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AN ARTIFICIAL INTELLIGENCE-BASED FORECASTING OF THE DYNAMICS OF RELATIVE PROFIT RATES AT A FINANCIAL CRISIS JUNCTURE: A MODEL, A CASE STUDY AND CRISIS MANAGEMENT POLICIES

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Abstract

The purpose of this paper is to (i) demonstrate that the behavior of the relative profit rates at financial crisis junctures in a dual financial system could be different than that of the other periods, (ii) show that relative profit rates (and their dynamics) at crisis junctures could be forecasted with a relatively high degree of accuracy via artificial intelligence algorithms and (iii) exemplify the possibility of crisis-management policies that can smoothen the trajectory of the relative profit rates and facilitate the control of possible erratic fluctuations at the crisis junctures in such systems. We employ a series of methodological tools involving (i) statistical tests, (ii) artificial intelligence algorithms and (iii) the system dynamics simulation method to achieve the three objectives outlined in the paragraph above. The results are of practical significance to the financial policy makers aiming to formulate and put in practice effective policies at crisis junctures.

JEL classification: G1, C6

Keywords: Dual Financial Systems, Dynamics of Relative Profit Rates, Artificial-Intelligence-Based– Forecasting, Crisis Junctures, Crisis Management

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Introduction

Crisis junctures could pose considerable difficulties for the analysis of financial processes. The reasons for these difficulties reside, in part, in the extraordinary complexities that could be brought about by the interactions of intricately convoluted multiple tendencies that may be present at such junctures. Such tendencies could lead to structural breaks in patterns of financial processes and fluctuations in markets that may be prone to instability and even chaos. In the presence of structural break-inclusive possible unstable, erratic, and even chaotic fluctuations, forecasting the trajectories of financial processes may present significant challenges that may not be adequately handled within the confines of the traditional methods. It is exactly the presence of such challenges that calls for the employment of new methods that may turn out to be highly effective in solving some of the problems posed by the challenges in question.

Artificial intelligence algorithms constitute a group of new methods that may be worth employing for the task of identifying the patterns displayed at the complicated junctures in dual financial systems where different types of financial institutions coexist within the same financial system. Examples of dual financial systems could be of multiple types such as systems consisting of state and federal banks of different varieties such in the USA or systems characterized by the joint presence of participatory banks based on profit-and-loss arrangements and conventional banks based on interest-earning arrangements, which exist in countries such as England, Turkey, Malaysia and Indonesia. We will explore the dual systems of joint participatory and conventional banks and use a case study (a particular sub-sectoral crisis juncture) relating to Turkey, the lessons of which are relevant to all countries with dual systems. The juncture we will examine involved multidimensional, difficult-to-analyze clashes between the years 2013 and 2016 in Turkey. During the period in question, Turkey experienced a conflict-loaded and gridlock-producing crisis of intricately interlinked social, political and economic dimensions, which resulted in an attempted coup in July 2016. Needless to say, not all social-political conflicts and crises lead to serious economic or financial consequences of sub-sectoral crisis proportions. But this one led to a crisis in the relevant subset of the banking system because the largest bank of the participation banking system (Asya Bank), which belonged to a sect/community and which maintained, at that time, around 30% of the participation deposits in Turkey ran into serious difficulties during the period in question and got closed down after the attempted coup, which was clear evidence of the crisis in that subpart of the banking system in Turkey (Sabah, 2016). For general accounts of the overall crisis, see: Alkan (2016) and Çakı (2018). The effect of the social-political conflicts and clashes of that period on the behavior of the deposit-holders at the participation banks is another dimension of the sub-sectoral crisis in question, the detailed description of which is beyond the scope of this paper. On the other hand, the effect of the crisis on the relative profit rates is a more concrete phenomenon reflective of many of the complexities associated with the crisis in question. Hence that is what we will focus on in this paper.

We will analyze this crisis with some task-specific systematic steps. Following a brief literature review in the second section of the paper, we undertake three tasks. First, we demonstrate the structural difference of the crisis-pertaining behavior of the relative profit rates from that of the other periods. Second, in the presence of the difficulties that the fluctuation-prone crisis junctures could present for the analysis of the topic, we show that relative profit rates (and their dynamics) could be forecasted with a relatively high degree of accuracy via artificial intelligence algorithms. Finally, incorporating, into a simulative framework some of the crisis-related patterns and relationships identified by the artificial intelligence algorithms, we exemplify the possibility of crisis-management policies that can smooth the trajectory of the relative profit rates and facilitate the control of possible erratic fluctuations at the crisis junctures. The concluding remarks are presented in the final section.

Literature review

The literature on general financial crises is of course quite rich. Aliber et al. (2023) provide an informative account of many of the crisis-related phenomena such as crashes, panics, contagion, and possible policy responses. There are also works exploring more specific issues such as financial policy reform (Hlaing & Kakinaka, 2018), financial chaos (Dusza, 2017), instability-suboptimality-and chaos-prone fluctuations at crisis junctures (Kara, 2023) and global imbalances in relation to financial globalization Liang (2012). Though the general crisis tendencies need to be taken into account by a finance-related work such as this, we should emphasize that what we indicate, argue for, and analyze in this paper is not the existence of a general crisis in the entire economy during that period but only a sub-sectoral crisis within a subset of the banking system that was heavily influenced by the social-political clashes in question. Thus, it suffices to provide evidence for the crisis in the subsector in question in the relevant period. The events that explicitly broke out in 2013 and ended in the military coup in 2016 swept aside 30% of the participation banking system and influenced the rest of the subsystem. This constitutes sufficient evidence of crisis proportion in the subsystem (inclusive of the participation banking) in question in view of (and in comparison with) the fact that an approximately 25% contraction in the banking system in 2001 was considered one of the most serious crises in Turkish banking history. Of course, the crisis in 2001 was an overall banking crisis while the one we analyze was a sub-sectoral crisis. Nevertheless, the relative contraction rates were similar and, as such, if the former was a unanimously-agreed upon crisis, the latter could and should be considered a crisis on the sub-sectoral scale. For various indicators of contraction of the banking sector in 2001 (see: Çoşkun & Eken, 2015). The performance of participation banking after the attempted coup is another story which is beyond the scope of this paper. For a historical assessment of the place of participation banking in the Turkish banking system, see: Ustaoğlu (2014) and Varsak (2017). Moreover, one definition of banking crisis in the literature refers to a situation in which a bank fails or compels the government to intervene (Racickas & Vasiliauskaite, 2012; IMF, 1998). The criteria contained in this definition are clearly met by the sub-sectoral crisis we examine in this paper (there are of course other dimensions of financial crises which are explored in the literature (see: Reinhart & Rogoff, 2014).

The complexity-driven diversity of the behavioral patterns displayed at that juncture is another indication of the unusual nature of the period in question. Clearly, crisis junctures could unfold and lead to a rich spectrum of patterns and outcomes. Rational and seemingly non-rational options and optimal as well as suboptimal behavioral patterns could often coexist side by side at such junctures and help create stable, unstable or even chaotic outcomes. For instance, the altruistic behavior of some of the deposit-holders of Asya bank during that period was an important social phenomenon that is worthy of further examination. Nevertheless, it is not only the behavior of the individuals but also the institutions that shapes the dynamics of interactions at such junctures. The role of institutions, including that of the government, adds further complexities to the emergence of those patterns and outcomes. The literature contains a variety of works exploring intricate dimensions of these possibilities in the usual periods as well as in crisis-periods. For instance, the issues associated with investor behavior and psychology are covered by a wide range of works including: Filip et al. (2015), Hoffmann et al. (2013), Kariofyllas et al. (2017), Klein et al. (2017), Yang et al. (2017), as well as Gennaioli and Schleifer (2018). Though patterns and outcomes in markets are closely connected with the behavior and psychology of market participants, there are intricate dimensions of chaotic and stochastic tendencies and emergent structures in markets that may not be completely and exclusively reduced to micro behavior and may require micro-macro-convoluted treatment of the market processes, which is a highly difficult task to undertake. How successful the literature has been in undertaking such a task is an open question. Nevertheless, the literature contains works covering chaotic and stochastic issues. Among these works are: Zhang and Wang (2017), Kyrtsou and Terreza (2002), Dakhlaoui and Aloui (2013), Gilmore (1993), Benhabib (1992), Cohen (1997), as well as Aoki (2001). Stochastic and chaotic tendencies are also related to the various dimensions of crisis and policy considerations, which are examined by works such as Kara (2023), Garel and Petit-Romec (2017), Grosse (2017), Hernandez and Mendoza (2017), Dzhagityan (2017), Sau (2013), Purica (2015), Bernanke et al. (2019), Minsky (2008) as well as Gaffeo and Molinari (2017). There are also potentially fruitful system dynamics approaches to the banking crises in particular and financial crises in general. Works in this terrain, such as Kassem and Saleh (2005) and Scholten (2016), if properly extended to capture the intricate details of financial relations, could shed some light on the complicated feedback structures characterizing crisis-prone processes. There also exist structural and evolutionary approaches described by Scazzieri (2018), which can be productively used in the analysis of various intricate details of these processes.

However comprehensive the literature's coverage may have been, crisis junctures present inexhaustibly rich problems for further study. One such problem is related to the analysis of the relative profit rates (profit -interest ratios), which reflect the dynamics associated with the participation and conventional banking systems, and which were heavily influenced by the clash and strategic gridlock experienced at the juncture in question. In this paper, we analyze the relative profit rates via artificial intelligence algorithms. The literature also contains artificial intelligence-motivated works on financial processes such as Urbanikova and Stubnova (2020), Lin et al. (2017), Korol and Fodadis (2022), Torky and Hassanian (2023) as well as Yang and Chen (2018), which explore issues ranging from the use of artificial neural networks in capital markets to artificial intelligence in dynamic environments. Our work differs from those in the literature in its unique blend of artificial intelligence algorithms and system dynamics that opens the doors to a wide array of policies we exemplify in this paper.

Materials and methods

Analogous to the financial systems of some countries with predominantly Muslim populations, the Turkish banking system includes conventional as well as participation banks. In contrast with the usual interest-earning arrangements of the conventional banks, participatory banks' deposits/funds are based on an agreed upon profit and loss sharing arrangement where returns on deposits are determined at the end of the period, depending on the funds' realized profits or losses. Whether the returns on deposits at convenventional and participatory banks, namely interest rates and profit rates, converge or diverge over time is a point of discussion in the literature (see: Saraç & Zeren, 2015; Sukmana & Ibrahim, 2017). There is of course a more general discussion about the similarities and differences between the conventional and participation (Islamic) banks (Gassouma et al., 2023). Though being subject to similar market forces may at times induce convergence between interest and profit rates, factors affecting the two subsystems of the banking system may differ in some periods, resulting in divergence in the rates in question in some periods (for a descriptive analysis of the various aspects of participation banks' practices, profits and some alternative instruments, see: Büyükakın and Bilal (2016) and Gökalp (2014). The efficiency and distributive implications of the participatory arrangements are pointed out in Kara (2001). Among the points or periods during which such a divergence could be observed are the sub -sectoral crisis junctures, a prime example of which occurred, in Turkey, during 2013-2016 – a period characterized by a political and social crisis with economic consequences that we mentioned in the introduction.

Clearly the divergence between the profit and interest rates could be properly captured by the values of the relative profit rate, which is defined as follows:

$$\textit{The relative profit rate at } t\left(r_t\right): \frac{p_t = \textit{profit rate at time } t}{\textit{interest rate at time } t}$$

where profit and interest rates at t are the averages in the relevant banking systems at t.

The data set for this study is available at "Türkiye Cumhuriyeti Merkez Bankası" (The Central Bank of Turkey) and "Katılım Bankaları Birliği" (the Union of Participation Banks in Turkey.) We have used the data for the overall period from January 2006 to June 2017 which is decomposed into two subperiods, namely the subsectoral crisis period, December 2013-December 2016 and the remainder.

In this paper, we will prove three propositions about the relative profit rates and the complexities associated with them at the crisis juncture in question.

Proposition 1: The distribution of the relative profit rates at the crisis juncture is not the same as the distribution of the relative profit rates at other junctures.

In other words, we need to show that, compared to other periods, the relative profit rates behave differently at crisis junctures. Using the Mann-Whitney U test, we prove the proposition in Section 3. The Chow test also indicates the presence of structural breaks associated with the crisis juncture.

In view of the different distribution and hence pattern the relative profit rates displayed at the relevant crisis juncture, could we forecast its trajectory with a high degree of accuracy? The answer to this question is the subject of the second proposition.

Proposition 2: Changes in the relative profit rates at the crisis juncture in question could be forecasted with a high degree of accuracy via artificial intelligence algorithms.

To prove the proposition, we will construct a time series forecasting model which we will implement using the data mining and machine learning program WEKA (for descriptions of WEKA-related tools and functions, see: Frank et al., 2022). Other programs such as R and MATLAB could be used as well). In our model, the change in relative profit rates will be taken to be the target variable, which is influenced by a number of variables such as the change in the closing values of the stock market, the change in the bond rates, the change in the TL-dollar exchange rates and the change in inflation rates in Turkey, which will be named, along the lines of the program's terminology, as the "overlay variables" that are relevant to the forecasting of the target variable. We will add the HP filter- extracted cycle for the change in the relative profit rates to the list of the overlay variables.

The main artificial intelligence/machine learning algorithm we will choose for the purpose of forecasting is support vector machine regression (for applications of support vector machines in finance, see: Cao et al., 2005, Tang & Sheng, 2009 as well as Tang et al., 2009). Support vector machines could also be used for classification. The central organizing general principle underlying the method revolves around finding the best hyperplane separating the data points belonging to different classes. This is done by maximizing the margin between closest data points in different classes. The method is highly flexible and generally yields accurate results in both low and high dimensional cases.

We will use a couple of interrelated metrics for the forecasting accuracy, the first of which is "the normalized root mean squared error" (NRMSE), the definition of which pre-requires the concept of the root mean squared error (RMSE), which is the square root of the sum, over all observations, of the squares of the differences between the predicted and actual values of the changes in the relative profit rates divided by the number of observations. NRMSE is defined as:

$$\begin{gathered} NRMSE \;= RMSE \,/\, \textit{the range of the changes} \\ \textit{in the relative profit rates during the crisis period} \end{gathered}$$

The second (interrelated) metric is the degree of forecasting accuracy, which is 1-NRMSE.

The high degree of forecasting accuracy produced by the support vector machine regression and the associated trajectories for the relative profit rate will be given in Section 3.

The success in forecasting, which is important in itself, also paves the way for successful crisis management-possibilities/policies. The relationships and patterns revealed or identified during the process of forecasting could be used to control the trajectories of the financial processes, which is the subject of the third proposition.

Proposition 3. There exist tax policies that can smoothen the relative profit trajectory at crisis junctures.

The method we will use to prove this proposition is one of a artificial intelligence-integrated system dynamics simulation framework where we will incorporate the results of a particularly simple, easy-to-interpret artificial intelligence algorithm, such as linear regression, into a simulative model and undertake policy simulations.

The system dynamics simulation method could be simply described in terms of four different components, namely the “stock variables” which represent the accumulated values of some key variables, the “flow variables” which represent the changes in the stock variables, the “auxiliary variables” which influence (or are influenced by) the other variables in the system and the “feedback relations” or connections which describe the relations or chains of causal dependencies among the variables in system. A proper formulation of a system dynamics model would require the specification of some or all of these components. In the illustrative model we will construct, the relative profit rate is the stock variable, the change of which will be the flow variable. The changes in the closing values, the bond rates, the exchange rates and the inflation rates described above could function as the auxiliary variables. Depending on the type of relations/patterns revealed by the artificial intelligence algorithm employed, some algorithm-selected particular lagged values of the variables in the model could serve as auxiliary variables as well. A simulation diagram representing the relations among the chosen variables in our model will be described and a particular policy-induced trajectory of the relative profit rates will be derived in the following section.

Results

The results associated with the first proposition

Before we proceed with the proof of this proposition, we need to first check whether the distribution of the relative profit rate for the overall period in question is normal. Both the Kolmogorov-Smirnov and Shapiro-Wilk tests indicate that the relative profit rate during the period in question are not normally distributed. Thus, to prove the proposition, we need to use a non-parametric test such as the Mann Whitney U test. Using the test in question, we ended up rejecting the null hypothesis stating that the distributions are the same across the periods. The relevant SPSS output is as follows (Table 1).

Table 1a: The Mann Whitney U test results

Null Hypothesis	Test	Sig.	Decision
The distribution of relative profit rate is the same across categories of two periods	Independent - samples Mann Whitney U Test	0.000	Rejected the null hypothesis

Asymptotic significances are displayed. The significance level is 0.05

Source: Author's own work (produced with SPSS).

Alternatively, we employed the Chow test which also indicates that there is a break at the beginning of the crisis period, leading to the rejection of the no-break hypothesis.

Table 1b: The Chow Test results

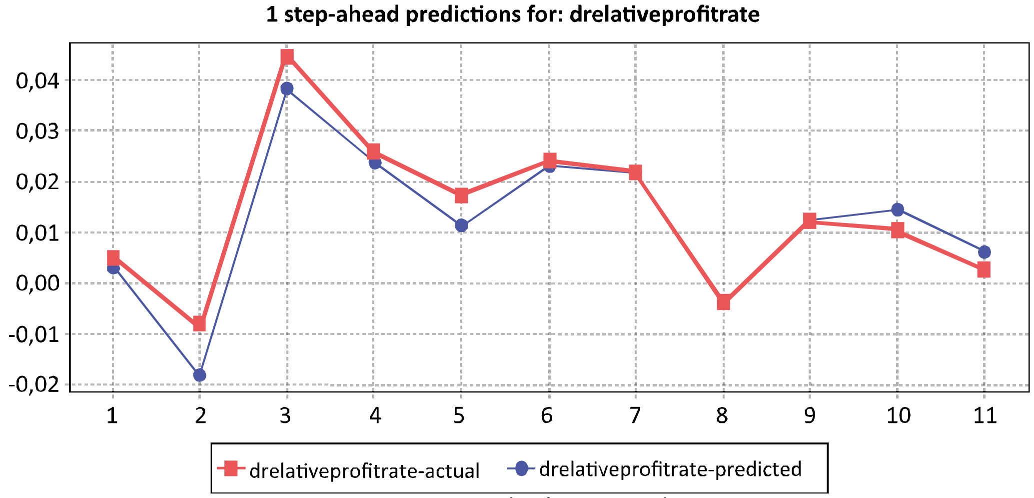
Chow Breakpoint Test: 2013M12			
Null Hypothesis: No breaks at specified breakpoints			
Varying regressors: All equation variables			
Equation Sample: 2006M01 2016M01			
F-statistic	88.20419	Prob. F (1,119)	0.0000
Log likelihood ratio	67.10433	Prob. Chi-Square (1)	0.0000
Wald Statistic	88.20419	Prob. Chi-Square (1)	0.0000

Source: Author's own work (produced with SPSS).

The results associated with the second proposition

We split/decomposed the data into two subsets and used 70% for training and 30% for testing. With the program WEKA, we run the attribute-selected support vector machine regression algorithm, which captures the underlying dynamics and enables us to forecast the change in the relative profit rates. The results yield a NRMSE value of 0.08 for the testing data and hence a degree of forecasting accuracy of 0.92 (92%), which is fairly high, indicating successful forecasting. The trajectories associated with this forecasting are given in Figure 1 and Figure 2, where "relative profit rate" indicates the change in the relative profit rates.

Figure 1: The forecasting of the change in relative profit rates with the testing data (produced with WEKA)

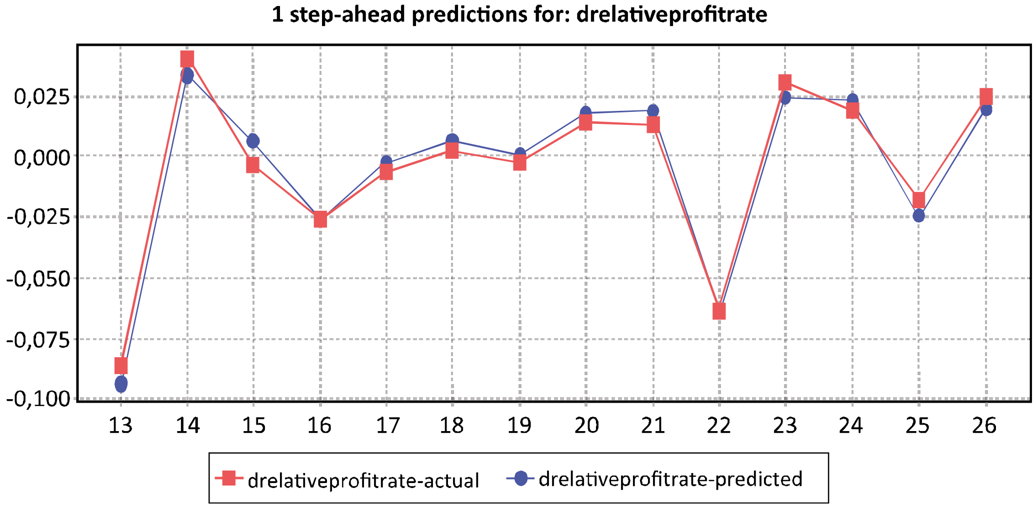


Source: Author's own work.

As displayed in Figure 1, the chosen artificial intelligence/machine learning algorithm (the support vector machine regression) yields accurate forecasts of the change in relative profit rate with the testing data.

The numerical results indicate that future values of the relative profit rates could be forecasted with a 92% accuracy at the juncture under study.

Figure 2: The forecasting of the change in relative profit rates with the training data (produced with WEKA)

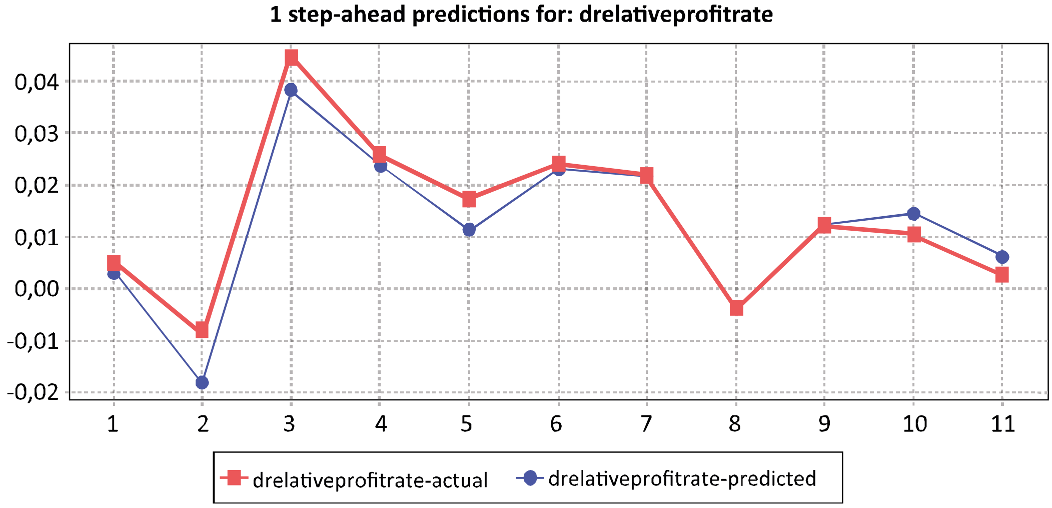


Source: Author's own work.

As an extension, Figure 2a displays the trajectories for the change in the relative profit rate and the change in the stock market return. The trajectories are obtained via M5P algorithm.

M5P algorithm accurately forecasts, as shown in Figure 2, the change in the relative profit rate and the change in the stock market return.

Figure 2a: The forecasting of the changes in the relative profit rate and stock market return with training data (produced with WEKA)



Source: Author's own work.

The results associated with the third proposition

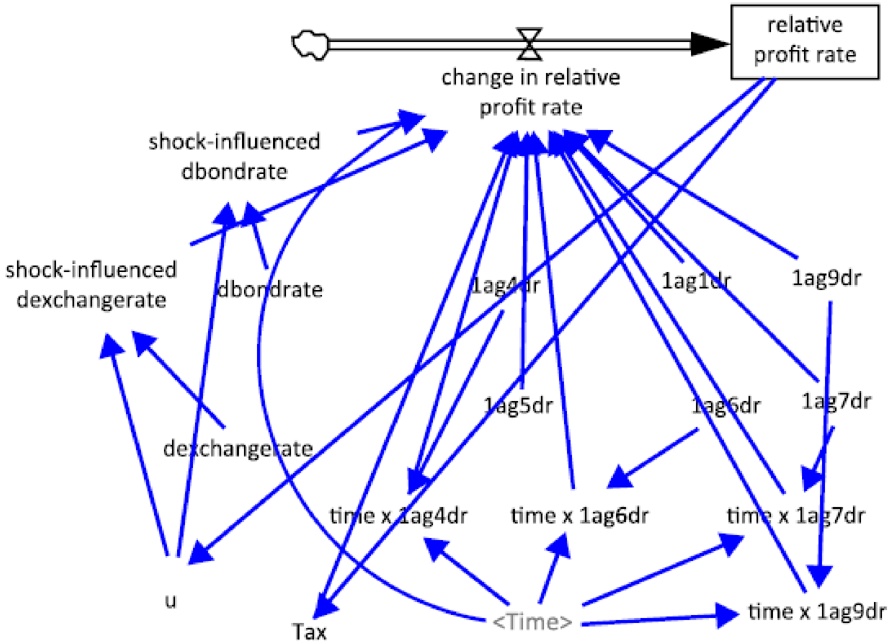
To prove the proposition suggesting policy-induced changes at the crisis juncture, we need to find a policy that leads to a measurable smoothing of the trajectory of the change in relative profit rate. The algorithm-produced estimation obtained with WEKA is as follows (To be compatible with the program's allowed symbolization, we will omit the spaces between the words in variable names). The estimated equation captures the dynamics underlying the change in relative profit rates:

$$\begin{aligned}
&Drelativeprofitrate = -0.352 + -0.0244 * dbondrate + \\
&-0.1893 * dexchangerate + 0.002 * ArtificialTimeIndex + \\
&0.2972 * Lag_drelativeprofitrate - 1 + -0.2825 * \\
&Lag_drelativeprofitrate - 5 + -0.7103 * \\
&Lag_drelativeprofitrate - 6 + \\
&-0.2886 * Lag_drelativeprofitrate - 7 + \\
&-0.545 * Lag_drelativeprofitrate - 9 + \\
&-0.0353 * ArtificialTimeIndex * Lag_drelativeprofit - 4 + \\
&0.0436 * ArtificialTimeIndex * Lag_drelativeprofitrate - 6 + \\
&0.0327 * ArtificialTimeIndex * Lag_drelativeprofitrate - 7 + \\
&0.0284 * ArtificialTimeIndex * Lag_drelativeprofitrate - 9
\end{aligned}$$

For the sake of convenience, let us choose the linear regression algorithm with the training data and incorporate the results it generates into a system dynamics simulation model. We have used the set of overlay variables including the changes in the closing values, the bond rates, the exchange rates and the inflation rates to estimate and forecast the target variable.

The lag-related terms symbolize the lagged values of the relevant variable for the indicated periods. The equation indicates that, in addition to the "dbondrate" and "dexchangerate", drelative profit values which are lagged for 1, 5, 6, 7 and 9 periods influence the target variable. Similarly, 4^{th}, 6^{th}, 7^{th} and 9^{th} lagged values (of the relative profit rates) times an artificial time index-variable have some influence on the dependent variable as well. We can construct a simulation model incorporating these influences. To demonstrate that, in addition to these influences, the policy we will propose works even in the presence of shocks characteristic of crisis junctures, we can introduce to the model some additional complexity by adding some stochastic terms to the "dbondrate" and "dexchangerate" variables. These relations are incorporated into the following system dynamics simulation diagram (Figure 3) which we have drawn using the program VENSIM. We can take alternative routes of the analytical kind exemplified in Kara (2007, 2013) as well as Kara and Osman (2006). However, for sufficiently complex stochastic terms and feedback relations, there may not exist analytical solutions.

Figure 3: The simulation diagram

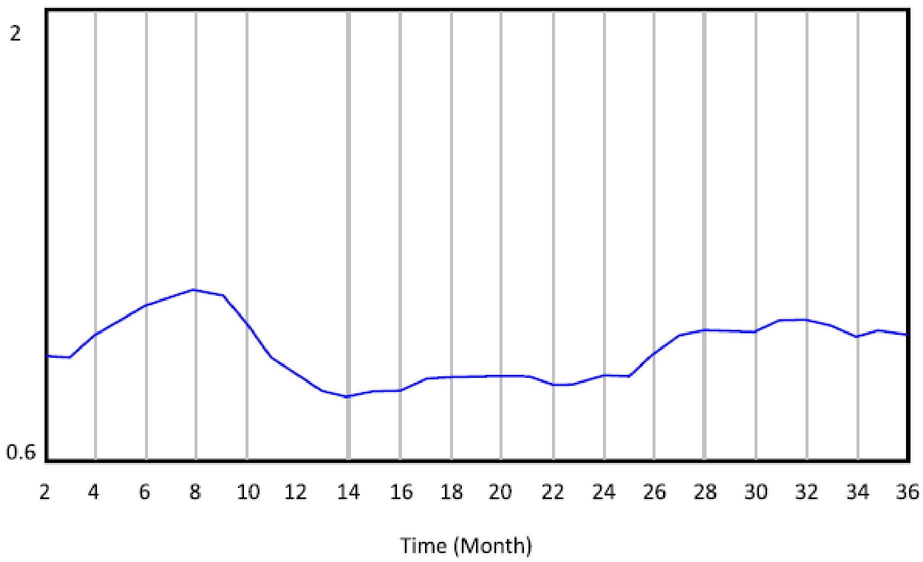


Source: Author's own work (produced with VENSIM).

For the sake of illustration, we will assume that the “shock-influenced dbondrate” = ”dbondrate”-0.2u, where u is a uniformly distributed random variable taking values between -5% and +5% of the relative profit rate. Similarly, the “shock-influenced dexchangerate” = “dexchangerate”+u (Alternative numerical values could be taken for exemplification purposes).

We will now introduce/design a tax that forces the change in the relative profit rate downwards by 2.5% when the relative profit rate is greater than 1 and upwards when it is lower than 1. This tax leads to the trajectory given in Figure 4. The trajectory without any tax is displayed in Figure 5.

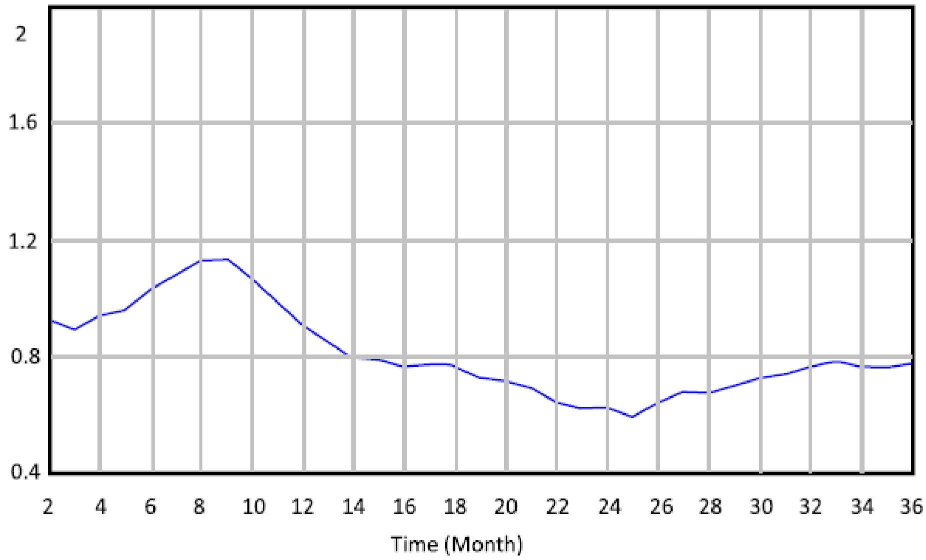
Figure 4: The relative profit trajectory with the tax (produced with VENSIM)



Source: Author's own work (produced with VENSIM).

To roughly see/measure the extent to which the imposed tax smoothes the relative tax trajectory, we can compare the variance of the relative profit rates before and after the tax. The before-tax variance of the trajectory was 0.070 while the after-tax variance of the simulated trajectory is 0.009. The tax appeared to have reduced the variance quite significantly, leading to a relatively smoothened trajectory. This exemplifies and hence demonstrates the possibility that there exist policies involving for instance taxes that can smooth the relative profit trajectory and help control the trajectory at crisis junctures.

Figure 5: The relative profit trajectory without any tax



Source: Author's own work (produced with VENSIM).

A deterministic tax is not the only instrument that can smooth the trajectories of financial variables. There are many other alternatives. For instance, taxes could be made a function of the stochastic fluctuations that could be represented by means, variances or some other statistical features. Other potentially influential instruments involving incentives and sanctions, or some prudential measures could also be designed in deterministic and stochastic varieties. The optimal parameters of these interventions could be determined via an extended version of the system dynamics simulation setup exemplified above.

Concluding remarks

In this paper, we demonstrated the validity of three propositions dealing with some of the key complexities of relative profit rates at crisis junctures in a dual financial system. First, we showed that the distribution of the relative profit rates at the crisis juncture is not the same as the distribution of the relative profit rate at other junctures, indicating the presence of structural breaks. In view of this difference and likely complications at crisis junctures present to the analysis and forecasting of financial processes, we demonstrated that changes in the relative profit rate (and their dynamics) at the crisis juncture in question could be forecasted with a high degree of accuracy via artificial intelligence algorithms, which is the subject of the second proposition. Finally, with successful prediction of relative profit rate at hand, we illustrated, via the third proposition, that there exist policies that can smooth the relative profit trajectory at crisis junctures, signifying the possibility of successful crisis-management policies.

Thus, besides their non-negligible theoretical importance, the three propositions outlined and demonstrated in this paper may be of practical significance to policy making. The propositions in question could guide the policy makers in their undertakings of two fundamental tasks. One task is to accurately forecast the market-driven trajectory or pattern of the relative profit rates (or any other financial process for that matter) and hence figure out what the market trends entail for the future. This has consequences for optimal policy making. Accurate forecasting of the market-driven patterns enables the policy makers to intervene so as to optimally influence the trajectory in question, which is the second important task that can be undertaken and that has been exemplified in the paper. Though we illustrated the possibility of only one policy through which policy makers could influence the predicted trajectory so as to achieve certain policy objectives, one can come up with other policies, the parameters of which could be estimated through artificial intelligence algorithms. Overall, artificial intelligence algorithms could serve as a basis for a crisis-management program. An inquiry into the designs of such additional policies that could underlie effective crisis management programs is worthy of future research.

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