SIMULATING BANKRUPTCY – THE EFFECTS OF BAILOUTS

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KEYWORDS
soft budget constraint, Monte Carlo simulation

ABSTRACT

In our paper, we attempt to connect Kornai's soft budget constraint concept with the methodology used in financial option pricing. To our knowledge, this approach is unprecedented in the literature. Due to the option pricing framework, the effects of bailouts are not described as individual, socio-economic phenomena, but as statistical ones. We show how Markov chains and Monte Carlo simulation can be used in answering some questions arising in connection with hospitals' bailouts. Our results suggest that in case of more institutions, the effectiveness of the bailouts depends primary on how much the liquidity and bankruptcy processes of the hospitals are correlated – and not on the division of the bailouts among them.

INTRODUCTION

One of János Kornai's most important contributions to economics is the concept of soft budget constraint (SBC), the precise description of the syndrome, and the distinction between SBC and a pure bailout. The SBC syndrome has several similarities with options. In a paper presented at the conference celebrating the 90th birthday of Professor Kornai, two of the current authors attempted to describe the relationship between the call and put options used in financial markets, and the SBC phenomenon (Vidovics-Dancs and Száz 2018).

Following the methodology frequently used in option pricing, we model the liquidity situation of a hypothetical institution (e.g. a hospital) as a stochastic process, departing from the traditional economic, case study oriented analysis of SBC. We restrict ourselves to the analysis of statistical consequences, omitting the interpretation of the wide range of specific cases.

Besides the many similarities of SBC and options, there is a significant difference: the obligee does not exercise the option, instead receives it as an uncertain gift (or, successfully lobbies for it in the case of trouble). What is more, the potential bailor ex-ante positively denies the existence of the bailout option. However, such bailouts can take place several times. A further difference is that there is no defined strike price.

The analysis of SBC usually concentrates on moral hazard, i.e., that the institutions in trouble expect a bailout, which can lead to a less responsible operation on the systemic level. We have a different focus. Using MC simulation, we analyse the statistical consequences of an uncertain number of bailouts in bankruptcy situations. How does a given probability of bailouts increase the chances of survival?

First, we briefly discuss some features of health care funding and the main factors influencing the expenditures (and hence the liquidity situation) of hospitals. Then, we use the method of trinomial trees to describe the liquidity situation of a hypothetical hospital, and how it is affected by bailouts. We also raise the question of how the survival of hospitals is affected if bailout efforts are concentrated on one hospital or are divided among them. Finally, we run simulations based on the previously introduced model.

FUNDING AND COSTS OF HEALTH CARE

The funding of health care systems varies from country to country, but basically follows some schemes, mostly based on one of the models developed between the end of the 19th century and the mid-20th century. Reforming the financing of care is a recurring topic in the policies of both developing and developed countries, as the lack of resources is a problem that is constantly on the agenda, regardless of the current prosperity of the economy. In recent decades, most countries have experienced a continuously increasing health care spending, both nominally and as a percentage of GDP (Table 1).

Communications of the ECMS, Volume 33, Issue 1,
Proceedings, ©ECMS Mauro Iacono, Francesco Palmieri,
Marco Gribaudo, Massimo Ficco (Editors)
ISBN: 978-3-937436-65-4/978-3-937436-66-1(CD) ISSN 2522-2414

Table 1: Current expenditure on health care as a percentage of GDP (both public and private, source of data: OECD 2018)

Country	1970	1980	1990	2000	2010	2017
France	5.2	6.7	8.0	9.5	11.2	11.5
Germany	5.7	8.1	8.0	9.8	11.0	11.3
Hungary	…	…	6.4*	6.8	7.5	7.2
Japan	4.4	6.2	5.8	7.2	9.2	10.7
UK	4.0	5.1	5.1	6.0	8.5	9.6
USA	6.2	8.2	11.3	12.5	16.4	17.2

*1991

Costs of health care

According to the latest OECD report published in the summer of 2018, the areas most affected by the increase in health expenditure are outpatient care, long-term care, retail pharmaceuticals, and inpatient care. Though the latter's expenditure has risen at the lowest rate (by 2.2%), it accounts for a quarter of overall health expenditure. Outpatient care also receives about a quarter of overall health expenditure, while the share of long-term care varies considerably from country to country (0.7–28%) (OECD 2018). 50–80% of community health expenditure in developing countries is spent on maintaining and operating hospitals (Shepard et al. 1998).

Hospital care is, therefore, a major contributor to health spending, yet under-financing is a global problem. However, access to care and the quality of care are moral issues, so they cannot be subordinated to cost coverage alone. Inpatient care guaranteed by the state should be available regardless of the hospitals' liquidity situation. It is, therefore, an exciting question to decide on the principles of a financial rescue for providers.

The operation and revenues of hospitals are based on uncertainties (Gaynor and Anderson 1995) because the demand for their services is unpredictable and can only be estimated. This is especially true for acute care facilities, where there should always be a free capacity to meet any emerging need at any time. However, it is not necessarily true that an empty bed is disadvantageous to the hospital, as providing a more complicated, costly case may result in a loss for the hospital.

According to a division of hospital care costs, there are fixed and variable, direct and indirect costs (Weiss et al. 2014; Macario et al. 1995). The most significant fixed items are wages, machinery and equipment, and other services. Variable costs are mostly related to patient care, where the cost of a case may depend on the severity of the case and the characteristics of the patient.

The case-mix funding of inpatient care – after the financing based on past hospital stay and retrospective cost reimbursement – already has the ability to rely on real-time accounting (Wiley 1992). DRG (Diagnosis Related Groups) Funding (Fetter et al. 1980) was introduced gradually throughout the 1990s worldwide. As a result of DRG-based accounting, without knowing the progressivity – the professional potential – of a hospital and the potential of its different departments, it is difficult to predict any variable cost.

Causes of increasing costs

The most important factors behind the increase in health care costs are the development of technology and life sciences, the aging population, and changes in disease composition (Jamison et al. 2013). In addition, state-funded systems are often burdened with overuse (Morgan et al. 2015), that is, social security-based or public funding of health care is in itself an essential contributing factor to increasing costs.

One aspect of this issue is the decision makers' insensitivity to costs: as social security covers the costs of treatments, neither the patients nor the doctors take the financial costs into account when they decide on the treatments. Therefore, they use more, or more costly treatments than if they were affected by the financial incentives. Malpractice lawsuits also give incentives to doctors to use more treatments (even if they are probably not necessary) to protect themselves against such cases (Kessler and McClellan 1996).

The phenomenon called moral hazard also plays its part in increasing health care costs (Arrow 1963). Moral hazard means that if someone is insured against a specific adverse event, she will have fewer incentives to do everything to avoid that event. Social security means such an insurance: if you have health problems, the financial costs of the treatments will be covered by social security. That is, you have less incentives to put every effort in remaining healthy. The consequence is that if people put less effort in maintaining their health (doing exercises, eating healthy foods, etc.), then more of them will suffer from health problems, which increases the usage of the health care system. Naturally, this doesn't mean that in a social security-based system people do not care about their health at all, because even if the financial costs of treatments are covered, a worse health status still decreases their welfare significantly. So, moral hazard does not mean they have no incentives to live a healthy life, but fewer incentives to do so.

A third explanation of overspending in health care is a more general feature of public institutions and companies: their soft budget constraint (Kornai 1979). If a hospital spends more than its revenues (not necessarily on treatments, but, e.g. on facility management or maintenance), then it can expect additional funding from the government. The softness of the budget constraint means that hospitals (or other public institutions) have fewer incentives to operate cost efficiently. The regular additional funding provided by the government influences the expectations of the managers of the hospital, which can lead to less and less efficient management.

An additional factor that can lead to increased spending is that if hospitals (or other public institutions) have yearly budgets, they have incentives to exhaust the budget even if they could have fewer expenditures. The reason behind this is that if they do not do so (they have a "profit"), they can expect that next year's funding will be lower as the government can conclude that a lower amount of money is enough for the institution to operate properly.

MODELLING THE LIQUIDITY SITUATION OF A HOSPITAL

The basic model

In the following section, we show how the liquidity situation of a hypothetical hospital can be modelled by using the method of trinomial trees. In the stylized model, the hospital starts at the level of $K = 100$, which we deem the necessary level of liquidity. Liquidity can improve, remain the same, or deteriorate with given probabilities:

- it improves by $u = 20$ units with a probability q_u;
- it remains the same with a probability q_m;
- it deteriorates by $d = -u = -20$ units with a probability $q_d = 1 - q_u - q_m$.

We assume that $q_u = q_d = 0.4$ and $q_m = 0.2$. Liquidity cannot be lower than 0 or higher than 200. This means that in each period the hospital is in one of 11 states (denoted by $j = -5; -4; \ldots; 0; \ldots; 4; 5$).

If liquidity is below the necessary $K = 100$ level ($j < 0$), the hospital faces the risk of going bankrupt. We assume that the probability of bankruptcy in case of liquidity problems is $p_c = 0.4$. Table 2 shows the probability distribution of the liquidity states. The cell in column j and row i shows the probability that the hospital is in the j^{th} state in the i^{th} year. Column *D* on the left-hand side of the table shows the probabilities that the hospital has gone bankrupt by the given year. With these parameter values, 58.5% of hospitals cease to operate in 10 years, 71.3% in 20 years.

Table 2: The trinomial random walk model of liquidity, with the possibility of bankruptcy ($p_c = 0.4$)

	D	-5	-4	-3	-2	-1	0	1	2	3	4	5
0							100%					
1						40,0%	20,0%	40,0%				
2	16,0%				9,6%	12,8%	29,6%	16,0%	16,0%			
3	25,0%			2,3%	4,2%	15,7%	15,4%	21,4%	9,6%	6,4%		
4	33,8%		0,6%	1,3%	4,8%	9,1%	15,4%	14,3%	13,1%	5,1%	2,6%	
5	40,1%	0,1%	0,4%	1,4%	3,1%	8,4%	11,0%	14,2%	10,4%	7,3%	2,6%	1,0%
6	45,5%	0,1%	0,4%	1,0%	2,7%	6,1%	9,9%	11,4%	10,7%	6,6%	3,8%	1,6%
7	49,7%	0,2%	0,3%	0,9%	2,0%	5,4%	8,0%	10,5%	9,3%	7,1%	4,1%	2,5%
8	53,2%	0,1%	0,3%	0,7%	1,7%	4,3%	7,1%	9,0%	8,9%	6,8%	4,7%	3,1%
9	56,0%	0,1%	0,2%	0,6%	1,4%	3,8%	6,1%	8,2%	8,1%	6,8%	4,9%	3,8%
10	58,5%	0,1%	0,2%	0,5%	1,2%	3,2%	5,4%	7,3%	7,6%	6,6%	5,2%	4,2%
11	60,5%	0,1%	0,2%	0,4%	1,0%	2,8%	4,8%	6,7%	7,1%	6,4%	5,4%	4,6%
12	62,3%	0,1%	0,1%	0,3%	0,9%	2,5%	4,3%	6,1%	6,7%	6,3%	5,5%	4,9%
13	63,9%	0,1%	0,1%	0,3%	0,8%	2,2%	3,9%	5,6%	6,3%	6,1%	5,6%	5,1%
14	65,3%	0,0%	0,1%	0,3%	0,7%	2,0%	3,6%	5,2%	5,9%	6,0%	5,6%	5,3%
15	66,6%	0,0%	0,1%	0,2%	0,6%	1,8%	3,3%	4,8%	5,6%	5,8%	5,6%	5,4%
16	67,7%	0,0%	0,1%	0,2%	0,6%	1,7%	3,0%	4,5%	5,4%	5,7%	5,6%	5,5%
17	68,7%	0,0%	0,1%	0,2%	0,5%	1,5%	2,8%	4,3%	5,2%	5,5%	5,6%	5,6%
18	69,6%	0,0%	0,1%	0,2%	0,5%	1,4%	2,6%	4,0%	5,0%	5,4%	5,6%	5,6%
19	70,5%	0,0%	0,1%	0,1%	0,4%	1,3%	2,5%	3,9%	4,8%	5,3%	5,5%	5,6%
20	71,3%	0,0%	0,0%	0,1%	0,4%	1,3%	2,4%	3,7%	4,6%	5,2%	5,4%	5,5%

Next, we assume that with a given p_h probability, the government bails out the hospital in case of bankruptcy. Table 3 shows how the probability distribution is affected if $p_h = 0.3$. If we compare the results in Tables 2 and 3, we can see that the chance of survival improves by 12.4% in 10 years, and by 10.6% in 20 years.

Table 3: The trinomial random walk model of liquidity, with the possibility of bankruptcy and bailout ($p_c = 0.4$, $p_h = 0.3$)

	D	-5	-4	-3	-2	-1	0	1	2	3	4	5
0							100%					
1						40,0%	20,0%	40,0%				
2	11,2%				9,6%	12,8%	34,4%	16,0%	16,0%			
3	17,5%			2,3%	4,2%	17,6%	19,0%	23,4%	9,6%	6,4%		
4	24,2%		0,6%	1,3%	5,3%	10,7%	20,3%	16,1%	13,8%	5,1%	2,6%	
5	29,2%	0,1%	0,4%	1,6%	3,5%	10,7%	15,2%	16,9%	11,3%	7,6%	2,6%	1,0%
6	33,8%	0,1%	0,5%	1,1%	3,4%	8,2%	14,3%	14,0%	12,0%	7,0%	4,0%	1,6%
7	37,5%	0,2%	0,4%	1,0%	2,6%	7,5%	12,0%	13,3%	10,8%	7,8%	4,3%	2,6%
8	40,8%	0,1%	0,3%	0,8%	2,4%	6,3%	10,9%	11,8%	10,6%	7,6%	5,0%	3,2%
9	43,6%	0,1%	0,3%	0,8%	2,0%	5,7%	9,6%	11,0%	9,9%	7,8%	5,3%	3,9%
10	46,1%	0,1%	0,2%	0,6%	1,8%	5,0%	8,8%	10,0%	9,5%	7,6%	5,8%	4,5%
11	48,3%	0,1%	0,2%	0,6%	1,6%	4,5%	7,9%	9,3%	8,9%	7,6%	6,0%	5,0%
12	50,2%	0,1%	0,2%	0,5%	1,4%	4,1%	7,2%	8,6%	8,6%	7,5%	6,2%	5,4%
13	52,0%	0,1%	0,2%	0,4%	1,3%	3,7%	6,6%	8,0%	8,2%	7,4%	6,4%	5,7%
14	53,6%	0,1%	0,1%	0,4%	1,2%	3,4%	6,1%	7,5%	7,8%	7,3%	6,5%	6,0%
15	55,0%	0,1%	0,1%	0,4%	1,0%	3,1%	5,7%	7,1%	7,5%	7,2%	6,6%	6,2%
16	56,3%	0,1%	0,1%	0,3%	1,0%	2,9%	5,3%	6,7%	7,2%	7,1%	6,7%	6,4%
17	57,5%	0,0%	0,1%	0,3%	0,9%	2,7%	4,9%	6,3%	6,9%	7,0%	6,7%	6,5%
18	58,7%	0,0%	0,1%	0,3%	0,8%	2,5%	4,6%	6,0%	6,7%	6,9%	6,7%	6,6%
19	59,7%	0,0%	0,1%	0,3%	0,8%	2,4%	4,4%	5,7%	6,5%	6,8%	6,7%	6,7%
20	60,7%	0,0%	0,1%	0,2%	0,7%	2,2%	4,2%	5,5%	6,3%	6,6%	6,7%	6,7%

In the case of one single hospital, the process can be described as a Markov chain, whose transition matrix is shown in Table 4. If liquidity is adequate ($0 \leq j \leq 5$), then transition probabilities are 40%, 20%, and 40%. If the hospital faces trouble, then the probability of bankruptcy is 40%. In the case of bankruptcy, the hospital is bailed out with the probability of 30% and is not bailed out with the probability of 70%. Therefore, from a potentially dangerous situation ($j < 0$), the hospital is bailed out (gets back to the starting point, $j = 0$) with a probability of $0.4 \cdot 0.3 = 0.12$, and goes bankrupt with a probability of $0.4 \cdot 0.7 = 0.28$. The original random walk continues with the probability of 60%.

Table 4: The transition matrix of the Markov chain

	D	-5	-4	-3	-2	-1	0	1	2	3	4	5
D	1,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
-5	0,28	0,360	0,24	0,00	0,00	0,00	0,12	0,00	0,00	0,00	0,00	0,00
-4	0,28	0,24	0,12	0,24	0,00	0,00	0,12	0,00	0,00	0,00	0,00	0,00
-3	0,28	0,00	0,24	0,12	0,24	0,00	0,12	0,00	0,00	0,00	0,00	0,00
-2	0,28	0,00	0,00	0,24	0,12	0,24	0,12	0,00	0,00	0,00	0,00	0,00
-1	0,28	0,00	0,00	0,00	0,24	0,12	0,36	0,00	0,00	0,00	0,00	0,00
0	0,00	0,00	0,00	0,00	0,00	0,40	0,20	0,40	0,00	0,00	0,00	0,00
1	0,00	0,00	0,00	0,00	0,00	0,00	0,40	0,20	0,40	0,00	0,00	0,00
2	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,40	0,20	0,40	0,00	0,00
3	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,40	0,20	0,40	0,00
4	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,40	0,20	0,40
5	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,40	0,60

Table 5 shows how the probabilities of bankruptcy and bailout affect the probability that the hospital ceases to operate in 20 years. Naturally, it increases as bankruptcies become more probable, and decreases if the government is more willing to bail out the hospitals.

Table 5: The probability that the hospital ceases to operate in 20 years, as a function of the probabilities of bankruptcy (p_c) and bailout (p_h)

60,7%	0%	10%	15%	20%	30%	40%	ph
0%	0	0	0	0	0	0	
10%	0,459	0,424	0,406	0,388	0,349	0,307	
20%	0,610	0,574	0,555	0,534	0,490	0,440	
30%	0,676	0,643	0,625	0,606	0,562	0,512	
40%	0,713	0,683	0,666	0,648	0,607	0,558	
50%	0,738	0,710	0,695	0,678	0,638	0,591	
pc							

The case of more hospitals

In this subsection, we turn to the case of two hospitals and analyse how their chances of survival depend on the bailout strategies of the government. We assume that they are practically identical, in each period their liquidity changes in the same direction, unless one of them is bailed out. Even if both are in the same problematic situation, it does not necessarily mean that both of them go bankrupt – although, the risk of bankruptcy is the same. The same trinomial process forms the liquidity situations of the two hospitals, the only differences can be due to bankruptcy or bailout.

If there are two hospitals, the government has to decide whether it concentrates its bailout efforts on one of the hospitals or treat them equally. For example, it can bail out one of them with a 30% probability, or it can provide a 15% bailout probability for both. Table 6 shows how these decisions affect the probabilities that both hospitals exist after 20 years (first row of the tables), one of them exists (second row), or both have gone bankrupt (last row). According to Table 5, the survival probabilities strongly depend on the probabilities of bankruptcy and bailout. In Table 6, we present two cases: in the left panel the case introduced in the previous subsection ($p_c = 0.4$, $p_h = 0.3$), in the right panel the case of a much lower risk of bankruptcy combined with a more lenient government ($p_c = 0.1$, $p_h = 0.4$).

Table 6: Survival probabilities, depending on whether the bailout efforts are concentrated or divided

pc		0-30	15-15		pc		0-40	20-20
40%	2	**11,3%**	11,1%		**10%**	2	37,5%	37,5%
	1	45,4%	44,5%			1	**48,4%**	47,5%
	0	43,3%	**44,4%**			0	14,1%	**15,0%**

As it can be seen from Table 6, the probability that both hospitals cease to operate in 20 years is somewhat higher if the bailout efforts are divided among them, both in the case of high and low risks of bankruptcy. However, concentrating the bailout efforts seem to have a smaller effect on the chance that both hospitals survive 20 years (the difference is 0.2% and 0% in the two cases, respectively); instead, it makes it more probable that one of them survives.

It is important to mention that in the previous calculation we did not take into account that if one of the hospitals go bankrupt, then after that point the bailout efforts can be concentrated to the other hospital, even if initially they were divided among the hospitals. That is, the timing of bankruptcy matters.

SIMULATION OF THE LIQUIDITY STATES

Based on the previously introduced trinomial model, we can run simulations on the liquidity situation of a hospital (one realization is presented in Table 7). Using the transition probabilities above ($q_u = q_d = 0.4$, $q_m = 0.2$), a series of random numbers define whether the liquidity situation improves (1), remains the same (0) or deteriorates (-1) in a given period; this is shown in column *X*. Column *Xc* shows whether the hospital would go bankrupt (1) if liquidity were below the necessary level, while column *Xh* shows whether the hospital would be bailed out (1) in case of bankruptcy. The product of these two columns (*XcXh*) has a value of 1 if the hospital would face bankruptcy in the case of low liquidity and it would be bailed out. However, bankruptcies and bailouts can take place only if liquidity is below the necessary level (the variable *Ytrouble* takes a value of 1). Therefore, hospitals are actually bailed out if $Ytrouble \cdot XcXh = 1$.

Table 7: A realization of our simulation

	n	N	qd	qm	qu	pc	ph			
	20	**5**	**40%**	**20%**	40%	**40%**	**30%**			szim
	1	2	3	4	5	6	7	8	9	
i	Ym	Yst	Yh	Y trouble	X	Xc	Xh	XcXh	bailout	
0	0	0	0							
1	1	1	1	0	1	0	0	0	0	
2	0	0	0	0	-1	1	0	0	0	
3	-1	6	0	1	-1	1	1	1	1	
4	-1	6	0	0	0	1	0	0	0	
5	-2	6	-1	1	-1	0	1	0	0	
6	-1	6	0	0	1	0	0	0	0	
7	0	6	1	0	1	0	0	0	0	
8	-1	6	0	0	-1	0	1	0	0	
9	0	6	1	0	1	0	1	0	0	
10	-1	6	0	0	-1	1	0	0	0	
11	0	6	1	0	1	1	1	1	0	
12	0	6	1	0	0	0	0	0	0	
13	0	6	1	0	0	0	0	0	0	
14	1	6	2	0	1	1	0	0	0	
15	0	6	1	0	-1	0	1	0	0	
16	-1	6	0	0	-1	1	1	1	0	
17	0	6	1	0	1	1	0	0	0	
18	0	6	1	0	0	0	0	0	0	
19	1	6	2	0	1	0	1	0	0	
20	**2**	**6**	**3**	0	1	0	0	0	0	
					2	**8**	**8**	**3**	**1**	sum

The first three columns show the liquidity situation of the hospital under three scenarios, based on the random numbers in columns *X*, *Xc* and *Xh*. *Ym* shows a simplified scenario, in which hospitals cannot go bankrupt, that is, the value of *Ym* in a given year is merely the sum of the *X* values up to that year. The only restriction is that according to our original assumptions, it has to remain between -5 and 5. In the scenario of column *Yst* we incorporate bankruptcies, but not the bailouts. This means that if liquidity is below the necessary level and the risk of bankruptcy realizes (both *Ytrouble* and *Xc* has a value of 1), then the hospital ceases to operate (denoted with a value of 6) and remains inoperational during the remaining periods. In the realization shown in Table 7, bankruptcy takes place in the third year.

The scenario in column *Yh* contains bailouts as well as bankruptcies. As in column *Yst*, bankruptcy would take place in the third year, but because $Xh(3) = 1$, the hospital is driven back to the starting liquidity situation (state 0) through the bailout. It can also be seen that the hospital would have faced bankruptcy in several later periods (and would have been bailed out in years 11 and 16), were its liquidity below the necessary level. Bankruptcy takes place only if both *Ytrouble* and *Xc* take the value of 1. If *Xh* is also 1, the hospital is saved, if it is 0, the hospital ceases to operate.

CONCLUSION AND FURTHER QUESTIONS

Our computerised simulations based on the structure presented in Table 7 show that in the case of more hospitals, the main factor that affects their survival is not how the bailout efforts are distributed among them (see the discussion regarding Table 6), instead it depends mainly on how correlated the liquidity situations of the hospitals are, how correlated the bankruptcy cases are. Specifically: the main question is whether columns *X* and *Xc* are the same for the different hospitals or they are formed by different random series.

The case of column *Xh* is somewhat different; it is a policy decision which hospital receives help if there is a need and opportunity for a bailout:

- there is a preferred institution (A), and B can expect bailout only if A does not exist;
- the hospitals receive bailouts in turns;
- the hospital in a worse situation is bailed out;
- the bailouts are random.

Another important related question is whether the government should intervene only in the case of bankruptcy or should it try to improve the liquidity situation of a hospital even without bankruptcy if it is in the danger zone. This could be an especially important factor in such a version of the model, where the probability of bankruptcy depends on the amount of liquidity shortage and the length of the period of inadequate liquidity (a longer period of low level of liquidity may more probably urge creditors to start the bankruptcy procedure).

Another possible direction of further research is the incorporation of the effects of bailouts on transition probabilities in the model. This leads us back to the concept of soft budget constraint: if a hospital is bailed out, it may expect bailouts in the future as well, and the fewer incentives to operate efficiently may result in a worse liquidity situation.

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