THE NATURE OF UNCERTAINTY IN ANTICIPATING AND COPING WITH CRISES: A SEMIOTIC APPROACH

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Abstract

The movements in financial markets have been modelled and interpreted through the history by various disciplines. All the economist, the psychologist, the sociologist but also the anthropologist, can provide an interesting vision useful to a better understanding of the financial phenomena. The most actively mathematical models and numerical data have been used. But even though quotations seem objective for investors, they face of overwhelming uncertainty. As the market is above all a social institution with social interaction and despite the fact that financial economics is one of the social sciences where the empirical data is the most numerous, it cannot reduce market to a set of figures. Quotations still remain social constructions and therefore the quotation does not summarize the actors communicative action but is only a reflection of it.

As an example of semiotical approach the purpose of the article is to analyze whether using Google Trends as one of the most widely used online search methods, would it have been possible to forecast the beginning of the ongoing financial crisis. In other words: would it have been possible to predict that there is a bubble in the real estate market in the USA since the beginning of 2006.

The analysis is based on online data for the period 2004-2010 and is based on the T-Statistics and regression analysis. We had an assumption that at the time when real estate prices were moving up people had suspicions about the possibility of having bubble in the prices. Our assumption found proof and all statistically significant relationships were in line with the theoretical foundations though some aspects of the results may be debatable. Nevertheless, we found that this method may be a good tool for having the indication of people´s moods and views.

1. INTRODUCTION

As it is well known, business cycles, financial cycles and economic cycles are extremely irregular in duration and timing. Over the last decades, the world economy has experienced numerous crises. First, the Wall Street crash of October 1987, a little more than two years later Japan´s stockmarket bubble collapsed, Europe´s exchange rate mechanism had its debacle on 1992-93, then in 1994 the bond market crashed, same year, a bit later, the Mexican crisis occured, in 1997 East Asia went into turmoil, a year later Russia´s default and associated shockwaves shook the world until recent 2008 crisis. Economists have used a lot of time to study what are the causes for these cycles and experts continuously readjusting their interpretations and estimates to crisis trajectory, speed and causes.

Recent events remind us how vulnerable are financial institutions and markets to financial contagion, where one failing institution takes many others down and starts a cascade of failures. Same happened in the second half of the 2008 when Lehman Brother field to bancruptcy. This event was a sign which symbolic meaning caused panic in financial markets and in global economy as well. Large financial institutions came under stress; banks, faced with fears about infection, rationally sought to protect themselves from other banks and restricted their lending policy. Because of the uncertainity and fear banks caused persistent stress in financial markets. The same phenomena characterizes stronger, financially stable countries as well, where apparently healthy fundamentals and praised policies were not left unaffected.

This paper tries to show that analysing and predicting causes of the large fluctuations and crisis is a result of human behaviour and often irrational. As mathematical models are imperfect taking into consideration human factors and social reality then interdiscilpinary approach is needed.

The purpose of the paper is to improve the necessity of new methodological approach in explaining and considering human behavior, collective factor and social reality as well as sign process, semiosis and action mechanism itself. In order to better grasp the influence and contagious effect of the irrationality the paper gives an example of the spread of U.S recent crises which would have been predictable by using an alternative measure of economic uncertainty based on the frequency of internet searches.

The paper is divided into five parts. First one explains the phenomenon of semiotics in the context of financial markets. The other gives an example of using alternatiive method for getting information about the ngoing situation and predicting the futuure. Third one presents empirical data about the real estate bubble and explains the methodology used. The next section provides results of regression analysis and the discussion of the results. The paper ends with conclusion.

2. SEMIOTICS IN THE CONTEXT OF FINANCIAL MARKETS

History has proved that market habitually overreacts and underreacts to events that has influence to human emotions and behaviour. So is the history of markets seen as a complex set of recurrent human errors. As it is seen, human thinking and behaviour is the key element in financial markets that collectively acting similarily causes the fluctuations of the markets because the psychology, rationalization and investing behavior of a individual investor is directly related to the thinking, feeling and acting of all investors.

Financial markets represent a very complex social reality that may take various forms. Elements and sets of figures with esoteric meaning base in representations. Markets represent a unique playground that performs an enormous role in global economy and our everydays´ life. This complexity may be reduced to qualitative or quantitative explaining frames but none of them gives no satisfactory results. An ultimate explanation of the financial markets does not exist.

As reality is very complex phenomena that consists of texts and contexts and is dependent in time and space on interaction and other variables then, based on logic and logical models, every object of research dictates its´ approach.

Semiotics researches the reality and the relationship between human mind and its reality. Julia Kristeva, a philosopher, sociologist, psychoanalyst and literary critic, defines semiotic research as activity during which new models with similar structure to research object will be constructed. „Semiotics uses linguistic, mathematical and logical models, demystifying through them assumed objectivity of the scientific discourse“ (Kristeva 1969: 196-204; Nöth 1992).

A semiotics in the context of financial markets assumes that we analyze the quotation and its meaning in a particular surrounding world. For each financial market, a pluralist study of the interaction structure would deserve to be carried out. It means studying the factors that determine the quotations in a particular financial market. Because of the fact that financial interaction is directly inserted into the complexity of the social world, a semiotics of the financial market assumes an interdisciplinary study of the quotation determination process.

Financial markets are described by inadequate prior information; they include many variables and are characterized by fuzzy elements. Market structures are extremely difficult for analytical description, and their dynamics is hard to predict. Therefore the study of the financial markets behavior is a very actual question. When investors approach the financial markets, they find they need to make decisions in the face of overwhelming uncertainty. Even though the quotations seem objective for investors, they remain social constructions and therefore the quotation does not summarize the actors communicative action but is only a reflection of it. As an example we analyze the result of the agents reactions to the real estate prices in U.S. from 2004-2010 and their suspicions for having bubble in the prices.

3. AN EXAMPLE OF USING GOOGLE TRENDS FOR PREDICTING THE FUTURE

The goal of the experiment was to investigate whether it would have been possible to forecast the ongoing financial crisis by using Google Trends database. The analysis is based on online data for the period 2004-2010 and is based on the T-Statistics and regression analysis.

The theoretical motivation bases on findings that agents respond to increased uncertainty by intensifying their information search. We had an assumption that at the time when real estate prices were moving up people had suspicions about the possibility of having bubble in the prices. Our assumption found proof and all statistically significant relationships were in line with the theoretical foundations. So the research proved that using Google Trends as one of the additional tools for getting information or indication predicting the present is an alternative mechanism for getting more information about people´s thoughts and moods.

The purpose was to investigate whether it would have been possible to foresee the housing market sharp drop in prices by using the search term “Housing bubble” frequency in one of the most used online search engine Google Trends. Google Trends is a real-time daily and weekly index of the volume of queries.

Theoretical considerations are following: as the prices in real estate market had for long time risen, there could have been suspicion that prices are reaching or have already reached to a higher level than the houses actually worth are. In other words, there could have been the suspicion that part of the price is so called a bubble. In this situation it is natural looking for the further information for getting better picture about the situation and most probably people use internet and different search engines. As Google is the most widely used search engine people put relevant keywords into searching window and they´ll get information about the topic they´re interested. So there is an assumption that because of fear or greed or just curiosity the frequency of the search terms like “Housing market bubble” or “housing bubble” most likely increased just before the real bubble in U.S. real estate market.

4. METHODOLOGY AND DATA

Data:

- The average real price of the housing market in U.S., 2004-2010, quarterly data
- The frequency of the keyword “Housing bubble” entered in United States into Google Trends search engine, 2004-2010, weekly data

Dependable variable in the model is the average real price (PRICE) in the U.S. and independent variable the frequency of the keyword “Housing bubble” (FREQUENCY). Therefore we have a model in the form of:

PRICE = a_0+a_1*FREQUENCY+u

Graphic survey of the data confirms the initial hypothesis.

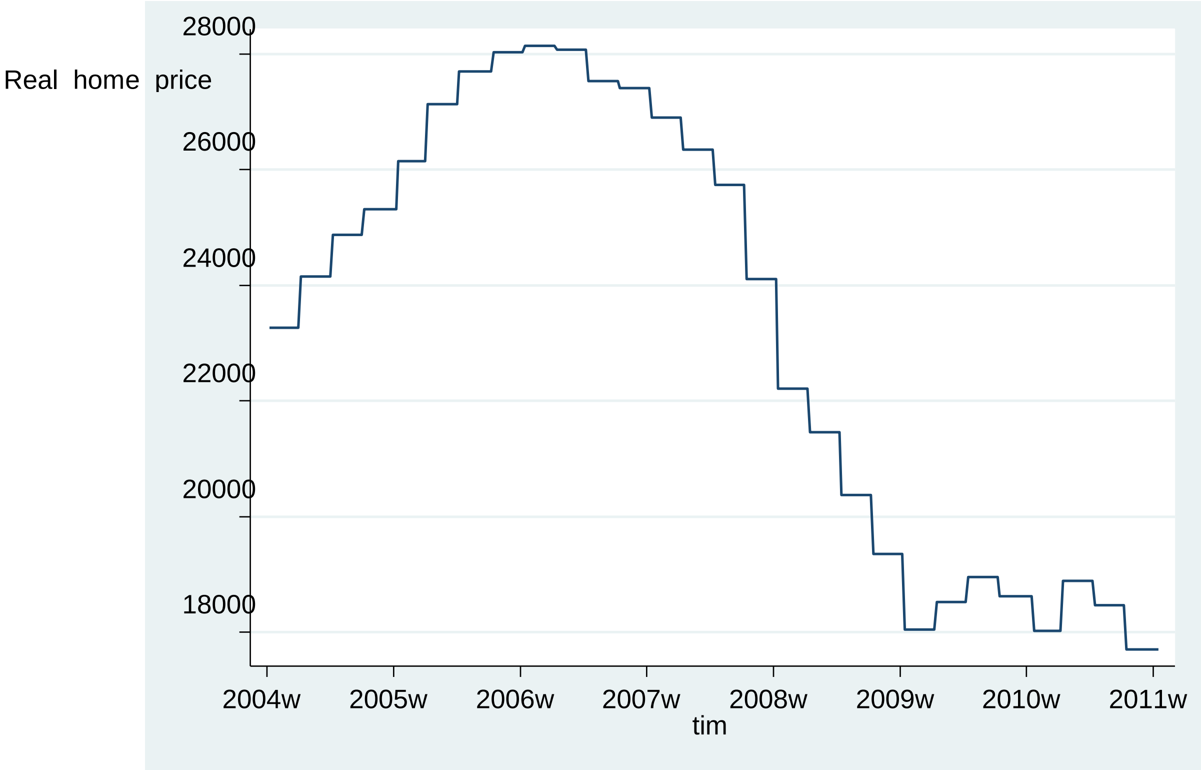

Figure 1. Price of the housing

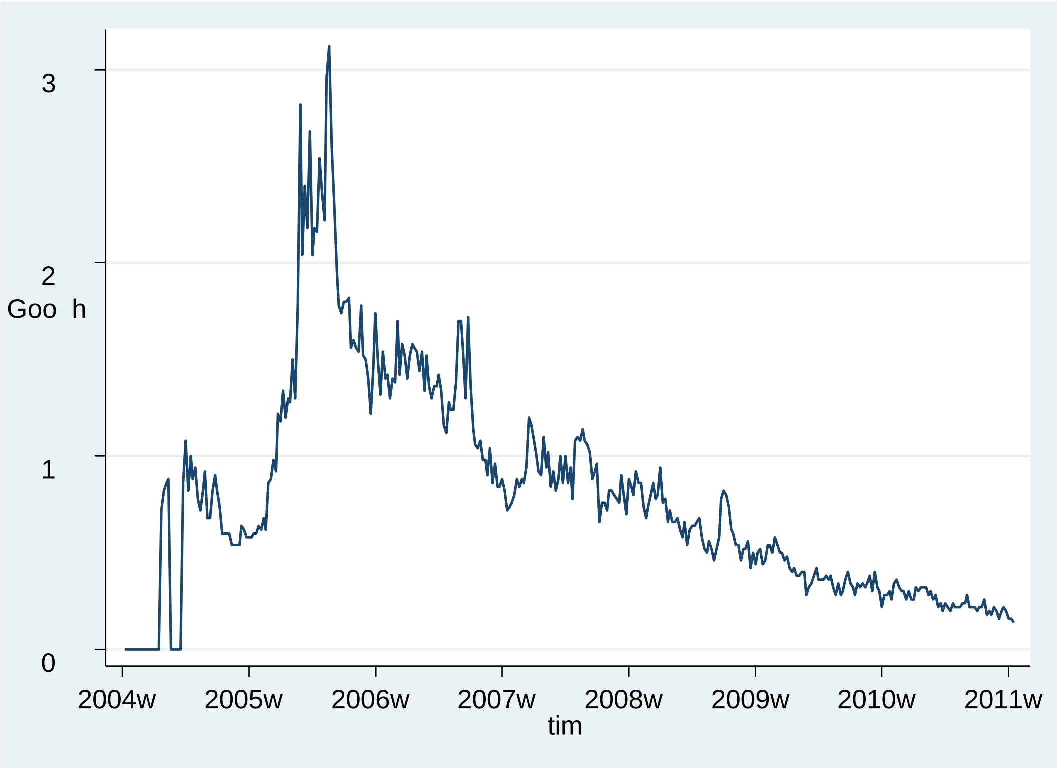

Figure 2. Search frequency of the “Housing bubble”

As it is seen in the results and figures, after relatively stable value in real estate sector in 2004 the frequency of the “housing bubble” is rising rapidly in the 2005. This is an indication that investors did have doubts about the sustainability of such growth and they begin to suspect that they might invest into the bubble. As a major part of the agents were not rational and they expected the tendency of the growth to be continued, the prices of the houses followed their rapid upward trend.

The frequency of the ´housing market bubble´ remained at a very high level until the end of the 2006 and started to decline after the burst of the housing market bubble when the prices began to fall rapidly.

It is important to mark one peculiarity of the model. The link between the variables PRICE and FREQUENCY is not expected throughout the whole period but especially at a very high level of a variable frequency value. We assume that the high value of the FREQUENCY will result in a delayed decrease in the variable PRICE. Therefore there is included an additional variable dummy D which has a value of 1 when a variable frequency value is more than 1.5 times the arithmetic average of the variables, and otherwise it is equal to 0. The model thus acquires a shape:

$PRICE = a_0+a_1*FREQUENCY+a_2*D+u$

By theoretical considerations the parameter a2 could thus be negative. Parameter a1 should come as positive because there is an assumption that people will search more when the prices are high and when the prices are falling they search less. But it is quite difficult to assume the causal link between the values of the same period. Rather there is assumption that the frequency affects the price. The impact of the frequency to the price should be unfold rather at a certain time lag which means that it is necessary to include the lags of the variable FREQUENCY.

As we have the data where FREQUENCY is given by weekly data and PRICE as quarterly then the value of the variable PRICE values each week by the corresponding quarter of its average value which means that the variable values are changing after every 13 period.

Taking into account the mentioned issues, there is switched into model the lag of the FREQUENCY in the time periods of 13, 26, 39 and 52.

$PRICE = a_0+a_1*FREQUENCY+a_2*D+a_3*FREQUENCY(-13)+a_4*FREQUENCY(-26)$
$+a_5*FREQUENCY(-39)+a_6*FREQUENCY(-52)+u$

This means that the impact to the price is tested quarterly, by half-year period, three-quarter period and yearly.

Since we are dealing with time series there is a risk that there may be included the trend in the data. By controlling it we have included into model the time as additional variable where each value corresponds to the sequence number of the each observation in chronological order. Thus the model acquires a shape:

$PRICE = a_0+a_1*FREQUENCY+a_2*D+a_3*\ FREQUENCY_{(-13)}+a_4*\ FREQUENCY_{(-26)}+a_5*\ FREQUENCY_{(-39)}+a_6*\ FREQUENCY_{(-52)}+a_7*TIME+u$

5. RESULTS AND DISCUSSION

As it is seen from the table below the evaluated model is statistically important and significant level (93%) and with a good level of description. Both, the frequency and D (the significance level of the latter is 0.1) are statistically significant variables with logical signs. When the frequency of the ´housing market bubbles´ is very high (D=1) then the price of housing is lower. Also, all of the remaining variables in the model are statistically significant.

Source	SS	df	MS
Model	4.8063e+11	7	6.8662e+10
Residual	3.6867e+10	306	120481704
Total	5.1750e+11	313	1.6533e+09

Number of obs	= 314
F(7, 306)	= 569.89
Prob > F	= 0.0000
R-squared	= 0.9288
Adj R-squared	= 0.9271
Root MSE	= 10976

Real_home_~e	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
Goo_h_b	9646.799	2880.346	3.35	0.001	3979.008	15314.59
Dummy	-5091.939	2698.594	-1.89	0.060	-10402.09	218.2104
Goo_h_b						
L13.	5927.235	2349.337	2.52	0.012	1304.334	10550.14
L26.	7915.799	2360.404	3.35	0.001	3271.123	12560.48
L39.	6330.743	2169.044	2.92	0.004	2062.614	10598.87
L52.	8081.417	1687.49	4.79	0.000	4760.864	11401.97
trend	-287.8292	14.47703	-19.88	0.000	-316.3163	-259.3421
_cons	259048.5	5348.721	48.43	0.000	248523.5	269573.4

Thus, we can write the model as:

$$PRICE = 259049 + 9647FREQUENCY - 5092D + 5927FREQUENCY_{-13} + 7916FREQUENCY_{-26} + 6331FREQUENCY_{-39} + 8081FREQUENCY_{-52} - 288TrREND + u$$

Negative sign of the trend is not very logical. Most probably it is not a linear trend. Since the figures were rather similar to hyperbole, we tried to bring into model the trend taken into squares but anything significant changed and the variables of the trend causes the multicollinarity.

Source	SS	df	MS
Model	4.9001e+11	8	6.1251e+10
Residual	2.7488e+10	305	90124124.6
Total	5.1750e+11	313	1.6533e+09

Number of obs =	314
F(8, 305) =	679.63
Prob > F =	0.0000
R-squared =	0.9469
Adj R-squared =	0.9455
Root MSE =	9493.4

Real_home_~e	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
Goo_h_b	15134	2548.582	5.94	0.000	10118.97	20149.03
Dummy	-21133.85	2814.28	-7.51	0.000	-26671.71	-15595.98
Goo_h_b						
L13.	8490.844	2047.394	4.15	0.000	4462.038	12519.65
L26.	11393.21	2069.747	5.50	0.000	7320.421	15466
L39.	10073.72	1911.522	5.27	0.000	6312.275	13835.16
L52.	14368.63	1584.276	9.07	0.000	11251.13	17486.12
trend	-762.9044	48.22238	-15.82	0.000	-857.795	-668.0137
trendruut	1.198746	.1175052	10.20	0.000	.967523	1.42997
_cons	281149.7	5108.202	55.04	0.000	271097.9	291201.4

. estat vif

Variable	VIF	1/VIF
trendruut	71.99	0.013891
trend	66.57	0.015022
Goo_h_b	7.41	0.134887
Dummy	5.15	0.194102
Goo_h_b		
L13.	4.56	0.219417
L26.	4.40	0.227229
L39.	3.77	0.265159
L52.	2.75	0.363507
Mean VIF	20.83	

Diagnostics:

Multicollinarity is tested by based on VIF and 1/VIF. If the VIF is larger than 10 or 1/VIF smaller than 0,1 then there is a multicollinarity in the model. In our case there is no multicollinarity in the model.

Variable	VIF	1/VIF
Goo_h_b		
--.	7.08	0.141175
L13.	4.49	0.222773
trend	4.49	0.222822
Goo_h_b		
L26.	4.28	0.233564
L39.	3.63	0.275302
Dummy	3.54	0.282208
Goo_h_b		
L52.	2.33	0.428323
Mean VIF	4.26	

Testing the autocorrelation we have used the Durbin-Watson statisticians and the test of Breusch-Pagan. Both indicators indicate the presence of the autocorrelation in the model.

Durbin-Watson d-statistic(8, 314) = .1120546

. estat bgodfrey, lags(1 4 8)

Breusch-Godfrey LM test for autocorrelation

lags(*p*)	chi2	df	Prob > chi2
1	281.293	1	0.0000
4	286.200	4	0.0000
8	286.827	8	0.0000

H0: no serial correlation

The Ramsey test gives no good results which might indicate to specification errors in the model.

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Ramsey RESET test using powers of the fitted values of Real_home_price
       Ho:  model has no omitted variables
                 F(3, 303) =    258.94
                  Prob > F =      0.0000
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The ARCH-LM test provides the evidence that there is also an autoregressive heteroskedastivity in the model.

LM test for autoregressive conditional heteroskedasticity (ARCH)

lags(p)	chi2	df	Prob > chi2
1	247.869	1	0.0000
13	244.408	13	0.0000
26	243.337	26	0.0000

H0: no ARCH effects vs. H1: ARCH(p) disturbance

Thus we can say that there still has a possibility for improvements but on the positive side the model is statistically significant and with a good level of description and it is also consistent with the logic of the signs of the parameters in the model and there exists no multicollineary. We tried to improve the model in the following way. Since it is assumed that there is relation only with the high frequency and with the lag, then it is reasonable instead of ordinary dummy variable and lags to bring into model accordingly the lags of 13, 26, 39 and 52 dummy variables. We got the model:

$PRICE = a_0+a_1*FREQUENCY+a_2*D13+a_3*D26+a_4*D39+a_5*D52+a_7*TIME+u$, where D13, D26, D39 and D52 are accordingly dummy variables of the period lags of 13., 26., 39. and 52.

Source	SS	df	MS
Model	4.9236e+11	6	8.2060e+10
Residual	3.6110e+10	359	100584013
Total	5.2847e+11	365	1.4479e+09

Number of obs =	366
F(6, 359) =	815.84
Prob > F =	0.0000
R-squared =	0.9317
Adj R-squared =	0.9305
Root MSE =	10029

Real_home_~e	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
Goo_h_b	23640.61	1396.264	16.93	0.000	20894.73	26386.5
D13	-2966.735	2538.278	-1.17	0.243	-7958.496	2025.027
D26	12104.67	2626.862	4.61	0.000	6938.696	17270.64
D39	8494.707	2605.31	3.26	0.001	3371.121	13618.29
D52	18553.06	2073.632	8.95	0.000	14475.07	22631.05
trend	-203.9401	5.635977	-36.19	0.000	-215.0238	-192.8564
_cons	243566.7	1739.596	140.01	0.000	240145.7	246987.8

Now we carry out a regression analysis. Additionally to the searching frequency of the housing bubble is added an independent variable with 4 lags and dummy (High_bub_sf) with the value of 1 when the frequency is very high or significantly increased and in other cases with the value of 0.

Housing price (realhomeprice) with the first-order difference:

Source	SS	df	MS
Model	356962637	6	59493772.8
Residual	911527265	16	56970454.1
Total	1.2685e+09	22	57658631.9

Number of obs =	23
F(6, 16) =	1.04
Prob > F =	0.4339
R-squared =	0.2814
Adj R-squared =	0.0119
Root MSE =	7547.9

D. realhomepr~e	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
housingbub~s						
D1.	82339.69	76135.74	1.08	0.296	-79060.87	243740.3
LD.	217343.6	178536.1	1.22	0.241	-161136.1	595823.2
L2D.	72617.57	88360.92	0.82	0.423	-114699.2	259934.4
L3D.	-62814.14	65292.17	-0.96	0.350	-201227.4	75599.08
L4D.	4497.197	27367.06	0.16	0.872	-53518.38	62512.78
High_bub_sf	-22337.44	13781.58	-1.62	0.125	-51553.08	6878.21
_cons	384.2079	3295.183	0.12	0.909	-6601.267	7369.683

Housing price (realhomeprice) with the second-order difference:

Source	SS	df	MS
Model	168594355	6	28099059.2
Residual	944087364	16	59005460.2
Total	1.1127e+09	22	50576441.8

Number of obs	= 23
F(6, 16)	= 0.48
Prob > F	= 0.8162
R-squared	= 0.1515
Adj R-squared	= -0.1667
Root MSE	= 7681.5

D2. realhomepr~e	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
housingbub~s						
D1.	-23709.06	77483.61	-0.31	0.764	-187967	140548.8
LD.	30880.29	181696.8	0.17	0.867	-354299.7	416060.3
L2D.	80925.46	89925.22	0.90	0.382	-109707.5	271558.4
L3D.	-104902.5	66448.07	-1.58	0.134	-245766.1	35961.08
L4D.	2889.806	27851.56	0.10	0.919	-56152.85	61932.47
High_bub_sf	-2503.232	14025.56	-0.18	0.861	-32236.1	27229.63
cons	249.3372	3353.519	0.07	0.942	-6859.805	7358.479

We can see that none of the variables in the model is not statistically significant. Thus it seems that it is not relevant to describe with the frequency of "housing bubble" the prices of the housing. It means that we need additional variables. However, leaving out the model the lag of the 4th variable we got the results where dummy variable becomes important (if the dependent variable is in a model as first-order difference):

Source	SS	df	MS
Model	487806282	5	97561256.4
Residual	919136788	18	51063154.9
Total	1.4069e+09	23	61171437.8

Number of obs	= 24
F(5, 18)	= 1.91
Prob > F	= 0.1425
R-squared	= 0.3467
Adj R-squared	= 0.1652
Root MSE	= 7145.8

D. realhomepr~e	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
housingbub~s						
D1.	81605	71149.13	1.15	0.266	-67873.77	231083.8
LD.	251719.3	142614.4	1.77	0.095	-47902.34	551340.9
L2D.	61211.7	61866.38	0.99	0.336	-68764.75	191188.1
L3D.	-43487.4	35158	-1.24	0.232	-117351.6	30376.83
High_bub_sf	-24876.77	10512.39	-2.37	0.029	-46962.48	-2791.056
_cons	865.7023	2611.375	0.33	0.744	-4620.593	6351.998

6. CONCLUSION

Uncertainty governs our lives. The expectations and actions of markets rely not just accurate calculation of probabilities about the future but are the result of the collective action that is directed by social or mass media, personal experience, expert opinion, social convention etc. Besides, the calculations of probabilities based on past history may be misleading or even radically inaccurate.

We studied the predictability of search trends using most popular Google search queries and based on the event of the U.S real estate bubble which has caused the global financial crisis. We assumed that long before the bubble had burst, people should have had suspicions about the sustainability of the high prices of the houses. Therefore we expected them for getting further information about the relevance of the prices and first place is to find some news and articles about the topic with typing into Googles´ search window relevant keywords. We found that peoples´ interest about the housing bubble was extremely high in the years of 2005 and 2006 and our assumption found improvement. Still our model is not giving any perfect results and there is still possibilities for improvements. However the research question and the model gave us a good additional indication about the people´ mood and suspicions which may help us in the future by predicting the trends and short-term movements in different spheres.

As human behaviour influences market, it could be besides fundamentals and technical analysis useful to analyze the causes what and how influences human behaviour and how individual behaviour becomes collective. It could be useful not only in prospective but in retrospective as well.

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