployment rate; *I*: investment; Rx: excess equity return).

Table 6
RMSEs of models that include non-linear transformations of leverage as predictors.

Forecast model	In-sample RMSEs					Out-of-sample RMSEs				
	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*
F	0.74	0.78	0.67	0.69	0.92	0.97	0.87	0.76	0.85	1.10
F, PC-LEV asym	0.68	0.71	0.59	0.64	0.90	1.02	0.93	0.78	0.93	1.25
F, MED-LEV asym	0.66	0.68	0.57	0.62	0.88	0.95	0.88	0.75	0.86	1.26
PC-LEV asym	0.89	0.93	0.83	0.93	0.98	1.13	1.18	1.08	1.21	1.19
MED-LEV asym	0.85	0.89	0.77	0.88	0.96	0.98	1.02	0.86	1.02	1.20
F, PC-LEV sq	0.68	0.71	0.60	0.64	0.88	1.16	1.04	0.79	1.03	1.40
F, MED-LEV sq	0.66	0.68	0.57	0.62	0.87	1.01	0.98	0.74	0.89	1.49
PC-LEV sq	0.89	0.92	0.85	0.93	0.95	1.35	1.33	1.20	1.35	1.31
MED-LEV sq	0.85	0.89	0.79	0.88	0.93	1.08	1.14	0.91	1.08	1.40

Note: This table shows RMSEs for forecast models that include non-linear transformations of leverage indicators (Λ_t), as predictors; see Eq. (2). The suffix 'asym' denotes inclusion of the asymmetric term max(0, Λ_t). The suffix 'sq' denotes inclusion of the squared term $(\Lambda_t)^2$. The following predictors are also included: the past change in real activity ($Y_t - Y_{t-1}$), the macro-financial factors (Φ_t) and Λ_t.
The first row shows absolute RMSEs of the 'Just ΔY' forecast model. The remaining rows show relative RMSEs, with respect to the 'Just ΔY' model. The model variants are listed in the first column (see main text for descriptions).
'In-sample RMSEs' are based on regressions 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 windows (forecast evaluation period: 1993q3–2010q3).
Columns labeled 'GDP',…,'Rx' pertain to the different forecasted variables (IP: industrial production; UE: unemployment rate; *I*: investment; Rx: excess equity return).

than in the baseline models. The Web Appendix also reports results for forecast regressions that predict changes of real activity at a longer horizon (than the 4-quarter horizon considered so far). Again, the negative link between leverage and future real activity remains (but it is weaker, the longer the horizon).[19] A VAR analysis likewise confirms this finding: positive innovations to leverage trigger a prolonged decrease in GDP growth (see Web Appendix).

Furthermore, it seems interesting to investigate whether there are non-linearities and asymmetries in the link between leverage and (future) real activity. We thus consider the following extension of Eq. (1):

$$Y_{t+4} - Y_t = \beta_0 + \beta_1 (Y_t - Y_{t-1}) + \beta_2 \Phi_t + \beta_3 \Lambda_t + \beta_4 f(\Lambda_t) + \varepsilon_{t+4}, \tag{2}$$

[19] As mentioned above, we also ran forecast regressions that include leverage and between one and eight macro-financial principal components (factors) as predictors (NB the specifications above use four factors). The highly statistically significant negative link between leverage and future real activity holds irrespective of the number of included macro-financial control factors — the slope coefficients of leverage and their *p*-values are very stable when the number of factors is changed. This holds both for regressions over the whole sample periods, and for the 40-quarter rolling estimation windows. (See the Web Appendix.)

Table 7
Regression coefficients of leverage in forecast models that also include non-linear transformations of leverage as predictors.

	Whole sample					**% Rolling windows with significant negative coefficient**				
Forecast model	**GDP**	**IP**	**UE**	***I***	**Rx**	**GDP**	**IP**	**UE**	***I***	**Rx**
F, PC-LEV asym	−0.38**	−0.39*	0.11	−0.40**	−0.48	0.28	0.10	0.03	0.23	0.00
	{0.62}	*{0.60}*	*{0.76}*	*{0.61}*	*{0.20}*	*{0.28}*	*{0.12}*	*{0.04}*	*{0.23}*	*{0.07}*
F, MED-LEV asym	−0.36**	−0.29	0.10	−0.42**	−0.60*	0.23	0.10	0.12	0.33	0.09
	{0.63}	*{0.63}*	*{0.78}*	*{0.65}*	*{0.22}*	*{0.23}*	*{0.13}*	*{0.13}*	*{0.33}*	*{0.12}*
PC-LEV asym	−0.58***	−0.53**	0.16	−0.48**	−0.54*	0.58	0.13	0.00	0.46	0.03
	{0.34}	*{0.31}*	*{0.53}*	*{0.19}*	*{0.05}*	*{0.58}*	*{0.13}*	*{0.09}*	*{0.46}*	*{0.04}*
MED-LEV asym	−0.59***	−0.44**	0.15	−0.50***	−0.61**	0.65	0.14	0.01	0.42	0.16
	{0.40}	*{0.37}*	*{0.60}*	*{0.28}*	*{0.08}*	*{0.65}*	*{0.14}*	*{0.09}*	*{0.42}*	*{0.17}*
F, PC-LEV sq	−0.43***	−0.49***	0.35***	−0.38***	−0.27	0.54	0.71	0.14	0.62	0.22
	{0.62}	*{0.60}*	*{0.76}*	*{0.61}*	*{0.22}*	*{0.54}*	*{0.77}*	*{0.57}*	*{0.62}*	*{0.33}*
F, MED-LEV sq	−0.44***	−0.50***	0.38***	−0.45***	−0.39	0.77	0.74	0.12	0.88	0.48
	{0.63}	*{0.63}*	*{0.78}*	*{0.65}*	*{0.25}*	*{0.77}*	*{0.74}*	*{0.61}*	*{0.88}*	*{0.57}*
PC-LEV sq	−0.57***	−0.50**	0.55**	−0.46*	−0.35	0.80	0.93	0.00	0.91	0.33
	{0.35}	*{0.32}*	*{0.52}*	*{0.19}*	*{0.10}*	*{0.80}*	*{0.93}*	*{0.55}*	*{0.91}*	*{0.43}*
MED-LEV sq	−0.63***	−0.56***	0.59***	−0.57***	−0.39*	0.86	0.96	0.00	1.00	0.46
	{0.40}	*{0.37}*	*{0.57}*	*{0.28}*	*{0.13}*	*{0.86}*	*{0.96}*	*{0.64}*	*{1.00}*	*{0.58}*

Note: The *Left panel* (labeled '*Whole sample*') shows standardized slope coefficients (β_3) of leverage in forecasting eq. (2) (note: the equation also includes a non-linear function of leverage, as a regressor); estimation period: 1993q3–2010q3. Asterisks indicate significance levels (based on Newey-West HAC *t*-statistics): *10%, **5%, ***1%. Numbers in brackets are R^2 coefficients of corresponding regression equations.
The *Right panel* (labeled '*% Rolling windows with significant negative coefficients*') 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 shares for significantly negative and positive coefficients).
The left column lists model variants (see main text for descriptions). The suffix 'asym' denotes inclusion of the term max(0, Λ_t); the suffix 'sq' denotes inclusion of the leverage growth indicator squared, $(\Lambda_t)^2$.
Columns labeled 'GDP', …,'Rx' pertain to the different forecasted variables (IP: industrial production; UE: unemployment rate; *I*: investment; Rx: excess equity return).

Table 8
Regression coefficients of non-linear transformations of leverage.

	Whole sample					**% Rolling windows with significant negative coefficients**				
Forecast model	**GDP**	**IP**	**UE**	***I***	**Rx**	**GDP**	**IP**	**UE**	***I***	**Rx**
F, PC-LEV asym	−0.06	−0.15	0.39	0.03	0.36	0.07	0.20	0.01	0.09	0.09
	{0.62}	*{0.60}*	*{0.76}*	*{0.61}*	*{0.20}*	*{0.32}*	*{0.22}*	*{0.17}*	*{0.33}*	*{0.13}*
F, MED-LEV asym	−0.13	−0.33	0.44*	−0.05	0.33	0.06	0.36	0.00	0.07	0.33
	{0.63}	*{0.63}*	*{0.78}*	*{0.65}*	*{0.22}*	*{0.23}*	*{0.39}*	*{0.22}*	*{0.30}*	*{0.54}*
PC-LEV asym	0.06	0.08	0.62*	0.04	0.42	0.09	0.19	0.04	0.13	0.14
	{0.34}	*{0.31}*	*{0.53}*	*{0.19}*	*{0.05}*	*{0.33}*	*{0.19}*	*{0.19}*	*{0.33}*	*{0.14}*
MED-LEV asym	−0.02	−0.15	0.65***	−0.09	0.42	0.09	0.28	0.00	0.14	0.36
	{0.40}	*{0.37}*	*{0.60}*	*{0.28}*	*{0.08}*	*{0.17}*	*{0.28}*	*{0.39}*	*{0.26}*	*{0.48}*
F, PC-LEV sq	0.02	−0.04	0.19	0.01	0.35	0.10	0.23	0.06	0.09	0.10
	{0.62}	*{0.60}*	*{0.76}*	*{0.61}*	*{0.22}*	*{0.35}*	*{0.28}*	*{0.26}*	*{0.35}*	*{0.22}*
F, MED-LEV sq	−0.02	−0.13	0.22*	−0.04	0.30	0.07	0.41	0.06	0.07	0.43
	{0.63}	*{0.63}*	*{0.78}*	*{0.65}*	*{0.25}*	*{0.25}*	*{0.48}*	*{0.33}*	*{0.30}*	*{0.64}*
PC-LEV sq	0.11	0.14	0.26**	0.06	0.35*	0.14	0.19	0.09	0.13	0.17
	{0.35}	*{0.32}*	*{0.52}*	*{0.19}*	*{0.10}*	*{0.26}*	*{0.19}*	*{0.29}*	*{0.23}*	*{0.23}*
MED-LEV sq	0.09	0.04	0.25**	0.02	0.34*	0.14	0.29	0.04	0.16	0.41
	{0.40}	*{0.37}*	*{0.57}*	*{0.28}*	*{0.13}*	*{0.25}*	*{0.29}*	*{0.28}*	*{0.26}*	*{0.54}*

Note: The *Left panel* (labeled '*Whole sample*') shows standardized slope coefficients (β_4) for the non-linear function of leverage, in forecasting Eq. (2); estimation period: 1993q3–2010q3. Asterisks indicate significance levels (based on Newey-West HAC t-statistics): * 10%, ** 5%, *** 1%. Numbers in brackets are R^2 coefficients of corresponding regression equations.
The *Right panel* (labeled '*% Rolling windows with significant negative coefficients*') shows the share of coefficients for the non-linear functions of leverage 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 non-linear terms at 10% level (i.e., sum of shares for significantly negative and positive coefficients).
The left column lists model variants (see main text for descriptions). The suffix 'asym' denotes inclusion of the term max(0, Λ_t); the suffix 'sq' denotes inclusion of the leverage growth indicator squared, $(\Lambda_t)^2$.
Columns labeled 'GDP', …,'Rx' pertain to the different forecasted variables (IP: industrial production; UE: unemployment rate; *I*: investment; Rx: excess equity return).

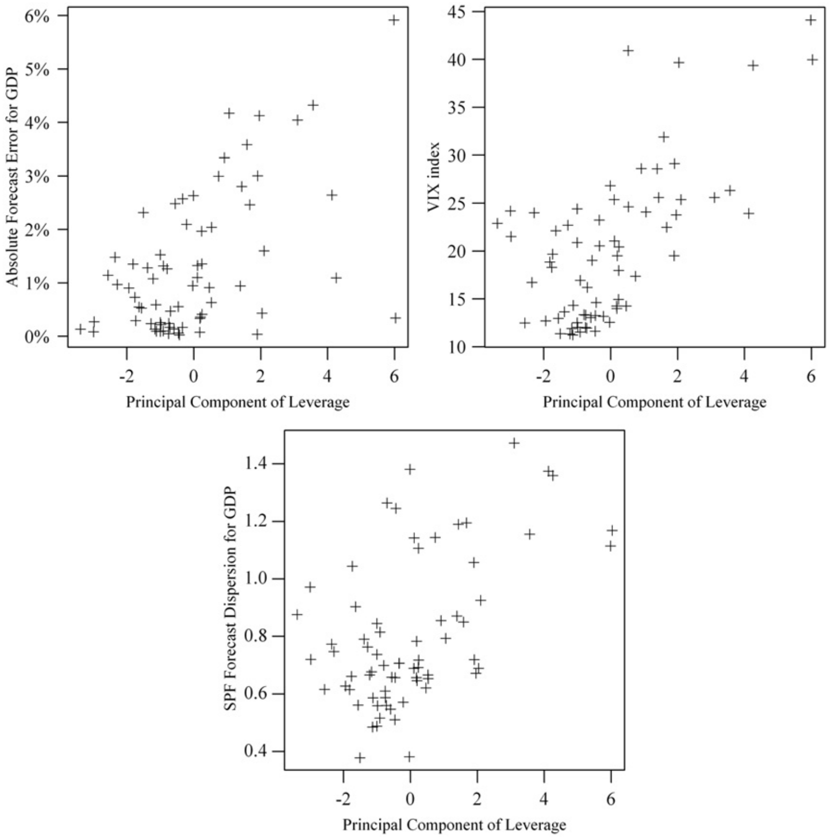

Fig. 4. The figure shows scatter plots of absolute forecast errors for GDP (in %) between t and $t+4$, of equity volatility index (VIX) at t, and of date t cross-sectional dispersion of SPF forecasts of GDP growth between t and $t+4$ vs. the first principal component (of the YoY change) of sectoral log leverages between $t-4$ and t. The forecast errors pertain to forecast model 'F' (four macro-financial factors used as predictors), based on rolling 40-quarter estimation windows. The sample period (t) is 1992q3–2009q3.

where $f(\Lambda_t)$ represents a non-linear function of the (year-on-year) leverage measure Λ_t. We use $f(\Lambda_t)=\max(0, \Lambda_t)$, to allow responses to differ across positive and negative (YoY) leverage changes (Kilian and Vigfusson, 2009); we also consider $f(\Lambda_t)=(\Lambda_t)^2$, in order to test for a disproportionate impact of large swings in leverage. As shown in Tables 6–8, the augmented models exhibit considerably worse out-of-sample forecasting performance. However, the link between future real activity growth and leverage growth Λ_t remain negative and significant. By contrast, the coefficients for the asymmetry terms are rarely significant and their signs show no consistent pattern. We also allowed for non-linear effects of leverage changes over lags greater than one year. Again, we find no support for significant non-linearities. Furthermore, we tested for multiplicative interactions between leverage and the other regressors. These interactions terms are rarely significant, and they markedly reduce out-of sample forecast performance (but leverage growth remains strongly negatively significant as a predictor of future real activity growth). See the Web Appendix for the detailed sensitivity and robustness results.

In summary, the in-sample and out-of-sample results suggest very clearly that leverage is a statistically significant *negative* predictor for future real activity growth. 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 any better than conventional macro-financial predictors.

The negative relation between leverage and future real activity growth seems broadly consistent (at least qualitatively) with the predictions of recent structural macro models with financial intermediaries.[20] Theoretical research also suggests that leverage might matter for the conditional *volatility* of future real activity and returns: essentially, an increase in leverage today

[20] See, e.g., the models in Aikman and Paustian (2006), Meh and Moran (2010) and Kollmann et al. (2011). These models predict that a negative transitory shock to private sector total factor productivity lowers bank leverage. Such a shock also lowers GDP, on impact, but subsequently GDP is predicted to revert to its pre-shock level; hence, leverage is negatively correlated with *future* GDP growth. (The mechanisms that induce the fall in leverage differ across models; e.g., in Kollmann et al. (2011) it is due to the fact that household savings and the supply of deposit decrease, which leads banks to finance a larger share of their asset holdings by raising equity). An exogenous negative shock to bank capital is likewise predicted to decrease future output. We leave for future research a detailed empirical evaluation of this new class of models.

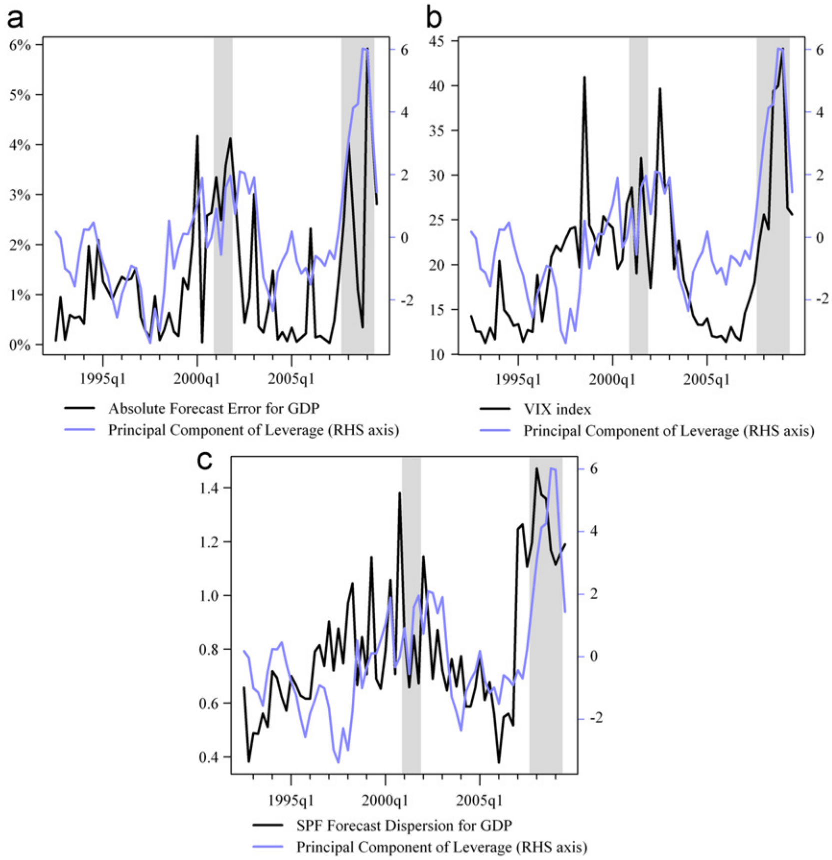

Fig. 5. Time series plots of absolute future forecast errors, VIX, forecast dispersion and leverage. Each panel shows time series plots of the first principal component of the YoY change in sectoral log leverages between $t-4$ and t, and another variable. *Panel (a)*: absolute forecast error for GDP (in %) between t and $t+4$. *Panel (b)*: equity volatility index (VIX) at 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 Fig. 4.) The forecast errors pertain to forecast model 'F' (four macro-financial factors used as predictors), based on rolling 40-quarter estimation windows. The sample period (t) is 1992q3–2009q3. Shaded areas indicate NBER recessions.

should amplify the effect of future shocks.[21] This would imply a positive link between leverage and uncertainty about future economic conditions. The next section documents that such a link exists in the data — and that it is powerful.[22]

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).[23]

Fig. 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.) Fig. 5 plots time series of these variables (using the same timing convention). The absolute forecast errors in Figs. 4 and 5

[21] See, e.g., Krugman (2008), Devereux and Yetman (2010), and Kollmann and Malherbe (2011) for discussions of mechanisms through which leverage may amplify the effect of shocks.

[22] Previous research has documented that the conditional volatility of real activity is time-varying (e.g., Giannone et al. (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.

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

Table 9
Regressions of absolute out-of-sample forecast errors on leverage and macro-financial factors.

Forecast model	GDP	IP	UE	*I*	Rx
CB	0.22 {.01; .05}	0.38 {.04; .14}	0.24 {.01; .06}	0.25 {.05; .06}	0.42 {.00; .18}
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}
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}
F, PC-LEV	{.00; .44}	{.01; .25}	{.01; .33}	{.00; .32}	{.00; .49}
F, MED-LEV	{.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** of leverage, ***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. The 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 eight leverage series jointly as regressors (in parentheses: p-values of a joint significance test of all eight leverage variables, based on a 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 eight sectoral leverage series. The row labeled 'MED-LEV' uses the median of the standardized YoY change of the eight 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 (p-value is for joint significance tests). All regressions include a constant.

Table 10
Regressions of cross-sectional *dispersion* of SPF forecasts for GDP, IP, UE and I (four quarters ahead), and of equity price volatility index (VIX), on leverage and macro-financial factors.

	Forecast dispersion				
	GDP	IP	UE	*I*	VIX
CB	0.01 {.92; .00}	0.05 {.70; .00}	0.01 {.92; .00}	−0.02 {.87; .00}	0.38 {.01; .15}
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}
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}
F, PC-LEV	{.00; .34}	{.01; .21}	{.01; .10}	{.00; .36}	{.00; .36}
F, MED-LEV	{.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** of leverage, ***p*-values (1st figure in parentheses)** and **R^2 coefficients (2nd figure in parentheses)** of: (i) regressions of the cross-sectional dispersion of 4-quarter-ahead SPF forecasts made at date t for GDP, industrial production (IP), the unemployment rate (UE) and private investment (I), 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. The 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 eight individual leverage series jointly (in parentheses: p-values of a joint significance test of all eight 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 eight 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 (p-value is for joint significance test). All regressions include a constant.

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.) Figs. 4 and 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.

Tables 9 and 10 provide regression evidence on the link between leverage and conditional future volatility/dispersion. Table 9 regresses absolute date $t+4$ forecast errors for each of our five dependent variables on (annual YoY changes of) our eight sectoral log leverage variables observed at t (see first eight rows of Table); we also regress absolute forecasts errors on all eight sectoral leverage series *jointly*, and on the principal component and median value of (YoY changes of) sectoral log leverages. Table 9 furthermore shows results that obtain when the four macro-financial factors are added as regressors. In Table 10, 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 (Column 5) are regressed on the regressors used in Table 9.

In almost all regressions, the slope coefficients of leverage are positive and highly statistically significant.[24] 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 35% of the variances of the absolute GDP forecast errors, of SPF cross-sectional GDP forecast dispersion, and of VIX (see R^2 coefficients).[25] 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 a statistically significant negative link between leverage and future real activity, and a significant positive link 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 macroeconomic and financial predictors commonly used by forecasters. However, leverage information would *not* have 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 (Fama-French 'MKT' return vs. T-bill return)	K. French website

(b) Leverage

Series label	***Variable***	***Source***
SBD	Securities Brokers and Dealers leverage ratio	Flow of Funds
CB	Commercial Banks leverage ratio	Flow of Funds
INS	Life and casualty insurance leverage ratio	Flow of Funds
SBD	Securities Brokers and Dealers 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 market value	Datastream
INS-MV	US-Insurance index: total assets / equity market value	Datastream
FIN-MV	US-Fin. Services index: total assets / equity 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

[24] 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.

[25] As pointed out by a referee, a GARCH-type model could also be used to assess the effect of leverage on volatility. A one-period-ahead GARCH variance equation that includes leverage as a regressor supports the notion that leverage is significantly positively related to future output volatility. (Implementing a GARCH set-up for a horizon of four (or more) quarters raises major challenges beyond the scope of this paper.)

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)	3-month U.S. T-bill	Federal Reserve Board	Quarterly return
18)	2-year U.S. Treasury bond	Federal Reserve Board	Quarterly return
19)	5-year U.S. Treasury bond	Federal Reserve Board	Quarterly return
20)	U.S. Treasury term spread: 10yr –3month par yield	Federal Reserve Board	Quarterly difference
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)	Fama-French HML factor	K. French website	–
27)	Fama-French Momentum factor	K. French website	–
28)	Fama-French SMB factor	K. French website	–
29)	Fama-French Short-term reversal factor	K. French website	–
30)	Fama-French 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

Note: 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. Where applicable, variables were used in seasonally-adjusted form as provided by the data source. 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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