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19 July 2017

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July 19, 2017

Abstract

I use the GARCH-MIDAS framework of Engle et al. (2013) to examine the relationship between the macro economy and stock market volatility, focusing on the role played by survey-based sentiment indicators compared to macroeconomic variables. I find that once the information in sentiment indicators is controlled for, backward-looking macroeconomic data does not include useful information for predicting stock return volatility. On the other hand, forward-looking macroeconomic variables remain useful for forecasting stock market volatility after sentiment data is taken into account. The term spread is the best predictor for stock return volatility over long horizons.

JEL Classification: G17, G12, C53

Keywords: stock market volatility, volatility components, MIDAS, survey data, macro finance link

*I thank Markku Lanne and Matthijs Lof, as well as the participants of the FDPE Econometrics Workshops and the SoFiE 2016 Summer school, for useful suggestions and comments. I gratefully acknowledge financial support from the OP Group Research Foundation, the Yrjö Jahnsson Foundation and the Academy of Finland.

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1 Introduction

Stock market volatility is crucial for asset allocation and risk management, and it can also be interpreted as a measure of risk and uncertainty. Therefore, it is important to understand, model and forecast stock return volatility accurately. While short-term volatility (e.g., daily) is well described and forecasted by, for example, GARCH models and stochastic volatility models[1], longer horizon modelling and forecasting of volatility (e.g., monthly or quarterly) relies on, for example, autoregressive models for realised volatility, predictive regressions and component GARCH models. It is well established by, for example, Fama and French (1989) and Schwert (1989a), that risk premiums and stock market volatility are countercyclical. The research on the macroeconomic determinants of stock market volatility has its roots in Schwert (1989b) and Officer (1973), but much of the early literature found links that are weaker than expected. The recent financial crisis underlined the importance of understanding the sources of volatility, leading to new interest in determining how the macroeconomy affects financial market volatility. For example, component GARCH models – where volatility is decomposed into a transitory high-frequency component and a slowly evolving low-frequency component – have recently provided robust evidence in favour of macroeconomic determinants of (low-frequency) financial market volatility.[2] Knowledge of the macroeconomic variables affecting volatility improves our understanding of why volatility varies over longer time periods and can enable more precise volatility forecasts, especially over long horizons.

The main aim of this paper is to compare the information content of macroeconomic fundamentals and survey-based sentiment data for stock return volatility in the GARCH-MIDAS[3] framework of Engle et al. (2013). The GARCH-MIDAS model decomposes volatility into two components: a short-term (GARCH) component (e.g., daily frequency) which fluctuates around a long-term trend (e.g., quarterly frequency). The low-frequency component of volatility is directly determined by macroeconomic variables. It is clear from earlier research[4] that there is a vast number of potentially good explanatory variables for stock market volatility. The GARCH-MIDAS literature has found a large set of useful predictors by including

[1] See, for example, Poon and Granger (2003) for a survey, or Andersen et al. (2006) for an overview of volatility forecasting.

[2] For example, Engle and Rangel (2008), Engle et al. (2013) and Conrad and Loch (2014).

[3] GARCH-MIDAS stands for a generalised autoregressive conditional heteroskedasticity (GARCH) model, combined with a mixed data sampling (MIDAS) approach, see Section 3 for details.

[4] For example, Christiansen et al. (2012) and Conrad and Loch (2014). See Section 2 for details.

one variable at a time (or the level and volatility of the same variable) into the MIDAS polynomial.[5] I focus on models containing different types of variables in order to investigate how including survey-based sentiment data affects the explanatory power of macroeconomic data. I determine whether the in-sample fit and the out-of-sample forecasting ability of GARCH-MIDAS models can be improved by combining information in the two types of indicators. This paper builds on Engle et al. (2013), who introduced the GARCH-MIDAS model, and Conrad and Loch (2014), who, using the GARCH-MIDAS framework, found many macroeconomic and sentiment variables useful for modelling long-term stock market volatility.

First, I establish a baseline using GARCH-MIDAS models driven by one variable at a time.[6] Contrary to earlier literature, I use a real-time macroeconomic data set to match the information sets of the agents at the time and accurately take into account data revisions. I also argue that the recession probabilities given by professional forecasters – a novel measure in this context – proxy the business cycle, making them interesting predictors for stock return volatility. Principal components based on the macroeconomic and sentiment data are used to infer the usefulness of summarising information in the variables.

Next, I determine the relative and combined importance of macroeconomic data and sentiment indicators as drivers of long-term stock return volatility by including different types of variables simultaneously in the GARCH-MIDAS model. These results are compared to the baseline obtained earlier. This allows us to infer the marginal benefit for the in-sample fit from adding a second variable into the model.

Finally, I explore the out-of-sample forecasting performance of the GARCH-MIDAS specifications in order to determine whether stock return volatility forecasts can be improved by simultaneously utilising information in macroeconomic variables and survey-based sentiment data. I take the GARCH(1,1) model as a benchmark for the out-of-sample forecasts, in line with Asgharian et al. (2013), which, to the best of my knowledge, is currently the only paper to compare the forecasting ability of GARCH-MIDAS models to the standard GARCH(1,1) model.[7] A new perspective on the comparison of the baseline GARCH-MIDAS models is given by the Model Confidence Set (MCS) procedure by Hansen et al. (2011), which allows

[5]The exception is realised volatility, which was included together with other explanatory data in the MIDAS polynomial in Conrad and Loch (2014) and Asgharian et al. (2013). Asgharian et al. (2013) summarised information in several variables using principal components analysis.

[6]This section closely follows Conrad and Loch (2014), largely confirming their results.

[7]However, the set-up in Asgharian et al. (2013) differs in many regards from the set-up here.

simultaneously comparing the performance of all models.

My main conclusion is that once the information in sentiment indicators is controlled for, backward-looking macroeconomic data, such as industrial production, does not contain useful information for stock return volatility. Forward-looking macroeconomic variables (housing starts and the term spread) remain useful for explaining and predicting stock market volatility even after sentiment data is included. On the other hand, adding a survey-based sentiment indicator to the GARCH-MIDAS specification rarely improves the forecasting performance of the models where the term spread or housing starts is the only explanatory variable. Over long horizons the term spread is the best predictor of stock return volatility, while the (asymmetric) GARCH(1,1) model is difficult to beat at short horizons.

The remainder of the paper is organised as follows. Section 2 reviews the relevant literature and discusses the relationship between stock market volatility and the macro economy. The GARCH-MIDAS framework of Engle et al. (2013) is presented in Section 3, and Section 4 describes the data. Section 5 presents the in-sample results, while Section 6 discusses the out-of-sample forecasts. Finally, Section 7 concludes.

2 Stock market volatility, sentiment and the macro economy

It is widely accepted that stock return volatility is countercyclical, and that on the aggregate level the value of future cash flows depends on the state of the economy. The theoretical link between stock market volatility and the macro economy is formalised in, for example, Veronesi (1999), who presented a rational expectations equilibrium model where the stock market overreacts to bad news in good times and underreacts to good news in bad times. Other theoretical explanations include the present value models of Campbell (1991) and Campbell and Shiller (1988), as well as models with time-varying volatility in fundamentals (i.e., dividends and consumption growth rate), such as Bansal and Yaron (2004). Mele (2007) developed a framework where countercyclical stock market volatility is a result of returns being more sensitive to changes in the economic environment when it is weak than when it is strong, resulting in risk premia being more volatile in bad times than in good times. From a theoretical perspective it can be argued that stock market volatility affects the real economy, but also that the real economy affects stock return volatility. For example, the uncertainty hypothesis of Romer (1990) suggested that higher volatility on the stock market leads to higher uncertainty regarding future macroeconomic conditions, resulting in lower economic activity. On the other hand, a weaker economic environment leads to higher uncertainty regarding future investment opportunities, and hence increased uncertainty regarding the dividend flow, which can be reflected as higher stock market volatility.

The link from confidence indicators to stock market volatility can be thought of as being directly analogous to the link between macroeconomic fundamentals and volatility: if confidence indicators describe the current and/or expected economic situation, also confidence indicators should be linked to volatility in a countercyclical manner.[8] In particular, forward-looking sentiment data can plausibly relate to expectations of future dividends and returns. In the case of excess returns Campbell and Diebold (2009) use survey data to conclude that expectations regarding business conditions affect expected excess returns and reduce the explanatory power of more conventional financial predictors, such as the term premia.

In practice the role of sentiment data depends on whether economic agents (households, firms, analysts) form their expectations, summarised by sentiment indicators, on information already contained in macroeconomic fundamentals, or on a larger set of data also comprising information on, for example, expected economic conditions. In both cases confidence indicators might contain more information than macroeconomic fundamentals, which tend to be backward-looking indicators or describe just one sector of the economy. If sentiment indicators contain additional information compared to macroeconomic data, they can be useful when modelling and forecasting stock market volatility.

Empirically the success in linking macroeconomic variables to stock market volatility has been mixed. In his seminal paper Schwert (1989b) found that volatility is higher during recessions, but the evidence in favour of macroeconomic predictability of stock return volatility in the US is weak. The results echo those in Officer (1973). Extending the research of Schwert (1989b) to an international setting Davis and Kutan (2003) failed to establish a solid link between macroeconomic volatility and stock market volatility. Mixed results were reported by Errunza and Hogan (1998) (European and US data) and Pierdzioch et al. (2008) (German data), while Paye (2012), using US data and predictive regressions, found little evidence of out-of-sample predictability improvements using macroeconomic data over

[8]This is in line with the "news" view of consumer confidence, i.e., that there is a relationship between confidence and the macro economy because confidence includes information regarding current and future states of the economy (Barsky and Sims, 2012).

benchmark AR models, although forecast combinations help and Granger causality is found. On the other hand, Hamilton and Lin (1996) found that a bivariate ARCH framework with Markov-switching for industrial production and stock market volatility is useful for forecasting volatility in the US, with recessions accounting for a large part of variation in volatility. Including several macroeconomic and financial predictors in predictive regressions and using a Bayesian Model Averaging approach, Christiansen et al. (2012) showed that especially variables which can be thought of as proxies for credit risk, funding illiquidity or connected to the time-varying risk premia add significant out-of-sample predictive power for volatility in the US. Arnold and Vrugt (2008) showed that dispersion in the forecasts by professional forecasters is related to stock market volatility in the US, but the link disappears after 1996. For a large cross section of countries Diebold and Yilmaz (2008) determined that volatility in macroeconomic variables leads to more volatile stock markets.

Component GARCH models for stock return volatility, where the low-frequency component of volatility is driven by macroeconomic variables, have recently provided robust links between the macroeconomy and stock market volatility. Engle and Rangel (2008) suggested a Spline-GARCH model, which combines multiplicatively a high-frequency GARCH part and a slow-moving deterministic component based on macroeconomic variables. They found using a panel with 50 countries that macroeconomic volatility significantly influences low-frequency stock market volatility. Building on this idea Engle et al. (2013) developed the GARCH-MIDAS model, which combines a high-frequency GARCH component with a low-frequency component based on macroeconomic data and inspired by the MIxed DAta Sampling (MIDAS) literature. They found that macroeconomic data is useful for explaining and forecasting volatility in the US when performance is compared to a GARCH-MIDAS model with realised volatility driving the long-term component. Using the GARCH-MIDAS framework and a wide selection of macroeconomic variables Conrad and Loch (2014) concluded that macroeconomic data improves volatility forecasts in the US (compared to a similar benchmark as in Engle et al. (2013)) especially for long forecasting horizons. Summarising information in macroeconomic and financial data using principal components, Asgharian et al. (2013) concluded that the GARCH-MIDAS model significantly improves the one-step-ahead forecast accuracy relative to a standard GARCH model (US data), while Asgharian et al. (2015) showed that macroeconomic uncertainty is a useful predictor of US stock market volatility.

3 The GARCH-MIDAS model

The GARCH-MIDAS model by Engle et al. (2013) is a multiplicative two-component model for the conditional variance, where the high-frequency component is modelled as a standard GARCH model, while the low-frequency component is determined by economic data.[9] The high-frequency component can be thought of as fluctuating around a slow-moving long-term trend, which is driven by variables evolving at a lower frequency than returns. The MIxed DAta Sampling (MIDAS) approach, introduced by Ghysels et al. (2004)[10], deals with the challenges related to using data sampled at different frequencies within the same model. The key feature of MIDAS is capturing the lag structure of the explanatory variables by a known function which depends on only a few parameters.

Following the interpretation in Engle and Rangel (2008), which builds on the log-linear dividend-ratio model in Campbell (1991) and Campbell and Shiller (1988), the stock return on day i and in period (month or quarter) t can be modelled as having a multiplicative specification for the conditional variance:

$$r_{i,t} = E_{i-1,t}(r_{i,t}) + \sqrt{\tau_{i,t}\ g_{i,t}}\ \varepsilon_{i,t}, \quad \varepsilon_{i,t} \mid \Phi_{i-1,t} \sim N(0,1), \quad \forall i = 1, ..., N_t$$

where $\Phi_{i-1,t}$ represents the information set up to day $i-1$, and N_t is the number of trading days in period t. $\sigma^2_{i,t} = \tau_{i,t}\ g_{i,t}$ is the total conditional variance, where τ_t[11] is the long-term volatility component and $g_{i,t}$ the GARCH component. It is assumed that $E_{t-1}(r_{i,t}) = \mu$, that is, the expected return is constant. The model builds on the idea that the unexpected return, i.e., $r_{i,t} - E_{i-1,t}(r_{i,t})$, depends on news shocks, which affect dividends, interest rates or risk premia. The shocks can have short or long horizon effects, which motivates the division of volatility into a short-term and a long-term component.

It is well established that stock return volatility is asymmetric[12], i.e., that positive and negative news have different impact on volatility. Stock returns have been found negatively correlated with their volatility, and this has been attributed to the leverage effect (Black, 1976) or time-varying risk premia (see Awartani and Corradi (2005)). To capture the asymmetry I

[9] The presentation of the model follows closely Engle et al. (2013).

[10] Discussed in detail in Ghysels et al. (2004), Ghysels et al. (2005), Ghysels et al. (2006), Ghysels et al. (2007), Andreou et al. (2010), and Wang and Ghysels (2015).

[11] $\tau_{i,t}$ is fixed for all i in period t, so I drop the subscript i to ease notation and emphasise that τ_t evolves at a lower frequency than $g_{i,t}$.

[12] See e.g. Awartani and Corradi (2005) and the references therein.

use the asymmetric GJR-GARCH model (by Glosten et al. (1993))[13]:

$$g_{i,t} = \omega + (\alpha + \gamma D_{i-1,t})\frac{(r_{i-1,t} - \mu)^2}{\tau_t} + \beta g_{i-1,t} \tag{1}$$

where $D_{i-1,t}$ is an indicator function, taking the value 1 when $(r_{i-1,t} - \mu) < 0$ and 0 otherwise. Thus, γ describes the degree of asymmetry in volatility. ω is normalised to $\omega = 1 - \alpha - \beta - \gamma/2$ so that $E_{t-1}(g_{i,t}) = 1$. To ensure stationarity the condition $\alpha + \beta + \gamma/2 < 1$ is imposed. In addition, I assume $\alpha > 0$, $\beta \geq 0$ and $\alpha + \gamma \geq 0$ to ensure the variance remains positive.

Following Engle et al. (2013) the MIDAS polynomial with two explanatory variables (X_1 and X_2, which are, for example, macroeconomic variables) takes the form:[14]

$$log\ \tau_t = m + \theta_1 \sum_{k=1}^{K} \varphi_k(\omega_{11}, \omega_{12}) X_{1,t-k} + \theta_2 \sum_{k=1}^{K} \varphi_k(\omega_{21}, \omega_{22}) X_{2,t-k}, \tag{2}$$

where $\varphi_k(\omega_{11}, \omega_{12})$ and $\varphi_k(\omega_{21}, \omega_{22})$ are weighting schemes (see examples below, e.g., Figure 2), and K is the number of lags of explanatory data included. The logarithmic specification ensures non-negativity of the long-term volatility component (τ_t) even when the macroeconomic variables take negative values. If the variables do not affect stock market volatility (i.e. $\theta_1 = \theta_2 = 0$), all volatility is captured by the short-term component and the model collapses to the asymmetric GARCH model with $\tau_t = m$, i.e. unconditional volatility is constant. The standard GARCH model is therefore nested in the GARCH-MIDAS specification. The sign of θ_i is interpretable: $\theta_i > 0$ implies that higher values of X_i are linked to higher long-term volatility in stock returns.

Conrad and Loch (2014) used the MIDAS polynomial in (2) to investigate whether economic variables are important for the low-frequency volatility component after the information in past squared returns have been accounted for (i.e., X_1 is a measure of realised volatility while X_2 is the macroeconomic data).[15] In addition, Engle et al. (2013) studied the combined effect of the level and volatility of a macroeconomic variable. I concentrate on specifications including a macroeconomic (X_1) and a sentiment (X_2) variable, but also use a specification with three explanatory variables, to control for the information in realised

[13] This is the same short-term component as in Conrad and Loch (2014).

[14] Additional variables can be included in the MIDAS polynomial in a straightforward manner, but each variable increases the parameter space by three new parameters.

[15] Asgharian et al. (2013) used different weighting schemes but studied the same question.

volatility. The MIDAS polynomial thus allows directly comparing the importance of different types of variables within the same model.

A flexible but parsimonious weighting scheme is the beta lag polynomial[16], which ensures positive weights (ensures non-negativity of volatility) adding up to one (this normalisation allows identifying θ_1 and θ_2):

$$\varphi_k(\omega_1, \omega_2) = \frac{(\frac{k}{K})^{\omega_1 - 1}(1-\frac{k}{K})^{\omega_2 - 1}}{\sum_{j=1}^{K}(\frac{j}{K})^{\omega_1 - 1}(1-\frac{j}{K})^{\omega_2 - 1}}, \quad \text{where } \sum_{k=1}^{K} \varphi_k(\omega_1, \omega_2) = 1.$$

The weight parameters, ω_1 and ω_2, govern the shape of the weighting scheme and can be freely estimated or fixed before estimation. The beta polynomial allows both monotonously decreasing weights ($\omega_1 = 1$) and hump-shaped weights ($\omega_1 < \omega_2$). If $\omega_1 = 1$ the rate of decay is determined by ω_2, where a larger value indicates faster decay. When ω_2 is very large (e.g., $\omega_2 > 100$) all weight is on the most recent value of the variable. If $\omega_2 < \omega_1$ all weight can be on very distant lags, which can be seen as counterintuitive. If $\omega_1 = \omega_2 = 1$ the weights are equal ($1/K$) for all lags, which corresponds to a moving average. Clearly counterintuitive weighting schemes can be ruled out by restricting the weight parameters. Each explanatory variable has its own weighting scheme, meaning that the shape of the weighting scheme can be different for different variables included in the same MIDAS polynomial.

To assess how much the variation in a particular variable explains of the overall expected volatility, Engle et al. (2013) suggested calculating variance ratios: $\frac{Var(log(\tau_t))}{Var(log(\tau_t g_{i,t}))}$. The variance ratio can be interpreted as a measure of fit in the sense that the higher the variance ratio is, the larger is the share of the total expected volatility that can be explained by the long-term component. However, a low variance ratio does not necessarily imply poor model fit, as it can also be a result of smooth movements in the underlying variable (Conrad and Loch, 2014). The GARCH-MIDAS model can be estimated using maximum likelihood (or QML if the assumption of normally distributed errors does not hold).[17]

[16]Also used by, for example, Engle et al. (2013) and Conrad and Loch (2014). Weighting schemes are discussed in more detail in Ghysels et al. (2007).

[17]While consistency and asymptotic normality of the QML estimator for the rolling window GARCH-MIDAS model with realised volatility was established in Wang and Ghysels (2015), it has not been shown for the more general GARCH-MIDAS model with macroeconomic variables.

4 Data

I use the continuously compounded daily stock market return on the CRSP index from January 1973 to December 2015.[18] For the explanatory data I concentrate on the quarterly frequency with a sample period from Q1 1970 to Q4 2015[19].

A natural explanatory variable for stock market volatility is (lagged) realised volatility. The sum of squared returns ($\sum_{i=1}^{N_t} r_{i,t}^2$) is a commonly used measure for realised volatility (e.g., Engle et al. (2013) and Conrad and Loch (2014)). However, already Taylor (1986) and Ding et al. (1993), among others, explored the advantages of using the absolute value of returns when modelling especially the low-frequency component of volatility. More recently, using a GARCH-MIDAS model and intra-daily data, Ghysels et al. (2006) concluded that absolute returns outperform squared returns when forecasting quadratic variation in returns on short horizons (up to one month).[20] Absolute returns could thus outperform squared returns also on longer horizons. Hence I also use $\sum_{i=1}^{N_t} |r_{i,t}|$ as a measure of realised volatility.

As **macroeconomic data** I use industrial production, the Aruoba-Diebold-Scotti Business Conditions Index (ADS index[21]) and housing starts from the Philadelphia Fed. Industrial production is a traditional macroeconomic variable for modelling and predicting stock return volatility, as it is a timely measure of output in the economy. The ADS index, which includes for example labour market indicators and industrial production, tracks business conditions in real time. Housing starts gives an early indication of future economic activity, and is therefore often considered a forward-looking macroeconomic variable. For both industrial production and housing starts I use the annualised quarterly rate of growth (i.e., $100\left((X_t/X_{t-1})^4 - 1\right)$). As the long-term component of the GARCH-MIDAS model depends on several lags of the explanatory data, taking into account all the revisions of the data can be important. Hence, for the macroeconomic data I use the last available vintage in each quarter of the real-time data sets.[22] I also include the term spread, defined as the difference between the 10-year Treasury bond yield and the 3-month T-bill rate. The term spread and housing starts were among the best predictors for stock return volatility in Conrad and Loch (2014).

[18] The data were extracted from Kenneth French's Data Library.

[19] Three years of explanatory data is needed to estimate the GARCH-MIDAS model for the first period.

[20] Ghysels et al. (2006) found that realised power, based on intra-daily data, is the best measure for realised volatility, but I restrict myself to daily data which is widely available for a long time period.

[21] For details, see `https://www.philadelphiafed.org/research-and-data/real-time-center/business-conditions-index`.

[22] Prior to 2008 real-time vintages of the ADS index are unavailable.

I define **sentiment data** as survey-based confidence indicators[23]:

- **Household sentiment:** University of Michigan consumer confidence data (first differences), including forward-looking sub-indices: the News Heard index and the Buying conditions index. The News Heard index can be seen as a proxy for general sentiment in the economy, since it surveys the kind of news regarding business conditions the respondents have recently read. The Buying conditions index is chosen over other forward-looking sub-indices because it has the lowest correlation with the main index.[24]

- **Business confidence:** The forward-looking ISM New Orders index as well as the ISM Recession indicator (New Orders - Inventories) (levels). These describe the demand of manufacturing businesses, which can be seen as a proxy for near-term business conditions. Note that the survey asks about the changes in production, new orders etc. that occurred during the month. Thus, the ISM report does not survey expectations, but rather gives a "real-time" assessment of the near-term economic situation.[25]

- **Professional expectations:** Survey of Professional Forecasters (SPF) data from the Philadelphia Fed. To describe expectations regarding the business cycle I use the probability given by professional forecasters that GDP will decline in a certain quarter (one or four quarters ahead).[26] An interesting feature of the one quarter ahead recession probability is that it replicates, in real time, relatively well the official NBER recession dates. Hence it can be seen as a valid proxy for the current economic situation, whereas the four quarters ahead probability can be argued to summarise expectations regarding the business cycle.

Standard unit root tests confirm the stationarity of all the series. As I will include different types of data in the same MIDAS polynomial, I consider the information overlap in sentiment indicators and macroeconomic data using correlations. Table 2 shows that squared and absolute returns are, as expected, highly correlated (0.92). The correlation between absolute returns and the macro/sentiment variables varies between the virtually zero correlation with

[23]Thus the term spread, which can be argued to be a sentiment measure for the financial markets, is primarily labelled macroeconomic data.

[24]The correlation of the Buying conditions index with the main index is 0.74, versus around 0.95 for the Expected index and the 12 months ahead Business conditions index (over the 1970-2015 sample).

[25]See `https://www.instituteforsupplymanagement.org/` for details.

[26]Two data points are missing from the early part of the four quarters ahead series. I replace these by values from the previous quarter.

Table 1: Descriptive statistics: Q1 1970 - Q4 2015

	Number of observations	Mean	Standard deviation	Minimum	Maximum
CRSP daily returns	10 849	0.04	1.05	-17.41	11.35
Sum of squared returns	184	67.71	105.13	11.38	1095.50
Sum of absolute value of returns	184	44.54	22.59	20.00	208.03
Consumer confidence index	184	0.06	5.27	-14.70	16.50
News Heard index	184	0.09	17.70	-59.00	52.00
Buying conditions index	184	0.20	8.64	-39.00	25.00
ISM New Orders index	184	54.84	7.58	27.27	71.90
ISM Recession indicator	184	8.30	6.81	-12.73	30.70
SPF 1Q ahead recession probability	184	19.27	16.44	2.16	74.78
SPF 4Q ahead recession probability	184	17.29	5.85	4.51	33.34
Industrial production (first release data)	184	2.41	3.12	-10.37	11.20
ADS index (latest data)	184	-0.09	0.82	-3.32	1.69
Housing starts (first release data)	184	7.00	43.24	-70.91	229.76
Term spread	184	1.72	1.24	-1.40	3.80

forward-looking variables, such as the four quarters ahead recession probability (0.07), and the relatively high correlation with coincident or lagging indicators, such as the ADS index (-0.45). The correlation between the recession probabilities one and four quarters ahead is small (0.09), while for the other sentiment measures the sub-indices are highly correlated with each other. Industrial production and the ADS index are highly correlated with the ISM indices and the one quarter ahead recession probability, but only moderately correlated with the consumer sentiment indicators, and not at all correlated with the four quarters ahead recession probability. Housing starts is only moderately correlated with any of the sentiment indicators, while the term spread has a relatively high correlation with the ISM Recession indicator (0.46), but is only moderately correlated with the other sentiment measures. As expected, the one quarter ahead recession probability is highly correlated with contemporaneous measures for economic activity, while the four quarters ahead probability is mostly correlated with forward-looking variables, such as the term spread (-0.24).

As including many variables simultaneously in the MIDAS polynomial is infeasible, I use principal components analysis to aggregate information in all macroeconomic and sentiment variables. As the variables are measured on different scales I base the principal components (PC) on the correlation matrix. Table 3 shows the correlations between the eleven principal components and the eleven variables. The first PC is highly correlated with most of the variables, but in particular with the ISM indices, the ADS index, industrial production and the one quarter ahead recession probability. Hence it captures current business conditions. The

Table 2: Correlation matrix for the macro and sentiment variables

	Σr^2	$\Sigma\|r\|$	CC	NH	BC	NO	RI	IP	HS	ADS	TS	1Q
$\Sigma\|r\|$	0.92	1										
Consumer confidence	-0.20	-0.20	1									
News Heard index	-0.19	-0.15	0.80	1								
Buying conditions index	-0.21	-0.21	0.74	0.55	1							
ISM New Orders index	-0.35	-0.40	0.24	0.19	0.33	1						
ISM Recession Indicator	-0.27	-0.27	0.39	0.40	0.40	0.66	1					
Industrial production	-0.22	-0.27	0.16	0.13	0.24	0.76	0.43	1				
Housing starts	-0.18	-0.17	0.20	0.22	0.25	0.19	0.34	0.11	1			
ADS index	-0.39	-0.45	0.27	0.18	0.33	0.83	0.56	0.78	0.30	1		
Term spread	0.06	-0.01	0.19	0.17	0.22	0.26	0.46	0.05	0.21	0.09	1	
SPF 1Q ahead	0.40	0.45	-0.20	-0.15	-0.30	-0.73	-0.53	-0.65	-0.19	-0.74	-0.24	1
SPF 4Q ahead	0.11	0.07	-0.19	-0.20	-0.20	-0.13	-0.21	-0.06	-0.16	0.01	-0.24	0.09

Σr^2 denotes the sum of squared returns, $\Sigma|r|$ denotes the sum of absolute value of returns. Sample period: Q1 1970 - Q4 2015. First release data is used for industrial production and housing starts. Latest available data is used for the ADS index.

Table 3: Correlation between the principal components and the explanatory variables

	PC 1	PC 2	PC 3	PC 4	PC 5	PC 6	PC 7	PC 8	PC 9	PC 10	PC 11
Consumer confidence	-0.60	-0.65	0.35	-0.06	0.04	-0.01	0.07	-0.02	0.14	-0.19	0.17
News Heard index	-0.53	-0.66	0.29	-0.01	0.03	0.35	0.20	-0.04	-0.06	-0.15	-0.11
Buying conditions index	-0.64	-0.49	0.25	-0.03	-0.00	-0.48	-0.20	0.03	-0.09	-0.09	-0.07
ISM New Orders index	-0.84	0.38	-0.05	-0.12	-0.05	0.05	-0.11	-0.07	0.18	0.23	0.14
ISM Recession indicator	-0.80	-0.04	-0.26	-0.02	0.18	0.29	-0.34	0.19	-0.12	-0.08	0.00
SPF 1Q ahead	0.77	-0.38	0.04	0.10	0.04	0.13	-0.32	-0.35	0.09	-0.00	-0.04
SPF 4Q ahead	0.23	0.38	0.53	0.26	0.67	-0.00	-0.01	0.05	0.00	0.04	0.02
Industrial production	-0.71	0.51	0.21	-0.05	-0.07	0.01	0.05	-0.34	-0.24	-0.08	0.03
ADS index	-0.82	0.43	0.13	0.11	-0.08	-0.01	-0.01	-0.02	0.23	-0.11	-0.20
Housing starts	-0.40	-0.17	-0.32	0.83	-0.09	-0.04	0.06	-0.04	-0.02	0.02	0.05
Term spread	-0.39	-0.22	-0.65	-0.21	0.51	-0.13	0.14	-0.17	0.04	-0.02	-0.03

Sample period: Q1 1970 - Q4 2015. First release data is used for industrial production and housing starts. Latest available data is used for the ADS index.

second PC has the highest correlations with the consumer confidence indices. The third PC is mostly correlated with the term spread and the four quarters ahead recession probability, but also housing starts and the consumer confidence index. Thus it describes the forward-looking components of the data. The remaining principal components are either primarily correlated with just one variable or not very correlated with any of the variables. Hence, I use the first three principal components as explanatory variables in the MIDAS polynomial.

5 In-sample results

In Section 5.1 I establish baseline results using the GARCH-MIDAS model with one explanatory variable.[27] I largely confirm the results in Conrad and Loch (2014) using a different

[27]The estimations are executed in Matlab, building on the basic code provided by Engle et al. (2013).

stock return index and real-time macroeconomic data. In Section 5.2 I include two different explanatory variables in the same MIDAS polynomial in order to determine the relative and combined importance of macroeconomic variables and survey-based sentiment data.

5.1 Baseline results

The optimal lag length (K) for the explanatory data in the long-term component is selected based on the data. I choose the K which maximises the value of the log-likelihood function when K is allowed to be 4, 8, 12, 16, 20 or 24 quarters. For all specifications the value of the log-likelihood function is maximised at either 8 or 12 lags, levelling off after this. Therefore I use three years of lagged data, i.e., $K = 12$ (quarterly data) for all models.[28] I keep K fixed at 12 for the remainder of the paper.

Next, the shape of the weighting scheme ($\varphi_k(\omega_1, \omega_2)$), i.e., whether restricted ($\omega_1 = 1$) before estimation or not, is determined for each explanatory variable based on a likelihood ratio test (LRT) between the two specifications. As explained in Section 3, the restricted scheme forces the weights to be decaying, i.e., recent data matters the most for long-term volatility. In Table 4 I report the model preferred based on the LRT.[29] The related p-value is reported below the value of the LLF. The significance of the weight parameters in Table 4 relate to testing $\omega_i = 1$.[30]

The GARCH mdoels parameters are consistently, robustly and similarly estimated for all specifications (Table 4). The parameter determining the degree of asymmetry in volatility (γ) is always highly significant and positive, indicating, as expected, that lower-than-expected returns lead to a higher conditional variance. Interestingly, the basic GJR-GARCH(1,1) model has clearly the lowest γ. The choice of an asymmetric GARCH model is thus well-motivated. $\alpha + \beta + \gamma/2$ is clearly below one, indicating that the GARCH model is stationary. Overall, the GARCH parameters in the GARCH-MIDAS specifications get values roughly in line with the estimates for the basic asymmetric GARCH(1,1) model (last row in Table 4).[31]

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[28] Since by construction the last weight in the beta polynomial is zero, I use $K + 1$ lags in the estimation, where the 13^{th} lag always gets the weight zero. This follows the convention in Conrad and Loch (2014).

[29] In the interest of parsimony significance level $\alpha = 0.05$ is used. For the models driven by the four quarters ahead recession probability, the term spread, and the third PC an unrestricted weighting scheme would have been chosen if $\alpha = 0.10$. Conrad and Loch (2014) used an unrestricted weighting scheme for the term spread.

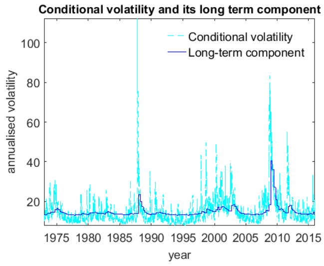
[30] Testing $\omega_i = 0$ is of little interest, since zero is an arbitrary number in the context of the beta weighting scheme. If $\omega_1 = \omega_2 = 0$ the weighting scheme is symmetric and U-shaped.

[31] I do not report the estimates of the GARCH parameters for the rest of the paper. They are similarly and robustly estimated throughout the specifications. Full results are available upon request.

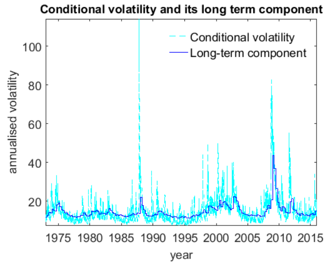
Table 4: Estimation results for GARCH-MIDAS model with one explanatory variable

	μ	α	β	γ	θ	ω_1	ω_2	m	LLF	BIC	VR
Sum of squared returns	0.0475***	0.0194***	0.8790***	0.1281***	0.0040***	1	6.8566**	-0.4502***	-13861.54	2.5614	17.32
	(0.0075)	(0.0051)	(0.0147)	(0.0199)	(0.0005)		(2.3670)	(0.0834)	(1.0000)		
Sum of absolute value of returns	0.0477***	0.0145***	0.8655***	0.1380***	0.0200***	1	10.4845***	-1.1051***	-13841.19	2.5576	29.08
	(0.0074)	(0.0053)	(0.0149)	(0.0196)	(0.0018)		(2.2189)	(0.1068)	(0.1111)		
Consumer confidence index	0.0467***	0.0194***	0.8960***	0.1150***	-0.1631***	1.9237*	2.9414**	-0.1561*	-13861.45	2.5622	12.46
	(0.0075)	(0.0051)	(0.0141)	(0.0189)	(0.0291)	(0.5073)	(0.8499)	(0.0908)	(0.0022)		
News Heard index	0.0462***	0.0196***	0.8946***	0.1159***	-0.0679***	1.9094***	1.9495***	-0.1596*	-13859.06	2.5618	13.87
	(0.0075)	(0.0050)	(0.0141)	(0.0188)	(0.0121)	(0.2863)	(0.3321)	(0.0887)	(0.0000)		
Buying conditions index	0.0468***	0.0166***	0.8903***	0.1221***	-0.1241***	1	2.0376***	-0.1597*	-13849.86	2.5592	17.97
	(0.0075)	(0.0053)	(0.0141)	(0.0190)	(0.0182)		(0.2644)	(0.0802)	(0.1695)		
ISM New Orders index	0.0452***	0.0148***	0.9002***	0.1173***	-0.0477***	1	4.5293**	2.4384***	-13861.46	2.5613	12.86
	(0.0076)	(0.0054)	(0.0137)	(0.0185)	(0.0093)		(1.6570)	(0.5147)	(1.0000)		
ISM Recession indicator	0.0461***	0.0181***	0.8979***	0.1141***	-0.0719***	1	2.1000***	0.4400***	-13861.59	2.5614	11.42
	(0.0075)	(0.0051)	(0.0138)	(0.0185)	(0.0118)		(0.3553)	(0.1301)	(0.1628)		
SPF 1Q ahead recession probability	0.0458***	0.0168***	0.8943***	0.1209***	0.0165***	1	14.3322	-0.4911***	-13857.88	2.5607	12.41
	(0.0075)	(0.0051)	(0.0138)	(0.0192)	(0.0039)		(21.1620)	(0.1230)	(1.0000)		
SPF 4Q ahead recession probability	0.0446***	0.0179***	0.9013***	0.1158***	0.0637***	1	1.0000***	-1.2796***	-13855.52	2.5602	12.20
	(0.0075)	(0.0048)	(0.0126)	(0.0179)	(0.0150)		(0.3292)	(0.2728)	(0.0502)		
Industrial production	0.0458***	0.0178***	0.8994***	0.1137***	-0.0517***	1	3.9477***	-0.0452	-13871.76	2.5632	7.27
	(0.0076)	(0.0052)	(0.0139)	(0.0186)	(0.0125)		(0.9182)	(0.0954)	(0.3702)		
ADS index	0.0457***	0.0163***	0.9002***	0.1144***	-0.4045***	1	5.4703***	-0.2149**	-13865.89	2.5622	10.37
	(0.0075)	(0.0053)	(0.0139)	(0.0184)	(0.0810)		(1.3579)	(0.0929)	(0.5147)		
Housing starts	0.0466***	0.0182***	0.8963***	0.1161***	-0.0172***	3.2783	5.3376*	-0.0758	-13855.09	2.5610	17.55
	(0.0075)	(0.0051)	(0.0140)	(0.0185)	(0.0036)	(1.4716)	(2.6191)	(0.0920)	(0.0000)		
Term spread	0.0470***	0.0195***	0.8945***	0.1146***	-0.2746***	1	1.6930	0.3066**	-13861.56	2.5614	12.25
	(0.0075)	(0.0050)	(0.0145)	(0.0192)	(0.0504)		(0.4746)	(0.1219)	(0.0568)		
Principal component 1	0.0455***	0.0141***	0.8949***	0.1218***	0.2271***	1	3.3543***	-0.1823**	-13851.46	2.5595	16.40
	(0.0075)	(0.0054)	(0.0141)	(0.0191)	(0.0321)		(0.6808)	(0.0838)	(0.6048)		
Principal component 2	0.0458***	0.0203***	0.8959***	0.1146***	0.3407***	5.6805	2.7358	-0.1755*	-13852.90	2.5606	15.59
	(0.0075)	(0.0050)	(0.0134)	(0.0182)	(0.0885)	(4.0586)	(1.3600)	(0.0912)	(0.0000)		
Principal component 3	0.0457***	0.0165***	0.8955***	0.1194***	0.4607***	1	1.0404	-0.1917**	-13848.26	2.5589	16.27
	(0.0075)	(0.0049)	(0.0139)	(0.0190)	(0.0754)		(0.2971)	(0.0862)	(0.0578)		
GJR-GARCH(1,1)	0.0465***	0.0217***	0.9037***	0.1068***	-	-	-	0.8689***	-13884.09	2.5638	-
	(0.0075)	(0.0049)	(0.0133)	(0.0181)				(0.0929)			

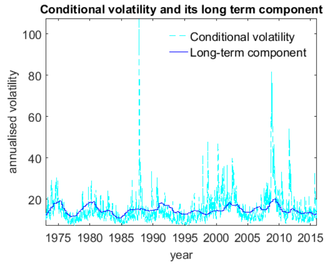
*Bollerslev-Wooldridge QMLE robust standard errors are reported below the parameter estimates. *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively. LLF is the value of the log-likelihood function, BIC is the Bayesian Information Criteria and VR is the variance ratio from Section 3, multiplied by 100. The MIDAS polynomial:* $\log \tau_t = m + \theta \sum_{k=1}^{K} \varphi_k(\omega_1, \omega_2) X_{t-k}$, *where X stands for the explanatory data, as stated in the first column. All models are estimated with a restricted* ($\omega_1 = 1$) *and an unrestricted weighting scheme. The model reported in the table is chosen based on a likelihood ratio test between the restricted and unrestricted specifications. The related p-value is reported below the LLF.*



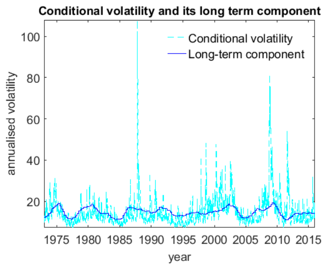
(a) Sum of squared returns



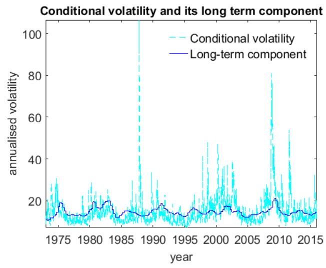
(b) Sum of absolute value of returns



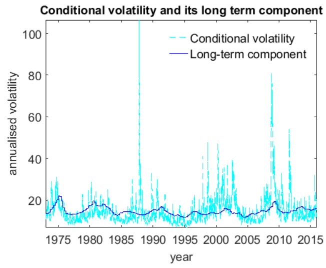
(c) Consumer confidence index



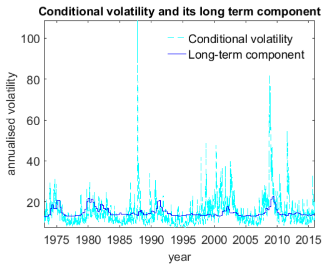
(d) News Heard index



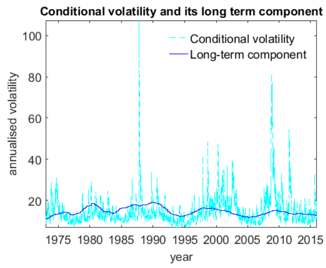
(e) ISM New Orders index



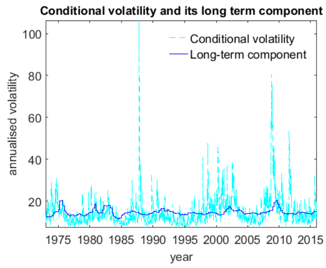
(f) ISM Recession indicator



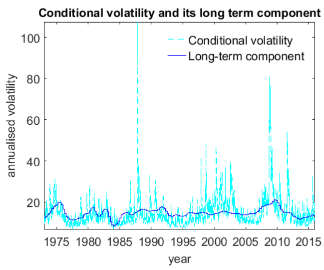
(g) SPF 1Q ahead recession probability



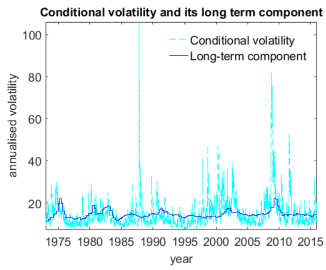
(h) SPF 4Q ahead recession probability



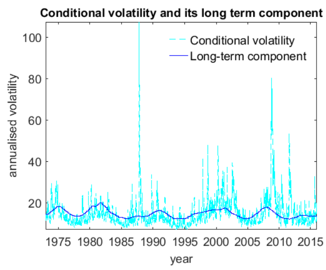
(i) Industrial production



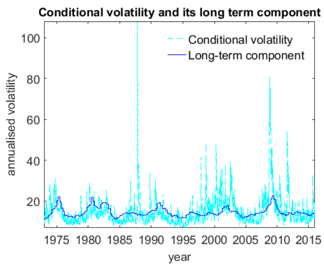
(j) Housing starts



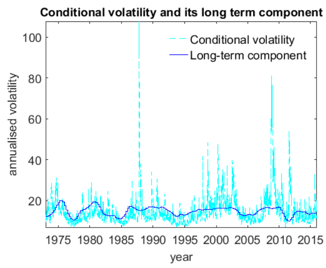
(k) ADS index



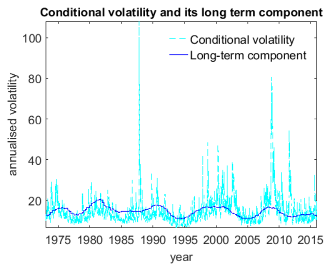
(l) Term spread



(m) Principal component 1



(n) Principal component 2



(o) Principal component 3

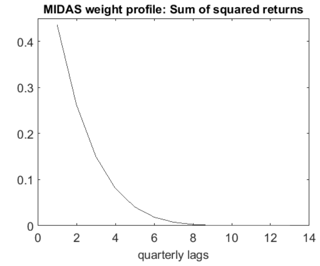
Figure 1: Total ($\tau_t g_{i,t}$) and long-term (τ_t) volatility (annualised) of selected GARCH-MIDAS models from Table 4

Figure 1 shows how the GARCH-MIDAS model decomposes volatility into two components, by plotting total volatility and the extracted long-term component separately. It is clear that the long-term components based on different variables capture long-term volatility in very different ways. The parameter θ determines how the explanatory data affects long-term volatility. It is highly significant in all specifications and has the expected sign (Table 4): positive for the realised volatility measures and the recession probabilities, and negative for macroeconomic variables and consumer and business sentiment. A positive estimate for the recession probabilities indicates that a higher probability of a recession among professional forecasters translates into higher stock market volatility. The highly significant estimates for the recession probabilities indicate that they can be useful in modelling long-term stock market volatility. The estimates of θ for all three principal components are positive, largely in line with the correlations between the factors and the explanatory variables (see Table 3). Overall the results strongly support the countercyclical nature of long-term stock market volatility.

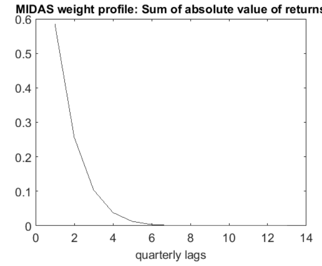
The variance ratio of the GARCH-MIDAS model where the long-term component is driven by the quarterly sum of the lagged absolute value of returns is roughly 29%, which is clearly greater than for any other variable, and clearly greater than for the model driven by the quarterly sum of the lagged squared returns (17.3%). Realised volatility based on the absolute value of returns thus seems to incorporate a large amount of useful information for explaining long-term stock market volatility. The good in-sample fit is also evident from Figure 1b.

Considering the macroeconomic and sentiment data, the long-term components driven by housing starts and the Buying conditions index explain a large share of the total variance (more than 17%), while the long-term component based on the term spread explains 12.3%. The principal components driven models have relatively high variance ratios of around 16%, indicating it can be useful to summarise information. On the other hand, the variance of the long-term component determined by industrial production only accounts for 7.3% of the total variance. Based on the variance ratios, the forward-looking News Heard index and the Buying conditions index outperform the main consumer confidence index.

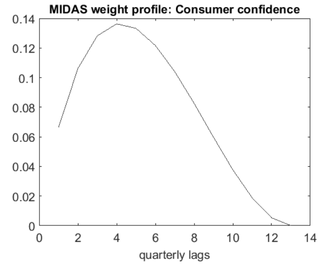
The weights of the twelve lags of the macroeconomic and confidence variables are plotted in Figure 2. Engle et al. (2013) noted that $\omega_1 = 1$ is optimal for realised volatility, and this is echoed in my results. Decaying weights is also intuitive: recent information in realised volatility is more important than older information. For the consumer confidence indicators



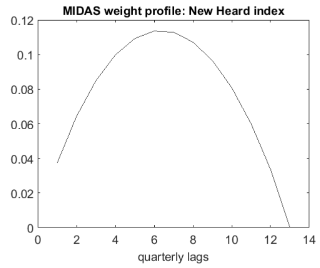
(a) Sum of squared returns



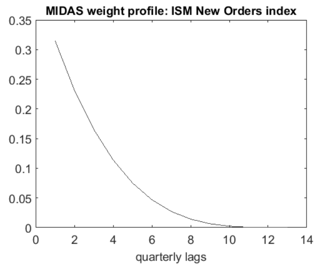
(b) Sum of absolute value of returns



(c) Consumer confidence index

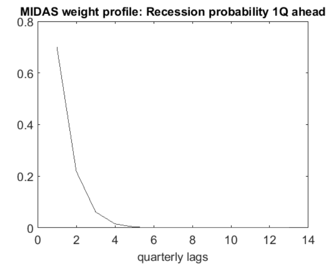


(d) News Heard index

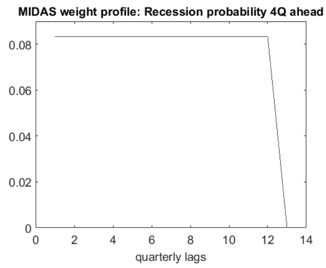


(e) ISM New Orders index

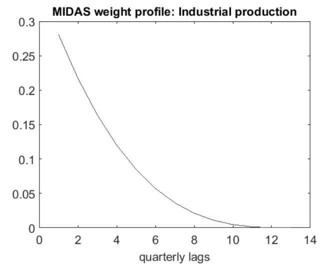
(f) ISM Recession indicator



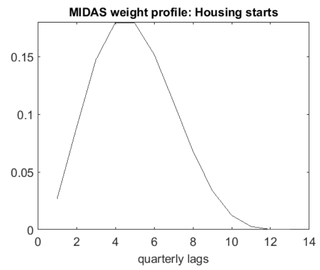
(g) SPF 1Q ahead recession probability



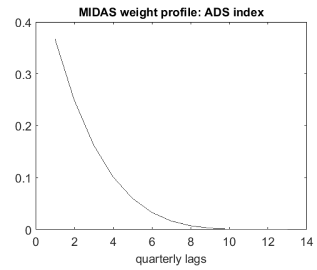
(h) SPF 4Q ahead recession probability



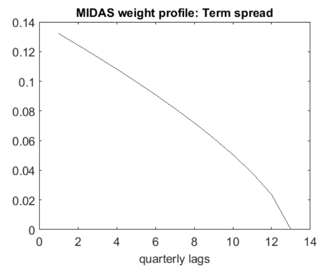
(i) Industrial production



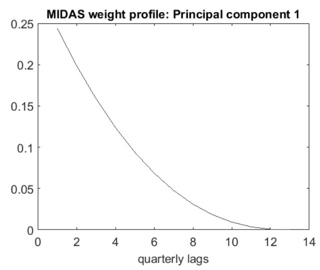
(j) Housing starts



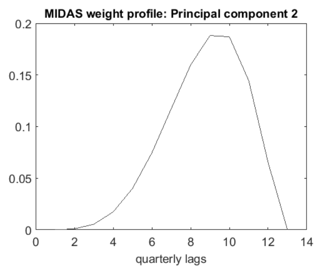
(k) ADS index



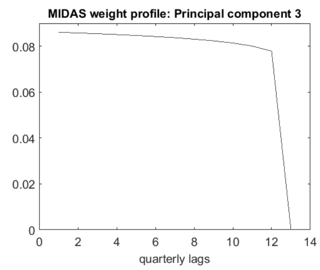
(l) Term spread



(m) Principal component 1



(n) Principal component 2



(o) Principal component 3

Figure 2: Weighting schemes of selected GARCH-MIDAS models from Table 4

the optimal weighting schemes are often hump-shaped, indicating that older information is more important for volatility than very recent information. Conrad and Loch (2014) interpreted hump-shaped weighting schemes as a sign that the variable is forward-looking, while monotonously declining weights imply that the variable is lagging or coincidental.[32] Thus, business confidence, which gets decaying weights, seems to anticipate stock market volatility less than consumer confidence. The lags of the four quarters ahead recession probability are equally weighted, while the fastest decay in weights is seen for the one quarter ahead recession probability, for which only the first five lags get a non-zero weight. As expected, industrial production and the ADS index have decaying weighting schemes, while the largest weight for housing starts is on the fourth and fifth lags, which supports the perception that housing starts is a forward-looking indicator. The first principal component has decaying weights, the second one has a hump-shaped weighting scheme, while the third one has close to equal weights for all lags. These weighting schemes seem plausible, as the first PC is mainly correlated with indicators for current business conditions which have decaying weights themselves, the second one with consumer confidence data (hump-shaped weights), while the third PC has the highest correlation with the term spread and the four quarters ahead recession probability, which both have relatively flat weighting schemes.

These results remain robust to including realised volatility in the specifications (see Appendix 1), indicating that macroeconomic data and survey-based sentiment indicators explain parts of the long-term stock market volatility not captured by past returns.[33].

5.2 Combining macroeconomic variables and sentiment indicators

In order to examine the combined and relative information content of macroeconomic variables and survey-based sentiment indicators I include one of both in the same MIDAS polynomial (Table 5). The significance of their respective coefficients (θ_1 and θ_2) can be used to assess whether both are simultaneously useful for explaining volatility. The variance ratios reveal whether the variables are able to explain more of the total conditional variance together than on their own. As the term spread can also be interpreted as a sentiment indicator, I include specifications where the term spread is combined with the other macroeconomic

[32]On the other hand, Asgharian et al. (2013) interpreted weights which are not monotonically decreasing as counterintuitive, always enforcing the restriction $\omega_1 = 1$.

[33]This is in line with the conclusion in, for example, Conrad and Loch (2014) and Asgharian et al. (2013)

data. As a robustness check, to control for the information in realised volatility, I also include results with three explanatory variables in the MIDAS filter: the absolute value of returns (RV), a macroeconomic variable and a sentiment indicator (Table 6).

For each variable I keep the earlier choice of a restricted or unrestricted weighting scheme, but re-estimate the weight parameter(s) (ω_i). In most cases the weight parameter(s) are similar regardless of the other variables included (compare, e.g., Table 4 with Table 5, and Table 10 with Table 6). For example, for the absolute value of returns and industrial production ω_2 implies a very similar speed of decay in all specifications. For housing starts the inclusion of RV occasionally leads to weighting schemes with almost all weight on the third lag (see Figure 3k), but mostly it has a similar hump-shaped pattern as earlier. The term spread as well as the four quarters ahead recession probability get in many cases very gradually decaying weights. For the one quarter ahead recession probability all the weight is on the first lag ($\omega_2 \approx 100$ in Table 5 and Table 6). This is not surprising as the information in the lags of the recession probability can plausibly be assumed to be already included in other data.

The intuitive sign of θ is retained in all cases where the parameter is statistically significant. The effect of industrial production or the ADS index on long-term volatility is mostly insignificant or only weakly significant when survey-based sentiment measures are included (with the exception of the recession probabilities), while the sentiment indicators remain significant. This effect is clearly more pronounced when information in the absolute value of returns is accounted for (Table 6). This implies sentiment indicators capture information in and beyond backward-looking macroeconomic variables.

Housing starts get highly significant estimates for θ, and with the occasional exception of a consumer confidence indicator so do the sentiment indicators. Controlling for information in absolute returns does not significantly influence these results. The term spread and the sentiment indicators are simultaneously highly significant (Table 5), but when information in the absolute value of returns is taken into account there is only weak evidence of sentiment indicators containing additional useful information for long-term stock market volatility (Table 6). It is noteworthy that the four quarter ahead recession probability is highly significant throughout the specifications, indicating it includes information different from that in the macroeconomic data and the absolute value of returns.

Table 5: Estimation results for GARCH-MIDAS model where macroeconomic data (θ_1) and sentiment indicators (θ_2) are combined

	θ_1	θ_2	ω_{11}	ω_{12}	ω_{12}	ω_{22}	m	LLF	BIC	VR
Industrial production + ISM New Orders index	0.0094	-0.0527***	1	11.5561*	1	4.9374*	2.6929***	-13861.08	2.5630	12.85
	(0.0150)	(0.0128)		(6.1113)		(2.1013)	(0.6852)			
Industrial production + ISM Recession indicator	-0.0297*	-0.0569***	1	2.3946**	1	2.4504***	0.3794***	-13859.47	2.5627	12.64
	(0.0160)	(0.0134)		(0.5426)		(0.5120)	(0.1299)			
Industrial production + Consumer confidence index	-0.0277	-0.1301***	1	2.8377*	1.8151	3.2016*	-0.0985	-13859.54	2.5636	14.07
	(0.0201)	(0.0366)		(1.0516)	(0.5636)	(1.2498)	(0.0950)			
Industrial production + News Heard index	-0.0307	-0.0607***	1	1.9038	1.8017***	2.0675**	-0.0930	-13857.17	2.5631	15.46
	(0.0248)	(0.0145)		(1.3685)	(0.2928)	(0.4777)	(0.0974)			
Industrial production + Buying conditions index	-0.0144	-0.1087***	1	3.2066*	1	2.1619***	-0.1309	-13849.78	2.5609	18.14
	(0.0171)	(0.0248)		(1.1601)		(0.3608)	(0.0829)			
Industrial production + SPF 1Q ahead recession probability	-0.0305**	0.0125***	1	2.7557***	1	110.0872***	-0.3462***	-13855.28	2.5619	13.93
	(0.0143)	(0.0024)		(0.6225)		(18.4064)	(0.1027)			
Industrial production + SPF 4Q ahead recession probability	-0.0659***	0.0601***	1	2.3224***	1	1.6101	-1.0800***	-13843.98	2.5598	18.16
	(0.0174)	(0.0144)		(0.5021)		(0.6443)	(0.2555)			
Industrial production + Term spread	-0.0334**	-0.2182***	1	3.9053**	1	1.9518	0.2787**	-13856.40	2.5621	14.33
	(0.0138)	(0.0550)		(1.1787)		(0.8477)	(0.1175)			
ADS index + ISM New Orders index	-0.0674	-0.0432***	1	95.0806***	1	3.8238**	2.1839***	-13860.57	2.5629	12.85
	(0.0608)	(0.0101)		(18.8739)		(1.3943)	(0.5654)			
ADS index + ISM Recession indicator	-0.2155**	-0.0499***	1	3.7904***	1	2.3083***	0.2247	-13858.92	2.5626	12.91
	(0.1085)	(0.0148)		(0.9516)		(0.4976)	(0.1598)			
ADS index + Consumer confidence index	-0.2492*	-0.1088**	1	3.8644*	1.9296	3.6232	-0.1947**	-13857.84	2.5632	14.92
	(0.1405)	(0.0424)		(1.7069)	(0.7273)	(2.1272)	(0.0914)			
ADS index + News Heard index	-0.2364*	-0.0517***	1	3.9626	1.8057**	1.9758**	-0.1969**	-13854.87	2.5627	16.14
	(0.1282)	(0.0170)		(4.3496)	(0.3477)	(0.4516)	(0.0889)			
ADS index + Buying conditions index	-0.1295	-0.1013***	1	4.1363*	1	2.2044***	-0.1804**	-13849.36	2.5608	18.18
	(0.1175)	(0.0263)		(1.6389)		(0.3635)	(0.0848)			
ADS index + SPF 1Q ahead recession probability	-0.2185**	0.0114***	1	3.6427***	1	102.8511***	-0.4201***	-13855.14	2.5619	14.02
	(0.1082)	(0.0030)		(1.0102)		(27.5078)	(0.0954)			
ADS index + SPF 4Q ahead recession probability	-0.4504***	0.0568***	1	3.2091**	1	1.5774	-1.2317***	-13840.93	2.5593	18.97
	(0.1213)	(0.0141)		(0.8873)		(0.7144)	(0.2569)			
ADS index + Term spread	-0.2614***	-0.2010***	1	5.4811***	1	1.7930	0.1401	-13853.99	2.5617	15.06
	(0.0921)	(0.0566)		(1.7233)		(0.8110)	(0.1347)			

Table 5 *continued*

	θ_1	θ_2	ω_{11}	ω_{12}	ω_{12}	ω_{22}	m	LLF	BIC	VR
Housing starts + ISM New Orders index	-0.0124***	-0.0336***	3.0179	5.6088	1	2.6225	1.7294***	-13848.45	2.5615	18.85
	(0.0035)	(0.0118)	(1.6312)	(3.1802)		(1.3706)	(0.6363)			
Housing starts + ISM Recession indicator	-0.0123***	-0.0462***	3.6012	5.5130	1	2.1319	0.2776**	-13846.03	2.5611	19.73
	(0.0038)	(0.0130)	(2.1981)	(4.2150)		(0.8814)	(0.1224)			
Housing starts + Consumer confidence index	-0.0146**	-0.0580	3.3170	4.6905	2.3895	6.8953	-0.0898	-13851.41	2.5629	20.60
	(0.0060)	(0.0461)	(2.4023)	(4.3894)	(1.9295)	(11.6006)	(0.0946)			
Housing starts + News Heard index	-0.0146***	-0.0102	4.1046**	7.3857**	21.6840	8.5296	-0.0912	-13851.90	2.5630	17.18
	(0.0035)	(0.0064)	(1.4643)	(2.7288)	(19.5847)	(5.7758)	(0.0903)			
Housing starts + Buying conditions index	-0.0082**	-0.0833***	4.8977*	8.4215	1	2.2164**	-0.1258	-13844.01	2.5607	22.32
	(0.0036)	(0.0236)	(2.1431)	(4.8056)		(0.5367)	(0.0825)			
Housing starts + SPF 1Q ahead recession probability	-0.0112***	0.0108***	4.9216*	7.3163*	1	132.8746***	-0.3298***	-13842.39	2.5604	20.65
	(0.0032)	(0.0024)	(2.1447)	(3.5370)		(11.5682)	(0.1025)			
Housing starts + SPF 4Q ahead recession probability	-0.0127***	0.0440***	3.5068	5.5728	1	1.0711	-0.8807***	-13841.05	2.5601	18.99
	(0.0037)	(0.0143)	(1.9079)	(3.5743)		(0.4422)	(0.2625)			
Housing starts + Term spread	-0.0121***	-0.2023***	3.7123*	6.6700*	1	1.1767	0.2314**	-13844.35	2.5608	21.03
	(0.0031)	(0.0542)	(1.5282)	(3.0147)		(0.6030)	(0.1147)			
Term spread + ISM New Orders index	-0.1678**	-0.0299**	1	1.8883	1	4.6093	1.7497***	-13854.69	2.5618	14.97
	(0.0703)	(0.0134)		(1.1121)		(2.9227)	(0.6561)			
Term spread + ISM Recession indicator	-0.1781**	-0.0398**	1	1.1967	1	2.6646***	0.4702***	-13856.68	2.5622	14.04
	(0.0736)	(0.0173)		(0.5843)		(0.6272)	(0.1285)			
Term spread + Consumer confidence index	-0.2237***	-0.1043***	1	1.0000	2.2166	4.6187	0.2112*	-13850.36	2.5619	18.55
	(0.0587)	(0.0317)		(0.4770)	(0.7549)	(2.2339)	(0.1259)			
Term spread + News Heard index	-0.2021***	-0.0479***	1	1.0000	1.9236***	2.3406*	0.1720	-13850.17	2.5618	19.43
	(0.0679)	(0.0151)		(0.7844)	(0.3449)	(0.7133)	(0.1330)			
Term spread + Buying conditions index	-0.1413**	-0.0886***	1	1.0000	1	2.3946**	0.0727	-13846.39	2.5603	19.58
	(0.0618)	(0.0219)		(0.7149)		(0.5538)	(0.1248)			
Term spread + SPF 1Q ahead recession probability	-0.1679***	0.0101***	1	1.3024	1	98.8281	-0.0809	-13852.44	2.5614	14.66
	(0.0636)	(0.0030)		(0.6478)		(84.3426)	(0.1753)			
Term spread + SPF 4Q ahead recession probability	-0.2089***	0.0481***	1	1.3085	1	1.1668	-0.6619**	-13845.14	2.5600	17.11
	(0.0626)	(0.0155)		(0.4378)		(0.4084)	(0.3327)			
Principal component 1 + Principal component 2	0.2736***	0.3310***	1	1.5617	1.4911	1.9478	-0.1948**	-13841.16	2.5602	19.66
	(0.0651)	(0.1064)		(0.3667)	(0.5367)	(0.5435)	(0.0790)			
Principal component 1 + Principal component 3	0.1178***	0.3059**	1	4.2741*	1	1.0000	-0.1967**	-13840.93	2.5593	19.42
	(0.0441)	(0.0998)		(1.7533)		(0.4990)	(0.0810)			
Principal component 2 + Principal component 3	0.1630	0.3207***	6.9464	3.5122	1	1.0000	-0.1934	-13842.67	2.5604	18.42
	(0.1188)	(0.1084)	(17.5974)	(4.6873)		(1.1889)	(0.0863)			

*Bollerslev-Wooldridge QMLE robust standard errors are reported below the parameter estimates. *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively. LLF is the value of the log-likelihood function, BIC is the Bayesian Information Criteria and VR is the variance ratio from Section 3, multiplied by 100.*

The MIDAS polynomial: log $\tau_t = m + \theta_1 \sum_{k=1}^{K} \varphi_k(\omega_{11}, \omega_{12}) X_{1,t-k} + \theta_2 \sum_{k=1}^{K} \varphi_k(\omega_{21}, \omega_{22}) X_{2,t-k}$, *where* X_1 *denotes the macroeconomic data and* X_2 *the sentiment data, as stated in the first column.*

Table 6: Estimation results for GARCH-MIDAS model where realised volatility (θ_{RV}), macroeconomic data (θ_1) and sentiment indicator (θ_2) are combined

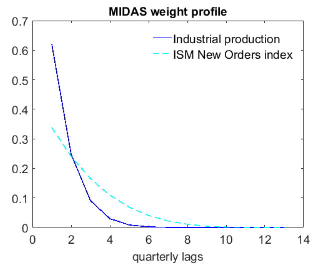
	θ_{RV}	θ_1	θ_2	ω_{12}	ω_{21}	ω_{22}	ω_{31}	ω_{32}	m	LLF	BIC	VR
Industrial production + ISM New Orders index	0.0173***	0.0142	-0.0329***	10.4245***	1	13.2304	1	6.9057	0.7831	-13827.76	2.5397	32.65
	(0.0023)	(0.0130)	(0.0114)	(3.5228)		(9.2100)		(3.7840)	(0.6609)			
Industrial production + ISM Recession indicator	0.0168***	-0.0057	-0.0355***	11.3968***	1	3.5415**	1	2.3334***	-0.6535***	-13829.37	2.5400	31.68
	(0.0024)	(0.0131)	(0.0118)	(3.4916)		(1.0026)		(0.4928)	(0.1842)			
Industrial production + Consumer confidence index	0.0164***	-0.0109	-0.0678**	11.4497**	1	3.5776*	1.9565	4.5068	-0.9171***	-13830.03	2.5598	32.93
	(0.0025)	(0.0153)	(0.0332)	(4.0824)		(1.3792)	(1.1862)	(4.2416)	(0.1494)			
Industrial production + News Heard index	0.0164***	-0.0023	-0.0425***	11.4362***	1	4.7689	1.6088***	1.7534***	-0.9388***	-13825.51	2.5590	34.19
	(0.0024)	(0.0124)	(0.0117)	(4.0009)		(3.8697)	(0.3135)	(0.3740)	(0.1438)			
Industrial production + Buying conditions index	0.0157***	-0.0010	-0.0661**	9.8321**	1	3.5994*	1	2.7471	-0.9094***	-13821.94	2.5386	35.02
	(0.0029)	(0.0153)	(0.0261)	(4.3850)		(1.3368)		(1.2009)	(0.1638)			
Industrial production + SPF 1Q ahead recession probability	0.0159***	-0.0077	0.0079***	10.5135**	1	3.7213***	1	104.3401***	-1.0598***	-13828.21	2.5398	30.90
	(0.0024)	(0.0139)	(0.0024)	(4.1165)		(1.0465)		(11.0329)	(0.1619)			
Industrial production + SPF 4Q ahead recession probability	0.0167***	-0.0265*	0.0433***	12.3181***	1	3.1766**	1	1.4707	-1.6675***	-13813.58	2.5371	35.07
	(0.0024)	(0.0140)	(0.0114)	(3.3433)		(1.0159)		(0.5208)	(0.2133)			
Industrial production + Term spread	0.0180***	-0.0090	-0.1734***	10.2906***	1	4.9675*	1	2.3551	-0.7058***	-13818.66	2.5380	36.17
	(0.0023)	(0.0106)	(0.0404)	(3.2205)		(2.0550)		(0.8992)	(0.1514)			
ADS index + ISM New Orders index	0.0164***	-0.0317	-0.0237***	12.2719***	1	98.7464***	1	4.5555	0.3461	-13828.83	2.5399	32.31
	(0.0023)	(0.0545)	(0.0089)	(3.5982)		(20.7691)		(2.4088)	(0.5596)			
ADS index + ISM Recession indicator	0.0170***	-0.0246	-0.0354***	11.1753***	1	93.7056***	1	2.2089**	-0.6791***	-13829.35	2.5400	31.64
	(0.0022)	(0.0506)	(0.0120)	(3.1818)		(25.7094)		(0.4798)	(0.1815)			
ADS index + Consumer confidence index	0.0161***	-0.0879	-0.0618*	11.7971**	1	5.3866	2.1214	4.9370	-0.9427***	-13829.78	2.5598	32.91
	(0.0028)	(0.1157)	(0.0342)	(4.4492)		(3.3866)	(1.2836)	(4.6139)	(0.1382)			
ADS index + News Heard index	0.0160***	-0.0442	-0.0391***	12.1426***	1	122.6766***	1.7173**	1.7936**	-0.9311***	-13824.92	2.5589	34.14
	(0.0023)	(0.0564)	(0.0114)	(4.1862)		(19.2362)	(0.3600)	(0.3859)	(0.1249)			
ADS index + Buying conditions index	0.0159***	0.0196	-0.0704***	9.5048*	1	17.5468	1	2.7237*	-0.9185***	-13821.86	2.5386	35.12
	(0.0031)	(0.0685)	(0.0224)	(4.3807)		(13.8407)		(1.0141)	(0.1599)			
ADS index + SPF 1Q ahead recession probability	0.0161***	-0.0332	0.0079**	10.1930**	1	5.2771*	1	119.6018***	-1.0924***	-13828.42	2.5398	30.77
	(0.0028)	(0.1283)	(0.0032)	(4.6013)		(2.2543)		(14.5171)	(0.1668)			
ADS index + SPF 4Q ahead recession probability	0.0162***	-0.1856*	0.0427***	12.8086***	1	4.7718*	1	1.3853	-1.7159***	-13812.42	2.5369	35.28
	(0.0026)	(0.0992)	(0.0112)	(3.8418)		(2.0861)		(0.5004)	(0.2008)			
ADS index + Term spread	0.0177***	-0.0623	-0.1716***	10.4262***	1	8.1081	1	2.2447	-0.7258***	-13818.55	2.5380	36.15
	(0.0026)	(0.0777)	(0.0411)	(3.4549)		(7.2559)		(0.8598)	(0.1439)			

Table 6 *continued*

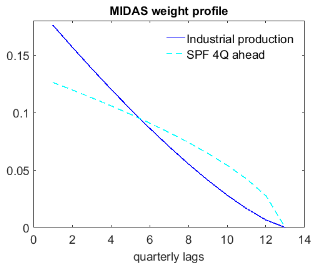
	θ_{RV}	θ_1	θ_2	ω_{12}	ω_{21}	ω_{22}	ω_{31}	ω_{32}	m	LLF	BIC	VR
Housing starts + ISM New Orders index	0.0160***	-0.0034***	-0.0241***	14.2477***	63.4650	184.6014	1	3.3280*	0.4012	-13818.60	2.5577	34.85
	(0.0021)	(0.0011)	(0.0087)	(3.6651)	(68.4976)	(194.2064)		(1.2671)	(0.5407)			
Housing starts + ISM Recession indicator	0.0152***	-0.0065**	-0.0276**	13.3818***	5.4467	11.4242	1	1.9363*	-0.6284***	-13820.85	2.5581	35.07
	(0.0026)	(0.0030)	(0.0111)	(3.5700)	(3.9703)	(11.2808)		(0.5425)	(0.1881)			
Housing starts + Consumer confidence index	0.0160***	-0.0071	-0.0283	12.0602	5.3342	10.2916	2.3212	7.9796	-0.8944***	-13823.76	2.5373	35.62
	(0.0025)	(0.0062)	(0.0615)	(3.6905)	(3.7215)	(11.5025)	(7.4285)	(46.9846)	(0.1431)			
Housing starts + News Heard index	0.0160***	-0.0029**	-0.0335***	13.3811***	75.9280***	221.3514***	1.8955*	0.9187***	1.8649**	-13817.37	2.5361	35.74
	(0.0020)	(0.0011)	(0.0101)	(3.6365)	(17.6929)	(63.2431)	(0.4671)	(0.4390)	(0.1145)			
Housing starts + Buying conditions index	0.0152***	-0.0027**	-0.0565***	11.6238**	83.3029***	239.7271***	1	2.6196	-0.8810***	-13814.94	2.5570	36.77
	(0.0026)	(0.0011)	(0.0210)	(4.5400)	(20.1721)	(69.9393)		(1.1843)	(0.1426)			
Housing starts + SPF 1Q ahead	0.0145***	-0.0065**	0.0061***	12.3925***	5.8725*	11.2957	1	124.1099***	-0.9469	-13820.36	2.5580	34.31
recession probability	(0.0024)	(0.0027)	(0.0022)	(3.8422)	(2.5845)	(6.5402)		(8.0812)	(0.1382)			
Housing starts + SPF 4Q ahead	0.0181***	-0.0032***	0.0391***	11.5761***	73.2730**	210.3613**	1	1.1644	-1.7001***	-13807.79	2.5557	36.06
recession probability	(0.0018)	(0.0011)	(0.0112)	(2.7419)	(33.1725)	(100.2050)		(0.3756)	(0.2022)			
Housing starts + Term spread	0.0172***	-0.0032***	-0.1738***	11.6129***	67.1410***	194.3099***	1	1.7757	-0.6797***	-13809.35	2.5560	38.55
	(0.0019)	(0.0394)	(0.0010)	(3.3089)	(23.3492)	(73.5247)		(0.7737)	(0.1440)			
Term spread + ISM New Orders index	0.0178***	-0.1504***	-0.0129	10.2544***	1	2.7704	1	3.3304	-0.0556	-13817.75	2.5379	36.03
	(0.0023)	(0.0454)	(0.0117)	(3.1067)		(1.2320)		(4.1836)	(0.6761)			
Term spread + ISM Recession indicator	0.0184***	-0.1716***	-0.0064	9.6631***	1	2.1541	1	3.0622	-0.6945***	-13819.09	2.5381	36.02
	(0.0022)	(0.0485)	(0.0121)	(2.8241)		(0.7871)		(1.4884)	(0.1760)			
Term spread + Consumer confidence index	0.0173***	-0.1760***	-0.0385*	9.2594*	1	1.7040	2.6410	8.5016	-0.6906***	-13816.05	2.5572	37.66
	(0.0026)	(0.0407)	(0.0225)	(4.1066)		(0.7761)	(1.3352)	(7.3206)	(0.1607)			
Term spread + News Heard index	0.0169***	-0.1542***	-0.0228*	10.0129**	1	1.7078	1.6123	2.1424	-0.7078***	-13816.10	2.5573	37.52
	(0.0024)	(0.0520)	(0.0132)	(4.0224)		(1.1243)	(0.4736)	(1.3441)	(0.1562)			
Term spread + Buying conditions index	0.0177***	-0.1552***	-0.0273**	7.9089**	1	1.7355	1	5.9910**	-0.7451***	-13812.84	2.5370	37.96
	(0.0024)	(0.0406)	(0.0112)	(3.3674)		(0.8425)		(2.3647)	(0.1513)			
Term spread + SPF 1Q ahead recession probability	0.0177***	-0.1565***	0.0034	9.3177***	1	2.2260	1	138.1807***	-0.8067***	-13817.88	2.5379	35.52
	(0.0021)	(0.0468)	(0.0024)	(3.0584)		(0.9305)		(11.7946)	(0.1502)			
Term spread + SPF 4Q ahead recession probability	0.0182***	-0.1518***	0.0337***	9.7986***	1	1.7206	1	1.4284	-1.3701***	-13806.10	2.5357	38.26
	(0.0020)	(0.0451)	(0.0117)	(2.8543)		(0.7154)		(0.5586)	(0.2485)			
Principal component 1 + Principal component 2	0.0159***	0.1784***	0.2977***	9.9813**	1	1.4988	1.0541	1.6271	-0.9421***	-13811.26	2.5564	37.52
	(0.0026)	(0.0606)	(0.0853)	(4.1577)		(0.4154)	(0.4693)	(0.5219)	(0.1353)			
Principal component 1 + Principal component 3	0.0170***	0.0351	0.2907***	10.5690***	1	7.1175	1	1.2407	-0.9945***	-13807.38	2.5360	38.12
	(0.0023)	(0.0279)	(0.0669)	(3.2262)		(5.2626)		(0.4153)	(0.1205)			
Principal component 2 + Principal component 3	0.0178***	0.1248*	0.2723***	9.8181**	1.6686	1.7995	1	1.0000	-1.0336***	-13806.67	2.5555	38.69
	(0.0025)	(0.0733)	(0.0743)	(3.5425)	(1.5112)	(0.8142)		(0.4571)	(0.1300)			

*Bollerslev-Wooldridge QMLE robust standard errors are reported below the parameter estimates. *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively. LLF is the value of the log-likelihood function, BIC is the Bayesian Information Criteria and VR is the variance ratio from Section 3, multiplied by 100.* $RV_t = \sum_{i=1}^{N_t} |r_{i,t}|$. $\omega_{11} = 1$ *in all specifications.*

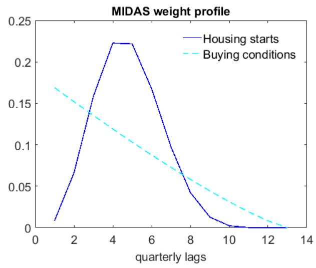
The MIDAS polynomial: $\log \tau_t = m + \theta_{RV} \sum_{k=1}^{K} \varphi_k(1, \omega_{12}) RV_{t-k} + \theta_1 \sum_{k=1}^{K} \varphi_k(\omega_{21}, \omega_{22}) X_{1,t-k} + \theta_2 \sum_{k=1}^{K} \varphi_k(\omega_{31}, \omega_{32}) X_{2,t-k}$, *where* X_1 *denotes the macroeconomic data and* X_2 *the sentiment data, as stated in the first column.*



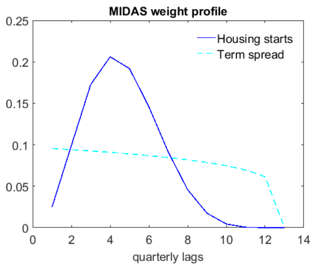
(a) Industrial production and ISM New Orders index



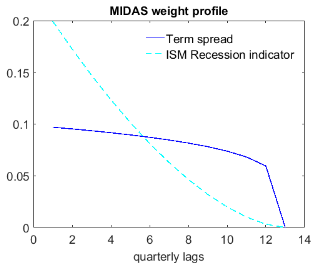
(b) Industrial production and SPF 4Q ahead recession probability



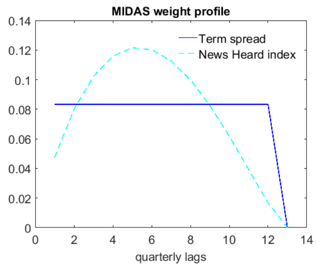
(c) Housing starts and Buying conditions index



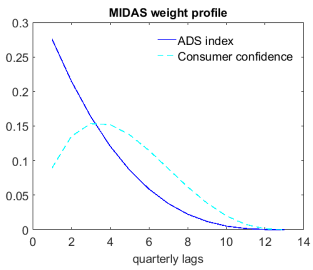
(d) Housing starts and term spread



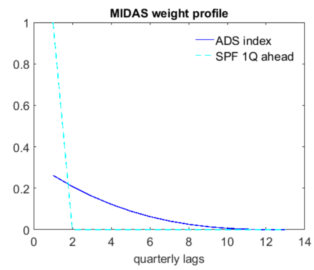
(e) Term spread and ISM Recession indicator



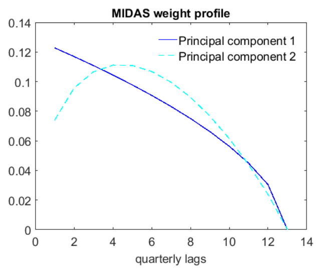
(f) Term spread and News Heard index



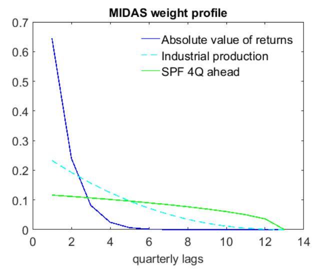
(g) ADS index and consumer confidence index



(h) ADS index and SPF 1Q ahead recession probability

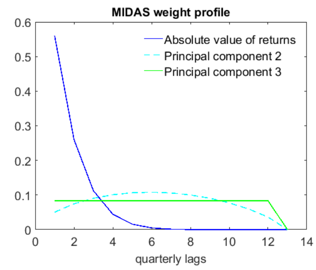


(i) Principal component 1 and 2



(j) Absolute value of returns, industrial production and SPF 4Q ahead recession probability

(k) Absolute value of returns, housing starts and term spread



(l) Absolute value of returns, PC 2 and PC 3

Figure 3: Weighting schemes of selected models from Table 5 and Table 6.

According to the variance ratios in Table 6 all specifications are able to explain more than 30% of the total variation, some close to 40%, when the absolute value of returns is included. However, comparing the variance ratios in Table 5 to those in Table 4 we can see that the gains from including both macroeconomic and sentiment data into the same model are in general relatively small, indicating that macroeconomic variables and sentiment data contain mostly overlapping information for stock market volatility. On the other hand, for example, the variance ratio for the model based on only the term spread is 12.3%, while the variance ratio for the model with only the consumer confidence index is 12.5% (Table 4). The long-term volatility component based on a combination of these series explains almost 19% of the total variance (Table 5). The model driven by only industrial production has a variance ratio of 7.3%, while the model with the four quarter ahead recession probability has a variance ratio of 12.2%. In the model combining these two series the variance ratio rises to 18.2%. The model combining housing starts with the term spread explain a significant 21% of the total variance. The principal components summarise information in the economy well, leading to some of the highest variance ratios (between 18.4% and 19.7%, Table 5).

6 Out-of-sample forecasts

The in-sample results highlighted the superiority of past absolute returns and forward-looking data for stock return volatility. In this section I consider whether these results extend to an out-of-sample context. I start by determining whether the baseline GARCH-MIDAS models (where the long-term component is based on one explanatory variable) outperform the asymmetric GARCH(1,1) model in forecasting volatility. In order to narrow down the set of potential forecasting models for stock return volatility I apply the Model Confidence Set (MCS) procedure by Hansen et al. (2011) to the baseline models. The MCS approach allows the construction of a set of models which contain the best model with a certain level of confidence. In Section 6.2 I examine whether the models combining information from macroeconomic and sentiment data are superior to models with only one explanatory variable, from an out-of-sample forecasting perspective.

As the short-term GARCH components are similar across all GARCH-MIDAS specifications, the largest gains in forecasting can be achieved in long-term forecasts. Thus, I consider forecasts for 1, 2, 3 and 4 quarters ahead. The one-step ahead volatility prediction is given directly by equations (1) and (2). For further horizons we need to iterate forward the daily GJR-GARCH model forecasts and combine this short-term forecast with a forecast for the long-term component, τ_t. For the GJR-GARCH model the forecast for day i is formed as:

$$E\left[g_{i,t}|F_{N_{t-1},t-1}\right] = 1 + (\alpha+\beta+\gamma/2)^{i-1}(g_{1,t}-1), \tag{3}$$

where N_t is the number of trading days in the quarter and $F_{N_{t-1},t-1}$ denotes the information set in period $t-1$. The forecast for total volatility for period t can be expressed as:

$$E\left[\sum_{i=1}^{N_t} g_{i,t}\tau_t\varepsilon_{i,t}^2|F_{N_{t-1},t-1}\right] = \tau_t\left[N_t + (g_{1,t}-1)\frac{1-(\alpha+\beta+\gamma/2)^{N_t}}{1-\alpha-\beta-\gamma/2}\right]. \tag{4}$$

This forecast can be iterated for any forecast horizon. Following Conrad and Loch (2014) I create non-overlapping quarterly forecasts by summing the daily forecasts over the respective quarter while keeping τ_t fixed at its one-step ahead prediction for all horizons.[34] Because the forecast of the GARCH component converges to its (constant) unconditional expectation as the forecast horizon increases, in the long run the forecast differences of the different models are entirely driven by the long-term component.

The first estimation period is Q1 1973 - Q4 1998, and the out-of-sample period is Q1 2000 - Q1 2015 (61 quarters). The forecasts are evaluated against realised volatility calculated as the sum of squared daily returns ($RV_t = \sum_{i=1}^{N_t} r_{i,t}^2$). I use a rolling window estimation scheme, moving forward the estimation period one quarter every period. For each variable I keep the earlier choice of a restricted or unrestricted weighting scheme, but re-estimate the weight parameter(s) each period.[35] The principal components are calculated recursively, including data only up until the end of the estimation period. I compare the forecasting accuracy of the models using the ratio between their mean absolute forecast errors (MAFE). The widely used mean squared forecast errors (MSFE) exaggerate the differences in forecasting performance

[34] The long-term component could be forecast using forecasts for the explanatory data. The SPF data set includes professional forecasts for industrial production and housing starts, but the volatility predictions are not significantly altered by using the forecast data. Thus, the results using the forecasts are available upon request. On the other hand, Conrad and Loch (2014) improve the forecasting performance of GARCH-MIDAS models driven by backward-looking macroeconomic data by using two-sided GARCH-MIDAS specifications utilising SPF forecast data, see Conrad and Loch (2014) for details.

[35] Earlier I chose the restricted weighting scheme for the term spread, while Conrad and Loch (2014) chose the unrestricted one. To have comparable out-of-sample results, I allow an unrestricted weighting scheme for the term spread, which accommodates a potential shift in the shape over time. The differences in the forecasts produced by the models with the different weighting schemes are small. Results are available upon request.

during volatility peaks and especially the financial crisis, when in fact the practical difference in forecasting performance is relatively small.[36] The statistical significance of the differences in forecasting performance is assessed using the (unconditional) predictive ability test by Giacomini and White (2006).

6.1 Forecasting with the baseline models

It is clear from Table 7 that the GJR-GARCH(1,1) model is significantly more difficult to beat than the commonly used benchmarl: the GARCH-MIDAS model with realised volatility as the only explanatory variable. One period ahead none of the GARCH-MIDAS models perform significantly better than the benchmark, with the GARCH-MIDAS model driven by the first principal component being the best model.[37] At longer horizons, the term spread, the consumer confidence sub-indices as well as the second and third PC significantly outperform the GJR-GARCH(1,1) model. Most GARCH-MIDAS specifications produce lower average forecast errors than the benchmark at some horizons at least, although the differences are not generally statistically significant.[38]

The Model Confidence Set (MCS) procedure by Hansen et al. (2011) determines the set of models that includes the best model(s) at a pre-specified level of confidence out of an initial set of candidate models.[39] It first determines the relative performance of the different models, and then tests whether all models are equally good (equivalence test). If not, the model with the worst sample performance is eliminated (based on an elimination rule). Hence it does not require choosing a benchmark model. The process is repeated until equal performance cannot be rejected among the remaining models at the pre-specified level of confidence. The surviving models form the MCS, which includes the best model(s) with a certain probability. Commonly used significance levels, also used in this paper, are $\alpha = 0.10$ and $\alpha = 0.25$.

[36]When the forecasts are compared to a realised volatility measure based on daily data and the MAFE is used to rank the forecasts, the problem of ranking the models robustly arises, see Patton (2011). This needs to be kept in mind when interpreting the results. I include MSFE ratios in Appendix 3 and discuss the differences in model rankings where appropriate. Mostly the results are qualitatively similar. As a robustness check, I also present MSFE ratios where the financial crisis period has been removed. The main conlusions of this paper are robust to removing the financial crisis period, see details in Appendix 4.

[37]This contrasts the results in Asgharian et al. (2013), where the GARCH(1,1) model was the worst model for one period ahead forecasts (although the differences were not statistically significant), when the models were ranked by total volatility. Longer horizons were not considered

[38]The ranking of the models using MSFE ratios is similar to the MAFE ratios, see Table 12 in Appendix 3. Most differences occur for the one quarter ahead horizon, for the ISM Recession indicator, and the four quarters ahead recession probability.

[39]For more technical details on the MCS procedure and its bootstrap implementation see Appendix 5 and in particular Hansen et al. (2011).

Table 7: MAFE ratios of GARCH-MIDAS models against GJR-GARCH(1,1) model

	1 quarter ahead	2 quarters ahead	3 quarters ahead	4 quarters ahead
Sum of squared returns	1.24	1.30	1.30	1.28
Sum of absolute value of returns	1.17	1.25	1.26	1.26
Consumer confidence index	0.98	0.97	0.96	0.96
News Heard index	0.99	0.95*	0.92**	0.91***
Buying conditions index	0.97	0.93**	0.92**	0.93*
ISM New Orders index	0.99	0.99	0.97	0.96*
ISM Recession indicator	1.04	1.06	1.05	1.03
SPF 1Q ahead recession probability	0.96	0.99	1.01	1.00
SPF 4Q ahead recession probability	1.02	0.98	0.96	0.95
Industrial production	1.03	1.00	0.99	0.98
ADS index	0.99	1.00	0.99	0.98
Housing starts	1.00	0.95	0.94	0.93*
Term spread	1.07	0.92**	0.87***	0.85***
Principal component 1	0.95	0.95	0.96	0.94
Principal component 2	1.02	0.97	0.93***	0.93***
Principal component 3	1.04	0.96	0.91***	0.89***

Benchmark model: GJR-GARCH(1,1). MAFE ratio: $\frac{MAFE_{GMX}}{MAFE_{GARCH}}$, *where GMX stands for the GARCH-MIDAS model driven by macroeconomic or sentiment data (X). A value below 1 means the GARCH-MIDAS model outperforms the GJR-GARCH(1,1) model. *, ** and *** indicate a rejection of the null hypothesis of equal (unconditional) predictive ability at the 10%, 5% and 1% level, respectively, according to the Giacomini and White (2006) test.*

The MCS procedure can only separate between models if the data (here the mean absolute forecast errors) is informative enough. The longer the forecasting horizon, the more important is the long-term component, and the more the forecast errors vary between models. This is reflected in Table 8, where at the one quarter ahead horizon most of the models are chosen into the 90% confidence set, while at the three and four quarters ahead horizons only the GARCH-MIDAS model driven by the term spread is included in the set of superior models. The MCS thus strongly favours the term spread as a predictor for stock return volatility over long horizons.

The GARCH-MIDAS models driven by realised volatility (either squared returns or the absolute value of returns), the ISM Recession indicator and industrial production are not included in the MCS at any horizon. Hence, they do not seem to be very useful variables for forecasting stock return volatility. It is noteworthy that the GJR-GARCH(1,1) model is only included in the MCS for the one quarter ahead horizon, and is eliminated relative early for the other horizons. Thus, macroeconomic and sentiment data seem to improve volatility forecasts, especially over long horizons. It is also interesting that the GARCH-MIDAS model driven by the term spread is not included in the MCS at the one quarter ahead horizon, while

Table 8: MCS on the baseline GARCH-MIDAS models

	1 quarter ahead	2 quarters ahead	3 quarters ahead	4 quarters ahead
Sum of squared returns	17	17	17	17
Sum of absolute value of returns	16	16	16	16
Consumer confidence index	4*	7*	7	9
News Heard index	7*	3**	4	3
Buying conditions index	3**	2**	3	6
ISM New Orders index	5*	11	10	8
ISM Recession indicator	14	15	15	15
SPF 1Q ahead recession probability	2**	10	14	13
SPF 4Q ahead recession probability	10*	9	9	7
Industrial production	12	14	12	12
ADS index	6*	13	11	11
Housing starts	9*	4**	6	5
Term spread	15	1**	1**	1**
Principal component 1	1**	5**	8	10
Principal component 2	11*	8	5	4
Principal component 3	13	6*	2	2
GJR-GARCH(1,1)	8*	12	13	14

*Ranking of models based on the MCS procedure by Hansen et al. (2011), applied to the models in Table 4. Calculated with the MCS package in R. Number 17 means the model was eliminated first, while number 1 signifies the last remaining model. Loss function: mean absolute forecast error. $B = 10000$, w chosen based on an $AR(p)$ model on the loss differences (see R package for details) and block bootstrap is used. See Appendix 6 for robustness checks on different w. $\alpha = 0.10, 0.25$, * indicates the forecast is included in $\hat{M}^*_{90\%}$ and ** that it is included in $\hat{M}^*_{75\%}$. Note that the MCS procedure is for non-nested models, while the GJR-GARCH(1,1) model is nested in the other specifications.*

being the best model for all further horizons. This indicates we need separate models and explanatory variables for different forecasting horizons.

For the one quarter ahead horizon variables describing current economic conditions perform well. The 75% confidence set includes the first principal component (related to current business conditions), the one quarter ahead recession probability and the Buying conditions index. For the two quarters ahead horizon the MCS includes fewer models, and in particular models driven by forward-looking variables. The 75% confidence set includes the term spread, the forward-looking sub-indices of consumer confidence, housing starts and the first PC. In addition, the 90% MCS includes the third PC (related to forward-looking variables) and the consumer confidence index. Therefore, the results highlight the importance of the term spread, housing starts and forward-looking confidence data for longer horizons, and indicators describing current economic conditions for short horizons.

6.2 Forecasting with models combining macroeconomic data and sentiment indicators

To determine whether out-of-sample forecasting performance can be improved by combining information in macroeconomic and sentiment data, I compare the forecasting performance of the models including both types of data (from Section 5.2) to the more parsimonious models driven by one variable at a time (from Section 5.1) using MAFE ratios and the (unconditional) predictive ability test of Giacomini and White (2006).[40] The benchmark model in the top panel in Table 9 is the GARCH-MIDAS model driven by macroeconomic data, and the panel thus describes the marginal benefit of using a GARCH-MIDAS model combining macroeconomic and sentiment data over a model only driven by macroeconomic data. The benchmark model in the middle panel is the GARCH-MIDAS model driven by sentiment data, and the panel thus describes the additional explanatory power provided by adding macroeconomic data to a GARCH-MIDAS model driven by sentiment data. The bottom panel is a robustness check, considering models combining information in two of the principal components.

The main take-away from Table 9 is that including the term spread in the long-term component is clearly beneficial from a forecasting perspective (for horizons longer than one quarter), as reflected in the statistically significant improvements in the mean absolute forecast errors when the term spread is added as an explanatory variable (middle panel, column labelled "Term spread", and top panel, last row). The evidence in favour of adding sentiment data to a GARCH-MIDAS model driven by the term spread is weaker (top panel, column labelled "Term spread"): mostly the forecasts are similar to the model driven by only the term spread, while in some cases forecasting performance worsens significantly.

The models combining housing starts with sentiment data tend to produce lower mean absolute forecast errors than the models driven by only sentiment data (middle panel, column labelled "Housing starts"), but only few of the improvements are statistically significant. Adding sentiment data to a GARCH-MIDAS model driven by housing starts leads to mixed results (top panel, column labelled "Housing starts"): for consumer confidence indicators the forecast errors are generally slightly lower and for the other sentiment indicators slightly higher than for the model driven by only housing starts. These differences are not, however,

[40]The main conclusions are robust for the MSFE ratios, see Table 13, although statistical significance is weaker. The main qualitative differences are discussed in Appendix 3.

statistically significant.

Turning to industrial production and the ADS index, adding survey-based sentiment data to a GARCH-MIDAS model driven by backward-looking macroeconomic data tends to improve forecasting performance (top panel, columns labelled "Industrial production" and "ADS index"), in particular when the forward-looking sub-indices of consumer confidence are used. On the other hand, adding either industrial production or the ADS index to a model driven by sentiment data is not generally beneficial (middle panel, columns labelled "Industrial production" and "ADS index").

Furthermore, Table 9 confirms that the one quarter ahead recession probability lowers the forecast errors on short horizons while forward-looking data (such as the term spread and consumer confidence sub-indices) seems useful over longer horizons – in line with the nature of the variables. It is also evident from Table 9 that there are no clear or consistent gains in forecasting from using the more complicated GARCH-MIDAS models. This can be seen by comparing the MAFE ratios of the top and middle panel of Table 9, and noting that the corresponding ratios in the two panels are rarely both less than one (e.g., first entry in top panel (0.99) versus first entry in middle panel (1.04*)). Thus the combined models rarely improve forecasts (at least significantly) compared to both baseline GARCH-MIDAS models.

Combining the information in two principal components can lead to improved forecast over long horizons (bottom panel, Table 9). The results echo those in the top and middle panels: adding the third PC (highest correlation with the term spread) improves forecasts compared to models driven by only the first or second PC (column labelled "Principal component 3"), while adding the second PC (highest correlation with consumer confidence indices) improves forecasts compared to a model driven by only the first PC, but not compared to a model driven by only the third PC (column labelled "Principal component 2"). Including the first PC (related to current business conditions) does not improve forecasts, in line with the results for industrial production and the ADS index (column labelled "Principal component 1").

Table 9: MAFE ratios: two variables (macro + sentiment) vs. one variable (macro/sentiment) driving the long-term component

Benchmark: GARCH-MIDAS model driven by macroeconomic data (as indicated by the first row)

	Industrial production				ADS index				Housing starts				Term spread			
	1Q	2Q	3Q	4Q	1Q	2Q	3Q	4Q	1Q	2Q	3Q	4Q	1Q	2Q	3Q	4Q
Consumer confidence	0.99	0.99	1.00	1.01	0.99	0.97	0.96	0.98	0.99	0.98	0.99	1.00	1.00	0.98	1.00	1.01
News Heard index	0.98	0.96**	0.94***	0.93***	0.99	0.94*	0.92***	0.93***	1.01	1.00	0.96*	0.96	0.98	0.99	1.00	1.00
Buying conditions	0.97	0.94*	0.92**	0.96	1.01	0.94*	0.93**	0.96	1.00	0.98	0.97	0.98	0.99	0.98	0.99	1.02
ISM New Orders index	0.97	0.98	0.98	0.97	0.99	0.99	0.98	0.98	1.02	1.02	0.99	0.98	1.00	1.04**	1.04*	1.04
ISM Recession indicator	1.03	1.09*	1.08	1.06	1.08	1.05	1.05	1.05	1.02	1.04	1.05	1.03	1.00	1.05*	1.06*	1.07***
SPF 1Q ahead	0.93	0.98	1.01	1.01	0.95	0.98	1.00	1.01	0.95	1.00	1.03	1.02	0.96	1.00	1.03	1.05**
SPF 4Q ahead	1.01	0.99	0.96	0.96	1.02	0.98	0.96	0.96	1.01	1.01	1.00	0.98	1.03	1.02	1.03	1.04
Term spread	1.03	0.93**	0.89***	0.87***	1.05	0.93**	0.88***	0.87***	1.04	0.97	0.92***	0.90***				

Benchmark: GARCH-MIDAS model driven by sentiment data (as indicated by the first column)

	Industrial production				ADS index				Housing starts				Term spread			
	1Q	2Q	3Q	4Q	1Q	2Q	3Q	4Q	1Q	2Q	3Q	4Q	1Q	2Q	3Q	4Q
Consumer confidence	1.04*	1.03	1.04**	1.03**	1.01	1.00	0.99	1.00	1.02	0.97	0.97	0.97	1.09	0.94*	0.91***	0.89***
News Heard index	1.02	1.01	1.01	1.00	0.99	1.00	0.99	1.00	1.02	1.01	0.97	0.98	1.05	0.96**	0.94***	0.93***
Buying conditions	1.03*	1.01	0.99	1.01	1.03*	1.01	1.00	1.00	1.03	1.00	0.99	0.98	1.09*	0.97	0.94***	0.92***
ISM New Orders index	1.01	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.04	0.99	0.95	0.95*	1.08	0.97	0.93***	0.92***
ISM Recession indicator	1.02	1.03**	1.02	1.01	1.03	1.00	0.98	1.00	0.98	0.94*	0.94	0.94	1.02	0.92**	0.87***	0.88***
SPF 1Q ahead	1.00	1.00	1.00	1.00	0.98	0.99	0.98	0.99	0.99	0.97	0.96	0.95**	1.07	0.94**	0.89***	0.89***
SPF 4Q ahead	1.02	1.01	0.99	0.99	0.99	0.99	0.99	0.99	1.00	0.98	0.97*	0.96**	1.08	0.96*	0.93***	0.93***
Term spread	0.99	1.01	1.02	1.01	0.98	1.00	1.00	1.01	0.98	1.00	0.99	0.99				

Benchmark: GARCH-MIDAS model driven by the PC indicated by the row

	Principal component 1				Principal component 2				Principal component 3			
	1Q	2Q	3Q	4Q	1Q	2Q	3Q	4Q	1Q	2Q	3Q	4Q
Principal component 1					1.07	0.99	0.95	0.95*	1.07	0.99	0.95	0.92**
Principal component 2	0.99	0.97	0.99	1.00					1.04	0.98	0.98	0.96**
Principal component 3	0.98	0.99	1.00	1.01	1.03	1.00	1.00	1.01				

Top panel: MAFE ratio of a GARCH-MIDAS model with macroeconomic and sentiment data driving the long-term component relative to a GARCH-MIDAS model driven by only macroeconomic data (corresponding to the column): $\frac{MAFE_{macro+sentiment}}{MAFE_{macro}}$*. Middle panel: MAFE ratio of a GARCH-MIDAS model with macroeconomic and sentiment data driving the long-term component relative to a GARCH-MIDAS model driven by only sentiment data (row):* $\frac{MAFE_{macro+sentiment}}{MAFE_{sentiment}}$*. A value below 1 means the model combining macroeconomic and sentiment data in the long-term component outperforms the model driven by only macroeconomic or sentiment data. Bottom panel: MAFE ratio of a GARCH-MIDAS model driven by two principal components relative to a GARCH-MIDAS model driven by one principal component:* $\frac{MAFE_{PC_{row}+PC_{column}}}{MAFE_{PC_{row}}}$*. *, ** and *** indicate a rejection of the null hypothesis of equal (unconditional) predictive ability at the 10%, 5% and 1% level, respectively, according to the Giacomini and White (2006) test.*

7 Conclusion

This paper studies the relative and combined information content and predictive ability of macroeconomic variables and sentiment indicators, building on the idea that sentiment indicators could summarise the state of the economy and describe expectations of future macroeconomic conditions in a way macroeconomic variables are not capable of. This paper thus complements earlier contributions where models driven by only one type of economic data at a time are considered. In addition, I extend the current literature by examining the information content in the absolute value of returns and SPF recession probabilities, and apply the MCS procedure of Hansen et al. (2011) in order to narrow down the set of potential forecasting models.

The main conclusion is that once information in sentiment indicators is controlled for, backward-looking macroeconomic data, i.e., industrial production and the ADS index, do not contain additional useful information for modelling or forecasting stock return volatility. Thus, consumers and businesses seem to take into account the current economic situation. In contrast, forward-looking variables, i.e., housing starts and the term spread, remain useful for explaining stock market volatility even after sentiment data are included. However, adding a sentiment indicator to a GARCH-MIDAS model driven by the term spread or housing starts rarely improves forecasting performance. Thus, there is little evidence that combining macroeconomic and sentiment data in the same MIDAS polynomial significantly improves forecasting performance compared to the best baseline GARCH-MIDAS specifications. In particular, over long horizons the GARCH-MIDAS model where the long-term component is based on the term spread seems superior. The MCS procedure confirms this conclusion.

It is outside the scope of this paper to consider the time-variation of the forecasting performance of the different GARCH-MIDAS models, but this remains an interesting area for future research. It would also be interesting to compare the forecasting performance of the whole class of GARCH-MIDAS models to other long-term volatility forecasting frameworks, in particular predictive regressions.

Bibliography

Andersen, Torben G., Tim Bollerslev, Peter F. Christoffersen, and Francis X. Diebold (2006) 'Volatility and correlation forecasting.' *Handbook of Economic Forecasting* 1, 777–878.

Andreou, Elena, Eric Ghysels, and Andros Kourtellos (2010) 'Regression models with mixed sampling frequencies.' *Journal of Econometrics* 158, 246–261.

Arnold, Ivo J., and Evert B. Vrugt (2008) 'Fundamental uncertainty and stock market volatility.' *Applied Financial Economics* 18, 1425–1440.

Asgharian, Hossein, Ai Jun Hou, and Farrukh Javed (2013) 'The importance of the macroeconomic variables in forecasting stock return variance: a GARCH-MIDAS approach.' *Journal of Forecasting* 32, 600–612.

Asgharian, Hossein, Charlotte Christiansen, and Ai Jun Hou (2015) 'Effects of macroeconomic uncertainty on the stock and bond markets.' *Finance Research Letters* 13, 10–16.

Awartani, Basel M. A., and Valentina Corradi (2005) 'Predicting the volatility of the S&P-500 stock index via GARCH models: the role of asymmetries.' *International Journal of Forecasting* 21, 167–183.

Bansal, Ravi, and Amir Yaron (2004) 'Risks for the long run: a potential resolution of asset pricing puzzles.' *Journal of Finance* 59, 1481–1509.

Barsky, Robert B., and Eric R. Sims (2012) 'Information, animal spirits, and the meaning of innovations in consumer confidence.' *American Economic Review* 102(4), 1343–1377.

Black, Fischer (1976) 'Studies of stock market volatility changes.' *Proceedings of the Business and Economic Statistics Section, Americal Statistical Association* pp. 177–181.

Campbell, John Y. (1991) 'A variance decomposition for stock returns.' *Economic Journal* 101, 157–179.

Campbell, John Y., and Robert J. Shiller (1988) 'The dividend-price ratio and expectations of future dividends and discount factors.' *Review of Financial Studies* 1, 195–228.

Campbell, Sean D., and Francis X. Diebold (2009) 'Stock returns and expected business conditions: Half a century of direct evidence.' *Journal of Business & Economic Statistics* 27(2), 266–278.

Christiansen, Charlotte, Maik Schmeling, and Andreas Schrimpf (2012) 'A comprehensive look at financial volatility prediction by economic variables.' *Journal of Applied Econometrics* 27(6), 956–977.

Conrad, Christian, and Karen Loch (2014) 'Anticipating long-term stock market volatility.' *Journal of Applied Econometrics* 30(7), 1090–1114.

Davis, Nicole, and Ali M. Kutan (2003) 'Inflation and output as predictors of stock returns and volatility: international evidence.' *Applied Financial Economics* 13(9), 693–700.

Diebold, Francis X., and Kamil Yilmaz (2008) 'Macroeconomic volatility and stock market volatility, world-wide.' *NBER Working Paper*

Ding, Zhuanxin, Clive W.J. Granger, and Robert F. Engle (1993) 'A long memory property of stock market returns and a new model.' *Journal of empirical finance* 1, 83–106.

Engle, Robert F., and Jose G. Rangel (2008) 'The SPLINE-GARCH model for low frequency volatility and its global macroeconomic causes.' *Review of Financial Studies* 21, 1187–1222.

Engle, Robert F., Eric Ghysels, and Bumjean Sohn (2013) 'Stock market volatility and macroeconomic fundamentals.' *The Review of Economics and Statistics* 95(3), 776–797.

Errunza, Vihang, and Ked Hogan (1998) 'Macroeconomic determinants of European stock market volatility.' *European Financial Management* 4(3), 361–377.

Fama, Eugene F., and Kenneth R. French (1989) 'Business conditions and expected returns on stock and bonds.' *Journal of Financial Economics* 25, 23–49.

Ghysels, Eric, Arthur Sinko, and Rossen Valkanov (2007) 'MIDAS regressions: Further results and new directions.' *Econometric Reviews* 26(1), 53–90.

Ghysels, Eric, Pedro Santa-Clara, and Rossen Valkanov (2004) 'The MIDAS touch: Mixed data sampling regression models.' *Finance.*

_ (2005) 'There is a risk-return tradeoff after all.' *Journal of Financial Economics* (76), 509–548.

_ (2006) 'Predicting volatility: getting the most out of return data sampled at different frequencies.' *Journal of Econometrics* 131(1-2), 59–95.

Giacomini, Raffaella, and Halbert White (2006) 'Tests of conditional predictive ability.' *Econometrica* 74, 1545–1578.

Glosten, Lawrence R., Ravi Jagannathan, and David E. Runkle (1993) 'On the relation between the expected value and the volatility of the nominal excess return on stocks.' *The Journal of Finance* 48(5), 1779–1801.

Hamilton, James D., and Gang Lin (1996) 'Stock market volatility and the business cycle.' *Journal of Applied Econometrics* 11(5), 573–593.

Hansen, Peter R., Asger Lunde, and James M. Nason (2011) 'The model confidence set.' *Econometrica* 79(2), 453–497.

Mele, Antonio (2007) 'Asymmetric stock market volatility and the cyclical behavior of expected returns.' *Journal of Financial Economics* 86, 446–478.

Officer, R.R. (1973) 'The variability of the market factor of the New York Stock Exchange.' *Journal of Business* 46, 434–453.

Patton, Andrew J. (2011) 'Volatility forecast comparison using imperfect volatility proxies.' *Journal of Econometrics* 160, 246–256.

Paye, Bradley S. (2012) 'Deja vol: Predictive regressions for aggregate stock market volatility using macroeocnomic variables.' *Journal of Financial Economics* 106, 527–546.

Pierdzioch, Christian, Jorg Dopke, and Daniel Hartmann (2008) 'Forecasting stock market volatility with macroeconomic variables in real time.' *Journal of Economics and Business* 60, 256–276.

Poon, Ser-Huang, and Clive W.J. Granger (2003) 'Forecasting volatility in financial markets: A review.' *Journal of Economic Literature* 41, 478–539.

Romer, C. (1990) 'The great crash and the onset of the great depression.' *The Quarterly Journal of Economics* 105, 597–624.

Schwert, William G. (1989a) 'Business cycles, financial crises, and stock volatility.' *Carnegie-Rochester Conference Series on Public Policy* 31, 83–126.

— (1989b) 'Why does stock market volatility change over time?' *Journal of Finance* 44, 1115–1153.

Taylor, Stephen J. (1986) *Modelling financial time series* (New York: John Wiley & Sons)

Veronesi, P. (1999) 'Stock market overreaction to bad news in good times: a rational expectations equilibrium model.' *Review of Financial Studies* 12, 975–1007.

Wang, Fangfang, and Eric Ghysels (2015) 'Econometric analysis of volatility component models.' *Econometric Theory* 31, 362–393.

Appendix 1 - Controlling for information in realised volatility

For macroeconomic data to be a useful predictor of volatility it needs to contain information in addition to that in past realised volatility (RV) (Conrad and Loch, 2014). In this appendix I check the robustness of my baseline results (Section 5.1) to including realised volatility (calculated as the absolute value of returns or as squared returns) in the MIDAS polynomial. For each variable I keep the earlier choice of a restricted or unrestricted weighting scheme, but re-estimate the weight parameter(s).

Table 10: Estimation results for GARCH-MIDAS model where the sum of absolute returns (θ_{RV}) and macroeconomic or sentiment data (θ_1) are combined

	θ_{RV}	θ_1	ω_{12}	ω_{21}	ω_{22}	m	LLF	BIC	VR
Consumer	0.0170***	-0.0802***	10.6052***	1.9203	3.8979	-0.9694***	-13830.18	2.5581	32.72
confidence	(0.0024)	(0.0293)	(3.6284)	(1.0372)	(2.9654)	(0.1336)			
News Heard	0.0166***	-0.0432***	11.1414***	1.6400**	1.7783**	-0.9545***	-13825.15	2.5572	34.19
index	(0.0021)	(0.0099)	(3.4340)	(0.3101)	(0.3622)	(0.1198)			
Buying	0.0157***	-0.0671***	9.7845**	1	2.7147*	-0.9128***	-13821.94	2.5558	35.03
conditions	(0.0028)	(0.0208)	(4.1850)		(1.0348)	(0.1517)			
ISM New Orders	0.0167***	-0.0255***	11.7220***	1	5.2617	0.4338	-13829.07	2.5571	32.27
index	(0.0023)	(0.0084)	(3.3276)		(2.6099)	(0.5357)			
ISM Recession	0.0172***	-0.0385***	10.8839***	1	2.2749***	-0.6596***	-13829.52	2.5572	31.60
indicator	(0.0021)	(0.0107)	(2.9249)		(0.4687)	(0.1808)			
SPF 1Q ahead	0.0165***	0.0086***	9.5659***	1	101.9786***	-1.1178***	-13828.52	2.5570	30.60
recession prob.	(0.0020)	(0.0020)	(3.1853)		(18.2811)	(0.1092)			
SPF 4Q ahead	0.0192***	0.0441***	9.9653***	1	1.1881	-1.8557***	-13817.35	2.5549	33.84
recession prob.	(0.0018)	(0.0114)	(2.2787)		(0.3566)	(0.1972)			
Industrial	0.0176***	-0.0224**	12.3893***	1	5.1430***	-0.9496***	-13836.32	2.5584	30.48
production	(0.0022)	(0.0104)	(3.1948)		(1.5368)	(0.1356)			
ADS index	0.0168***	-0.1748**	12.9404***	1	7.6250*	-0.9868***	-13834.52	2.5581	30.83
	(0.0025)	(0.0811)	(3.8606)		(3.3992)	(0.1284)			
Housing starts	0.0164***	-0.0085***	12.9551***	4.7594	9.6325	-0.9036***	-13825.26	2.5572	34.68
	(0.0023)	(0.0028)	(3.0916)	(2.4532)	(6.0706)	(0.1383)			
Term spread	0.0189***	-0.1856***	9.5499***	1	2.2600*	-0.7452***	-13819.34	2.5553	36.14
	(0.0019)	(0.0383)	(2.6351)		(0.7583)	(0.1378)			
Principal	0.0152***	0.1291***	12.4102***	1	3.8921***	-0.8997***	-13824.20	2.5562	33.37
component 1	(0.0023)	(0.0338)	(3.8862)		(1.0958)	(0.1256)			
Principal	0.0179***	0.2655***	10.2078***	2.5814	1.6577	-1.0256***	-13817.60	2.5558	35.82
component 2	(0.0024)	(0.0869)	(3.5273)	(2.3542)	(1.0018)	(0.1290)			
Principal	0.0182***	0.3287***	10.5585***	1	1.3047	-1.0475***	-13808.88	2.5534	37.90
component 3	(0.0019)	(0.0602)	(2.6342)		(0.3690)	(0.1060)			

*Bollerslev-Wooldridge QMLE robust standard errors are reported below the parameter estimates. *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively. LLF is the value of the log-likelihood function, BIC is the Bayesian Information Criteria and VR is the variance ratio from Section 3, multiplied by 100.*

The MIDAS polynomial: $\log \tau_t = m + \theta_{RV} \sum_{k=1}^{K} \varphi_k(1, \omega_{12}) RV_{t-k} + \theta_1 \sum_{k=1}^{K} \varphi_k(\omega_{21}, \omega_{22}) X_{t-k}$, where X stands for the explanatory data, as stated in the first column. $RV_t = \sum_{i=1}^{N_t} |r_{i,t}|$.

As expected, the variance ratios increase from Table 4, with especially large gains in specifications including the News Heard index, the four quarter ahead recession probability, and the term spread. The highest variance ratio (37.90) is achieved for the model augmented by the third principal component, highlighting the benefits of combining the information from many variables. Interestingly the first principal component, which produced the highest variance ratio of the PC driven models in Table 4, now has the lowest variance ratio, indicating it contains more overlapping information with realised volatility than the other principal components. This is logical, considering that the first PC is primarily correlated with indicators describing the current economic situation. Overall, the models now explain roughly 35% (25% for squared returns) of the total variance of stock returns.

Table 11: Estimation results for GARCH-MIDAS model where the sum of squared returns (θ_{RV}) and macroeconomic or sentiment data (θ_1) are combined

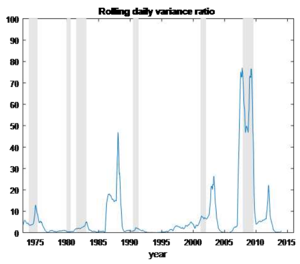
	θ_{RV}	θ_1	ω_{12}	ω_{21}	ω_{22}	m	LLF	BIC	VR
Consumer	0.0030***	-0.1196***	8.3162	1.7352	2.9167*	-0.3900***	-13844.98	2.5609	25.02
confidence	(0.0007)	(0.0297)	(4.6534)	(0.5626)	(1.1243)	(0.0859)			
News Heard	0.0030***	-0.0536***	8.9463**	1.7619**	1.7975**	-0.3937***	-13841.05	2.5601	26.59
index	(0.0005)	(0.0106)	(3.8731)	(0.3066)	(0.3189)	(0.0802)			
Buying	0.0040***	-0.0856***	2.3999	1.9534	6.5363	-0.4575***	-13832.83	2.5586	28.39
Conditions	(0.0009)	(0.0242)	(1.3584)	(0.7091)	(4.0256)	(0.0933)			
ISM New Orders	0.0030***	-0.0358***	8.8552*	1	4.6033*	1.5601***	-13843.15	2.5597	25.29
index	(0.0006)	(0.0091)	(4.0113)		(1.8791)	(0.5262)			
ISM Recession	0.0032***	-0.0559***	7.9209**	1	2.0713***	0.0571	-13842.04	2.5595	24.58
Indicator	(0.0005)	(0.0109)	(3.4253)		(0.3627)	(0.1321)			
SPF 1Q ahead	0.0035***	0.0127***	2.9977	1	109.3829***	-0.6734***	-13841.86	2.5594	21.87
recession prob.	(0.0009)	(0.0031)	(3.3032)		(20.2233)	(0.1237)			
SPF 4Q ahead	0.0035***	0.0497***	7.2575***	1	1.0000***	-1.3047***	-13837.90	2.5587	23.55
recession prob.	(0.0005)	(0.0129)	(2.5139)		(0.3157)	(0.2209)			
Industrial	0.0031***	-0.0363***	10.1377***	1	4.2046***	-0.3160***	-13853.19	2.5615	21.57
production	(0.0006)	(0.0123)	(3.5456)		(0.9987)	(0.0913)			
ADS index	0.0028***	-0.2865***	11.2862**	1	6.0176***	-0.4172***	-13849.23	2.5608	23.04
	(0.0006)	(0.0884)	(4.4465)		(1.7840)	(0.0768)			
Housing starts	0.0026***	-0.0123***	11.7165***	3.7883	6.4723	-0.3036***	-13841.23	2.5602	27.02
	(0.0006)	(0.0034)	(3.3902)	(1.8827)	(3.7025)	(0.0891)			
Term spread	0.0042***	-0.2529***	5.9237	1	2.0640	-0.0563	-13829.57	2.5572	30.70
	(0.0008)	(0.0406)	(4.0798)		(0.6853)	(0.1054)			
Principal	0.0026***	0.1776***	10.3429**	1	3.3891***	-0.3808***	-13835.73	2.5583	27.46
component 1	(0.0005)	(0.0340)	(4.2714)		(0.7503)	(0.0759)			
Principal	0.0033***	0.2765***	9.1938***	5.7006	2.6578	-0.4292***	-13832.36	2.5585	28.77
component 2	(0.0005)	(0.0906)	(2.5503)	(6.9269)	(2.2342)	(0.0767)			
Principal	0.0036***	0.4002***	8.0135***	1	1.1718	-0.4654***	-13822.44	2.5559	31.45
component 3	(0.0005)	(0.0631)	(2.6163)		(0.3065)	(0.0723)			

*Bollerslev-Wooldridge QMLE robust standard errors are reported below the parameter estimates. *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively. LLF is the value of the log-likelihood function, BIC is the Bayesian Information Criteria and VR is the variance ratio from Section 3, multiplied by 100.*

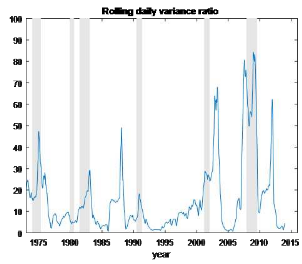
The MIDAS polynomial: $\log \tau_t = m + \theta_{RV} \sum_{k=1}^{K} \varphi_k(1, \omega_{12}) RV_{t-k} + \theta_1 \sum_{k=1}^{K} \varphi_k(\omega_{21}, \omega_{22}) X_{t-k}$, *where X stands for the explanatory data, as stated in the first column.* $RV_t = \sum_{i=1}^{N_t} r_i^2$.

Appendix 2 - Time-variation in variance ratios

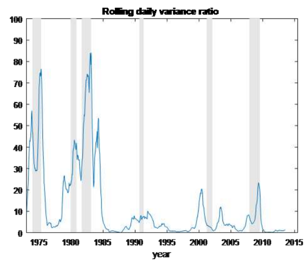
To illustrate the time-variation in variance ratios over the entire sample period I use full-sample parameter estimates and calculate the ratio between the variances of the long-term component and total expected volatility over a 500 day rolling window (roughly two years). The macroeconomic variables lose importance after the 1980s (Figure 4), whereas realised volatility has also recently been important. The time-varying variance ratios reveal important differences and significant variation in the abilities of the different GARCH-MIDAS models to explain volatility over time.



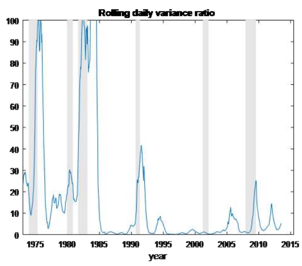
(a) Sum of squared returns



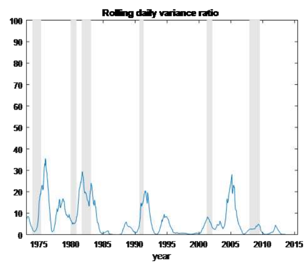
(b) Sum of absolute value of returns



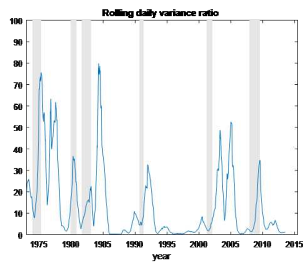
(c) Industrial production



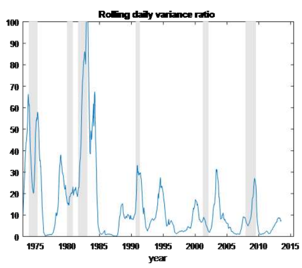
(d) Housing starts



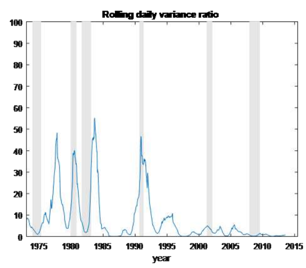
(e) Term spread



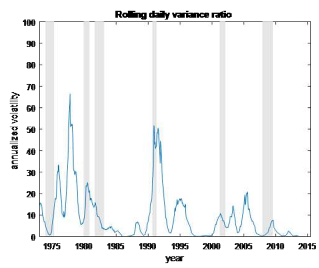
(f) News Heard index



(g) ISM New Orders index



(h) SPF 4Q ahead



(i) Term spread + SPF 4Q ahead

Figure 4: Time-varying variance ratios of selected GARCH-MIDAS models. Grey areas mark US recessions as dated by the NBER Business Cycle Dating Committee. The variance ratio can exceed 100%, since the variance of the long-term component can exceed the total expected variance of a model. The graph subtitles give the variable(s) driving the long-term component of the GARCH-MIDAS model.

Appendix 3 - Mean squared forecast error ratios

Table 12 reports MSFE ratios for the baseline models compared to the GJR-GARCH(1,1) model. Table 13 presents MSFE ratios between GARCH-MIDAS models driven by both a macroeconomic and sentiment indicator and GARCH-MIDAS models driven by one variable.

The main difference in Table 13 compared to Table 9 is that the differences in forecasting performance are less significant, despite occasionally clear differences in relative performance. This reflects the tendency of the MSFE loss function to give large weight to a few large forecast loss differences. The conclusions are also in general less clear cut than in the MAFE case, and there are, for example, larger differences in forecasting performance in particular one quarter ahead. Table 15, where the financial crisis periods have been removed, shows that these are more in line with the MAFE ratios in Table 9, highlighting the importance of the financial crisis for the MSFEs. Similarly for the bottom panel with the principal components, there are clear qualitative differences between the MAFE ratios in Table 9 and the MSFE ratios in Table 13, but these differences disappear or are alleviated when the financial crisis period is excluded in Table 15.

Table 12: MSFE ratios of GARCH-MIDAS models against GJR-GARCH(1,1) model

	1 quarter ahead	2 quarters ahead	3 quarters ahead	4 quarters ahead
Sum of squared returns	1.65	1.50	1.54	1.52
Sum of absolute value of returns	1.39*	1.38	1.42	1.43
Consumer confidence index	0.95	0.94	0.95	0.97
News Heard index	1.12	0.98	0.96	0.96
Buying Conditions index	1.18	0.89	0.91	0.93
ISM New Orders index	1.02	1.01	0.99	0.99
ISM Recession indicator	0.98	0.99	0.99	0.99
SPF 1Q ahead recession probability	0.87	0.99	0.98	1.00
SPF 4Q ahead recession probability	1.11*	1.04**	1.03*	1.02
Industrial production	1.07	1.00	0.99	0.99
ADS index	0.83	0.98	0.98	0.98
Housing starts	0.98	0.93	0.92	0.92
Term spread	1.45	0.98	0.92	0.91
Principal component 1	0.81	0.94	0.95	0.97
Principal component 2	1.37	1.01	0.97	0.96
Principal component 3	1.27	1.02	0.98	0.96

*Benchmark model: GJR-GARCH(1,1). MSFE ratio: $\frac{MSFE_{GMX}}{MSFE_{GARCH}}$, where GMX stands for a GARCH-MIDAS model driven by macroeconomic or sentiment data (X). A value below 1 means the GARCH-MIDAS model outperforms the GJR-GARCH(1,1) model. *, ** and *** indicate a rejection of the null hypothesis of equal (unconditional) predictive ability at the 10%, 5% and 1% level, respectively, according to the Giacomini and White (2006) test.*

Table 13: MSFE ratios: one variable (macro/sentiment) vs. two variables (macro + sentiment) driving the long-term component

Benchmark: GARCH-MIDAS model driven by macroeconomic data (as indicated by the first row)

	Industrial production				ADS index				Housing starts				Term spread			
	1Q	2Q	3Q	4Q	1Q	2Q	3Q	4Q	1Q	2Q	3Q	4Q	1Q	2Q	3Q	4Q
Consumer confidence	0.92	0.98	1.00	1.00	1.09	0.97	0.97	0.99	0.87	0.98	0.98	1.00	0.94	0.96	0.96	0.99
News Heard index	1.06	0.98	0.97	0.97	1.24	1.00	0.97	0.97	1.06	1.02	1.01	0.99	0.96	0.97	0.98	0.99
Buying conditions index	1.08	0.89	0.91	0.94	1.44	0.92	0.94	0.96	1.18	0.95	0.98	1.01	1.04	0.92	0.95	0.97
ISM New Orders index	1.01	1.01	1.00	1.00	1.14	1.03*	1.03*	1.02*	1.10	1.04*	1.03	1.03	0.98	1.05	1.05	1.05
ISM Recession indicator	0.91	1.00	1.00	1.00	1.35	1.04	1.02	1.02	1.01	1.04***	1.04*	1.04	0.91	0.98	0.99	1.01
SPF 1Q ahead	0.82	0.99	0.98	1.00	1.01	1.01	0.99	1.01	0.86	1.03*	1.01	1.03	0.88	0.99	1.00	1.01*
SPF 4Q ahead	1.11	1.03*	1.02	1.02	1.19	1.04*	1.02	1.02	1.13*	1.08	1.08	1.07	1.01	1.03**	1.03*	1.04
Term spread	1.36	0.96	0.93	0.92	1.61	0.99	0.94	0.93	1.45	1.02	0.98	0.97				

Benchmark: GARCH-MIDAS model driven by sentiment data (as indicated by the first column)

	Industrial production				ADS index				Housing starts				Term spread			
	1Q	2Q	3Q	4Q	1Q	2Q	3Q	4Q	1Q	2Q	3Q	4Q	1Q	2Q	3Q	4Q
Consumer confidence	1.03	1.04	1.04	1.02	0.95	1.01	1.00	1.00	0.90	0.97	0.94	0.94	1.43	1.00	0.94	0.93
News Heard index	1.01	1.00	1.00	1.00	0.92	0.99	0.99	1.00	0.93	0.97	0.96	0.95	1.24	0.96	0.95	0.94
Buying conditions	0.98	1.00	1.00	1.01	1.02	1.01	1.01	1.01	0.98	0.99	0.99*	1.00	1.28	1.02	0.96	0.95
ISM New Orders index	1.06	1.00	1.00	1.00	0.93	1.00	1.01	1.01	1.06	0.96	0.95	0.95	1.40	1.02	0.98***	0.96**
ISM Recession indicator	1.00	1.02*	1.01	1.00	1.15	1.03	1.01	1.01	1.02	0.97	0.97	0.96	1.35	0.97	0.93**	0.93*
SPF 1Q ahead	1.01	1.00	1.00	0.99*	0.97	0.99	0.99	0.99	0.98	0.96	0.95	0.95	1.48	0.98	0.94	0.93
SPF 4Q ahead	1.07	0.99	0.98	0.99	0.89	0.97	0.97	0.98	1.00	0.96*	0.96	0.96	1.32	0.96	0.93	0.93
Term spread	1.00	0.99	1.00	1.00	0.92	0.99	1.00	1.00	0.98**	0.97	0.97	0.98				

Benchmark: GARCH-MIDAS model driven by the PC indicated by the row

	Principal component 1				Principal component 2				Principal component 3			
	1Q	2Q	3Q	4Q	1Q	2Q	3Q	4Q	1Q	2Q	3Q	4Q
Principal component 1					1.35	1.03	0.98	0.96	1.45	1.06	1.01	0.99
Principal component 2	0.80	0.95	0.96	0.97					1.11	1.00	0.98	0.98
Principal component 3	0.93	0.97	0.98	0.99	1.03	1.00	1.00	1.01				

Top panel: MSFE ratio of a GARCH-MIDAS model with macroeconomic and sentiment data driving the long-term component relative to a GARCH-MIDAS model driven by only macroeconomic data (corresponding to the column): $\frac{MSFE_{macro+sentiment}}{MSFE_{macro}}$*. Middle panel: MSFE ratio of a GARCH-MIDAS model with macroeconomic and sentiment data driving the long-term component relative to a GARCH-MIDAS model driven by only sentiment data (row):* $\frac{MSFE_{macro+sentiment}}{MSFE_{sentiment}}$*. A value below 1 means the model combining macroeconomic and sentiment data in the long-term component outperforms the model driven by only macroeconomic or sentiment data. Bottom panel: MSFE ratio of a GARCH-MIDAS model driven by two principal components relative to a GARCH-MIDAS model driven by one principal component:* $\frac{MSFE_{PC_{row}+PC_{column}}}{MSFE_{PC_{row}}}$*. *, ** and *** indicate a rejection of the null hypothesis of equal (unconditional) predictive ability at the 10%, 5% and 1% level, respectively, according to the Giacomini and White (2006) test.*

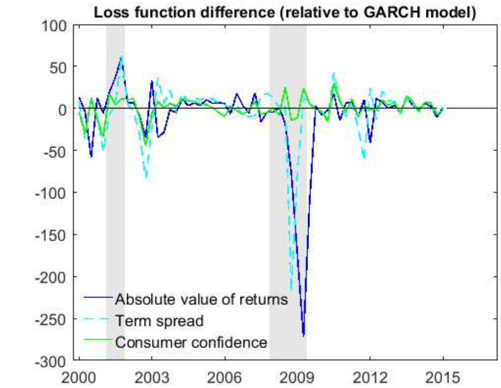
Appendix 4 - Robustness of MSFE ratios to excluding the financial crisis

The differences in the out-of-sample loss functions are very large during the financial crisis, especially when the losses are squared (see Figure 5). As a robustness check to the MSFE ratios presented earlier I redo Table 12 and Table 13 after excluding the financial crisis period. All in all I remove 4 periods: Q3 2008 - Q2 2009. This of course changes the interpretation of the MSFE ratios in the sense that it gives no weight to the models' forecasting performance during the financial crisis. Table 14 shows that the exclusion of the financial crisis improves the performance of the realised volatility driven models over the shortest horizon, while worsening it clearly over long horizons. The GARCH-MIDAS models are now all worse than the GJR-GARCH(1,1) model for one quarter ahead forecasts, indicating they were particularly useful during the financial crisis. On the other hand, over long horizons the results are not significantly altered. Notable exceptions are the GARCH-MIDAS models driven by the one quarter ahead recession probability and the first PC, which now perform clearly worse than before on all horizons, implying they were useful indicators during the financial crisis.

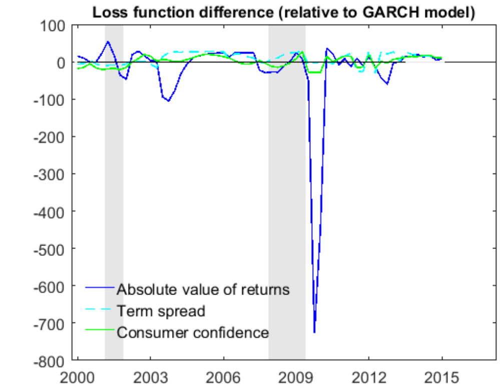
Table 14: MSFE ratios of GARCH-MIDAS models against GJR-GARCH(1,1) model, excluding the financial crisis

	1 quarter ahead	2 quarters ahead	3 quarters ahead	4 quarters ahead
Squared returns	1.10	2.06	3.96	3.81
Absolute value of returns	1.03	1.74	3.59	3.51
Consumer confidence	1.05	0.99	0.96	0.95
News Heard index	1.03	0.98	0.96	0.94
Buying Conditions	1.04	1.00	0.98	0.96
ISM New Orders index	1.06	1.04	1.00	0.96
ISM Recession indicator	1.10*	1.14**	1.11	1.06
1Q ahead recession probability	1.08	1.09	1.08	1.06
4Q ahead recession probability	1.12*	1.10*	1.06	1.04
Industrial production	1.04	1.01	0.99	0.97
ADS index	1.02	1.01	0.97	0.94
Housing starts	1.00	0.96	0.96	0.94*
Term spread	1.12	1.00	0.94	0.91
Principal component 1	1.03	1.04	1.05	1.03
Principal component 2	1.01	1.05	1.01	1.00
Principal component 3	1.14	1.06	1.02	0.99

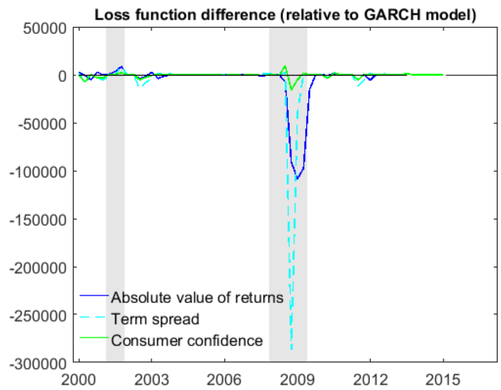
*Benchmark model: GJR-GARCH(1,1). MSFE ratio: $\frac{MSFE_{GMX}}{MSFE_{GARCH}}$, where GMX stands for a GARCH-MIDAS model driven by macroeconomic or sentiment data (X). A value below 1 means the GARCH-MIDAS model outperforms the GJR-GARCH(1,1) model. *, ** and *** indicate a rejection of the null hypothesis of equal (unconditional) predictive ability at the 10%, 5% and 1% level, respectively, according to the Giacomini and White (2006) test. The large peak in the forecast errors during the financial crisis has been removed (four periods removed: Q3 2008 - Q2 2009).*



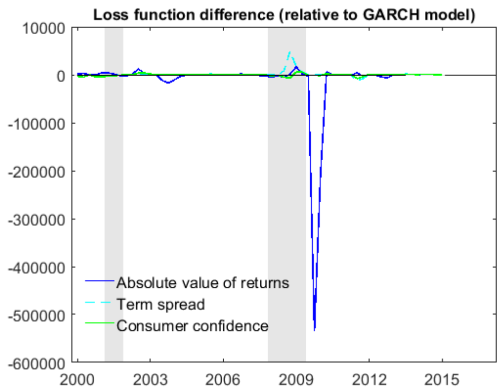
(a) Horizon: 1Q ahead. Loss function: absolute value



(b) Horizon: 4Q ahead. Loss function: absolute value



(c) Horizon: 1Q ahead. Loss function: squared errors



(d) Horizon: 4Q ahead. Loss function: squared errors

Figure 5: Loss function differences for selected GARCH-MIDAS models relative to the GJR-GARCH(1,1) model (i.e., $LOSS_{GARCH} - LOSS_{GMX}$), where GMX stands for the GARCH-MIDAS model driven by one explanatory variable (X), as indicated in the graph. Loss function and forecasting horizon as indicated in the subtitle for each graph.

Table 15: MSFE ratios excluding the financial crisis: one variable (macro/sentiment) vs. two variables (macro + sentiment) driving the long-term component

Benchmark: GARCH-MIDAS model driven by macroeconomic data (as indicated by the first row)

	Industrial production				ADS index				Housing starts				Term spread			
	1Q	2Q	3Q	4Q	1Q	2Q	3Q	4Q	1Q	2Q	3Q	4Q	1Q	2Q	3Q	4Q
Consumer confidence	1.03	0.99	0.98	0.99	1.07	1.04	0.99	1.00	0.99	0.99	0.99	1.00	1.01	0.99	0.98	0.99
News Heard index	1.00	0.98	0.97	0.96	1.03	0.97	0.97	0.98	1.02	0.98	0.93*	0.96	0.98	0.98	0.95	0.96
Buying Conditions	1.05	1.03	1.03	1.03	1.04	1.03	1.05	1.07	1.04	1.01	0.99	1.01	0.99	1.00	1.00	1.00
ISM New Orders index	1.02	1.05	1.04	1.01	1.06	1.07	1.09	1.08	1.06*	1.06*	1.00	0.98	0.99	1.01	0.97	0.94
ISM Recession indicator	1.08*	1.17**	1.15	1.13	1.13**	1.12	1.14	1.17*	1.06*	1.15**	1.12	1.08	1.02	1.01	0.96	1.00
SPF 1Q ahead	1.04	1.06**	1.07	1.07	1.06	1.05*	1.06**	1.09**	1.06*	1.09**	1.09	1.08	1.01	1.03**	1.04*	1.04
SPF 4Q ahead	1.10*	1.07	1.04	1.03	1.09*	1.06	1.05	1.09	1.10*	1.08	1.05	1.03	1.07**	1.06*	1.07*	1.07*
Term spread	1.03	0.97	0.95	0.92	1.10	0.99	0.97	0.96	1.11*	1.02	0.97	0.95				

Benchmark: GARCH-MIDAS model driven by sentiment data (as indicated by the first column)

	Industrial production				ADS index				Housing starts				Term spread			
	1Q	2Q	3Q	4Q	1Q	2Q	3Q	4Q	1Q	2Q	3Q	4Q	1Q	2Q	3Q	4Q
Consumer confidence	1.02	1.01	1.02	1.02	1.04	1.06	1.01	1.00	0.94	0.96	0.98	1.00	1.09	0.99	0.97	0.95
News Heard index	1.01	1.01	1.00	0.99	1.02	1.00	0.98	0.98	0.99	0.96	0.93	0.96	1.07	1.00	0.94**	0.93**
Buying Conditions	1.05*	1.04	1.04	1.05	1.02	1.04	1.04	1.06	0.99	0.97	0.96	0.99	1.07*	1.00	0.96	0.95
ISM New Orders index	1.01	1.02	1.02	1.02	1.02	1.03	1.06	1.06	0.99	0.98	0.96	0.95	1.05	0.96	0.92**	0.89***
ISM Recession indicator	1.02	1.04	1.02	1.03	1.05	0.99	1.00	1.04	0.96	0.97	0.96	0.95	1.04	0.88**	0.82***	0.85**
SPF 1Q ahead	1.00	0.99	0.98	0.97*	1.00	0.98	0.95	0.96	0.98	0.96	0.97	0.95**	1.05	0.94	0.91	0.89*
SPF 4Q ahead	1.02	0.99	0.96	0.96	1.00	0.98	0.96	0.95	0.98	0.95**	0.95*	0.94**	1.08	0.97	0.95	0.94
Term spread	0.96	0.99	0.99	0.99	1.00	1.00	1.00	1.00	0.98	0.98	0.98	0.99				

Benchmark: GARCH-MIDAS model driven by the PC indicated by the row

	Principal component 1				Principal component 2				Principal component 3			
	1Q	2Q	3Q	4Q	1Q	2Q	3Q	4Q	1Q	2Q	3Q	4Q
Principal component 1					1.07	1.02	0.98	0.96	1.09	1.00	0.96	0.94
Principal component 2	1.10*	1.01	1.01	0.99					1.14*	1.01	1.01	0.97
Principal component 3	0.99	0.98	0.99	0.98	1.01	1.01	1.00	0.98				

Top panel: MSFE ratio of a GARCH-MIDAS model with macroeconomic and sentiment data driving the long-term component relative to a GARCH-MIDAS model driven by only macroeconomic data (corresponding to the column): $\frac{MSFE_{macro+sentiment}}{MSFE_{macro}}$*. Middle panel: MSFE ratio of a GARCH-MIDAS model with macroeconomic and sentiment data driving the long-term component relative to a GARCH-MIDAS model driven by only sentiment data (row):* $\frac{MSFE_{macro+sentiment}}{MSFE_{sentiment}}$*. A value below 1 means the model combining macroeconomic and sentiment data in the long-term component outperforms the model driven by only macroeconomic or sentiment data. Bottom panel: MSFE ratio of a GARCH-MIDAS model driven by two principal components relative to a GARCH-MIDAS model driven by one principal component:* $\frac{MSFE_{PC_{row}+PC_{column}}}{MSFE_{PC_{row}}}$*. *, ** and *** indicate a rejection of the null hypothesis of equal (unconditional) predictive ability at the 10%, 5% and 1% level, respectively, according to the Giacomini and White (2006) test. The large peak in the forecast errors during the financial crisis has been removed (four periods removed: Q3 2008 - Q2 2009).*

Appendix 5 - Model Confidence Set procedure by Hansen et al. (2011)

This appendix presents a rough outline of the MCS procedure by Hansen et al. (2011) used in Section 6.1. The presentation follows closely Hansen et al. (2011), where details on the procedure can be found.

M^0 is the competing set of models or objects. M^* is the set of superior models, defined in Definition 1 in Hansen et al. (2011) as $M^* \equiv \{i \in M^0 : \mu_{ij} \leq 0, \forall j \in M^0\}$. The objective of the MCS procedure is to identify this superior set of models. Let's call δ_M the equivalence test and e_M the elimination rule.

Relative performance is defined as $d_{ij,t} \equiv L_{i,t} - L_{j,t}$, for all $i, j \in M^0$, where L is a loss function and i and j index the models. $\mu_{ij} \equiv E(d_{ij,t})$ is assumed finite and independent of t. Models are ranked according to their expected loss, so that model i is preferred to model j if $\mu_{ij} < 0$. Hansen et al. (2011) define the t-statistics

$$t_{ij} = \frac{\bar{d}_{ij}}{\sqrt{\widehat{var}(\bar{d}_{ij})}}, \quad for\ i, j \in M,$$

where $\bar{d}_{ij} \equiv \frac{1}{n}\Sigma_{t=1}^{n} d_{ij,t}$ and $\widehat{var}(\bar{d}_{ij})$ is the (bootstrapped) estimate of $var(\bar{d}_{ij})$. The test statistic then takes the form: $T_{R,M} \equiv max|t_{i,j}|$. The asymptotic distribution of the test statistic is non-standard, and thus needs to be estimated using bootstrap.

The MCS algorithm (Definition 2 in Hansen et al. (2011)):

Step 0: Set $M = M^0$.

Step 1: Test $H_{0,M}$ using the equivalence test δ_M and significance level α. $H_{0,M} : \mu_{ij} = 0, \forall i, j \in M$.

Step 2: i) If δ_M is accepted, define $\widehat{M}^*_{1-\alpha} = M$ to be the superior set of models (the MCS).

ii) If δ_M is rejected, there is evidence that not all objects are equally good $\Rightarrow$ use the elimination rule $e_{R,M} = arg\ max_{i \in M} sup_{j \in M} t_{ij}$ to identify the object to be eliminated. Repeat steps 1 and 2 ii) until δ_M is accepted.

Appendix 6 - Robustness of MCS results to changing w

It is not clear-cut how the block length parameter (w) should be chosen for the block bootstrap. Thus I check the robustness of the MCS results to the choice of block length, by fixing $w = 4, 8, 12$. In Table 8 the default option in the R package, where w is automatically chosen based on the number of significant terms in an AR(p) model on the loss differences (see R package documentation for details).

The MCS results are robust to changing the value of w to 4 and 8. Table 16 presents results for $w = 12$. In this case the only difference is that all models are included in the 90% confidence set on the one quarter horizon. Hence, the choice of block length does not significantly change the results.

Table 16: MCS on the baseline GARCH-MIDAS models

	1 quarter ahead	2 quarters ahead	3 quarters ahead	4 quarters ahead
Sum of squared returns	17*	17	17	17
Sum of absolute value of returns	16*	16	16	16
Consumer confidence index	4*	7*	7	9
News Heard index	7*	3**	4	3
Buying conditions index	3**	2**	3	6
ISM New Orders index	5*	11	10	8
ISM Recession indicator	14*	15	15	15
SPF 1Q ahead recession probability	2**	10	14	13
SPF 4Q ahead recession probability	10*	9	9	7
Industrial production	12*	14	12	12
ADS index	6*	13	11	11
Housing starts	9*	4**	6	5
Term spread	15*	1**	1**	1**
Principal component 1	1**	5**	8	10
Principal component 2	11*	8	5	4
Principal component 3	13*	6*	2	2
GJR-GARCH(1,1)	8*	12	13	14

*Ranking of models based on the MCS procedure by Hansen et al. (2011), applied to the models in Table 4. Calculated with the MCS package in R. Number 17 means the model was eliminated first, while number 1 signifies the last remaining model. Loss function: mean absolute forecast error. $B = 10000$, $w = 12$ and block bootstrap is used. $\alpha = 0.10, 0.25$, * indicates the forecast is included in $\hat{M}^*_{90\%}$ and ** that it is included in $\hat{M}^*_{75\%}$. Note that the MCS procedure is for non-nested models, while the GJR-GARCH(1,1) model is nested in the other specifications.*