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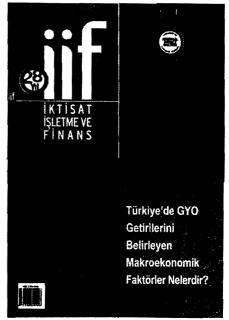
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An Agent Based Modeling Approach to the Check Payments Among SMEs in Turkey

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Abstract

Systemic risk and fragility became more important especially after the crisis of 2008. However, the burgeoning literature especially focuses on interbank and bank-firm credit networks. On the other hand, in developing countries, deferred check payments also compose another kind of credit networks and complement for the bank-firm credit lines. Check payments among SMEs even substitute for bank credits. Recent developments in Turkey offer an interesting setting in which we examine the fragility of check payment system. In this paper, we investigate whether the dramatic increase in nonpayments of checks have been due to the decline in growth or loosening of the legal sanctions. We analyze check payments using an agent based model. We can view check payments as a network structure where firms are nodes and check obligations are directed links. Firms' decision on whether paying their checks or not, depend on behavior of their neighbors and probable payoffs to their decisions. Our main finding is that lack of strict punishment can cause default cascades in check payment systems.

Keywords: Business Fluctuations, Financial Stability, Bankruptcy Chains, Agent Based Modeling.

JEL Classification: C63, D85, E32.

Özet. Türkiye'deki KOBİ'ler arasındaki Çek Ödemelerine Etmen Temelli Bir Yaklaşım

Sistemik risk ve finansal kırılganlığın önemi özellikle 2008 global finans krizinden sonra bir kez daha ortaya çıkmıştır. Bu konudaki araştırmalar özellikle bankalar arası ya da banka-firma kredi piyasalarına odaklanmıştır. Gelişmekte olan ülkelerde ileri vadeli çek ödemeleri banka kredilerini tamamlamakta, çoğu zaman da onun yerini almaktadır. Türkiye'de yakın geçmişteki gelişmeler bize, çek ödemelerindeki kırılganlığı ve istikrarı inceleyebileceğimiz ilginç bir model sunmaktadır. Bu çalışmada, 2012 yılında karşılıksız çeklerde görülen hızlı artışın, ekonomik büyümeden mi yoksa yasal düzenlemelerde yıl başında sağlanan esneklikten mi kaynaklandığını analiz etmeye çalıştık. Çalışmamızda, çek ödemelerini etmen tabanlı modelleme yaklaşımı ile analiz ettik. Çek ödemelerini, firmaların köşe, aralarındaki çek ödeme ilişkilerinin de yönlü bağlantı olduğu bir ağ yapısı olarak görebiliriz. Kurduğumuz modelde, firmalar çek ödeme kararlarını, komşu firmaların davranışlarını gözlemleyerek ve kendi davranışlarının muhtemel kazanç ve kayıplarını dikkate alarak vermektedir. Çalışmamızın ana bulgusu, karşılıksız çekler için caydırıcı bir cezalandırmanın olmaması halinde çek ödemelerinde ciddi kırılganlıkların yaşanabileceğidir.

Anahtar Kelimeler: Ticari Dalgalanmalar, Finansal İstikrar, İflas Zincirleri, Etmen Temelli Modelleme.

JEL Siniflamasi: C63, D85, E32.

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Introduction

Systemic risk has become the new buzzword after the global crisis of 2008-09. Since systemic risk has much to do with the emergent macroeconomic patterns and statistically abnormal deviations, economists now engage whether the influential macroeconomic and financial models which are based on normally distributed exogenous shocks are sound or not.

After the crisis, one of the issues about macroeconomic and financial models was setting microeconomic foundations of aggregate behavior. This was also emphasized in the famous letter of a group of economists¹, to the Queen of England in which they tried to answer the question "Why had nobody noticed that the credit crunch was on its way?":

- Everyone seemed to be doing their own job properly on its own merit. And according to standard measures of success, they were often doing it well...
- The failure was to see how collectively this added up to a series of interconnected imbalances over which no single authority has jurisdiction...
- Individual risks may rightly have been small, but the risk to the system as a whole was vast...

We can infer from the arguments above that, an economic system as a whole is something different from the sum of its components. The accompanying question of whether there is a way to reach aggregate behavior with the help of observing microeconomic behavior follows.

In mainstream paradigm, microeconomic foundations of aggregate behavior go back to Lucas (1976). Lucas claimed that, when generating government policy variables, traditional models did not take into account the dependence of private agent behavior, on government policy rules. So, they could misguide the policy makers about the effectiveness of their decisions. Therefore, Lucas proposed achieving aggregate behavior by first defining microeconomic units and attributing identical parameters to them. This way of thinking led the economists model the individuals (household or firm) as homogenous agents that have similar preferences and rationality. The logic behind this, is assuming that individual reflects the general expectations and beliefs of the society.

It was believed that, analyzing the behavior of representative agent and then summing up all the individuals would give the aggregate behavior of the economy. This proposition led to a reductionist approach in mainstream economics that is just summing up the market outcomes of individuals.

1 The Letter was signed by Prof. Tim Besley and Prof. Peter Hennessy and reflected opinions of 33 participants to the forum held by British Academy on 17 June 2009: "The Global Financial Crisis - Why Didn't Anybody Noticed?

On the other hand some researchers claimed that, reductionist approach of mainstream paradigm and the terms of "representative agent", "equilibrium", "rational behavior", and "optimization" were inadequate in explaining the aggregate behavior in a realistic manner.

Delli Gatti et al. (2010), claim that Lucas critique is wrong in three ways. First, they find the Lucas critique theoretically empty, because the subject of "assessing whether a given model is structural or not", is an empirical question. Second, in representative agent approach, individual preferences are not affected by policy changes, and this assumption does not suit the real practice. Finally, in representative agent models, aggregation is done with the assumption that individuals have homothetic and identical preferences which is again, unrealistic.

Delli Gatti et al. (2010) also claim that to be able to use reductionist approach, one must know that there is linear interaction between individuals. In their words: "...In terms of dynamical system theory, this means that the eigenvalues of the whole (high level system) are linear combinations of the eigenvalues of the parts (low level system)." Obviously, in real practice where there is information asymmetry, this is not the case.

In a real economy all players in a market do not have access to the full set of information and they have different sets of preferences that evolve in time. Furthermore, individuals observe each other and learn from each other. Some researchers offer a term that takes into account these points: "heterogeneous interacting agents". Heterogeneous interacting agents are accepted as agents that show the real life characteristics mentioned above.

The methodology that models heterogeneous interacting agents and complex adaptive systems is agent based modeling (or Agent Based Computational Economics (ACE) as in some studies). Agent based modeling is the methodology that allows to construct models with heterogeneous agents, based on simple rules of behavior and interaction. In an agent based model we do not know the resulting aggregate dynamics in advance. Agent based models are actually computer simulations of complex systems. The following is a very good explanation of agent based modeling (Tesfatsion & Judd, 2006):

"The ACE methodology is a culture-dish approach to the study of economic systems viewed as complex adaptive systems... As in a culture-dish laboratory experiment, the ACE modeler starts by computationally constructing an economic world, comprising multiple interacting agents (units). The modeler then steps back to observe the development of the world over time."

² Delli Gatti, Gaffeo, & Gallegati (2010); Gaffeo, Delli Gatti, Desidero, & Gallegati (2008), Delli Gatti, Di Guilmi, Gaffeo, Giulioni, Gallegati, & Palestrini (2005); Stiglitz & Gallegati (2011)

Recently, agent base models which take into account these concepts and heterogeneous interactive agents are more widely used to explain microeconomic foundations of macroeconomic behavior. For example, Stiglitz and Gallegati (2011), argue that representative agent approach cannot provide an adequate framework for understanding the economy even in more normal times and they claim that heterogeneous interacting agent framework provides an alternative, one which helps more to understand the interlinkages that gave rise to the global crisis.

After the crisis of 2008, Farmer and Foley (2009) also proposed agent based models to guide economic and financial policies:

"Agent-based models potentially present way to model the financial economy as a complex system, as Keynes attempted to do, while taking human adaptation and learning into account, as Lucas advocated. Such models allow for the creation of a kind of virtual universe, in which many players can act in complex—and realistic—ways. In some other areas of science, such as epidemiology of traffic control, agent based models already help policymaking."

Agent based modeling is closely related with and mostly makes use of network theory, which itself is an application area of graph theory. Network theory is an acceleratingly emerging area of study by statistical physicists, biologists, sociologists, economists and computer scientists, and gives perspectives for sociological and economic studies that use agent based modeling (Jackson, 2006). Jackson (2010) gives two important aspects of the study of networks from an economist's perspective. The first is understanding how network structure influences economic activity, and second, understanding the usefulness of economic tools in analyzing both network formation and influence.

Obviously, the most important financial network is credit networks between banks and firms. But there are other –usually informal- credit interlinkages that affect aggregate behavior. For example, Tüzemen et al. (2013) claim that households make use of money transfers from social networks as well as formal institutions when they experience money shortages. Check payments between SME's is another kind of financial networks.

The importance of tracking systemic risk and fragility in financial markets and payment systems has become more important especially after the global financial crisis of 2008. There are many economic indicators that are used by analysts and academicians for this purpose. One of them, which is not very common, is total amount and ratio of check bounces. One can easily expect that amount to be inversely correlated with the growth rate of an economy. For example, between years 2008 and 2011, rate of bounced checks in Turkey were 5.02%, 6.83%, 3.46%, and 2.91% by value. Meanwhile, economic

growth rates of Turkey were 0.7%, -4.8%, 9.2%, 8.5%.

In our study, we derive our methodological motivations from the above arguments and try to model a simple environment where players are small and medium enterprises (SME). In Turkish business environment of SME's, check is a very important means of payment, even as important as cash. Normally, a check must be paid at sight. But there is an established exercise in Turkish business about checks. In real life business practice, checks are signed with a forward date on it. On the average, checks are signed with a 90 days deadline. So, check is also a means of trade credit of net 90 day. This makes checks very important in Turkish business life.

Before 2012, legal sanction for not paying a check was imprisonment. In January 2012, a very important change in this regulation took place and imprisonment for unpaid checks was canceled. This change was largely known to public since second half of 2011. Figures 1a-1b and Table 1 present the value and rate of check bounces in number and value in 2011 and 2012. Figure 1b shows quarterly data of check bounce percentages for 2010, 2011, 2012 and only 1st quarter of 2013. Yellow bars show check bounces in 2012 in quarterly basis. Percentage increases in check bounce rates relative to the same quarter of the previous year are given above bars. Increase rates in 2012 quarters are noteworthy. In addition, 15.5% increase in the last quarter of 2011 relative to the last quarter of 2010 is also noteworthy because in this period the upcoming policy change was known to public. Table 1 and Figure 1a-1b are composed with the data of not only SMEs but all firms. Although our model includes only SMEs we lack data specific to them. However, we believe that trends are very much similar for SMEs.

Period	Total Checks (TL)	Bounced Checks (TL)	Percentage
2011-1	63,359,714,426	1,607,607,775	2.54
2011-2	71,164,477,729	1,701,846,686	2.39
2011-3	79,139,637,711	2,328,981,523	2.94
2011-4	80,579,515,318	2,912,254,095	3.61
2012-1	78,679,353,843	3,172,722,420	4.03
2012-2	81,069,583,239	3,332,634,039	4.11
2012-3	89,669,642,854	4,369,342,099	4.87
2012-4	100,516,922,389	. 5,342,738,354	5.32

Table 1: Quarterly Check Bounces in 2011 and 2012

There is an increase in check bounces both in volume and in rate, especially after July 2011. It can be because of either a macroeconomic shock that affects all firms or because of firm specific idiosyncratic shocks that show a contagious effect due to network structure, or both of them.

By the end of 2012, totally 16,217 million TL amount of checks bounced where the figure was 8,550 million TL for the previous year, corresponding to an increase of 89%. In the same period, total value of checks increased by only 19%. Does the sharp increase totally reflect deterioration in the economy or are there other reasons? Our research question is whether the dramatic surge in the share of bounced checks in 2012 is related with the relaxation of the penalty on non-payments.

In this study we analyze check payments in a network of SME's using an agent based modeling approach. We embed check payments in a network structure where firms are individual nodes and check obligations are directed links. In our model, firms decide to pay their checks, considering behavior of their neighbors and potential payoffs due to their decisions.

We start with a network where every player chooses to pay its check obligation. We then perturb the system by switching some nodes to decide not to pay their checks and simulate the system. We believe that, changing relative cost and benefits of fulfilling check payment obligation in the check network, shifts perception and behavior of players which in turn causes a change in aggregate results.

We establish Monte Carlo simulations to observe cascade formations³ and contagion dynamics among the population of agents. Second section gives definitions of our model, third section tells about the simulation and fourth section concludes our study.

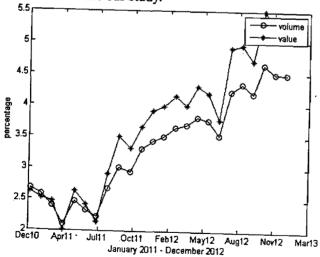


Figure 1a: Rate of Check Bounces

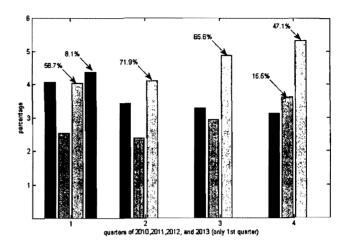


Figure 1b: Quarterly compared check bounce percentages

2 The Model

In our study, we do not intend to verify our results with empirical data as our setting is a very simplified model which lacks many real world characteristics. Our goal is to show that idiosyncratic shocks increase emergent systemic risk and may lead to an avalanche of bankruptcies. We believe, although we cannot compare our numerical findings with real life experience; the trends and mechanisms that we observe at the end of the simulations will give us insight about real life mechanisms of systemic risk and cascades of defaults.

We model an economy that is made of purely small and medium enterprises (SME). For simplicity we do not include banks, large firms, households etc. The model consists of N firms indexed by i=1,2,...N. Each firm undertakes transactions with other firms as seller or buyers of intermediate or finished goods. Firms make all of the payments by writing checks. So, there is a network of checks where nodes are firms, and check payment obligations are directed links. We denote a link in a network with, $c'_{ij} = 1$ which means, firm i is indebted to firm j at period t. For simplicity we normalize check amounts to 1. Also self-links are not allowed. We also make the simplifying assumption that $c_{ij} = \{0,1\}$ which means there may be at most one link between two firms in a period.

We randomly generate the check network at the beginning of each period. In real practice, business relations between SMEs are short termed in nature, while corporate firms establish long-term relationships. Second, in real life economics, check is such an important payment medium that it is frequently

³ As explained below, a cascade is believed to be formed when 70% of the firms in the model decide not to pay their checks.

accepted as liquid as cash4. In practice, checks travel through many firms as means of payment. Actually, it is very common that a firm may have to pay check debt to an unknown firm. Taking these two points into consideration we can argue that randomizing check network at the beginning of each period is realistic.

Each firm has also a decision variable which specifies whether the firm will be paying the due checks or not, with values 0 or 1. If decision variable of firm \hat{i} is $d_i = 0$, then the firm decides not to pay its checks. On the other hand $d_i = 1$ means that firm i will pay its checks. At the beginning of the simulation, decision variable of every firm is set to be 1.

We keep track of transactions at each period with a transaction matrix. Specifically, t_{ii} can take values of 0, 1, or 2.

0 no transaction occured between i and j at period t $t'_{ij} = \begin{cases} 1 & \text{i owed to } j \text{ at time } t \text{ and } paid \text{ its debt properly} \end{cases}$

2 i owed to j at time t but did not pay its debt

Firm i pays its debts if its decision is 1. So, if i owes to j, and i's decision variable is 1, $(c_{ij}^t = 1 \text{ and } d_i^t = 1)$ then $t_{ij}^t = 1$. It is obvious that $t_{ij}^t = 0$, if no transaction occurs $(c_{ij}^t = 0)$. Finally, if *i* owes to j, and *i*'s decision variable is 0, $(c_{ii}^{t} = 1 \text{ and } d_{i}^{t} = 0)$ then $t_{ii}^{t} = 2$.

There is also related network which keeps track of ratings that firms assign to each other. Specifically, $r'_{ij} = \{0, 1\}$ and \hat{i} may rate j as 0 or 1. If firm i paid its debt every time it owed to firm j, then j rates i as 1. Conversely, if i refuses to fulfill its obligations, then j decrements its rating to 0 and does not accept any check from i for a certain period of time. In order to make the model more realistic, we assume that after a certain number of periods individual ratings will be switched from 0 to 15.

After the check network is generated, every firm has checks received and checks given. Number of checks received for firm i at period t is $\sum_{i} c'_{ji}$ and similarly checks given is equal to $\sum_{i} c_{i}^{i}$.

A firm cannot collect its checks received if the decision variable of the

borrower is 0. So total amount of unpaid checks to firm i is $\sum_{d_j=0} c_{ji}^t$. Now, we define a variable of unpaid check rate which plays an important role at payment decision criteria of firms. In our model, firms decide to switch their decision from 1 to 0, looking at the rate of unpaid checks to them. Unpaid check rate of a firm is equal to

$$ucr_i^t = \sum_{d_j=0} c_{ji}^t / \sum_j c_{ji}^t.$$

5 In our simulation, we assume that it takes 10 periods to increase individual rating from 0 to 1.

Every firm observes its check collections each period. And we assume that, each firm has a psychological threshold level of self-organized criticality (λ) which is determined by the perception of agents about cost of not paying its checks. If the firm's uncollected check rate exceeds λ_1 the firm decides that it is either insolvent or in a danger zone and it does not pay its checks anymore. It is important that firm compares uncollected check rate with λ which is determined purely by payoffs of the game.

Let's think of a firm that does not pay its checks. This decision does not last forever. If the firm's collected check rate (1 - ucr) increase and exceeds some level -which we denote by λ_1 - the firm starts to pay its checks again. λ_1 is also determined psychologically but sanctions of not paying checks is critical. If a firm goes to prison for not paying checks, it cannot start to pay its checks even collected check rate increase.

To summarize, firms' decision to pay or not, depends on the following conditions:

- If $ucr > \lambda_1$, firms decide not to pay their checks
- If $ucr < \lambda_1$, firms decide to pay their checks again, where $\lambda_1 < \lambda_2$

The term self-organized criticality (SOC) is first proposed by Bak et al. (1987). The basic idea of agent based modeling is: "small differences in individual behavior may cause huge complexities in aggregate behavior". Self-organized criticality is a characteristic state of criticality, which is formed by self-organization in a long transient period at the border of stability and chaos. Thus, in our model firms have low and high levels of SOC to decide whether or not to pay checks.

If $d_i = 0$ and check collection rate of firm i exceeds high level of SOC, the firm switches back to decision 1. We denote, low SOC level by λ and high SOC level by λ_1 . SOC levels reflect the general psychology and foresight of firms about payoffs resulting due to their decisions. For example, if punishment for unpaid checks is going to prison, λ will be high.

3 Simulation

Using the setting in the previous period we simulate a check network. The model lacks many real life characteristics and players. In the benchmark model and the following scenarios we gradually change one parameter while keeping all others constant and observe the resulting aggregate behavior.

3.1 Initial Setting

We assume that the economy will run for a given period of times, where time period is indexed by t = 1, 2, ... T. At the first period of the simulation, the decision variable of all the firms are set to 1, and each firm rates every other firm as 1: $d_i = 1$, and $r_{ii} = 1$, \forall i, j. At the beginning of the second period

⁴ On 01 March 2013, Rifat Hisarcıklıoğlu, President of The Union of Chambers and Commodity Exchanges of Turkey said that they were estimating trade volume in Turkey in 2012 to be 2.9 trillion TL, and 2 trillion TL of this amount was supposed to be in checks and commercial papers.

we perturb the system by randomly choosing 'm' firms and by switching their decision to 0. So, 'm' is the number of perturbation.

At the beginning of each period the network is randomly generated. The probability of link formation between two firms in any period is 0.506. Then each firm sets its rating for other firms. Firm i rates firm j as 1 if either they haven't met in the last s periods or if they had met, and j paid its debt. If j fails to make its obligation in any period they make business, i will decrease j's rating to 0, and will not accept any checks from j for s periods. We assume that s is the number of periods bad files are kept between firms.

$$r_{ij}^{i+1} = \begin{cases} r_{ij}^{i} = 1 \text{ and i, j had no transaction, or} \\ 1 & \text{j owed to i and fulfilled obligation, or} \\ r_{ij} = 0 \text{ for the last s periods.} \\ 0 & \text{j owed to i in the last s periods but didn't fulfill its obligation} \end{cases}$$

After setting ratings, each firm determines its behavior for the term by setting decision variable, looking at the rate of uncollected receivables at the previous period. If the firm's decision variable is 1 in the previous period and ratio of uncollected receivables becomes greater than λ_1 in the beginning of the current period, the firm will change its decision to 0 in the current period. Similarly, if a firm's decision is 0 and percentage of collected checks is above a certain level, λ_2 , then it will switch to decision 1 again.

After each firm sets its decision, and rating for other firms for the current period; firms collect their checks received (or they cannot), pay their checks given (or they don't) and determine their uncollected check rate. Finally, transaction matrix is set according to the link formation and fulfillment of payments.

3.2 Benchmark Scenario

Initial set of parameters are determined as on Table 2. Note that $\lambda_2 = 1$, which means, a firm that switches to decision 0 cannot switch back decision 1 again. Number of firms, N, number of periods in a simulation, T, and number of periods to keep bad file, s, will be the same in the following scenarios.

We perturb the system in the 2nd period and then observe the number of decision-0 firms. If, throughout the simulation, ratio of decision-0 firms exceeds 70%, we decide a cascade is formed, which means the emergent systemic risk reached a level that lead the substantial majority of firms decide not to fulfill their check payment obligations. Therefore, we track the cascades to determine the effects of the parameter changes on the system wide outcomes.

Parameter	Value
Number of firms, N	100
Number of time periods, T	100
Number of time periods, 1	0.20
Low level of SOC, λ_1	
High level of SOC, λ_2	1
Number of periods for keeping bad file, s	10

We repeat 100 simulations with the same set of parameters, except m, and count the number of simulations that resulted with a cascade. Figure 2 shows number of cascades as we gradually increase m. As expected, number of cases in which cascades occur in the society is increasing with m. And the interesting point is the speed of contagion. As m increases, cascade formation fastens in an accelerated rate and cascades go from 0 to 100 within a very narrow band of m. Thus, we can say that when an initial systemic shock hits firms, ratio of firms initially affected by the shock is significant for aggregate behavior.

3.3 Second Scenario: Changing λ

As seen in Figure 2, no cascades form at the perturbation number (m) of 12. So, we keep that number constant and analyze the system by changing low level of SOC.

 λ_1 is a psychological level for the players that reflect their perception of payoff if they don't fulfill their obligations. If players think that cost of not paying a check will be high, then λ_1 , will also be high. Thus, perception of agents about payoffs and costs also affects behavior pattern.

⁶ The probability of 0.50 may be regarded as high for random network formation. With this probability, a connected network is generated in almost all terms. However, our research is not directly related with the link formation probability. We later made sensitivity analyses by gradually changing the probability of link formation. Different probabilities caused small changes in the speed of cascade formation (i.e. led to different slopes in Figures 2, 3, and 4) but, resulting mechanism and our main findings did not change.

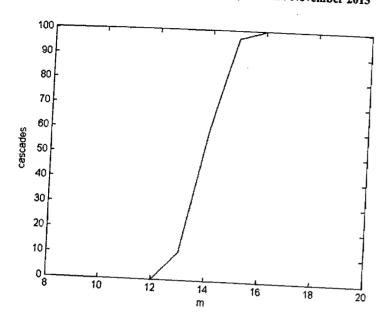


Figure 2: Increasing Perturbation Number (m)

Figure 3, shows what happens when we decrease λ_1 , with m=12 firms. Similar to the previous scenario, firms with d=0 are not allowed to switch

We gradually decrease λ_1 from 0.2 to 0.16. With $\lambda_1 = 0.2$ number of cascades among 100 simulations is 0, while it rises to 100 when $\lambda_1 = 0.16$. We believe this mechanism, even though partially, could have an influence in the increase in check bounces after July 2011. Legal regulation for unpaid change would be legitimized. So, a change in perceptions about cost of not paying checks -even before real implementation- could have also shifted to lack of data.

There is a narrow band where, a very small increase or decrease in λ_1 is enough for cascade formation. This is proven to be true with other simulations with different values of parameters. Thus, there is a threshold of λ_1 of players which is a turning point for cascade formation.

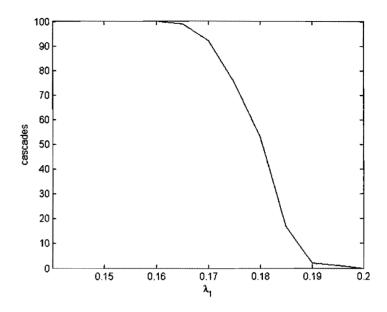


Figure 3: Cascade Numbers for Changing A

We do not have empirical data about the self-organized criticality levels before and after the cancellation of imprisonment. On the other hand, it can be easily guessed that, establishing a punishment like imprisonment or canceling it, will cause high jumps in SOC levels of players. And the possibility that level of cascade formation (0.17-0.19 in Figure 3) is between the psychological SOC levels of players between and after the change is high.

We argue that, the increase in check bounces as a result of a change in λ_1 , is very important to explain what happened in real practice. Even if the change in legal regulation may not be the only cause of increase in check bounces, as we see in Figure 3, this had a significant impact on the increase.

The policy change altered the setting such that, in the new setting, firms that did not fulfill their obligations for once or more have the chance of paying their checks again. In terms of our model, after cancellation of imprisonment, firms have the chance of switching back to decision-1. In the next scenario we model this setting.

3.4 Third Scenario: Changing λ

In our model, a sharp decrease in λ_1 lead the system to crash at a specific level of low threshold, which is a narrow band around 0.17 in Figure 3. Although our model lacks many real life characteristics, looking at Figure 3, one might expect a higher increase of check bounces in real life. In this

section we will gradually change λ_2 and observe whether it will trigger or inhibit check bounces.

We claim that, canceling the imprisonment also caused a decrease in λ_2 . A player cannot start to pay its checks if he is in prison. But he has the option of paying checks again if he continues to do business without the fear of being in jail. In order to check this idea, we kept λ_1 constant and gradually decreased λ_2 . Decreasing λ_2 implies the likelihood of actually increasing the chance of decision-0 players to turn back to game and fulfill their check payment obligations. As mentioned before, if a decision-0 firm collects its checks received with a percentage higher than λ_2 , than it switches to decision 1 again.

Figure 4 shows the results of simulation with m=12 firms, and $\lambda_1 = 0.16$. As seen in the figure, letting the players to fix their behavior, cause a high reduction in number of cascades. Even letting λ_2 near to 1 causes a striking decrease in the number of cascades. A 0.15 decrease in λ_2 , results number of cascades decrease from 100 to 60.

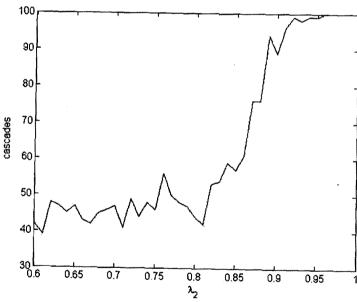


Figure 4: Cascade Numbers for Changing λ_1

We believe that canceling the prison sanction caused a decrease in both λ_1 and λ_2 for firms. λ_1 decreased because the cost of not paying a check is lower now. λ_2 also decreased because it is easier to start paying checks again when people do not go to prison or at least they do not fear so. As we

mentioned before we lack the empirical data to see the amount of decrease in λ levels. But two figures above tell us that, λ_1 and λ_2 , lead the system to a new stable level. For Turkey example we can say that, combination of these two effects played a very important role in the 89% increase in check bounces in 2012.

Finally, we plotted a 3D graph of λ_1 and λ_2 with m=12 to see the combined effect of changes in these two parameters. Figure 5, shows number of cascades with varying λ . Note that, a small difference in combination of λ_1 and λ_2 , results greater differences in number of cascades. In agent based modeling, it is assumed that small differences at micro level may cause huge differences in aggregate behavior. Our simple model also confirms this assumption.

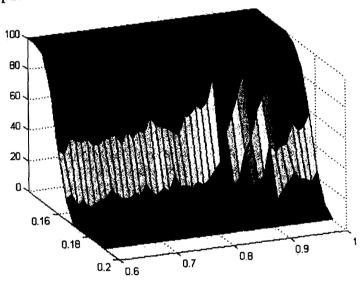


Figure 5: Number of Cascades vs λ_1 and λ_2

3.5 Policy Proposal

In second and third scenarios, we keep other parameters constant and change self-organized criticality levels. Simulations showed that changes in λ_1 and λ_2 have different impacts on aggregate behavior. When λ_1 decrease because of a decrease in cost of not paying checks, cascade formation increase. On the other hand, λ_2 may change either because of shifts in psychological perceptions or changes in physical settings like legal regulations. When λ_2 decrease, it becomes easier for non-payers to start paying checks again.

Cancellation of imprisonment in January 2012, caused a decrease in both λ_1 and λ_2 . Decrease in λ_1 triggered cascade formation while the other affected in just the opposite way. At the end, their combined effect caused an increase in check bounces.

Our proposal to decrease check bounces is not setting the imprisonment again. This practice has obvious negative sociological and economic drawbacks. Instead, we propose to make check performance of firms open to public. In real practice, only banks can reach the information of check performance of firms. Large corporate firms also have risk management departments that track firm performance and in practice they can reach the information informally via banks. On the other hand SME's lack the capability to keep track of financial reliability of other firms, as it is the case in our initial model. They can only know performance of firms which they have made business with.

We argue that letting check performance records to be free for all firms will increase the cost of avoiding a payment. Because firms will know that if they don't pay a check, all current and potential transaction partners will have this information and will not accept its checks. And this will increase λ_1 , without changing λ_2 , which in turn decrease check bounces in the economy.

4 Conclusion

We modeled a network of small and medium enterprises that interact with each other using checks as means of payment, with the help of a game theoretical agent based modeling approach. We assumed that players observe others they interact with and this affects their decisions. Besides, players have psychological perceptions about the results of their behavior. Thus, agents' perception of cost and payoffs besides his observations of interactions within the network determine his behavior which in turn shape the aggregate behavior.

We examine the effect of firms' cost-benefit perceptions about check payment decisions, on the aggregate behavior. Our model lacks many real world results and additionally our aim is not empirically confirming the results. On the other hand, the setting of the model shows that, a shift in cost perceptions of firms for not paying checks may cause default cascades. When firms think that cost for not paying a check is lower, they will more easily decide not to pay their checks, subject to the network structure of payments.

Our findings confirm that the change in regulation for legal sanction of not paying checks in January 2012 had significant impact on increase in check bounces (even though it may not be the sole reason and we lack the empirical data about the percentage of the effect). However, establishing the prison mechanism again will cause some sociological drawbacks. Moreover this will

increase high level of self-organized criticality, λ_2 , because firms cannot start to pay their checks again once they go to prison.

We argue in favor of letting all firms see each other's check payment performance records. Access to freely available records will decrease ratio of check bounces as it will increase low level of self-organized criticality, $\lambda_{\rm l}$.

Our model may be further developed in some aspects. First, we can modify our model such that, players decide in a hybrid model of random linkage and preferential attachment. In other words, players stick with their own decisions with a probability of δ , and decide according to behavior of their neighbors with a probability of $1 - \delta$. Second, in our model, all check amounts are equal to 1. A model in which check amounts differ, and check collections affect balance sheets of firms may maintain more realistic results. Finally, we can implement learning from neighbors model where, firm can learn performance of their neighbors' neighbors.

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Appendix Algorithm of the Simulation

The algorithm used to run the simulation in a C++ program is given below.

```
Construct class firms.
specify variables:
          decision
          checks received
          checks given
          unpaid checks
          unpaid check rate
          low threshold level
          high threshold level
Construct class economy.
   specify attributes:
          firms
          network
          transactions
          rating
          decision zero firm number
          unpaid check rate
          zero firm rate
          perturbation rate
          total number of checks
Set the number of firms in the simulation: P
Set the low SOC: It
Set the high SOC: ht
Set perturbation number: pn
Set number of periods, bad files will be kept: rp
Set number of periods: T
Set number of simulations: SN
Define an array of type economy with a lenght of "periods"
For period 1:
Set decision vaiable of all firms to 1
```

Set all elements of rating matrix to 1

Set checks received for every firm Set checks given for every firm

Generate network

Set transactions matrix

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Period 2:

Set every element of rating matrix equal to 1

Perturb system: randomly choose pn firms and switch their decision variable to 0.

Generate network for period 2

Determine amount of checks received, checks given,

unpaid checks, and unpaid check rate for firms.

Update transactions matrix

Determine economy varibales:

Number of decision zero firms, unpaid check rate, number of total checks etc.

For period 3 and following periods:

Set rating decision of firms for each other.

Set decision variable of each firm looking at unpaid check rate on the previous period.

Generate network

Determine amount of checks received, checks given, unpaid checks, and unpaid check rate for firms.

Update transactions matrix

Determine economy variables



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9.Gönderilen yazılar 1,5 satır aralıklı, tablo ve şekillerle birlikte en çok 25 A4 sayfası boyutunda olmalıdır. Yazı 12 puntoda Times New Roman ve Türkçe font kullanılarak hazırlanmalıdır. Şekil şartlarına veya dergi içeriğine uymayan yazılar ön inceleme sonrasında İktisat İşletme ve Finans Dergisince hakeme gönderilmeden yazar/lar'a lade edilir.

10.flf' ye gönderilen makalelerin şekil, grafik ve tabloların derginin belirttiği formata uygun olması gereklidir. Dipnotlar, grafikler ve tablolar olabildiğince atıf yapılan sayfada veya hemen devamında yer almalıdır. Grafik ve tabloların altındaki notlar bu materyalleri ana metne bakmaksızın anlaşılabilir hale getirme amacını taşımalıdır. Metne konan tablolar yazılım programı çıktısı olarak konmamalı, sonuçları yazır/lar kendileri tablo haline getirmelidir, tablolar mümkün olduğunca A4 kağıt boyutuna uygun düzenlenmiş olmalıdır. Grafiklerin bilgisayar yazılım programı çıktısı olmamaları, çizim veya çizim resim halinde ve A4 kağıt boyutunu aşmayacak şekilde düzenlenmiş olmaları gerekmektedir.

11. Gönderilen bütün makalelerin başında, Türkçe başlık, Türkçe özet, İngilizce başlık, İngilizce özet yer almalıdır. Özet kısımları 100-150 kelimeyi aşmamalıdır. Özetlerde; amaç, yöntem, bulgular ve sonuç bilgilerinin yer almasına özen gösterilmelidir. Özet kısımlarının altında anahtar kelimeler (keywords) İngilizce ve Türkçe olarak yazılmalıdır. Özetlerde kısaltma kullanılmamalıdır.

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