Quantifying market sentiments.
Extraction and real-time observation.

Michał Chojnowski

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Abstract

The article proposes an econometric method, which allows quantification of market sentiment from historical data. The method is based on the economic model, in which external shock in market sentiment affects beliefs about economy performance. Author uses Bayesian SVAR model to capture above-mentioned framework. Quantification of sentiments is an novel area of economic research, hence proposed method enables new possibilities to analyze and also to predict market behaviour.

An added value of the model is shown in accuracy of the forecasting models. Market sentiments should capture the unobserved factors, which affect the final decision of agents. Both linear and non-linear models were used to predict the market: ARIMAX and LSTAR. Forecasts are compared to the best performing ARIMA model as well as to naive forecast. Additionally, forecasts are also computed using well-known sentiment indices to shows similarity to extracted sentiments using proposed method.

The LSTAR model with sentiments provides up to 29% more accurate forecasts on the Polish car market, 5% on the US credit market and up to 17% on the Brazilian insurance market.

1 Introduction

Over the last decades there has been an increased number of research studies investigating the impact of market sentiments and the economy output. The most recent discussion arose after the crisis of 2008 when the real estate market bubble burst. There is a growing belief that market expectations may affect the final output of the economy. However, they do not influence the output directly, but rather by affecting the agents' perception. Economist have been investigating the dynamics between expectations and realizations of the economy to set it up properly within mathematical framework.

Market sentiments are more and more often recognized to be a driven force for business cycles. Understanding them better will allow the economists to describe more accurately a way the markets behave during a crisis. The current discussions focus more on the recent economy downturns, but market sentiments along with animal spirits and self-fulfilling prophecy theories have been a subject of a debate in the economic literature for almost a century. The first mentions of expectations shaping an equilibrium can be traced back to works of Arthur Pigou [Pigou, 1929] and John Keynes [Keynes, 1937]. In his concept of "beauty contest", Keynes proposed a game, in which players get rewarded, if they correctly guess a winner. Selecting the most attractive person a player does not judge contenders solely based on his own taste, but also has to take into consideration reasoning of other players and majority perception of beauty when betting. Before the decision is made, he defines his belief as well as affects the believes of others about his belief. Keynes argues that the same behaviours can be observed on the stock market and used to explain the "boom and bust" cycles.

What we have observed during recent crises in global economy brought some evidence to Keynes' concept. In 2008, the bust of US housing market spilled all over the globe. It is believed that the wrong risk assessment published by rating companies lead great number of investors to acquire bad mortgages [Acharya et al., 2010].

Additionally to above-mentioned moral hazard, another behaviour is to blame. Because banks were investors themselves, Gorton describes this crisis as run on securitized banking [Gorton, 2008].

Another example would be the sovereign crisis that hit Europe in 2012-2013. The problems with public debt in the Southern countries resulted in the fall of investor confidence in the whole European market, even though economic fundamentals of the Northern countries were in much better shape. The monetary union influenced investors' perception and created the belief that the crisis would affect the South and the rest of the Euro zone alike. The investors acted as if the crisis was inevitable and fell into what seems to be a self-fulfilling prophecy [De Grauwe and Ji, 2013], [De Grauwe, 2012],[Gärtner et al., 2012],[Bruneau et al., 2014],[Gerlach, 2010]. Beliefs like this circulate and spread quickly in the world of connected economies [Brzoza-Brzezina et al., 2020].

Although sentiments and other disturbances in beliefs known as externities are well-researched in the economic literature, they are rarely used in macroeconomics analyses. The reason for that is the results of some conducted researches show unusual behaviours of variables around the equilibrium, which complicates both the model and calculations. One of the widely disputed issues is the existence of multiple equilibira, which can be found in the research areas such as: imperfections of labour market [Diamond, 1982], coordination failure between agencies and unemployed [Howitt and McAfee, 1987], and strategic complementarity into agent's payoff [Cooper and John, 1988].

The analysis of externalities caused by discoordination was further developed by the introduction of sunspots into economic models. Sunspots are external random variables that do not influence economic fundamentals but upon which agents coordinate their decision [Prescott and Shell, 2002]. Such externalities help to illustrate irrational behaviours, even in rational-expectations equilibria, only if individuals believe those sunspots are a good predictor of future prices [Azariadis, 1981]. If companies face uncertainty in the non-smooth adjustments environment, they tend to stop their investment until future states are revealed.

Moreover, Cass and Shell elaborated on the sunspots' effect on consumption level and Farmer and Woodford showed that if agent's beliefs are not fully determined by economic fundamentals then there exist multiple stationary rational-expectations equilibria [Cass and Shell, 1983],[Farmer and Woodford, 1997]. Also Barro and King specified that changes in expectation of the future are not enough to cause business fluctuations, only shocks in technology are able to cause such cycles [Barro and King, 1984].

The breakthrough came with the implementation of global games into economics.

Models with imperfect information, in which multiple equilibria occur, may be rewritten to have a unique equilibrium by introducing the idiosyncratic noise to the private signals of players [Morris and Shin, 2000]. . When individuals are faced with uncertainty of other agents' information and, therefore, face uncertainty of the exact structure of the coordination game, they consider the probability of their private signal being over or under a threshold. The threshold represents the moment when change of strategy becomes profitable [Atkeson, 2000].

Additionally, if agents consider the expected profit under the given probability of the true state of the world surpassing threshold at which agents will receive winning payoff, then the aforementioned threshold variables have an unique solution and describe equilibrium of the coordination game

[Morris and Shin, 2000].

However, according to the Morris's model, both actions and beliefs are well coordinated. Once this assumption is relaxed, the fluctuations in the economic fundamentals still occurs, although the nature of those is different.

An implementation of external shock into second-order beliefs leads to a business cycle behavior of endogenous variables, even though the economy is set up in rational-expectation framework [Angeletos and La'O, 2013]. Benhabib et al. complement this idea by showing that even if fully-rational companies can closely observe economy and possess perfect forecast of their production, then still the inability of separating sentiments from preference shocks prevents them from establishing an unique stable equilibrium [Benhabib et al., 2015]. Thus, sentiments might drive persistent aggregate fluctuations [Benhabib et al., 2017].

Milani provides even more insight on the matter suggesting that the exogenous variation in market sentiments are responsible for the lion's share of the US business cycle, especially for shocks on sentiment related to the future investment expectations [Milani, 2017].

Moreover, Schaal and Taschereau-Dumouchel show that the coordination failure caused by complementary demand illustrates well the behavior of the US economy in the period 2005-2015 [Schaal and Taschereau-I

Although market sentiments and animal spirits are often regarded as the same type of externality in the literature, there are articles which aim to separate those two phenomena. According to the works of Barsky and Sims, the effect of animal spirit is a casual effect on economic activity, whereas the effect of a news shock shifts economic fundamentals permanently as it carries on information about the current and future states [Barsky and Sims, 2012].

Moreover, the market sentiments shock forces economic fundamentals to adjust to the new steady state, whereas under an animal spirit noise, the economy returns to its initial state [Blanchard et al., 2013],[Lorenz
Using this distinction, recent economic literature applied market sentiments into various fields of study; the most popular of them being the study of financial and monetary beliefs. As stock returns are highly correlated with a future production [Fama, 1981], orthogonal shocks in stock returns, labeled as technological opportunities, might drive business cycles, however, an unexpected shock in productivity does not [Jaimovich and Rebelo, 2009].

The econometric literature proposes several approaches to quantify market sentiments. The most common method is the inclusion of publicly accessible survey-based indices of customer confidence into a model. It was proven that without supporting time-series it is practically impossible to extract sentiments shock from a SVAR economic model [Blanchard et al., 2013]. However, if a consumer confidence index is included as an endogenous variable, it is still possible to set up an analysis of sentiment shock [Guay, 2016]. Additionally, the "wait-and-see" approach seems to be a result of a sentiments fluctuation, which corresponds with an increase in uncertainty of forecast survey [Bachmann et al., 2013].

Another method proposes an extraction of sentiments from SVAR residuals. With a proper set-up, it is possible to extract a sentiment from GDP residual and differentiate it from a news shock as well as random one [Brzoza-Brzezina et al., 2018]. Moreover, residuals can be used to dissect a demand-driven business cycle component excluding technology shocks, news about future productivity or inflationary demand shocks [Angeletos et al., 2018].

This paper elaborates on the method which uses SVAR model to detect market sentiments. On the contrary to the literature mentioned above, the author decided to focus rather on the market level sentiments than macroeconomic ones. The proposed general method allows to analyze and detect sentiments towards different goods or services, which wouldn't be be possible with aggregated survey-based indices. Furthermore, the method also combines the impact of sentiments on individual level with aggregated sentiment on the higher level.

It is assumed that each of the individuals on the market has access to the same public information, however, the interpretation of information might differ. From the outside perspective, it may seem as if individuals receive different private signals, therefore Bayesian SVAR model was used to include the assumption. For individual draw of matrix A_0, the sentiment is regarded as given, because it comes from an individual interpretation of commonly known economic fundamentals. Therefore the sentiment variance is zero and is consistent with the Blanchard restriction [Blanchard et al., 2013].

In accordance with Angeletos proposition, the real value of sentiments can be aggregated into a single random variable [Angeletos and La'O, 2013]. Therefore in our method, the final value of market sentiments is the median from all individual draws.

Additionally, the author checks the value of extracted sentiments for their application in forecasting. The hypothesis is that a model with more insight into market data should provide more accurate forecasts. Because sentiments do not affect the fundamentals directly, both linear and non-linear models were considered. Market sentiments in non-linear model are used as a threshold variable, which differentiates two groups on the market. These groups can be characterized as the optimists and pessimists [Angeletos and La'O, 2013].

This paper is structured as follows: firstly, in section 2the author presents the model, which extracts market sentiment from a given market in the form of a time-series. In section 3 the environment set-up is discussed. Afterwards, the extraction method is described in details. Then, in section 5, three applied examples are presented.

2 Sentiments

The economy operates within general equilibrium framework with imperfect information regarding other agents' type - an individual characteristic which represents potential possibilities to perform a trade e.g. productivity in case of firms or disposable income for customers. Agents at period t receive a distorted signal (denotend as $x^{'}_{i,t}$) which contains present and future information of agents' types (denoted as $\theta_{i,t}$). Based on that signal agents alocate their resources in the best of their interest. This framework is consistent with Keysian and RBS models, where expectations of agent i plays crucial role in current decisions, which corresponds to first-order beliefs .

Additionally, agents try to compare their private information to signals received by other agents. If everyone recieves the same signal or private signals are a common knowledge, then the case becomes trivial. However, when signals are distorted, guessing the true value of other's type becomes a difficult task. Hence agent's receive a second signal (denotend as $x^{''}_{i,t}$), which tells agent what information other might have received. Estimating the information knowing that other agents also received similiar signal is consistent with second-order beliefs.

Sentiments in that framework are an exogeneous variable, which skews the second-order signal (denoted by ξ_t). If sentiments are too high, whatever a signal other have received, the agent will choose certain action. Analogically, if sentiments are too low, an agent will follow a different action. Aforementioned definition is captured by Angeletos and La'O proposition [Angeletos and La'O, 2013]:

$$\begin{aligned} x^{'}_{i,t} &= \theta_{-i,t} + u^{'}_{i,t}, \\ x^{''}_{i,t} &= x^{'}_{-i,t} + \xi_t + u^{''}_{it}. \end{aligned} \tag{1}$$

In this article focus is put on the nature of the white noise $u^{'}_{i,t}$ and $u^{''}_{it}$. Information mostly comes from the data, which either are publicly available or easily accessible from plenty of articles. Therefore the signal, which agents receive is clear and the same for all. The noise comes from the interpretation of that signal though. That interpretation helps to mitigate the problem, which was presented in *News, noise and fluctuations* [Blanchard et al., 2013]. The signal is clear and publicly known, however, the interpretation of it is uknown. Therefore Bayesian Vector Autoregressive models (BSVAR) are introduced, in which each draw represents possible bundle of agents drawn from a population. Matrix $\mathbf{A_0}$ from BSVAR model represents how signals are interpreted by a given bundle of agents. Having distribution of individual signals sentiments can be extracted based on the equation (1) by substracting first-order signals of other agent's from the second-order one. As first-order signals of other players are not publicly known, the agent's guess has to come from other actions.

With no sentiments present, there would exist a linear combination of first-order signals, which translates into a second-order signal. Any volatility recorded between two beliefs is assumed to be caused by a sentiment.

$$\xi_t = E\left[x_{i,t}^{''}\right] - E\left[x_{-i,t}^{'}\right].$$

This dissonace between received information and undertaken action has a significant impact on the economy. Positive information shock boosts the output, which correlates with business cycle [Angeletos and La'O, 2013]. Sentiments directly influence the transition function of capital - the higher is the sentiment the more capital is being invested. Addtionally, sentiments may affect an equilibrium, hence any shock in information should creates a distruption, which has impact for future market performance [Benhabib et al., 2015]. Hence the positive information shock should increase willigness to purchase given good or invest in given product, which might result in higher sales. However, the sentiment might influence eagerness of the consumers as well, hence with increase in the sentiment clients might purchase goods using less available information. The willigness of sales is modeled using linear ARIMAX model, whereas the eagerness is modeled using nonlinear LSTAR model.

3 Environment

Consider an economy with N group of agents, which are either a representative consumer, a firm or a third party such as a bank or an insurer. Agents operates on $M \leq N$ markets. Consumers aim to maximize their log-utility while being contrained by their budget. Firms and other types of agents presented in this article aim to maximize their profit while being contrainted by their resouces.

In every period each of agents receive a distorted information regarding other agent's type. In this research type represents a characteristic which illustrates agent's availability to undertake a trade. This characteristic is labeled as individual potential (IP) further in the article. The first-order signal consists of other agents individual potentials, which are weighted by $\alpha_{i,j}$ - the lower absolute value the less important is the agent j to agent i. After receiving the signal $x_t^{'}$ each of the agents estimates other's signals to make a final decision about the trade. The aggregated result of agent's decision is labeled as collective response (CR). The signals are being estimated by observing other collective responses, which are weighted by $\gamma_{i,j}$. Parameter γ represents importance of $j-th$ agent's action in second-ordered signal of agent i. The sentiment ξ_t is the same for all the groups of agents and shift their perception of the second-order signal.

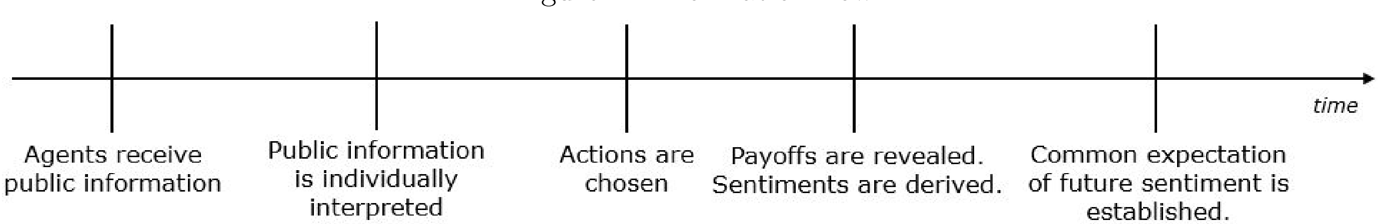
$$\begin{aligned}
\forall_{i\in N}\, x_{i,t}^{'} &= \sum_{j\in N/\{i\}} \alpha_{i,j} logIP_{j,t} + \epsilon_{i,t}^{'}, \\
\forall_{i\in N}\, x_{i,t}^{''} &= \sum_{j\in N/\{i\}} \gamma_{i,j} x_{j,t}^{'} + \xi_t + \epsilon_{i,t}^{''}, \\
\epsilon_{i,t}^{'} &\sim N(0, \sigma_{x'}), \\
\epsilon_{i,t}^{''} &\sim N(0, \sigma_{x''}).
\end{aligned} \tag{2}$$

After the signal reception, undertaken actions are revealed hence the true value of the sentiment is revealed as well. Afterwards common expectation of future sentiment values are set using exponential smoothing:

$$E_t\left[\xi_{t+1}\right] = \sum_{i=1}^{\infty} \tilde{\alpha}^i \xi_{t-i}.$$

Figure 1 summarises chronological order of information flow in each time period.

Figure 1: Information flow



4 Extraction

From equation (2) for each agent it is possible to extract sentiment as follows:

$$\forall_{i\in N}\, x_{i,t}^{''} - \sum_{\iota\in N/\{i\}} \gamma_{i,\iota} x_{\iota,t}^{'} = \xi_t + \epsilon_{i,t}^{''}. \tag{3}$$

Henceforth the sentiment is represented as a factor, which skews perception of an agent in a given economy. Even if there is a perfect information between agents (ϵ's are equal to 0) distortion still occurs [Angeletos and La'O, 2013]. If either $\alpha_{i,j}$ or $\gamma_{i,j}$ are set to zero, then it is assumed that there is no interest of i-th agent about j-th agent, which means they do not communicate or communication is one-way directed if $\gamma_{j,i}$ is different than 0. As all agents perceive the same sentiment, summing up equations (3) leads to disclosure of sentiment presence:

$$\sum_{i \in N} x^{''}_{i,t} - \sum_{i \in N} \sum_{\iota \in N/\{i\}} \gamma_{i,\iota} x^{'}_{\iota,t} = N\xi_t + \sum_{i \in N} \epsilon^{''}_{i,t} \propto \xi_t + \frac{1}{N} \sum_{i \in N} \epsilon^{''}_{i,t}. \tag{4}$$

Although signals come from endogeneous shocks, they are distorted by exogeneous noise and sentimets. For models with only first-order beliefs present in the model it is sufficient to use one time series for each of an agent (e.g. consumption and production as in Blanchard's example [Blanchard et al., 2013]). However, for models incorporating higher-order beliefs more time-series are needed to describe agent's reckoning. In case of second-order beliefs two variables are needed per agent - one, which describes individual potential to initiate a trade with an agent of other type (IP) and the second one describing final decision, or collective response of given type agents (CR). As sentiments are the only factor, which distorts second-order beliefs, any discrepancies between an agents' individual potential and collective response are expected to be caused by them. Those discrepancies are detected by a SVAR model with endogenous vector $\mathbf{y_t}$ consisting of two aforementioned variables: an agents' individual potential and collective response. Hence SVAR model takes following form:

$$\mathbf{A_0 y_t} = \sum_{\mathbf{p=1}}^{\mathbf{P}} \mathbf{A_p y_{t-p}} + \mathbf{B}\varepsilon_{\mathbf{t}},$$

$$\mathbf{y_t} = \begin{bmatrix} \Delta log(\mathbf{IP_t}) \\ \Delta log(\mathbf{CR_t}) \end{bmatrix}.$$

Let matrix $\mathbf{A_0}$ represent how shocks in $\mathbf{y_t}$ are interpreted by agents. In other words, matrix $\mathbf{A_0}$ is an transformation matrix from observable shock into individual signals. First-order signals relies solely on the individual potential of the agents. Second-order signals take into account what information other agents might have received by observing their collective response simultaneously considering one's own first-order signal as a reference point.

Elements of matrix $\mathbf{A_0}$ represents the weights each of agent gives to particular information flow. An analyst is able to impose zeros, if it is known that some agents do not communicate or one agent depends solely on the other one. For normalisation purposes matrix $\mathbf{B_0}$ is introduced with elements on its diagonal, otherwise it is equal to 0. Hence orthogonal shocks of the SVAR model are represented by a vector of signals agents have receive (denoted as a vector $\mathbf{\Delta x_t}$). To control for a fact, that an agent estimates other's private signals in respect to their own private signal, the second-order signal parameter δ_i is controlled by a shock from his own IP.

$$\begin{aligned}
\mathbf{A_0} &= \begin{bmatrix} 1 & \alpha_{1,2} & \alpha_{1,3} & \dots & 0 & 0 & 0 & \dots \\ \alpha_{2,1} & 1 & \alpha_{2,3} & \dots & 0 & 0 & 0 & \dots \\ \alpha_{3,1} & \alpha_{3,2} & 1 & \dots & 0 & 0 & 0 & \dots \\ \vdots & \vdots & \vdots & \ddots & \vdots & \vdots & \vdots & \vdots \\ \delta_1 & 0 & 0 & \dots & 1 & \gamma_{1,2} & \gamma_{1,3} & \dots \\ 0 & \delta_2 & 0 & \dots & \gamma_{2,1} & 1 & \gamma_{2,3} & \dots \\ 0 & 0 & \delta_3 & \dots & \gamma_{3,1} & \gamma_{3,2} & 1 & \dots \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \ddots \end{bmatrix}, \\
\mathbf{\Delta x_t} &= \begin{bmatrix} \Delta \mathbf{x_t}' \\ \Delta \mathbf{x_t}'' \end{bmatrix} = \mathbf{A_0}^{-1}\mathbf{B}\varepsilon_t. \qquad (5)
\end{aligned}$$

The literature states that SVAR model can be used for signal extraction only if the signals are "clear" (variance of noise ϵ from equation (4) is 0) [Blanchard et al., 2013]. To meet those requirements let's consider following framework. Signals $\mathbf{x_t}$ in the model presented in equation (5) comes from shocks in economic fundamentals, which are observable by everyone with the same access. Therefore no private noise is present within those shocks. However, the source of the noise is a personal perception of publicly known shocks. This approach helps to implement the idea, that signal shocks might be connected with forecast disagreement. Let's introduce infinitely many players to which one of the N classes is assigned (such as customer, firm, etc.). Each player receives a signal for whom it is a complete information. As the variance of a single point is zero, Blanchard requirement is met. However, the result is a private sentiment expectation - distorted version of a "true" sentiment value.

As infinitely many agents were introduced it is possible to extract infinitely many private sentiment expectations. As sentiment expectations are distributed in the same way as $\epsilon' s$, values of extracted sentiment expectations will gather around the true value of the sentiment. It is sufficient though to draw significantly many matrices $\mathbf{A_0}$ to simulate possible noises, which comes from interpretation. This scenario can be estimated with Sims-Zha Bayesian SVAR model [Sims and Zha, 1998], which is based on Litterman's priors. The values of metaparameters were tailored to the scenarios author has examined, although, some general rules were imposed. As a survey-based consumer confidence indices measure relatively the same phenomenon, the correlation between them and the sentiments should be as strong as possible. Moreover, as the Bayesian SVAR model is based on differences (equation (5), AR(1) metaparameter (λ_1) should be as low as possible. Additionally, because SVAR model measures the information which is still present in the economy, lag delay metaparameter (λ_3) should be also as low as possible. As no exogeneous variables are used, λ_5 is set to 1.

The final result of a method based on Bayesian SVAR model is an univariate time-series representing quantified values of differences in sentiments ($\Delta\xi_t$). Values in each period t are the median of private sentiment expectation's distribution for a given period.

Result check

Sentiments contain information regarding realization of present and future state of the world. Its presence is significant in every period of time, hence extraction method should also provide time-series, which are consistent regardless of the time-window. Therefore, out-of-sample analysis is performed to check usefulness of extracted sentiments and also to record and to evade possible overfitting. Hence forecasts including extracted sentiments should perform better than their counterpart models without them. Expectation of sentiments for upcoming period is calculated using an exponential smoothing with predefined value of parameter α (denoted onwards as $\tilde{\alpha}$). Agents analyse how off their prediction were from actuals and behave accordingly. Therefore residuals of exponential smoothing were used in forecasting models.

Sentiments as an exogeneous variable should be detected regardless the window used to estimate BSVAR model. Hence general results are confronted with distribution of sentiments from a rolling-window with 60 observations in each window. To quantify similarities, correlation between whole sample sentiments and median of rolling-window sentiments is calculated.

Two methods of sentiment implementation into forecasting models were examined. First method assumes linear relation interference of sentiments on a market performance, hence increase in sentiments are proportionate to increase in the mean. It can be modelled using ARIMAX with sentiments as an exogenous variable. Another method uses non-linear approach, where sentiments defines ratio between two type of consumers: reluctant and euphoric. This is consistent with global games approach presented by Morris and Shin, where consumers decide whether to invest or not to invest [Morris and Shin, 2001].

Binary action games can be easily applied to other markets e.g. on retail market, where type of game can be interpreted as to buy or not to buy or on a credit market as to take or not to take. Both types follow different autoregressive process to calculate their expectation of economic fundamentals. To model this scenario LSTAR model is used, where difference between expectation and realisation of a sentiment is the threshold variable.

5 Applications

This article examines three markets in three different countries: Polish car industries, US credit market and Brazilian insurance market. For each scenario I discuss the structure of a market, how to set-up BSVAR model and what improvements did market sentiments bring.

Polish car market

The aim of this scenario is to show differences between well-established leading consumer confidence index (WWUK) and extracted sentiment on a given market. This section will discuss why leading consumer confidence index is not as effective as extracted sentiment and what by how much extracted sentiments increases forecasting performance.

Set-up

There are two players present on the market: consumers and firms. The individual potential of the consumers are wages, which describe their disposable budget. The collective response of the consumers is consumption itself. It shows how eager consumers were to consume in each period of time. Firms' individual potential is a number of cars sold in given month per working day. The collective response is production, which represents GDP. Both of the players observe each other, hence $\mathbf{A_0}$ matrix is constructed as follows:

$$\mathbf{A_0} = \begin{bmatrix} 1 & \alpha_1 & 0 & 0 \\ \alpha_2 & 1 & 0 & 0 \\ \delta_1 & 0 & 1 & \gamma_1 \\ 0 & \delta_2 & \gamma_2 & 1 \end{bmatrix}$$

Metaparameters were set based on the rules explained in section *Extraction* - values are presented in Table 1.

Table 1: Metaparametrs for Sims-Zha Bayesian SVAR

Symbol	λ_0	λ_1	λ_3	λ_4	λ_5	μ_5	μ_6
Value	0.75	0.3	0.4	100	1	100	0.01

Data

All time-series are of monthly frequency within period Jan 2006 - Dec 2017. Number of registered cars are taken from Polish Car Industry Institute (PZPM) [Motoryzacyjnego, 2018]. In this research author has focused on passenger cars only. Macroeconomic data such as real wages, production and consumption are taken from Selected Monthly Macroeconomic Indicators published by Central Statistical Office.

Leading Consumer Confidence Indicators WWUK describes how households reckon their well-being, economic situation, unemployment for the next year. Values ranges between -100 and 100, where positive number indicates aggregated optimism whereas negative – aggregated pessimism. The number represents an average response from households. Those data are collected via CACI interview method and it is published monthly by Central Statistical Office of Poland.

All time-series (except WWUK) are logarithmized and they are subject to seasonal adjustment. Number of sold cars, consumption and production are additionally working-day adjusted.

Extracted market sentiment

In the Figure 2 (see Appendix) extracted car market sentiment is compared to the WWUK index. In 2008, just before the crisis comes, sudden drop in market sentiment is recorded whereas consumer confidence index remains at the same level for few next months. It is an example of "wait-and-see" behaviour - even though firms believes that the economy will perform well in the future, due to an uncertainty they decide to wait with the investment decision.

Analogically, consumers which face uncertainty are reluctant to invest their capital into credit goods such as cars. Moreover, both time series follows similar path, which makes them cointegrated. This observation is also consistent with the literature as both time series measure similar phenomenon. Differences between them can be recorded in period 2010-2012 though.

Extracted sentiments are more focused on a car industry only and the consumer confidence index describes a belief regarding an economy as a whole, increasing sentiments with decreasing confidence index illustrate the situation, where consumers beliefs that a car is a good investment even though economy is expected to perform worse. The prices might also influence those sentiments as firms might have been stocked after the crisis in 2008 and faced oversupply. Drop in the end of 2012 represents a correction for an overconfidence of the market as the economy has not recovered fast enough to meet consumers expectations.

Figure 2: Car industry sentiment vs leading customer confidence index - Poland

Note: *Dashed line represents consumer confidence index WWUK, whereas red, solid line represents extracted sentiment. Values of both series were normalized.*

Forecasts

Sentiments in this research are implemented in both linear and non-linear manner. Additionally, naïve forecast and random walk are calculated to put forecasting performance into perspective indicating if forecasting models are necessary in the first place. RMSE results of each models are normalized to the value of best-performing ARIMA model (ARIMA=100). For all the examined horizons (1-,2-,3-,4-,6- and 12-month ahead) ARIMA model is superior to aforementioned models. This point is emphasised at the beginning of analysis so any model, which outperforms ARIMA automatically outperforms the naïve forecast and the random walk forecast as well. LSTAR model with residuals as a threshold variable was chosen to determine if sentiments have a real impact on the forecasting performance. The results suggests that LSTAR model does not contribute to the forecast accuracy.

Sentiments seem not to interact with economic fundamentals in linear manner. ARIMAX models, either with WWUK or with extracted sentiments are similar to the ARMA models, which might suggest that those variables does not contribute to the model at all. This results are consistent with the literature though. Sentiments as the economic sunspots do not influence the payoffs such as market performance itself. If linear relation occurs, then this impact will be significant and extracted time series might not represent the sentiments.

However, if sentiments determine the action of given player then at least two regimes describing different behaviour should be recorded. One, where consumers and firms are reluctant to buy/sell a car and the second one where consumers and firms are dedicated to buy/sell a car. Thus sentiments define the ratio in a population between those two regimes. LSTAR model with extracted sentiments shows improvement in the short-term, however, LSTAR based on WWUK underperforms. It is not a surprising result as WWUK describes expectations of an overall economy, not the given state of the market. Therefore if market performance deviates from economy performance (see period 2010-2012), consumer confidence index falsely identifies the ratio.

Table 2: RMSE of Polish car market forecasts

Model / horizon	1 month	2 month	3 month	4 month	6 month	12 month
Benchmarks						
Naïve	176.21	158.94	136.80	153.29	140.92	136.09
Random walk	111.08	105.24	103.22	104.04	103.45	103.59
ARIMA	100.00	100.00	100.00	100.00	100.00	100.0
LSTAR	115.29	429.48	101.06	765.60	104.19	99.45
Linear models						
ARIMAX (WWUK)	102.53	101.95	99.75	99.80	101.44	100.11
ARIMAX (sentiments)	104.72	105.50	99.81	100.46	102.68	99.68
Non-linear models						
LSTAR (WWUK)	103.27	91.45	94.72	105.48	101.75	100.35
LSTAR (sentiments)	106.60	78.55	71.73	77.37	99.16	85.87

Values normalized to ARIMA performance.

American credit market

The aim of this scenario is to examine if sentiments of another market can influence other market as well. American credit sentiments were extracted and implemented into the housing market. The final result will indicate if credit sentiments can improve forecasting sales of houses and if credit market sentiment could forsee crash on housing market in 2008.

Set-up

There are three players present on the credit market: consumers, firms and banks. Consumers' individual potential of trade are wages, which represents their disposable income, whereas their collective action is a consumption itself. Firms' individual potential is a number of employed people, where theirs collective response is production. For banks, their individual potentail is a capital ratio - an indicator, which illustrates how well the capital is used to generate profits. The collective response of banks is volume of credits granted. All players obseve each other, hence $\mathbf{A_0}$ matrix is constructed as follows:

$$\mathbf{A_0} = \begin{bmatrix} 1 & \alpha_{1,2} & \alpha_{1,3} & 0 & 0 & 0 \\ \alpha_{2,1} & 1 & \alpha_{2,3} & 0 & 0 & 0 \\ \alpha_{3,1} & \alpha_{3,2} & 1 & 0 & 0 & 0 \\ \delta_1 & 0 & 0 & 1 & \gamma_{1,2} & \gamma_{1,3} \\ 0 & \delta_2 & 0 & \gamma_{2,1} & 1 & \gamma_{2,3} \\ 0 & 0 & \delta_3 & \gamma_{3,1} & \gamma_{3,2} & 1 \end{bmatrix}$$

Metaparameters were set based on the rules explained in section *Extraction* - values are presented in Table 3.

Table 3: Metaparametrs for Sims-Zha Bayesian SVAR

Symbol	λ_0	λ_1	λ_3	λ_4	λ_5	μ_5	μ_6
Value	0.9	0.7	0.6	1000	1	0.001	0.001

Data

All data are of monthly frequency in period 1964 - 2017 taken from Federal Reserve Bank of Saint Louis database. Consumers' individual potential is described by an average wage in private sector, whereas their action is described by personal consumption expenditures. Firms' output is described by Industrial Production Index and their production possibilities as number of employed people (Total Nonfarm Payrolls). Banks capability to grant a credit is described by capital ratio, whereas banks decision is illustrated by volume of credit granted. Then sentiments are used to forecast New Privately Owned Housing Units Started. All time series were logarithmized. First differences were used in the estimation process to guarantee stationarity.

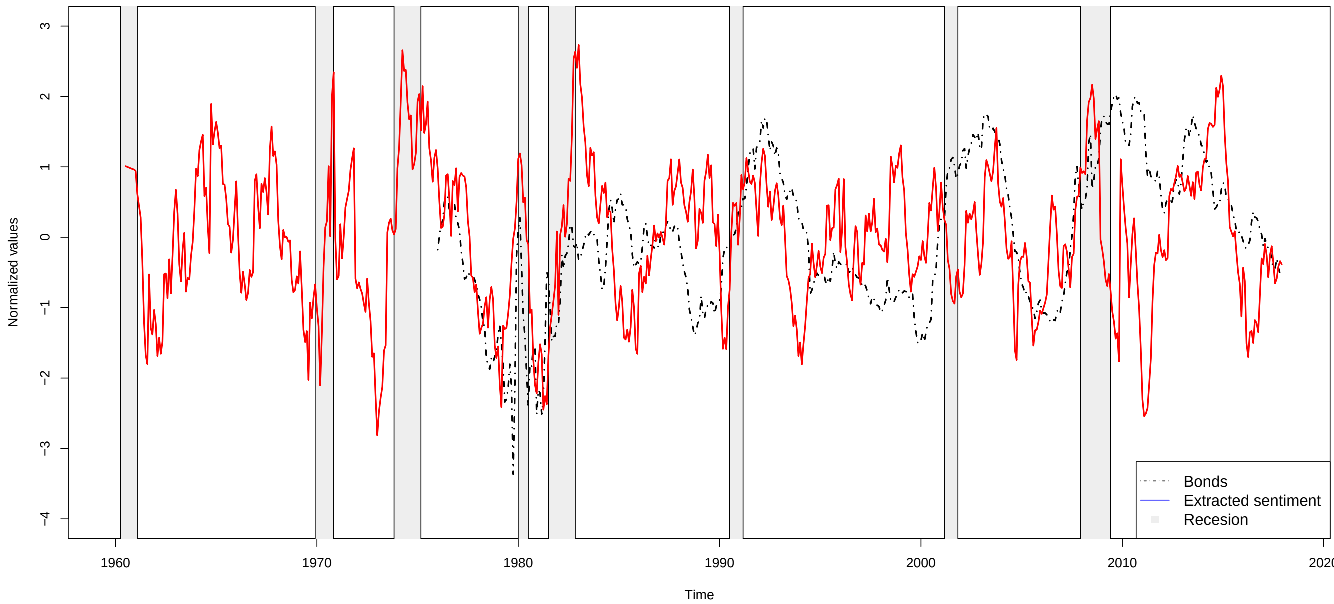
Extracted sentiment

As a benchmark author has taken a difference in maturity between 10-years and 2-years government bonds. This figure has recently being discussed as a predictor for upcoming crises as spread tend to growth just before crisis is recorded.

Extracted sentiments follows similiar behaviour as difference in maturities - when reaches given low level, the economy falls in the recession. Additionally, in years 1985 and 1993 sentiments reaches low levels without causing economy fall into recession. Eventhough it seems counter-intuitive, extracted sentiments in those periods provide more insight to credit market condition. In early 1980's USA was under a change in monetary policy approach - from price-driven to quantity-driven introduced by Volckner. This approached changed household saving habits from traditional deposit accounts to market mutual funds, which result in abnormal rise of money aggregates. The sudden peak in 1990's might be associate with sudden growth of velocityt of money (especially M2) in respect to opportunity cost. Changes made in Federal Open Market Commitee (FOCM) in 1994 have stabilized it. In 2010's the first peak can be associated with sovereign crisis in Europe. The counter action taken by FED was quantitative easing. The drop at the end of the time series was caused by 2016 elections and economic uncertainty regarding the upcoming years.

Overall, extracted sentiments successfully identifies moments, in which economy is vulnarable to downturns, however, they cannot on their own predict the next crisis with certainty.

Figure 3: Credit sentiments vs difference in bonds maturity - USA



Note: *Dashed line represents difference in 10-Year Treasury Constant Maturity Minus 2-Year Treasury Constant Maturity, whereas red, solid line represents inversed extracted sentiment. Values of both series were normalized. Grey areas represent recession periods.*

Forecasts

Two forecasting periods were examined formore detailed insight on sentiment's impact on housing market. The first period, which contains all possible forecasts (1970-2017) shows how in general sentiments are effecting housing market. The second period focuses on the time period around housing crash in 2008. The examined period has narrowed to 7 year interval - 3 years before the crash and 4 years after (2005-2012).

Table 4 shows that within long time period both benchamrk models: ARIMA and LSTAR are equally accurate. Additionally, linear models with exogenous variables does not bring any addtional value. Even though ARIMAX with extracted sentiments has accuracy as good as benchmark, the bonds difference ARIMAX's loses accuracy with forecast horizon. For non-linear models the bonds difference does not bring any improvement as well,although for extracted sentiments slight improvement can be recorded. It might indicate that credit market influence immobility market slightly, hence during the major turnovers the number of sold houses might be affected. However, slight changes might be too weak to overcome other factors.

If the analysis is narrowed down to pre- and post-crush period, there is more vivid insight on the impact of credit sentiments. LSTAR model with sentiments tends to overperform ARIMA model in the middle-term (4 - 6 months horizon). There is no significant difference between extracted sentiments and difference in bonds expect of 4 -month period, were bonds seems to predict downturn more precise.

Table 4: RMSE of US housing market forecasts 1970-2017

Model / horizon	1 month	2 month	3 month	4 month	6 month	12 month
Benchmarks						
Naïve	258.49	309.35	316.12	332.29	326.09	300.68
Random walk	189.44	150.25	134.50	134.08	127.81	130.23
ARIMA	100.00	100.00	100.00	100.00	100.00	100.0
LSTAR	98.96	100.75	100.89	99.98	99.90	101.70
Linear models						
ARIMAX (bonds)	100.00	101.05	101.37	101.42	103.14	106.03
ARIMAX (sentiments)	99.6	100.03	100.84	99.98	99.90	101.70
Non-linear models						
LSTAR (bonds)	100.25	101.59	100.06	102.73	106.35	101.05
LSTAR (sentiments)	100.06	100.42	99.56	98.71	97.38	99.13

Values normalized to ARIMA performance.
Values in brackets represent p-value of the Diebold-Mariano test

Table 5: RMSE of US housing market forecasts 2005-2012

Model / horizon	1 month	2 month	3 month	4 month	6 month	12 month
Benchmarks						
Naïve	200.00	256.00	269.97	294.96	330.88	313.40
Random walk	147.45	124.57	108.89	108.51	114.34	126.10
ARIMA	100.00	100.00	100.00	100.00	100.00	100.0
LSTAR	105.00	104.38	103.03	97.87	98.19	98.40
Linear models						
ARIMAX (bonds)	103.48	103.82	100.51	98.91	99.69	100.14
ARIMAX (sentiments)	105.80	103.29	101.14	100.76	100.01	102.16
Non-linear models						
LSTAR (bonds)	105.66	101.03	102.24	90.21	95.58	97.66
LSTAR (sentiments)	103.80	104.55	105.47	99.60	94.80	98.73

Values normalized to ARIMA performance.

Brazilian insurance market

In this section author investigates if it is possible to extract sentiments towards insurance products. Insurance product, contrary to goods or credit, does not have a tangible equivalent - it is rather a financial assurance if an event has occured.

Set-up

There are three players present on the insurance market: consumers, firms and insurance companies. Consumers individual potential of trade is depended on wages, which represents their disposable income, whereas their collective action is a consumption itself. Producers individual potential are eployed people, where theirs collective response is production. For insurance, their individual potentail is a return on equity, commonly used factor to asses performance of the insurer. The collective response is the amount of insured goods. All players obseve each other, hence $\mathbf{A_0}$ matrix is constructed as follows:

$$\mathbf{A_0} = \begin{bmatrix} 1 & \alpha_{1,2} & \alpha_{1,3} & 0 & 0 & 0 \\ \alpha_{2,1} & 1 & \alpha_{2,3} & 0 & 0 & 0 \\ \alpha_{3,1} & \alpha_{3,2} & 1 & 0 & 0 & 0 \\ \delta_1 & 0 & 0 & 1 & \gamma_{1,2} & \gamma_{1,3} \\ 0 & \delta_2 & 0 & \gamma_{2,1} & 1 & \gamma_{2,3} \\ 0 & 0 & \delta_3 & \gamma_{3,1} & \gamma_{3,2} & 1 \end{bmatrix}$$

Metaparameters were set based on the rules explained in section *Extraction* - values are presented in Table1.

Table 6: Metaparametrs for Sims-Zha Bayesian SVAR

Symbol	λ_0	λ_1	λ_3	λ_4	λ_5	μ_5	μ_6
Value	0.3	0.75	0.4	10	1	1	0.1

Data

Data are of monthly frequency and cover period Jan 2001 - Jun 2018. Consumption and production was taken from Federal Reserve Bank of Saint Louis database. Employment was approximated using the unemployment rate, which was taken from Federal Reserve Bank of Saint Louis database. To approximate number of employed labour employment Brazil population was multiplied by an employment rate[1]. Both equity and volume of non-life insurance sold was taken from Superintendencia de Seguros Privados database.

All time series were logarithmized. First differences were used in the estimation process to guarantee stationarity.

Extracted sentiment

Leading consumer confidence index IEC was takenas a benchmark. IEC represents how confident consumers are about upcoming months. It is expected that insurance sentiment will be inversly propotional to IEC index. The more consumers are certain about the future the lesser incentives are there to buy an insurance.

Figure 4 represents that situation. Red, solid line, which is an extracted sentiment, is inverse to the leading confidence index. The sentiments towards insurance has risen in 2012 when GDP growth has started to slow down. Another sudden drop is recorded in 2014, when Brazil headed towards recession. In 2007 opposite behaviour has be recorded. Brazilian economy has accelerated from 3,2% growth in 2005 to 6,1% in 2007. Within that period sentiment towards insurance has decrease rapidly and leading consumer confidence index has risen up.

The results indicates that the more optimistic are the consumers the smaller probability they assign to wealth depreciation, therefore they are less likely to purchase any insurance products.

[1] employment rate = 1 - unemployment rate

Figure 4: Insurane sentiment vs leading costumer confidence index - Brazil

Note: *Dashed line represents IEC leading consumer confidence index, whereas red, solid line represents extracted sentiment. Values of both series were normalized. Grey areas represent recession periods.*

Forecasts

For Brazilian insurance market forecast sentiments brings significant improvement. Linear models does not perform well even with sentiment added as endogenous variable. LSTAR model though utilise sentiments quite well. Middle-term forecasts outperform the benchmark by 10%, 16% and 18% in 6-, 8- and 10- month horizon respectively. Both IEC and extracted sentiments are equally useful.

Table 7: RMSE of volume non-life insurance forecasts

Model / horizon	1 month	3 month	6 month	8 month	10 month	12 month
Benchmarks						
Naïve	118.36	112.95	120.32	124.21	125.13	121.79
Random walk	100.34	348.89	346.46	100.00	324.01	317.16
ARIMA	100.00	100.00	100.00	100.00	100.00	100.0
LSTAR	84.79	275.95	105.33	94.64	286.41	89.22
Linear models						
ARIMAX (IEC)	103.51	100.78	101.71	100.40	100.83	100.70
ARIMAX (sentiments)	101.96	97.97	98.20	99.03	98.20	98.36
Non-linear models						
LSTAR (IEC)	112.72	107.79	89.83	84.23	82.81	101.40
LSTAR (sentiments)	115.85	110.80	102.89	83.58	89.43	88.33

Values normalized to ARIMA performance.

6 Conclusion

This article presents a consistent method to extract market sentiments from historical data. The results suggests that markets consists of at least two independent groups, which follows different autoregressive processes. Market sentiments defines the ratio of two groups present on the market in a given time. The distinction of two regimes increases forecasting performance, which was modelled by LSTAR. If linear models are used (ARIMAX), no significant improvement has been found.

To extract market sentiments Bayesian SVAR is used. SVAR model is constructed to capture signals each of the agent receive. Each of the draw of $\mathbf{A_0}$ matrix creates a noise in the signals.

Extracted sentiments follows the same trends as commonly accessible consumer confidence indices. However, extracted sentiments are tailored to illustrate given market. Therefore their inclusion into forecasting models brings more accurate results. Sentiments seems to influence the market with a given delay though bringing most value in middle-term forecasts. Depending on the market, the biggest difference between model with extracted sentiments and best-performing ARIMA is from 3 to 8 months ahead.

For a Polish car industry, the car market sentiments follows similar trend as leading consumer confidence index *WWUK*. Sentiments impact is recorded within 2-,3- and 4-months ahead leading to better forecasting performance by 29%.

The delayed response of market sentiments speak in favour of its influence on business cycle, previously discussed in theoretical models [Angeletos and La'O, 2013],[Benhabib et al., 2015],[Schaal and Taschereau-Possibility to foresee upcoming truns in market trends will help both companies to better allocate resources and policy makers to react accordingly to the situation. The research was conducted on three different markets in three different countries, hence the method presented in the artcile can be easily applicable on any given market.

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