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Nowcasting Private Consumption with TV Sentiment*

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Abstract

We perform principal components analyses of the University of Michigan Index of Consumer Sentiment and TV sentiment in order to gain information on their structure and information content. By introducing the new sentiment variable TV sentiment, gathered from sentiment from statements from over 10,000 TV news broadcasts in the United States, we find that TV sentiment adds great value in nowcasting private consumption. We further find that TV sentiment performs markedly better than the Index of Consumer Sentiment, suggesting that using sentiment from TV news has more explanatory power than survey-based sentiment.

Keywords: TV sentiment, consumer sentiment, private consumption

JEL classifications: D12, E21

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1 Introduction

1.1 Contextual Setting and Summary

As laid out in Uhl (2011) and Uhl (2012), sentiment in newspapers is a valid explanatory variable in private consumption behavior models. Although the newspaper is a widely accepted medium, the television industry has become the most influential in the last decade. The United States of America are one of the more prominent cases how television has influenced society. According to some industry polls done in the past years, most Americans obtain their information about news through television.[1] According to a recent survey of Nielsen (2010), the average American watches over five hours of television per day. Given these developments, we want to address the question whether watching TV news influences the watchers. Does the way of reporting and the content of TV news shows have an impact on private households and their behavior? In a study on the impact of how news stories are portrayed, Maier (2005) finds that the hard facts are not necessarily most important to the reader, but rather how these facts are presented. This component of how the news are presented on TV is what we call TV sentiment in this study. Given these findings, we examine sentiment in TV news broadcasts to identify a possible link between TV sentiment and the consumption behavior of households. We do this with a dataset that contains sentiment from four of the most widely watched TV news broadcasts in the US. We first perform principal components analyses of both the widely-used University of Michigan Index of Consumer Sentiment (ICS) and the new variables of TV sentiment. In an empirical exercise, we show the usefulness of financial variables and the principal components of the sentiment variables of the ICS and TV sentiment in a nowcasting environment. We find that TV sentiment is a valid variable to add in nowcasting private consumption, as it shows higher nowcasting power than the ICS, especially when coupled with financial variables, such as stock returns and interest rates.

This paper is structured as follows: this section gives an overview of the literature and the data, section 2 lays out the model, section 3 discusses the empirical results, while section 4 concludes.

[1] See Pew (2004) and Harris Interactive (2007).

1.2 Related Literature

Today's public obtains most information about world and economic affairs from the media, as we are constantly confronted with a news flow. But does this influence us – as consumers – in a way that we adjust our consumption behavior according to the news we read, hear or watch, in particular with regards to the economic development and state of the economy? Is it possible that consumers adjust their consumption behavior, when they hear news about the rising unemployment rate and that many people are being fired? Possibly, they might be more cautious given these news because they fear being laid off as well, thus spending less and saving more for potential bad times. Is it possible that the tone of the economic news reporting matters? For example, if journalists constantly report bad news about the economy, does this influence the consumer? Does such a phenomenon exist and if so, how can we measure it?

Recent studies have confirmed this phenomenon by showing that news have an impact on consumers, and that there is an influence on the consumer through sentiment. For example, Carroll (2003) finds that news coverage as well as volume of economic topics in news are relevant to the consumer. Given his findings, we can infer that people do pay attention to news. So, if news matter, does the style of reporting matter as well? In a theoretical study, Sims (2003) shows that the tone and volume of news matter to the ordinary people when they form their opinion of the state of the overall economy. This influence goes beyond the pure information content of a particular state of the economy, i.e. the hard facts do not always matter. Thus, according to Sims (2003), it is also important how news are being portrayed, i.e. sentiment in the news influences the consumers as well. Doms and Morin (2004) consider this issue empirically by examining whether the news media influences perceptions of consumers. They come to the conclusion that there is an effect of sentiment on household spending behavior because the tone and reporting in news affect consumers. Therefore, we want to consider the tone and reporting, i.e. the sentiment, of news more closely in order to make out a possible impact of sentiment on consumers. However, we do not only want to consider sentiment in relation to consumer behavior, but also other factors that might drive consumer behavior, such as stock prices and interest rates in order to account for wealth changes, as laid out in Ludwig and Slok (2002).

Other studies dealing with the impact of news on the public examine whether there is a bias in the media, which might ultimately reflect on and influence the public. Mullainathan and Shleifer (2005) identify theoretically that there are biases in economic and political news and that these are slanted towards the customers of the media outlet. Therefore, when examining sentiment in the media, we need to consider various channels or news shows on television in order to capture the most general picture possible. In a later study, Baron (2006) confirms that the news media plays an essential role in society and identifies issues in media bias. Recently, Gentzkow and Shapiro (2010) construct an index of media slant. They find that those newspapers with specific political views are more likely to be read by readers with similar views. The concept, or, the existence of media bias, is important to this study because it shows that there is a subjective component inherent in the news that goes beyond sheer hard facts.

In the studies discussed above, the media samples have mainly been taken from the print media. Only a few studies have dealt so far with audiovisual media outlets and their impact on the consumer. For example, Strömberg (2004) identifies large and highly significant effects of radio on voting behavior, while TV news broadcasts have only been looked at more recently. DellaVigna and Kaplan (2007) consider Fox News in cable markets and its impact on voting behavior in the US, taking media bias into account. Their results suggest that Fox News have a significant impact on viewers to vote Republican. Their findings suggest that a subjective component might be involved in TV reporting that influences the voters. On another note, the influence of TV has been examined on stock investors by Meschke and Kim (2011). In their study, they investigate CEO interviews, while documenting significant positive abnormal returns accompanied by abnormally high trading volume. They find evidence that enthusiastic individual investors are prone to trading more based on CNBC interviews, confirming that there might be a sentiment factor that influences people to act in a particular way. Therefore, in this analysis, we want to examine whether sentiment in TV news broadcasts have an impact on consumers, while at the same time controlling for wealth effects, such as stock prices and interest rates that are readily available. According to a study of Ang *et al* (2007), consumer sentiment surveys perform best in forecasting models. Given this finding, we want to use the ICS as a proxy to measure consumer sentiment.[2] Curtin

[2]See Curtin (1982) and Curtin (2007) for a discussion of the University of Michigan Indices.

(2007) shows the top sources of information on the economy among households.[3] In this survey, the most common source for information gathering in the US is television. Hence, we have a possible link between consumer and TV sentiment. Both variables might be useful to explain private consumption. In recent exercises, Kholodilin *et al* (2010) and Schmidt and Vosen (2011) both use Google Trends results to nowcast US private consumption in a real-time framework. We adapt an approach similar to Kholodilin *et al* (2010) who perform a principal component analysis of their various indicators. In a nowcasting environment, they show that Google Trends results are useful in nowcasting private consumption. In our analysis, we perform nowcasts with the variables at hand in order to test the nowcasting power of TV sentiment.

1.3 Data

The monthly TV sentiment dataset is from MediaTenor, a professional news sentiment provider. The sentiment data were compiled exclusively from US TV news shows on the US economy. Contrary to other approaches and studies, the sentiment was coded by humans, not by a machine or pre-defined automatic algorithm.[4] Tagged topics range broadly and contain possible links to the development and the state of the economy.[5] Important to note is that employees from MediaTenor are highly trained to adhere to a very specific pre-defined sentiment rating and coding table, in order to avoid subjectivity bias. The dataset is constructed from sentiment from four of the most widely watched news broadcasts in the US: ABC World News Tonight, CBS Evening News, FOX News, and NBC Nightly News. In total, statements in over 10,000 TV news shows were coded for sentiment from January 2005 to December 2009. The summary statistics of the individual sentiments from the four TV news shows are shown in table 1.

In order to better understand what drives the widely used ICS, we disentangle the index into its five components in order to get further clues what might drive consumer sentiment. The ICS is constructed from answers to five questions relating to current economic conditions

[3]See table 4 in Curtin (2007): Sources of Information on Official Rates of Unemployment, Consumer Prices, and Gross Domestic Product.

[4]See *Human Analysis vs. Software* for an evaluation of MediaTenor's approach vs. machine-based approaches, available at http://www.mediatenor.com/mca_brain_vs_software.php, last accessed 1 March 2011.

[5]For a more detailed description of the methodology that MediaTenor uses, go to http://www.mediatenor.com/mca_methodology.php, last accessed 1 March 2011.

Table 1: Summary Statistics of TV Sentiment Sources

	ABC World News Tonight	CBS Evening News	FOX News	NBC Nightly News
Mean	-0.4812	-0.4950	-0.4320	-0.5296
Median	-0.6610	-0.6220	-0.5326	-0.6000
Maximum	1.0000	0.5000	0.5714	0.7333
Minimum	-1.0000	-1.0000	-1.0000	-1.0000
Std. Dev.	0.4585	0.3716	0.3862	0.3702
Skewness	1.3849	0.9813	0.7632	1.2689
Kurtosis	4.7122	3.2176	2.7707	4.4263
Jarque-Bera	26.5090	9.7474	5.9559	21.1867
Probability	0.0000	0.0076	0.0509	0.0000
Sum	-28.871	-29.701	-25.922	-31.778
Sum Sq. Dev.	12.40349	8.146239	8.797797	8.084831
Observations (2005M01 - 2009M12)	60	60	60	60

Source: MediaTenor

of consumers as well as consumer expectations.[6] The five components of the ICS are made up of questions that consumers are asked with regards to their current buying conditions, their business conditions in 12 months and 5 years, the current conditions of their personal finances and their expected conditions of personal finances. Table 2 shows the summary statistics of the individual components. Monthly private consumption data were obtained from the ALFRED database.[7] As in Kholodilin *et al* (2010) who argued for real-time vintages of private consumption, we also use monthly unrevised real-time data. This applies for the ICS data as well, as the publication lag might be a crucial factor, and in order to obtain meaningful results that we can compare to the other data, we use unrevised "real-time" data as opposed to the final revised data. The ICS data were downloaded from Thomson Reuters Datastream. Breeden (1986) shows, for example, that interest rates have a potential impact on private consumption growth, so that we include short-term as well as long-term interest rates in our analysis. In order to account for changes in wealth effects, we include stock prices of the S&P 500 stock index.[8] The financial variables data were obtained from Thomson Reuters Datastream.

2 Modeling

2.1 Principal Components Analysis

In accordance with Kholodilin *et al* (2010), which base the construction of their Google indicator on the factor model of Stock and Watson (1999, 2002), we apply a principal components analysis[9] to the two sentiment indicators that we are going to implement: TV sentiment and the ICS. Contrary to Kholodilin *et al* (2010), we have less principal components, so it makes sense to consider all principal components in the nowcast later on. Table 3 shows the eigenvalues and eigenvectors of the principal components of TV sentiment. The first principal component covers 66% of the total variance, whereas the first three components cover 92%. In the Eigenvectors section, we can see that CBS and NBC have values

[6] A detailed description of the calculation of the index and the individual questions can be found on the homepage of the surveys of consumer from the University of Michigan and Thomson Reuters. See *Index Calculations,* http://www.sca.isr.umich.edu/documents.php?c=i, last accessed 20 February 2011.

[7] See ArchivaL Federal Reserve Economic Data. Available at http://alfred.stlouisfed.org/, last accessed 15 September 2010.

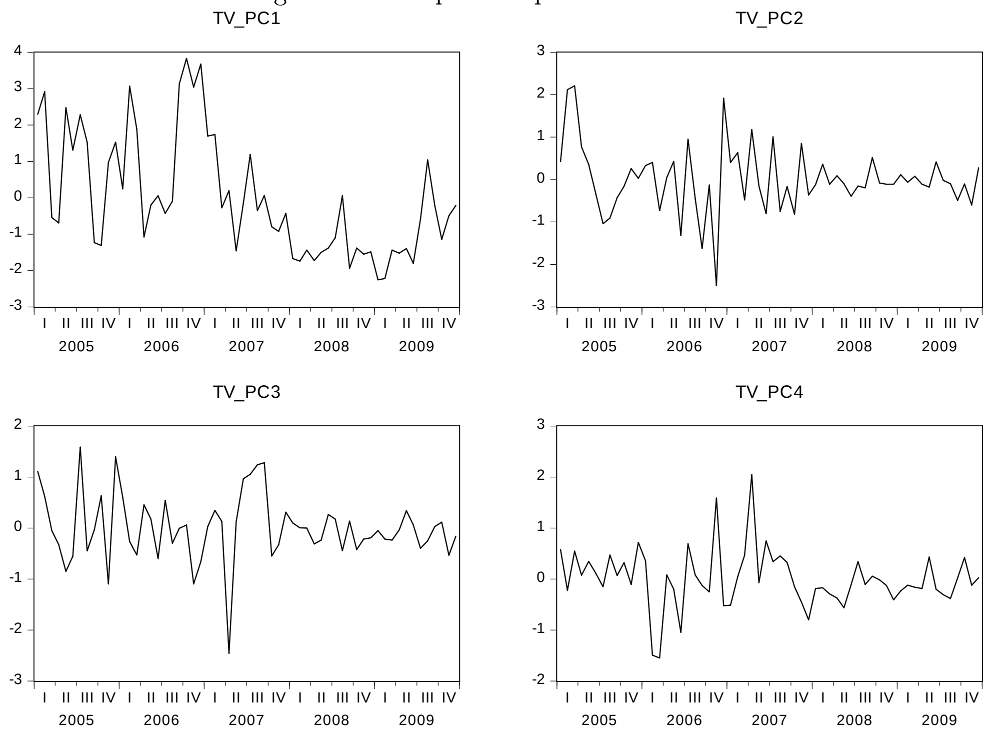
[8] See, for example, Ludwig and Slok (2002) for a detailed discussion of the effect of changes in wealth on private consumption.

[9] See also Gabriel (1971) for a more detailed discussion of how the principal components analysis is done here.

Table 2: Summary Statistics of the University of Michigan Index of Consumer Sentiment Components

	Buying Conditions	Business Conditions in 1 year	Business Conditions in 5 years	Personal Finance - Current Conditions	Personal Finance - Expected Conditions
Mean	139.1000	79.0167	83.6000	96.4000	117.2833
Median	149.0000	81.5000	83.5000	103.0000	118.0000
Maximum	172.0000	118.0000	107.0000	123.0000	133.0000
Minimum	88.0000	31.0000	59.0000	58.0000	96.0000
Std. Dev.	24.5893	24.2337	10.9949	22.0609	8.6516
Skewness	-0.4590	-0.2996	-0.1839	-0.4588	-0.3628
Kurtosis	1.7734	1.9862	2.3901	1.6428	2.6683
Jarque-Bera	5.8687	3.4673	1.2681	6.7105	1.5915
Probability	0.0532	0.1766	0.5304	0.0349	0.4512
Sum	8'346.000	4'741.000	5'016.000	5'784.000	7'037.000
Sum Sq. Dev.	35673.4	34648.98	7132.4	28714.4	4416.183
Observations (2005M01 - 2009M12)	60	60	60	60	60

Figure 1: Principal Components of TV Sentiment



over 0.50, so that these are possibly contributing the most to principal component 1. ABC is in the second principal component, whereas FOX News in the third. Given its small share in the eigenvalues analysis, principal component 4 is of minor importance. It is interesting to note that the various sentiment from the TV news shows contribute differently to the various components, rather than being "grouped" in one principal component. Hence, there must be differences in the style of reporting among the different news shows, which contribute differently to the total variance of the components. Fig. 1 shows the graph of the four principal components of TV sentiment. We note that the first principal component graph traces private consumption quite well, with the trough being at the end of 2008/beginning of 2009, the recent financial crisis. The other principal components do not show a distinct pattern.

Table 4 shows the principal components analysis of the ICS. The first three principal components make up over 97% of the total variance. In the first principal component, business conditions in one year as well as personal finance expectations appear the most relevant. Therefore, we can say that the first component is about future conditions, or expectations of consumers in the near future, i.e. in one year. The second principal component is about the

Table 3: Principal Components Analysis of TV Sentiment

Eigenvalues: (Sum = 4, Average = 1)

Number	Value	Difference	Proportion	Cumulative Value	Cumulative Proportion
1	2.6414	2.0330	0.6603	2.6414	0.6603
2	0.6083	0.1782	0.1521	3.2497	0.8124
3	0.4301	0.1100	0.1075	3.6799	0.92
4	0.3201	---	0.0800	4.0000	1

Eigenvectors (loadings):

Variables	PC1	PC2	PC3	PC4
ABC	0.4419	0.8824	0.1414	-0.0779
CBS	0.5290	-0.3032	-0.1855	-0.7706
FOX	0.5028	-0.3425	0.7333	0.3034
NBC	0.5216	-0.1099	-0.6386	0.5550

This table shows the principal components analysis of TV Sentiment. PC1 – PC4 stand for principal components 1 – 4.

current conditions, as the components current business conditions and current assessment of personal finances are the most relevant here. The third component aims at longer-term expectations, i.e. the variable business conditions in five years. Given its low eigenvalue, the fourth component appears to be of minor importance. However, it appears that it contains information on both current and expected personal finances, while the fifth component has information on the business conditions. Hence, we note that expectations about future conditions in one year explain the greatest share of the variance, while current conditions are second. Fig. 2 shows the graphs of the principal components of the ICS. The graph of the first principal component shows the recent financial crisis quite nicely, whereas the other components do not immediately show a discernible picture. We test the predictive accuracy of these components with nowcasts in the next step.

2.2 Nowcasting and Evaluation

As in Kholodilin *et al* (2010), our sample size is rather of limited size because the TV sentiment data is only available for five full years. We thus apply a parsimonious ARMA(1,2)-model of the following form:

$$\triangle \log c_t = k + \alpha_1 \triangle \log c_{t-1} + \beta x_t + \sum_{i=1}^{2} \theta_i \varepsilon_{t-i} + \varepsilon_t, \tag{1}$$

where $\triangle \log c_t$ refers to logged private consumption growth, x_t is an exogenous variable that can be a financial variable or a principal component of TV or the ICS, while ε_t is the error term. The ARMA(1,2)-model is chosen as in Uhl (2011) that this is the most suitable model for private consumption, which is also in accordance with the findings of Sommer (2007) and Carroll *et al* (2010). For the exogenous variable x_t, it can be either one of the three financial variables, one of the principal components of both TV and consumer sentiment, and a combination of these variables. We thus have 33 models that we run. Thus, the benchmark model without any of the indicators is an ARMA(1,2)-model:

$$\triangle \log c_t = k + \alpha_1 \triangle \log c_{t-1} + \sum_{i=1}^{2} \theta_i \varepsilon_{t-i} + \varepsilon_t. \tag{2}$$

Based on equations (1) and (2) we perform one-step ahead nowcasts with a similar methodology as in Kholodilin *et al* (2010). We use real-time vintages of private consumption,

Table 4: Principal Components Analysis of the University of Michigan Index of Consumer Sentiment

Eigenvalues: (Sum = 5, Average = 1)

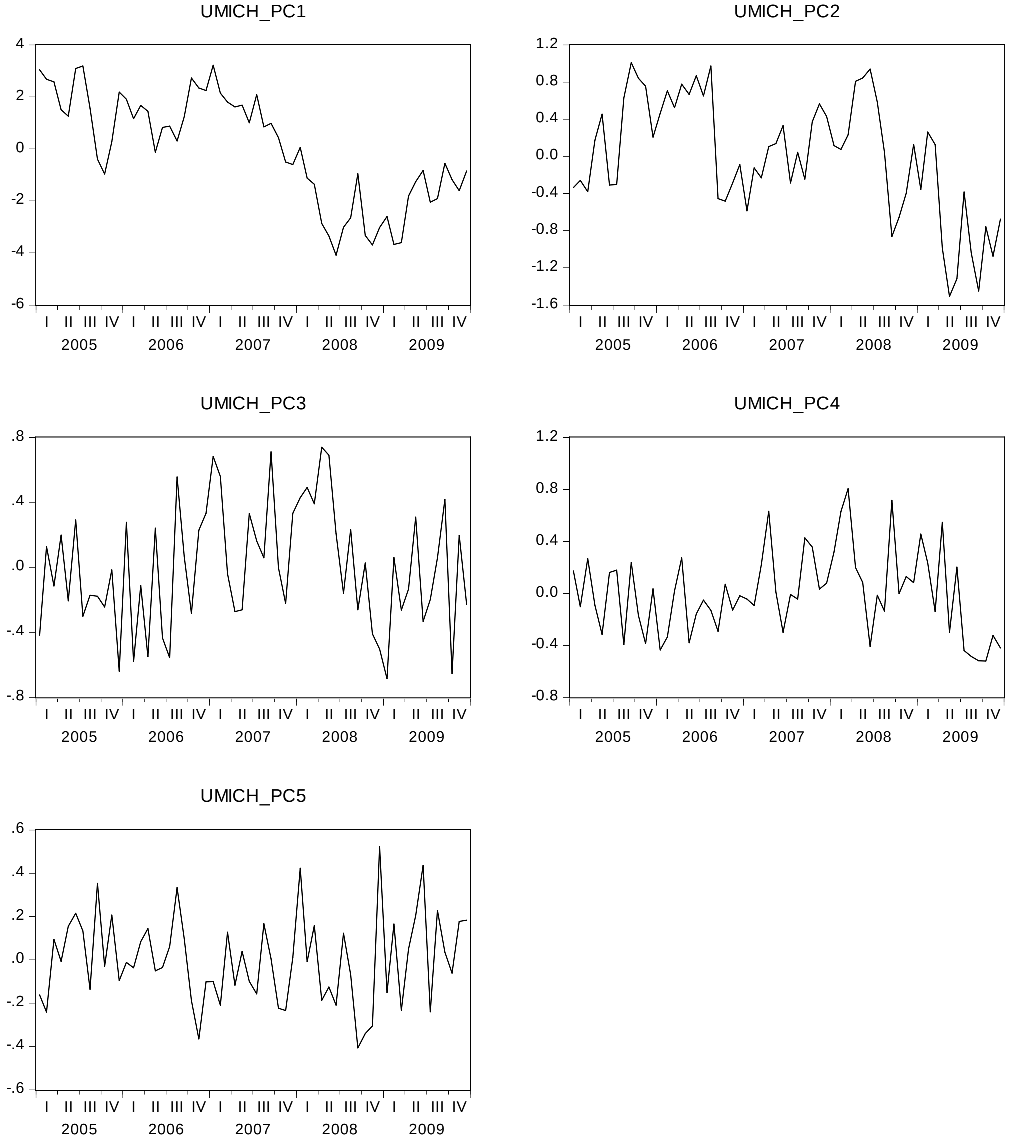
Number	Value	Difference	Proportion	Cumulative Value	Cumulative Proportion
1	4.3160	3.9118	0.8632	4.3160	0.8632
2	0.4042	0.2665	0.0808	4.7202	0.944
3	0.1377	0.0363	0.0275	4.8579	0.9716
4	0.1013	0.0606	0.0203	4.9592	0.9918
5	0.0408	---	0.0082	5.0000	1

Eigenvectors (loadings):

Variables	PC1	PC2	PC3	PC4	PC5
Buying Conditions	0.4517	0.4758	-0.0215	-0.2709	0.7041
Business Conditions in 1 year	0.4613	-0.2085	-0.0933	-0.7353	-0.4408
Business Conditions in 5 years	0.4365	-0.5164	0.6777	0.2281	0.1773
Personal Finance - Current Conditions	0.4380	0.5904	0.1701	0.3984	-0.5215
Personal Finance - Expected Conditions	0.4480	-0.3390	-0.7089	0.4186	0.0810

This table shows the principal components analysis of the ICS. PC1 – PC5 stand for principal components 1 – 5.

Figure 2: Principal Components of the ICS



as these flash estimates are the most relevant to economists and professional forecasters as well as policy makers. Kholodilin *et al* (2010) further make the case that the data are revised up to 23 months after the first flash estimate. This would in turn, they argue, shrink the already small sample, which applies here, too. We estimate the models, from which we then perform one-step ahead nowcasts for the period 2008M01 until 2009M12. Once the nowcast of the first month (2008M01) is done, the model is re-estimated with actual values of 2008M01. Then, it proceeds with a nowcast for the next month, i.e. 2008M02. This procedure is repeated until we reach the end of the nowcast period in 2009M12.[10] The evaluations of the nowcasts are based on each nowcast month. The Root Mean Squared Error (RMSE) is used to evaluate the accuracy of the various nowcasts:

$$\sqrt{\sum_{t=T+1}^{T+h} \left(\hat{y}_t - y_t\right)^2 / h}, \tag{3}$$

where the actual and forecasted value in period t is y_t and $\hat{y}_t$, respectively. In order to compare the accuracy of the nowcasts, we apply the Theil Inequality Coefficient as in Theil (1958):

$$\frac{\sqrt{\sum\limits_{t=T+1}^{T+h} \left(\hat{y}_t - y_t\right)^2 / h}}{\sqrt{\sum\limits_{t=T+1}^{T+h} \hat{y}_t^2 / h} + \sqrt{\sum\limits_{t=T+1}^{T+h} y_t^2 / h}} \tag{4}$$

The Theil Inequality Coefficient is always between zero and one, where zero indicates a perfect fit of the model.

3 Empirical Results

Table 5 shows the results of the nowcasts with the RMSEs and Theil Inequality Coefficients. We want to compare all 33 models and their nowcast accuracy. The first column shows the RMSE of the various individual nowcasts with the financial variables as well as the principal components of TV sentiment and the ICS as well as a combination of them. Column 2 shows the RMSE of the benchmark ARMA(1,2)-model, which is 0.003586. Hence, we compare this number with the RMSEs of all other models in order to see which models

[10]See Appendix A.1 for a detailed explanation of how the nowcasts are done.

perform better and which perform worse, i.e. which variables and principal components beat an ARMA(1,2)-model. Given that we have taken the study of Kholodilin *et al* (2010) as a reference, we want to show first how their benchmark model performs in our framework as opposed to the benchmark model of the form ARMA(1,2) that we employ in this study. Their benchmark model is a simple AR(1)-process as follows:

$$\triangle \log c_t = k + \alpha_1 \triangle \log c_{t-1} + \varepsilon_t. \tag{5}$$

The RMSE of their benchmark model is 0.00393, which is significantly higher than the RMSE of our benchmark model. This justifies the previous findings in the literature, suggesting that using an ARMA(1,2)-process in consumption behavior models is superior to an AR(1)-structure. Then, we take the financial variables S&P 500 stock returns as well as long- and short-term interest rates and apply these to the ARMA(1,2) model. For all three variables we achieve a lower RMSE than for our base model. The RMSE of the model with stock returns is significantly lower than that of the other two, thus suggesting that stock returns are superior to interest rates in nowcasting private consumption. This becomes evident when considering the much lower Theil Inequality Coefficient. When we combine all three variables, we get an even lower Theil Inequality Coefficient. Hence, combining the three financial variables is efficient in this nowcasting exercise because the different variables contain a different set of information. The stock price index possibly account for changes in wealth effects among households, whereas the interest rates possibly capture lending and financing conditions.

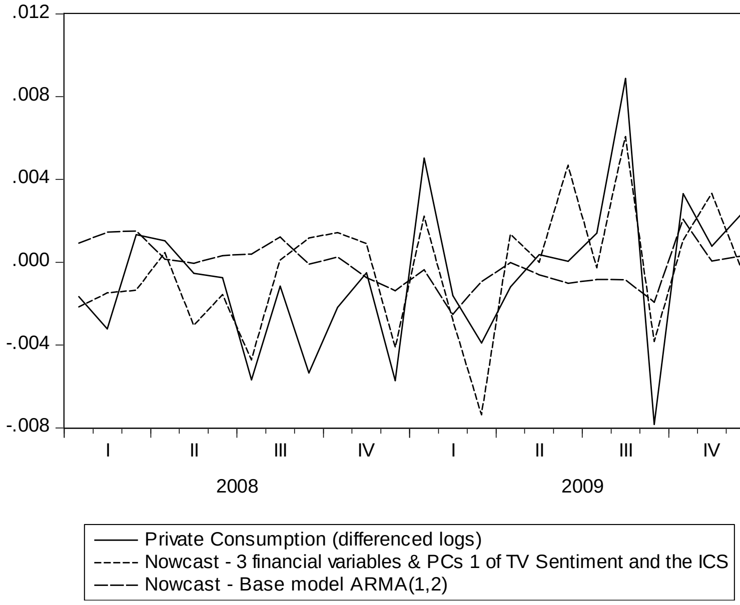
We then turn to the individual principal components of both the ICS and TV sentiment. The nowcasts of both the first principal components of the ICS and TV sentiment achieve the lowest RMSEs and Theil Inequality Coefficients. We therefore assume that the most relevant information for nowcasting private consumption of both sentiment variables is captured in the first principal components. When comparing the RMSEs of the first principal components of TV sentiment and the ICS, we note that the RMSE of TV sentiment is lower than that of the ICS. However, the Theil Inequality Coefficient is slightly lower for the first principal component of the ICS. Given that both the RMSEs and the Theil Inequality Coefficients are pretty close together, but markedly lower than our base model, we can say that

Table 5: Nowcasts with Root Mean Squared Errors (RMSE) of the models and Theil Inequality Coefficients

	One-step-ahead Nowcasts (2008M1 to 2009M12)		
	RMSE (1)	RMSE Benchmark-model ARMA(1,2) (2)	Theil Inequality Coefficient (3)
ARMA(1,2)	--	0.003586	0.757995
AR(1) - benchmark model of Kholodilin et al (2010)	0.00393	0.003586	0.847014
1) S&P 500 stock index (differenced logs)	0.003071	0.003586	0.531546
2) Long-term interest rates (differenced 10-year US Treasury rates)	0.0035	0.003586	0.747883
3) Short-term interest rates (differenced 3-month USD LIBOR)	0.003581	0.003586	0.747304
Variables 1) - 3) combined	0.003097	0.003586	0.521553
Principal Component 1 of UMICH ICS	0.003425	0.003586	0.644185
Principal Component 2 of UMICH ICS	0.003659	0.003586	0.76601
Principal Component 3 of UMICH ICS	0.003584	0.003586	0.761438
Principal Component 4 of UMICH ICS	0.00355	0.003586	0.74863
Principal Component 5 of UMICH ICS	0.003593	0.003586	0.754855
Principal Component 1 of TV Sentiment	0.003374	0.003586	0.654928
Principal Component 2 of TV Sentiment	0.003591	0.003586	0.757997
Principal Component 3 of TV Sentiment	0.003594	0.003586	0.762037.
Principal Component 4 of TV Sentiment	0.003537	0.003586	0.745298
Principal Components 1 & 2 of TV Sentiment	0.003308	0.003586	0.649755
Principal Components 1 & 3 of TV Sentiment	0.003379	0.003586	0.658408
Principal Components 1 & 4 of TV Sentiment	0.003371	0.003586	0.654318
Principal Components 2 & 3 of TV Sentiment	0.003602	0.003586	0.762141
Principal Components 2 & 4 of TV Sentiment	0.003547	0.003586	0.746664
Principal Components 3 & 4 of TV Sentiment	0.003544	0.003586	0.749454
Principal Components 1 & 2 of UMICH ICS	0.003412	0.003586	0.636161
Principal Components 1 & 3 of UMICH ICS	0.003402	0.003586	0.618899
Principal Components 1 & 4 of UMICH ICS	0.003025	0.003586	0.480916
Principal Components 1 & 5 of UMICH ICS	0.003236	0.003586	0.550416
Principal Components 2 & 3 of UMICH ICS	0.003664	0.003586	0.764112
Principal Components 2 & 4 of UMICH ICS	0.003558	0.003586	0.728842
Principal Components 2 & 5 of UMICH ICS	0.003661	0.003586	0.766773
Principal Components 3 & 4 of UMICH ICS	0.003548	0.003586	0.750667
Principal Components 3 & 5 of UMICH ICS	0.003591	0.003586	0.758139
Principal Components 4 & 5 of UMICH ICS	0.003557	0.003586	0.747333
Principal Components 1 of TV Sentiment and UMICH ICS	0.003307	0.003586	0.628981
Variables 1) - 3), Principal Components 1 & 2 of TV Sentiment	0.002821	0.003586	0.456257
Variables 1) - 3), Principal Components 1 & 4 of UMICH ICS	0.003064	0.003586	0.538144
Variables 1) - 3), Principal Components 1 of TV Sentiment and UMICH ICS	0.002697	0.003586	0.404195

(1) This column shows the Root Mean Squared Error of the respective forecasts.
(2) This column shows the Root Mean Squared Error of the benchmark ARMA(1,2) model.
(3) This column shows the Theil Inequality Coefficient, indicating the goodness of fit of the respective forecast.

Figure 3: Graph of nowcasts of base and best model and private consumption



both sentiment variables add value in nowcasting private consumption.

Next, we combine various principal components of both TV sentiment and the ICS to pairs in order to test whether this adds value to the nowcasts. The lowest RMSE and Theil Inequality Coefficient achieve the first and second principal components of TV sentiment. This makes sense, as these two components make up over 80% of the total variance. A more interesting result is that the first and fourth principal components of the ICS achieve by far the lowest RMSE and Theil Inequality Coefficient score. As described earlier in the principal components analysis section, the first component of the ICS aims at future conditions and expectations in one year, and the fourth at current and expected finances. Therefore, it is most important to the consumer how the near-term future expectations for the business conditions are, but it is also important how ones own personal finances are, both the current and the expected situation.

In a last step, we combine the three financial variables and the principal components of TV sentiment and the ICS, which performed the best in the previous nowcasts. Clearly, the nowcast that includes the financial variables and the first principal components of both the ICS and TV sentiment achieves the lowest RMSE and Theil Inequality Coefficient. When comparing the evaluation statistics of the nowcasts that include the financial variables and the best principal component pairs of the ICS and TV sentiment individually, we note that the nowcast with the first and second principal components of TV sentiment perform better than the nowcast with the first and fourth principal component of the ICS. Fig. 3 depicts private consumption, the nowcast from the base model, and the best nowcast with the financial variables and the first principal components of TV sentiment and the ICS. Even though the best nowcast tracks actual private consumption quite well, it becomes obvious that in especially times of crises, when the growth rates are more volatile, the nowcast is not entirely able to capture the large spikes, as in the third quarter of 2009. The base model is almost not able to track the volatility in the growth rates.

Therefore, we summarize the following findings: first, we show that an ARMA(1,2) structure as base model is superior to an AR(1) structure as suggested by Kholodilin *et al* (2010). Second, we find that stock returns of the broad-based stock index S&P 500 is suited for better nowcasts than interest rates. This is also in line with Ludwig and Slok (2002). Third, the first principal components of TV sentiment and the ICS are pretty much equally suited for nowcasting private consumption. Fourth, when combining the best pairs of the principal components of the ICS and TV sentiment, the first and fourth principal components of the ICS perform markedly better than the first and second principal components of TV sentiment. Last, but not least, when combining the financial variables with the best pairs of the principal components of the ICS and TV sentiment, TV sentiment adds more value to the nowcast than the ICS. Nevertheless, when combining the financial variables and the first principal components of both TV sentiment and the ICS, the best nowcasting result is achieved.

4 Conclusion

In this paper, we show with principal components analyses of the ICS and TV sentiment the nowcasting ability of these and other financial variables. Given that television news have the greatest share of news sources among the American population, we extend the existing literature of nowcasting private consumption by introducing a new sentiment variable that was created from sentiment from four of the most widely watched TV news broadcasts in the US. The sentiment was gathered from over 10,000 TV news broadcasts from January 2005 to December 2009. The principal components analysis of the ICS shows that future conditions and expectations of business conditions and personal finances explain the greatest share of the variance in the ICS. For TV sentiment, CBS and NBC news shows explain the greatest variance, with ABC and FOX news having inferior explanatory power. We further confirm the findings of Sommer (2007) and Uhl (2011) that an ARMA(1,2) structure is the superior base model than an AR(1)-model, as suggested in Kholodilin *et al* (2010). In the nowcast evaluation, we find that stock returns perform markedly better than interest rates. Further, we find that TV sentiment adds great value in nowcasting private consumption. This is rooted in the fact that the first principal component of TV sentiment achieves a lower RMSE in the nowcast than the first principal component of the ICS. When adding the financial variables to the best principal components pairs of TV sentiment and the ICS, TV sentiment also adds more value than the ICS. Nevertheless, when combining all three financial variables and the first principal components of both the ICS and TV sentiment, we achieve the best nowcast of private consumption. Hence, not only do financial variables and the widely used ICS add power in nowcasting private consumption, but also the newly introduced variable TV sentiment.

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Appendix

A.1 Nowcasts

The nowcasts are one-step ahead forecasts with coefficients from the ARMA(1,2)-regressions. The nowcasts follow the static method, which means that after each step when a nowcast is done for $t+1$, the actual values of the variables are taken, when proceeding with the next step nowcast at $t+2$. In this paper, the following ARMA(1,2) model is taken as follows:

$$y_t = x_t^{'}\beta + u_t,$$

$$u_t = \rho_1 u_{t-1} + \epsilon_t,$$

where y_t is private consumption and x_t refers to the independent variables, while

$$\epsilon_t = \phi_1 \epsilon_{t-1} + \phi_2 \epsilon_{t-2} + \varepsilon_t.$$

β is a vector of unknown parameters, and b are estimates of the unknown parameters β. The model is estimated with data up to $t = S-1$. The fitted residuals are defined as $e_t = y_t - x_t' b$. Given that the values of x_t are available, the nowcasts for $t = S$ are as follows:

$$\hat{y}_S = x_S^{'} b + \hat{\rho}_1 e_{S-1},$$

where the residuals $\hat{u}_t = \hat{y}_t - x_t^{'} b$ are formed from the nowcast values of y_t. The MA-error terms are estimates of the pre-sample $\epsilon_{S-1}, \epsilon_{S-1}, \ldots, \epsilon_{S-q}$ using the recursion:

$$\hat{\epsilon}_t = \hat{u}_t - \hat{\theta}_1 \hat{\epsilon}_{t-1} - \ldots - \hat{\theta}_q \hat{\epsilon_{t-q}},$$

given that the estimates of the q lagged innovations are available, so that we obtain

$$\hat{y}_S = \hat{\phi}_1 \epsilon_{S-1} + \hat{\phi}_2 \epsilon_{S-2},$$

for $t = 1, \ldots, S-1$, where S is the beginning of the nowcast period. See Pindyck and

Rubinfeld (1998) as well as the user guide of Eviews 7.0 as sources and for further information on the nowcasting procedure.