

NONLINEAR MODELING OF FINANCIAL STABILITY USING DEFAULT PROBABILITIES FROM THE CAPITAL MARKET

Lucian Liviu ALBU¹
Radu LUPU¹
Adrian Cantemir CĂLIN²
Iulia LUPU³

Abstract

Our study relies on a general assumption that prices contain a rational component, which is consistent with the rational expectations theory, and an irrational one, better explained by behavioural economics. We decompose the probabilities of default computed by Bloomberg for the listed Romanian companies by filtering the irrational component with newly proposed gauges. To check for the relevance of the rationality component, we use MiDaS models to study the relation with sectoral GDP gap dynamics for the corresponding companies. Employing regression related methods, we further divide the irrational part of default probabilities into a measure for fear and a measure for habit. After each transformation, we check the connection with the corresponding sectoral GDP gap. Our objective is to investigate the extent to which there is a connection between the macroeconomic expected activity, measured by the sectoral GDP gap and the risk of companies listed at the Bucharest Stock Exchange, quantified by probabilities of default. We embark on this journey with the assumption that the irrational component obfuscates the above-mentioned connections.

Keywords: probabilities of default, fear, loss aversion, asymmetric volatility, day-of-the-week-effect, MiDaS regressions

JEL Classification: G12, G41, G17

1. Introduction

A wide body of literature has been focusing on the investigation of connections between macroeconomic variables and financial markets in general. The main conclusion is that a functional capital market, with important levels of liquidity is a clear support and an efficient

¹ Institute for Economic Forecasting, Romanian Academy.

² Institute for Economic Forecasting, Romanian Academy, Bucharest University of Economic Studies. Corresponding author: cantemircalin@gmail.com.

³ "Victor Slăvescu" Centre for Financial and Monetary Research.

tool for the movement of capital. Additionally, an efficient capital market is ready to produce prices that provide expectations about the development of the real economy, reflecting the price discovery through bidding impulses from a large mass of investors in their pursuit to anticipate market dynamics. Hence, a connection of prices with the macroeconomic variables is theoretically well substantiated.

However, due to various measuring techniques and statistics, diverse models and accounting standards, the empirical studies failed to validate this connection in a consistent manner.

Among these series of reasons for lack of validation, we investigate the extent to which behavioural traits, such as habit and fear present in the price dynamics, could obfuscate these connections. Therefore, we extract these components from market dynamics in a succinct manner and we investigate the connections with the real economy at every step.

Given the fact that stock market prices are rather noisy we decide to use probabilities of default as proxies for market dynamics. These probabilities of default are extracted from the Bloomberg platform and they reflect a larger spectrum of market perspectives since they are functions of stock prices and the leverage ratio, taking into account the specific capital structure for each company.

The remainder of this paper is organized in the following manner. Section 2 deals with a brief review of the related literature. Section 3 is dedicated to data presentation and to the methodological framework. Section 4 discusses the main findings and Section 5 concludes.

2. Literature Review

As stated above, the current investigation is related to the literature that focuses on modelling the impact of fear on financial markets. A large part of this literature uses the market volatility index (VIX) as a starting point. This index accounts for investor fear and shows the perspective concerning future market volatility. As a rule of thumb, large values of VIX are associated with an elevated level of fear in the markets.

Modern financial theories perceive financial markets through the lens of a representative agent which is intrinsically rational. This rationality assumes that agents will make choices that are consistent with the principles of the expected utility theory and that their perspective is revised and reoriented correctly when faced with new information (Barberis and Thaler, 2003). Despite this orientation, the rationality of financial conduct has been deeply disputed by a solid block of literature which focuses on the character and constitution of financial judgments and actions (De Bondt *et al.*, 2008). This behavioural standpoint advocates that irrationality is ubiquitous and visible in phenomena such as: Availability bias (Tversky and Kahneman, 1973), Overconfidence (Barber and Odean, 2001; Scheinkman and Xiong, 2003; Puetz and Ruenzi, 2011), Mental accounting (Thaler, 1999; Barberis and Huang, 2001; Chen *et al.*, 2013), Overreaction (De Bond and Thaler, 1985; Blackburn and Cakici, 2017), Herding or crowding (Brown *et al.*, 2013), Loss aversion (Zou, 2017), Myopic loss aversion (Lee, 2016), Self-control, (Thaler and Shefrin, 1981) and Regret (Qin, 2015).

This collection of phenomena, together with other elements such as excess volatility, earnings and price momentums, or size and calendar effects enforce the idea of bounded rationality which can be summarized as the difference between theoretical rational actions and the observed behaviour. Returning to the specific literature, we notice that one of the most substantial encumbrances to the idea of rationality derives from the fact that emotions tend to affect financial decision making, which in turn is observed in asset dynamics. In other

words, a solid block of research hints at the idea that financial decisions can and will be influenced by both emotions and cognitive biases.

Olson (2006) argues that emotions are visible in both individual decisions and in cumulative tendencies found on financial markets. The first category has often been associated with investor mood, having as seminal exponent the work of Hirshleifer and Shumway (2013). Main drivers of investor mood have been found to be: daylight saving, seasonal depression, sports events, lunar phases or pollution (Kim, 2017). In relation to the latter case, Shiller (1984) reports that prices can be determined by social oscillations and mass psychology. This paves the way to the idea of investor sentiment, which denotes investor emotional opinion on a future market evolution.

The literature is also abundant in defining and characterising emotions. A relevant contribution of Tellegen, Watson, and Clark (1999) differentiates between positive affect and negative affect. The first set denotes pleasant emotional situations, navigating around happiness, optimism, enthusiasm or delight. On the opposite spectrum, negative affect includes feeling such as fear, anger, regret or depression.

In this paper, we consider that prices can be fragmented into rational and irrational components. Under this assumption, we try to isolate the rational component by filtering for fear and habit. We treat investor fear as a state of anxiety deriving from the uncertainty of future market dynamics. Carleton (2016) advances the idea that the fear of the unknown (hereinafter FOTU) may be considered the “fundamental fear”. The concept was deemed earlier by Joshi and Schultz (2001) as “the oldest and strongest kind of fear” and led to the development of a solid psychological literature. Within this bracket of academic interest, several studies such as Whiting *et al.* (2016) or Carleton (2016) hint to the idea that FOTU tends to be continuously and normally distributed in the population.

As we shall see in the next section, the vast majority of the scientific literature considers VIX as a proper measure for fear. We go beyond this general approach and introduce a new gauge that relies on the difference between the volatilities estimated by means of an E-GARCH(1,1) model and a simple GARCH(1,1). To our knowledge, this is the first study that aims to cloister fear effects in such an asymmetrical setup. However, we can trace a similar orientation to the seminal approach of Bollerslev and Todorov (2011). The authors make use of the particular structure of the jump tails and the associated pricing in order to formulate a new “Investors Fears index”.

After dealing with the fear component we account for habit effects by further removing all possible traces of the day of the week effect.

Besides the design of our novel VIF index, the paper contributes to the existing literature by offering a method capable of isolating the rational component of default probabilities. Lastly, our approach put forwards a series of results for the Romanian stock market.

Previous literature shows in general the relationship between VIX and different financial elements, artefacts or markets. Giot (2005) and Whaley (2009) determine a negative asymmetric association between stock returns and VIX dynamics. Smales and Kininmonth (2006) explore the link between foreign exchange market returns and investor fear (approximated by using VIX). The main conclusion of the study is that funding currencies tend to depreciated when VIX and therefore fear increases. In addition to this, the authors report that in times of financial turmoil, currency returns are even more reactive to fear dynamics. In a similar line, Smales (2016) performs a multi-market analysis (stock markets, bond markets and FX markets for US, Australia and New Zealand) on the relation between returns and fear levels (again measured by VIX and A-VIX for the case of Australia). As

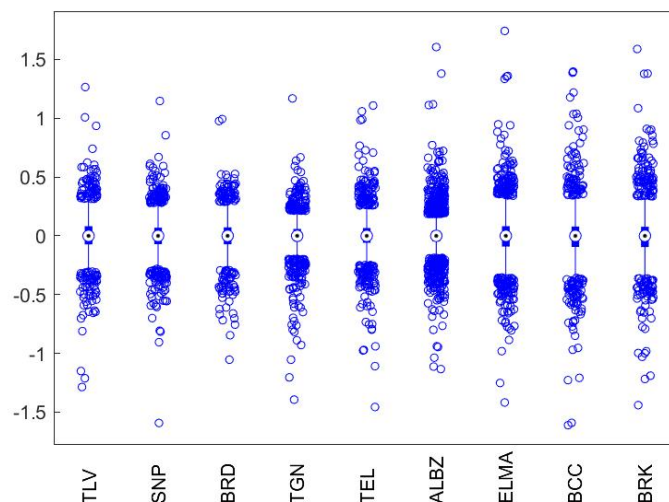
investor fear grows, the results reveal a downturn in stocks, bonds and AUD and NZD yields while the USD is found to appreciate.

Despite this strain of research, there are sparse studies that focus on alternative measures for fear. Bollersev and Todorov for example (2011) estimate a new investor fear index. It is built by observing the compensation for the variation in assets prices in relation to the compensation for the feasible eventualities of rare and vast jumps. Dhaene *et al.* (2012) aim at the same objective of constructing a new measure for the total market fear. In their approach, the new FIX index is a weighted sum of VIX, a component that accounts for liquidity and a component specific to herd behaviour and systemic risk.

3. Data and Methodology

We employed stock market data with daily frequency for the companies included in Romania's BET-XT index for the period 4th of January 2010 until 15th of November 2017. Out of the 25 companies, we eliminated those for which the data showed inconsistencies in more than 30% of the cases. This trimming procedure resulted in a set of nine companies for which we collected data regarding the probabilities of default as reported in Bloomberg. The distribution for each company is exhibited in Figure 1. The labels used in this chart are the tickers employed in the Romanian stock market

Figure 1
Distribution of the Daily Log-returns for the Nine Companies Selected for Our Analysis



Our daily probabilities of default were collected from the Bloomberg platform for each company in correspondence with the trading days selected for the log-return. These probabilities are estimated based on a Merton model that relies on the standard option pricing technique. The statistical properties of these variables are presented in Table 1

Table 1

Statistical Properties of Probabilities of Default for the Selected Companies

	TLV	SNP	BRD	TGN	TEL	ALBZ	ELMA	BCC	BRK	TLV
Mean	0.0007	0.0005	0.0006	0.0001	0.0011	0.0082	0.0011	0.0057	0.0004	0.0007
St. Dev	0.0005	0.0006	0.0003	0.0001	0.0008	0.0045	0.0017	0.0054	0.0003	0.0005
Skewness	1.1564	2.3192	0.2391	1.4865	0.7136	0.5697	1.1254	1.3905	0.5003	1.1564
Kurtosis	3.2891	7.7630	2.1504	4.8259	2.2563	3.5265	2.3772	4.0258	3.6368	3.2891
Min.	0.0002	0.0000	0.0002	0.0000	0.0001	0.0006	0.0000	0.0002	0.0000	0.0002
Max.	0.0022	0.0030	0.0013	0.0004	0.0032	0.0280	0.0041	0.0239	0.0013	0.0022

According to the mainstream approach, initiated by the seminal work of Merton (1974), the estimation of probabilities of default relies on a function that depends on prices. We build on the assumption that prices are driven by two separable sources: an irrational component and a rational one. According to this assertion, we extrapolated the analysis to consider that probabilities of default should also include these two separable sources of dynamics.

We therefore underscore that our purpose is to isolate the rational component residing in the dynamics of the probabilities of default. In order to do so, we intend to eliminate the irrational traces by means of proxies for the two key components. On the one hand, we identified a sentiment-related source, which we treat as fear, and which encompasses reactions of investors fed by loss aversion. On the other hand, we consider a source that relates to habit formation and spawns the manifestation of patterns or periodicity.

For the first component, we propose a measure for fear that relies on the loss aversion paradigm that generates larger volatilities for negative returns as opposed to positive returns and stands at the very root of a large class of asymmetric volatility models. We decided to treat the second component by means of estimating the mostly studied pattern in the literature, the day-of-the-week effect.

The first step of our approach resides in computing the difference between the results of two GARCH models calibrated for the returns of the 9 selected companies. We rely on the classic GARCH and on Nelson’s (1991) EGARCH setup, which have the following mathematical formulations.

GARCH model:

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^m \alpha_i a_{t-i}^2 + \sum_{j=1}^s \beta_j \sigma_{t-j}^2 \tag{1}$$

EGARCH model:

$$\log \sigma_t^2 = \omega + \sum_{i=1}^m \beta_i \log \sigma_{t-i}^2 + \sum_{j=1}^s \alpha_j \left[\frac{|a_{t-j}|}{\sigma_{t-j}} - E \left(\frac{|a_{t-j}|}{\sigma_{t-j}} \right) \right] + \sum_{j=1}^s \gamma_j \left(\frac{a_{t-j}}{\sigma_{t-j}} \right) \tag{2}$$

Our proposed index of fear consists in the computation of the difference between the outputs of these models. This approach is rooted in the assertion that the existence of asymmetric volatilities determines the simple GARCH model to inadvertently generate volatilities that do not reflect this phenomenon, while the simple EGARCH model is purposely designed to capture this aspect. We therefore consider that the difference between the two volatilities

could be perceived as a gauge of this asymmetry, which we decide it is fit to reflect the reluctance to negative returns.

This new fear index, referred as VIF in the rest of the document, is employed as explanatory variable in regressions where the dependent was the probabilities of default for each company in our sample.

$$PD_{t,i} = \alpha_i + \beta_i Fear_{t,i} + \epsilon_{t,i} \quad (3)$$

where: i counts the companies, t is the time index and $\epsilon_{t,i}$ are the residuals, which represent the probabilities of default filtered by fear. Given the fact that the current literature uses implied volatility indices as measures for fear, we also employed such measures for the Romanian market to allow for comparisons with our ad-hoc VIF statistic. Therefore, the explanatory variable $Fear_{t,i}$ is either VIF or a proxy for the implied volatility index, respectively. This means that we estimated two regressions for each company, one with VIF as explanatory variable and another one using the implied volatility for this role.

To filter our data from possible patterns, we used the residuals from the previous regressions as dependent variables in a set of other regressions that used dummy variables to account for the day-of-the-week effect.

$$\begin{aligned} \epsilon_{t,i}^2 = & \gamma_i + \delta_{Tues,i} DUM_{Tues,t,i} + \delta_{Wed,i} DUM_{Wed,t,i} + \delta_{Thu,i} DUM_{Thu,t,i} \\ & + \delta_{Fri,i} DUM_{Fri,t,i} + u_{t,i} \end{aligned} \quad (4)$$

where the DUM variables are the dummy variables that take the value 1 for one of the days of the week and 0 for the rest, allowing for Monday to represent the base-case. The residuals $u_{t,i}$ represent the rational probabilities of default, *i.e.* those values that were filtered by both fear and patterns. As previously mentioned, we estimated two regressions for each company: one for the VIF and another one for the classical measure of fear, a proxy for the volatility index.

During the analysis, after each filtering, we performed an analysis of the connections between the sectoral GDP gaps and the corresponding probabilities of default for the companies listed at the Bucharest Stock Exchange. Given their different frequencies, we had to use the MiDaS methodology to connect these variables. Our approach consisted in the employment of the Matlab tool developed by Ghysels (2017). For each possible connection we employ the following algorithms:

- unrestricted MIDAS polynomial approach suggested by Foroni, Marcelino and Schumacher (2005) (denoted by "UMIDAS");
- normalized beta probability density function, unrestricted and restricted cases with zero and non-zero last lag (denoted by "betaS" and "betaNNS");
- Normalized exponential Almon lag polynomial (denoted by "expAlmon");
- Almon lag polynomial of order P (denoted by "Almon");
- polynomial specification with step functions (denoted by "step").

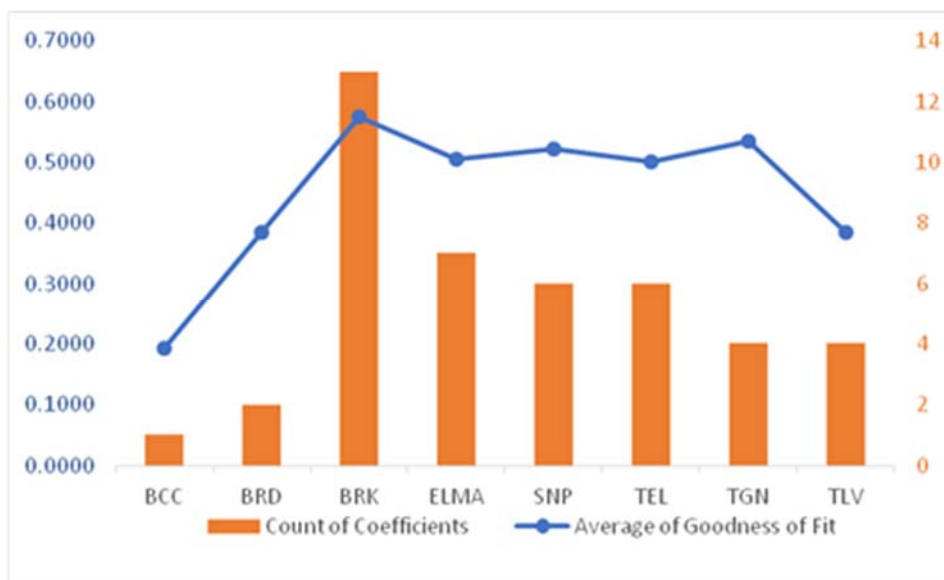
4. Results

This section exhibits the main results of our analysis that attempts to provide a new measure for fear and to offer a methodological framework for the isolation of the rational component of the probabilities of default.

In order to provide multiple perspectives for our analysis, we decided to investigate the relations by taking into account two types of series: the levels of the probabilities of default and their changes computed as first differences.

Figure 2 presents the results of the MIDAS regressions that led to significant coefficients and the corresponding values for the Goodness of fit.

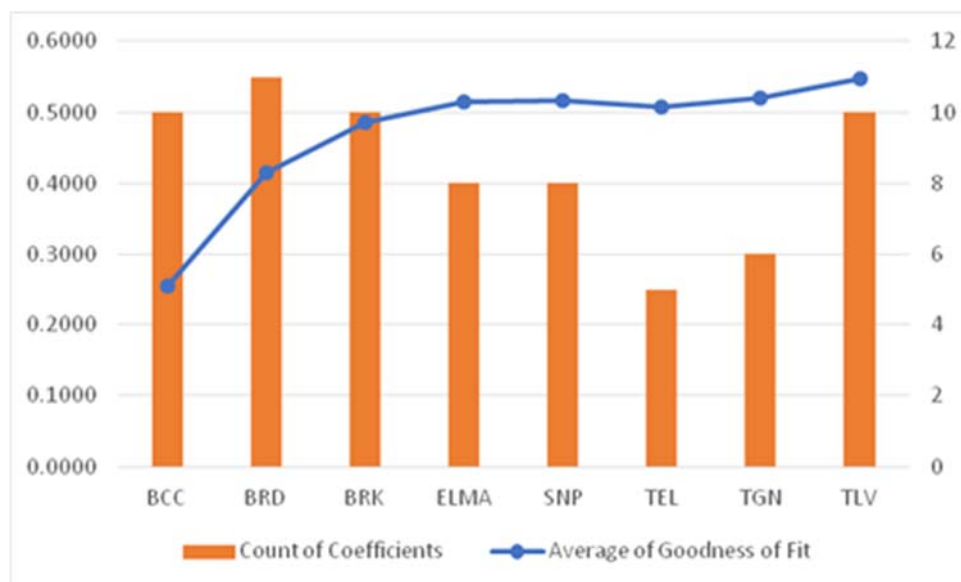
Figure 2
The results of the MIDAS regressions for the probabilities of default analysed as levels



We notice the existence of larger values for the Goodness of Fit coefficients for the series of differences as opposed to the series of levels. We could therefore consider that the changes in the probabilities of default have a higher chance to explain the dynamics of macroeconomic variables.

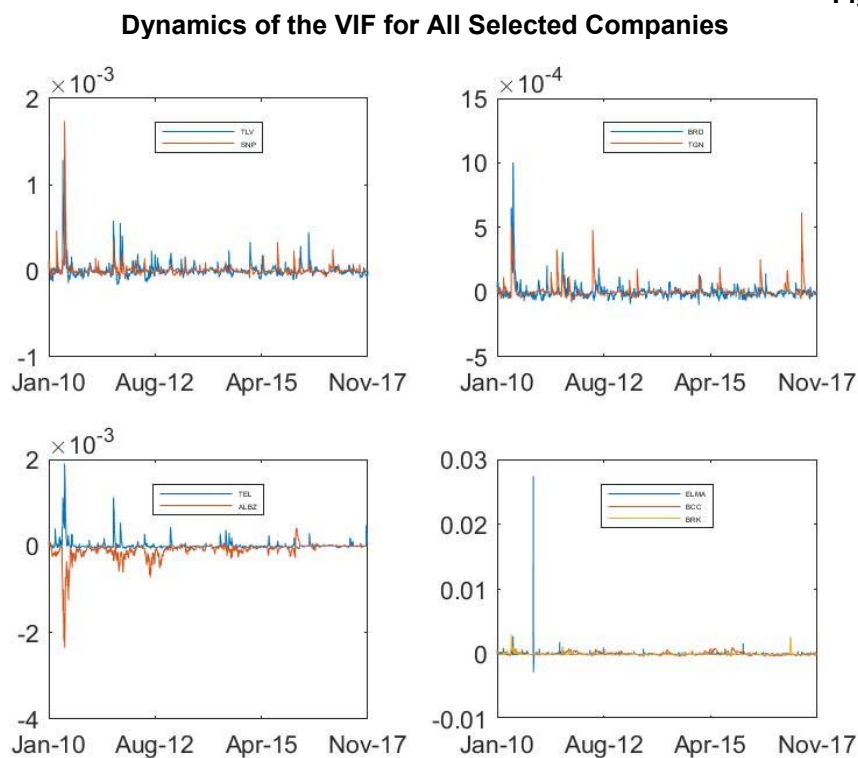
Figure 3 depicts the results of the MIDAS regressions that led to significant coefficients and the corresponding values for the Goodness of fit, this time for the probabilities of default considered as differences.

Figure 3
The results of the MIDAS regressions for the probabilities of default analysed as differences



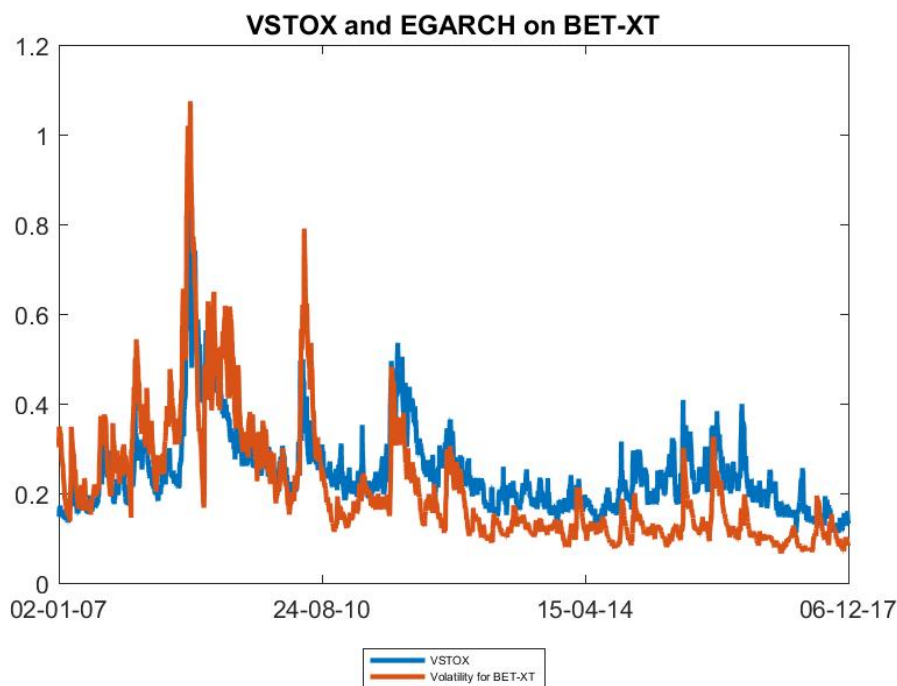
The computation of volatilities by means of both the GARCH and the EGARCH models rendered the values for our proposed fear index VIF. Figure 4 shows the dynamics of VIF for each company in our sample. We notice that the differences between these two measures are rather similar for most of the observed stocks. Our index seems to signal large values for the fear in almost the same time across the stocks in our sample. Nevertheless, we notice situations with negative values for this index, which could reveal either estimation problems for the volatility models or the existence of market exuberance for investors in the same period where large values of loss aversion are recorded for the other companies.

Figure 4



As mentioned in the methodology section, for reasons of robustness check, we also tried to use measures of fear according to the approach generally accepted in literature. Noticing that most of these approaches refer to implied volatility indices for such proxies, we attempted to develop a gauge that is meant to reflect this paradigm for the Romanian market. This effort is conducted by the fact that the Romanian stock market does not have a large-scale option market, with sufficient liquidity to allow us to estimate implied volatilities. We therefore tried to estimate one such forward-looking volatility measure by using the implied volatility index for the European stock market, *i.e.* the VSTOXX index. However, given the fact that this index is built on a portfolio of assets that does not include any of the Romanian companies, even though the two markets tend to be highly correlated, we estimated values for the forward-looking Romanian volatility. We obtained these values by extrapolating the connection between the forward-looking volatility for the European market and the historical volatility of the Romanian market in a simple linear regression.

Figure 5
The Evolution of European Implied Volatility Index and the Dynamics of
Volatilities Estimated with a Simple GARCH(1,1) Model
for the Romanian BET-XT Index



We notice in Figure 5 that the two variables have the same shape and they differ in some respect in the last period, but they feature simultaneous spikes. The results of this regression are presented in Table 2.

Table 2
Regression Results of the Volatilities of BET-XT on the Values of VSTOX

	Coefficients	Standard Error	t Stat	P-value
Intercept	0.136445	0.001971	69.242	0
VSTOX	0.503876	0.00776	64.9294	0

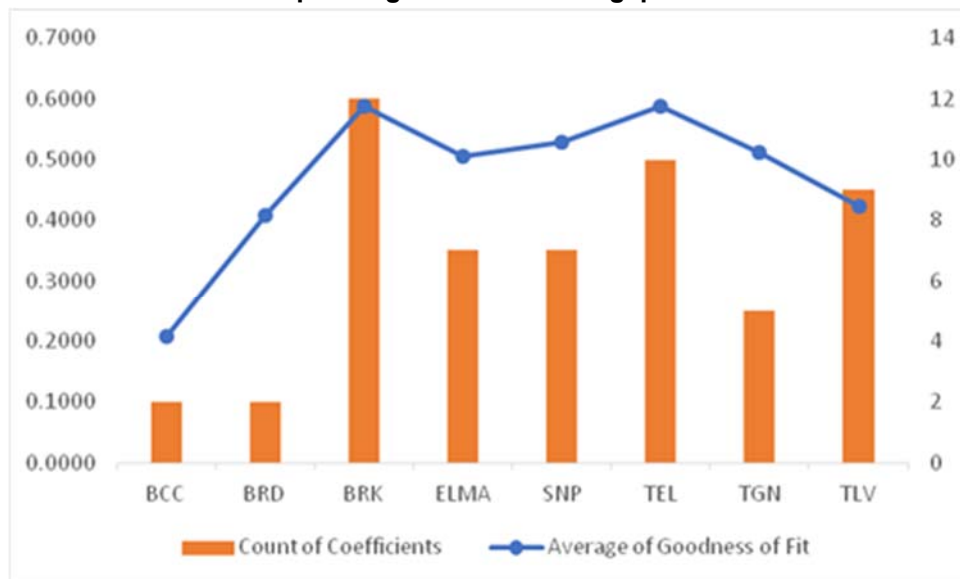
We notice that the regression provides significant results and we use them to generate forecasts for the possible evolution of the volatilities of the Romanian stock market in order to develop a measure of fear that resembles the mainstream approach to measuring this sentiment.

Figure 6 exhibits the results of the MIDAS regression that rendered significant coefficients together with their corresponding values for the Goodness of fit for the series of residuals

from the first regressions with the corresponding sectors of GDP gaps. For this case, the initial values of probabilities of default were employed as levels.

Figure 6

The results of the MIDAS regressions for the first regressions with the corresponding sectors of GDP gaps - levels



We notice that the regressions that take into account the levels of probabilities of default tend to be more significant for the residuals of the first regression as compared with the raw data (before filtering). For the differences, we notice similar results.

In a similar way to Figure 6, Figure 7 shows the results of the MIDAS regression that rendered significant coefficients together with their corresponding values for the Goodness of fit for the series of residuals from the first regressions with the corresponding sectors of GDP gaps. The difference from the above-mentioned case resides in the fact that at this point the initial values of probabilities of default are treated as differences.

Figure 7

The results of the MIDAS regressions for the first regressions with the corresponding sectors of GDP gaps - differences

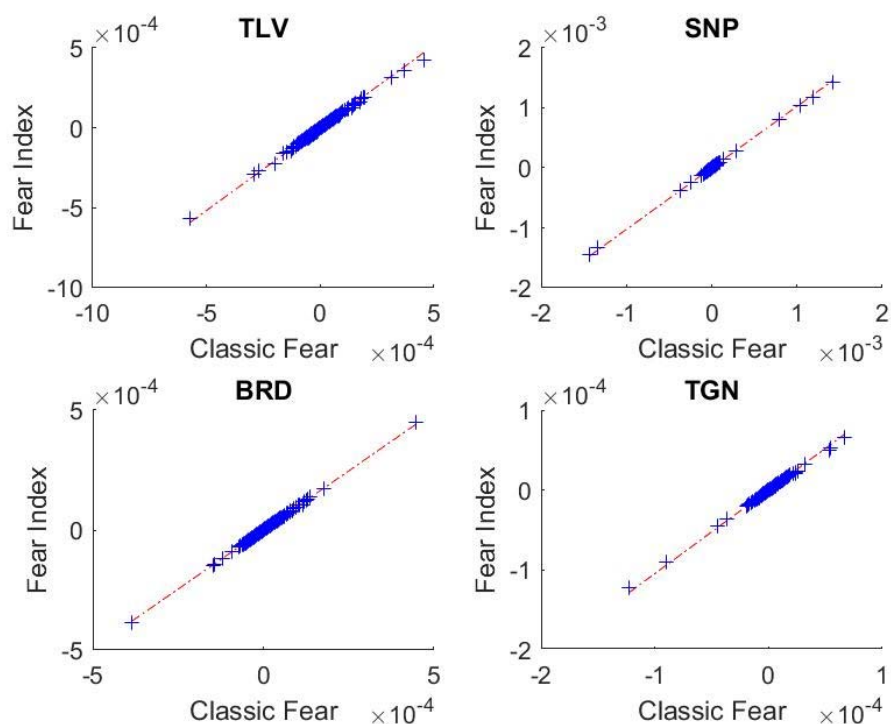


As mentioned in the Methodology section, we made two types of estimates: on the one hand, we estimated regressions in which the dependent variable was the proxy for the classical measure of fear. To do so, we used the forecast from the regression we mentioned above (with results presented in Table 2) as explanatory variable in a regression in which the dependent variable was the first difference of the series of probabilities of default. The resulted residuals were considered proxies for the volatilities of default, filtered by the effect of the fear sentiment.

These filtered probabilities were further employed as dependent variables in a regression in which the dependent variables consisted in a set of dummy variables that account for each day of the week, excepting Monday. The resulted second order residuals are representatives of probabilities of default filtered by both fear and day-of-the-week pattern.

Figure 8

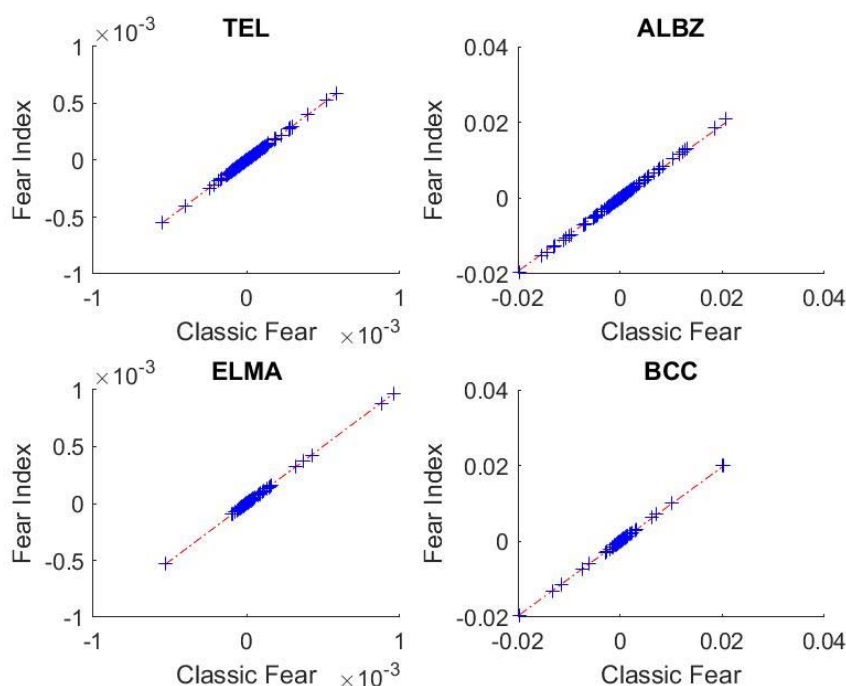
The Evolution of European Implied Volatility Index and the Dynamics of Volatilities Estimated with a Simple GARCH(1,1) Model for the Romanian BET-XT Index



On the other hand, we followed the same logic and built the same set of residuals in regressions where the explanatory variables were the values of the VIF indices and the same dummy variables in the second regression.

Our analysis compares the two series of residuals: the series obtained from using the VIF as explanatory variables and the ones in which the classical measure of fear was employed. Figures 8 and 9 exhibit an investigation of the distributional properties of these two series of regressions for the companies in our sample. We notice that the quantile-quantile plots show very similar distributions as the values lie on the first diagonal. However, we observe that a large concentration of the values is situated in the middle, with some spikes that deviate from the mean. This is proof that the distributions are not normal but that the deviations from normality are systematically the same for the two series of filtered probabilities of default, as all these values are situated on the first diagonal.

Figure 9
The Evolution of European Implied Volatility Index and the Dynamics of
Volatilities Estimated with a Simple GARCH(1,1) Model
for the Romanian BET-XT Index



In order to investigate these probability distributions, we computed the first four moments and ran the Jarque-Bera test for each company both for the probabilities of default filtered with the classical estimation of fear and with the VIF index.

The results of these computations are presented in Tables 3 and 4. We notice that the p-values for the normality tests are very low, which provides support for the argument that the distribution of the “rational” probabilities of default is not normal.

Table 3
Distribution Properties of Residuals from the Classic Estimation of Fear

	Mean	St. dev.	Skewness	Kurtosis	Jarque-Bera p-value
TLV	1.60E-22	3.45E-05	-3.90E-01	7.15E+01	0.001
SNP	-2.29E-21	6.89E-05	1.09E+00	3.28E+02	0.001
BRD	-4.97E-22	2.31E-05	1.80E+00	1.15E+02	0.001
TGN	-7.41E-23	4.95E-06	-7.94E+00	2.74E+02	0.001
TEL	3.29E-21	4.20E-05	1.56E+00	6.05E+01	0.001
ALBZ	1.10E-19	1.46E-03	3.35E-01	8.93E+01	0.001
ELMA	-4.02E-21	3.63E-05	1.64E+01	4.49E+02	0.001
BCC	-1.66E-20	8.62E-04	-1.56E+00	3.33E+02	0.001
BRK	-4.74E-21	2.77E-05	4.02E+01	1.75E+03	0.001

An analysis of the values of these statistics reveals that they have dynamical properties that resemble those of the log-returns, with large values for skewness and kurtosis, mean values very close to zero and very low values for the standard deviations. The existence of changing standard deviations is also supported by the large values of kurtosis.

The similarity of these statistical properties for the two series of filtered probabilities provides evidence that our proposed measure of fear has the same effect as the classical approach.

Table 4

**Distribution Properties of Residuals from the VIF Proposal
for the Estimation of Fear**

	Mean	St. dev.	Skewness	Kurtosis	Jarque-Bera p-value
TLV	-2.07E-21	3.43E-05	-7.55E-01	6.80E+01	0.001
SNP	-3.12E-21	6.89E-05	1.12E+00	3.28E+02	0.001
BRD	3.74E-22	2.31E-05	1.78E+00	1.15E+02	0.001
TGN	-2.72E-22	4.92E-06	-8.21E+00	2.76E+02	0.001
TEL	3.73E-21	4.20E-05	1.57E+00	6.06E+01	0.001
ALBZ	6.39E-20	1.46E-03	3.38E-01	8.93E+01	0.001
ELMA	-5.32E-21	3.63E-05	1.64E+01	4.49E+02	0.001
BCC	1.91E-20	8.62E-04	-1.59E+00	3.34E+02	0.001
BRK	-4.63E-21	2.77E-05	4.02E+01	1.75E+03	0.001

Figure 10 focuses on the second batch of regressions with the corresponding sectors of GDP gaps and presents the results of the MIDAS regressions that resulted significant coefficients together with their corresponding values for the Goodness of fit for the series of residuals when the initial values for the default probabilities have been employed as levels.

Coming back to the regressions of residuals from the second regression with respect to the corresponding sectoral GDP gaps, we notice that for the series of levels in probabilities of default, the number of significant regressions is rather similar with the one obtained after the first regressions, and better than the situation obtained for the regressions with the raw data.

Figure 10

The results of the MIDAS regressions for the second regressions with the corresponding sectors of GDP gaps - levels

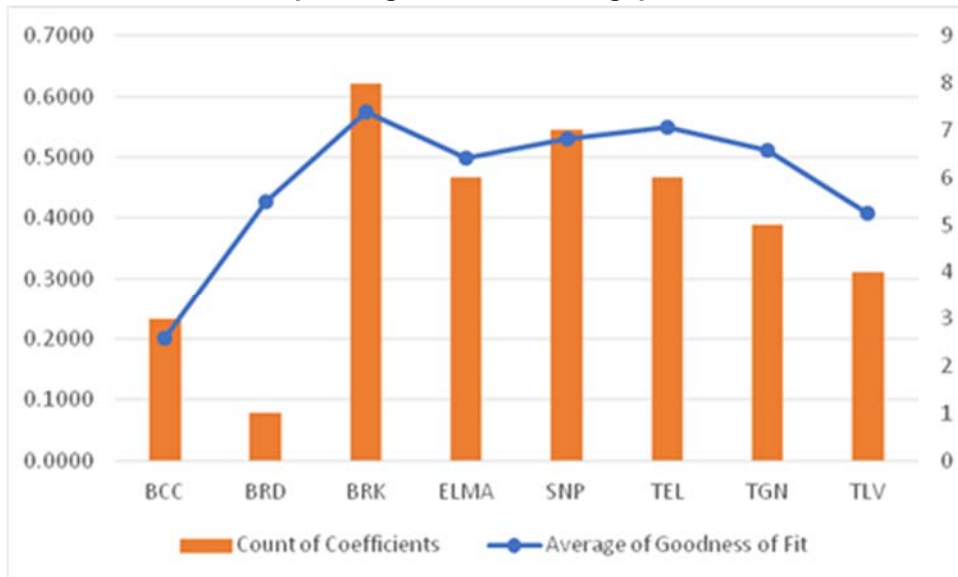


Figure 11

The results of the MIDAS regressions for the second regressions with the corresponding sectors of GDP gaps - differences

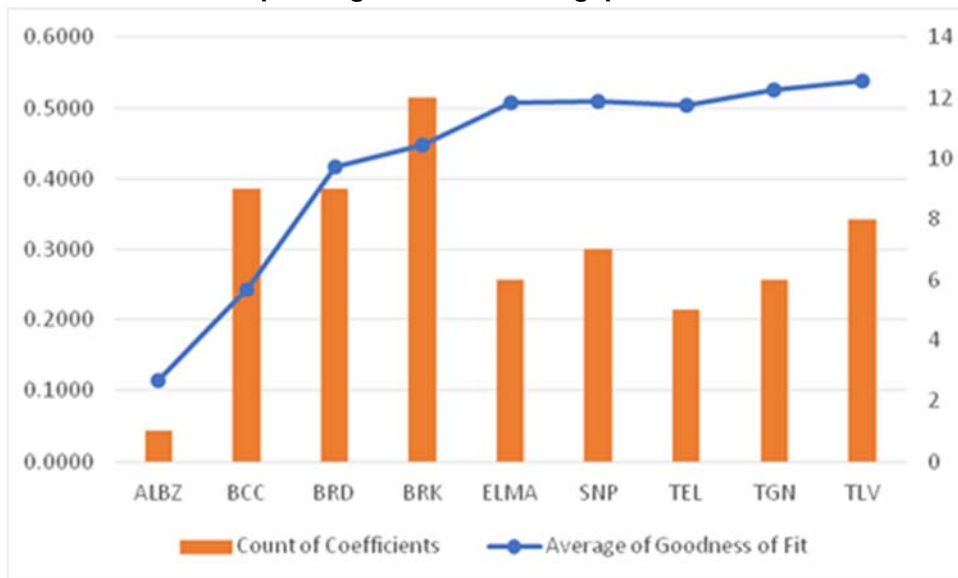


Figure 11 above depicts the results of the MIDAS regressions that produced significant coefficients together with their corresponding values for the Goodness of fit for the series of residuals from the second regressions with the corresponding sectors of GDP gaps. In the current case, the initial values of probabilities of default have been employed as differences. For the series of differences, these regressions tend to perform better, which is a proof that the second regressions are filtering the data a bit better than the first ones to extract the irrational component.

5. Conclusions

Our analysis provides a framework for the measurement of rational default probabilities in their connection with the macroeconomic specific activity, measured by the sectoral GDP gap. Our motivation is driven by the fact that the connections between financial markets and macroeconomic variables should be effective, at least for liquid and representative financial markets in developed economies. An analysis for the Romanian economy is rooted in the necessity to investigate the extent to which this market is expected to move to the status of “emerging” market in the near future.

In order to analyze these connections, we used series of probabilities of default extracted from the Bloomberg platform. We decided to employ these variables as proxies for market activity due to the fact that they reflect the capital structure perspective of each company and they are less noisy than market prices.

The main contribution is rooted in the assertion that the connection between market activity and macroeconomic variables is sometimes not clear due to behavioral traits of investors. We define these as irrational deviations from correct market prices and we try to estimate them by filtering out “fear”, computed by using an original proposition and habit, present in the “day of the week” effect.

In our analysis we test whether the connection with macroeconomic variables is present at each step: before filtering fear, post-filtering fear and before filtering habit and eventually after filtering habit too. We developed this investigation by using both the series of levels in probabilities of default and the series of changes with a MIDAS methodology that allows for the study of different frequencies.

On the one hand, we found that our measure for fear has the same performance as the mainstream measure that relies on implied volatilities and provides a set of filtered probabilities of default that have statistical properties very similar to those of log-returns. On the other hand, we found that the filters work well for the series of levels and they do not show significant improvement for the series of changes in probabilities of default. Given these findings, we could further our analysis with investigations at a larger scale, on developed stock markets.

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