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Original Research Article

Credit Benefit of Reverse Factoring in Iran: An Agent-Based Approach

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We investigate the effects of the implementation of reverse factoring on the credit risk level of financially constrained suppliers within a supply chain. To simulate the desired supply chain finance environment, an agent-based framework is developed. Short-term bank financing and reverse factoring are available financial instruments for suppliers. The estimations regarding the default probability of agents are calculated using formulations of the KMV (Kealhofer Merton Vasicek) model. It incorporates market-based information and company-specific financial data to estimate the likelihood of default and potential losses based on the estimation of the market value and volatility of the firm's asset and calculation of the distance to default. Results suggest that the adoption of reverse factoring significantly alleviates the credit risk levels of financially constrained members of a certain layer within a supply chain.

Keywords: Supply Chain Finance, Reverse Factoring, Credit Risk, Agent-Based Simulation
Jel Classification*:* G17, D81, C63

1 Introduction

A Supply Chain (SC) is a set of a companies' entire operations directly and indirectly interlinked and interacted to transform inputs into outputs that are delivered to the end customer [1]. The field of supply chain management (SCM) is concerned with the collaboration and coordination of several stakeholders to optimize the flow of goods, information, and finance along the entire SC [2]. The financial supply chain is different from the physical supply chain as it deals with the flow of cash instead of goods, and is in the opposite direction. Financial flows along the SC form an essential part of the continuum

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of the business operation [3] and despite the potential of Supply Chain Management (SCM), relatively few companies utilize inter-organizational network settings to drive financial performance in a collaborative way [4].

The theories of Financial Supply Chain Management (FSCM) and Supply Chain Finance (SCF) have been significantly developed in recent decades. In the literature, FSCM is mainly referred to as schemes implemented to focus on the supplier-buyer relationships and also managing the financial flow within a SC; a flow that is in the opposite direction of physical and informational flows [5]. SCF includes a range of financial instruments that are implemented to finance members of a SC and is generally considered a subset of FSCM [6]. Supply chain finance is an approach for two or more organizations in a supply chain, including external service providers, to jointly create value through the means of planning, steering, and controlling the flow of financial resources on an inter-organizational level [7]. The financial mechanisms of SCF are quite diverse. The main objective of an SCF mechanism is to focus on short-term financing solutions particularly regarding a firm's accounts receivable and payable [8].

Among various schemes under SCF, reverse factoring (RF) is quite popular and authors often identify SCF as a synonym of RF [9]. RF is defined as a financial agreement where a corporation facilitates early payment of its trade credit obligations to suppliers [10]. The intermediation of a financial institution is necessary for RF and the discounting of trade credit obligation is carried out considering only the credit risk of the buyer side of the contract, creating an opportunity of interest rate or credit arbitrage. Interest rate arbitrage is a form of "giving credit support" which occurs when either a supplier or buyer can gain access to financing at a similar rate of the better-rated buyer or supplier [11]. RF creates even more opportunities for SC. It is mentioned in the literature that the value of RF consists of both credit arbitrage and the option to enable production which can contribute greatly to SC efficiency [12].

Although we use the term RF in this paper, the results can be generalized to the Iranian economy since there is a financial instrument in place that makes the implementation of RF possible. This instrument is called Certificate of productive credit [1](the short form is pronounced GAAM in Farsi) and it is used to provide the supply chain with the necessary financial liquidity. The credit status of a buyer that is willing to initiate this process is first assessed by the financial intermediary and the maximum value of the securities is

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determined. Then the supplier and the value of the trade between the two parties is introduced to the financial intermediary and the securities are issued. The securities can be exchanged in the market or transferred to other suppliers in exchange for raw materials. The buyer can also keep the securities until the maturity date and then exercise them to gain their nominal value [13].

The model of this research is built based on the framework proposed by Weisbuch and Battiston [14]. The mentioned framework creates an agent-based approach toward simulating the working capital changes of agents through the ordering and delivery processes of a SC. Each SC member is modeled as an agent who selects its suppliers based on a set of attributes and makes ordering decisions to meet its production needs. Some major changes were made to the mentioned framework in this research. Financing was made available to agents with not enough liquidity to meet downstream demand. The mentioned financing can happen in the form of short-term bank loans or the selling of receivables to a third-party financial institution in the form of RF. In our model, a constant payment delay was considered in the modeling to accumulate receivables for firms and thus make RF possible. Results suggest that RF significantly reduces the default probability of suppliers in a supply chain.

2 Literature Review

Multiple studies have tried to shed light on the benefits of SCF for SC partners. As Hofmann et al. [15] point out, SCF leads supply chain partners towards a better working capital management by extending the payables period and narrowing the receivable period and thus having a positive impact on the cash conversion cycle (CCC or C2C) metric for both the supplier and the buyer. Tseng et al. [16] state that firms can enhance their performance through sustainable SCF and therefore improve their competitive advantages. Alleviating the supply risk is another benefit of SCF. As Moretto et al. [17] state, strategic suppliers are at the same time a key asset and a major risk source for focal companies; Hence offering SCF to financially constrained suppliers can bring stability to a firm's supply side.

The measure of cash conversion cycle was introduced by Richards et al. [18] to evaluate and control the working capital management efficiency of a firm. CCC is composed of the cycle time of inventories (DIO), cycle time of account receivable (DRO), and the cycle time of accounts payable (DPO). Deloof [19] suggests that shortening the cash conversion cycle of one firm positively contributes to its profitability. According to Hofmann et al. [15], improving a firm's CCC (extending payable period and shortening receivables

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period) might be achieved at the expense of its SC partners. For example, a trade credit contract extends both the payable period of the buyer and receivable period of the supplier which is not desirable for the supplier [15]. RF gives the supplier a chance to liquidate accounts receivable related to a creditworthy buyer and therefore overcome the mentioned disadvantage of trade credit.

Regarding the benefits of RF much work has been done. De Goeij et al. [20] discuss that the lack of knowledge about the benefits and mechanism of RF is the main impediment to its adoption by logistic service providers. Iacono et al. [20] believes that benefits such as competitive advantages, more desirable interest rates, and better working capital management can be achieved by RF, but these benefits are highly sensitive to market conditions. The spread in external financing costs has been mentioned to be a crucial element for the beneficial implementation of RF in multiple studies [22] [23] [24].

Pointing out the operational benefits of RF, Van der Vliet et al. [25] believe that supplier's service level can significantly improve by the use of RF. Wu et al. [26] compare RF with other financing schemes such as early payment and delayed payment and conclude that RF is the most profitable among the mentioned financing schemes when the retailer has a credit advantage over the supplier and also a third party financier is involved. Extensive comparison is carried out by Gao et al. [27] between purchase order financing and reverse factoring. By studying different scenarios, the authors show that SC efficiency is increased in situations that RF is available to SC members either solely or jointly with purchase order financing. In this paper, the credit risk benefits of RF are examined. We simulate a supply chain and test whether the active presence of RF alleviates the probability of default for financially constrained agents or not.

The KMV credit risk model which is used to estimate the default probability of agents in this research is a structural credit risk model. The work of Merton [28] based on the option pricing model proposed by Black et al. [29] was a start to this category of credit risk models. Structural models are based on the assumption that the value of a firm's equity can be viewed as a call option on the value of the firm's assets. By this notion, default happens if a firm's asset value drops below the value of its debt obligation at or before the time of maturity [30]. The KMV credit risk model is based on the extensions of the basic structural models by the work of Kealhofer [31], McQuown [32], and Vasicek [33], who founded KMV corporation in the late 80's [34]. KMV model formulates a measure of distance to default (DD)

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which can then be used to calculate the probability of default. The underlying theoretical assumption of the KMV model is the normal distribution of returns. Although this might not be the most realistic assumption, the KMV model is still being implemented in academic literature to measure the probability of default [35] [36] [37]. We also use the KMV model to assess the credit risk of agents in this research.

Gelsomino et al. [38] point out that financial institutions can consider SCF relationships within the SC to estimate the credit risk of members more accurately. Zhu et al. [39] divide the determinants of credit risk into two categories. Firm-specific determinants and SCF related determinants. Several techniques such as system dynamics modeling, fuzzy modeling, logistic regression, artificial neural network, and hybrid and ensemble machine learning models have been used by authors to estimate credit risk of SC members more precisely considering the two-mentioned categories [39] [40] [41] [42]. In this paper, we determine agents' credit risk with KMV formulation to avoid complexity and performance issues.

Agent-based modeling of a SC is quite popular among researchers. As Sergeyev [43] states, agent-based simulation and modeling make it possible to describe the behavior, processes of cooperation, coordination and inter-organizational interaction of participants of a supply chain and reconfigurable network structures of the supply chain. Several areas such as production scheduling [44], inventory management [45], SC resiliency [46], SC risk management [47], SC integration [48] and SC coordination [49] are investigated by the means of agent-based modeling. Mizgier et al. [50] investigated default propagation in multi-stage SCs by extending the framework proposed in [14] and following this stream of research, Hou et al. [51] studied different supplier selection rules.

3 Methodology

A 3-layer SC is studied in this research. The flows of order and product are shown in figure 1. Orders are received stochastically by agents in the first layer from outside of the network and passed to upstream. When orders reach agents in the last layer, the product flow starts.

The initial credit risk status of agents can be calibrated through the choice of the initial values of parameters such as cash, long-term debt, and fixed asset value. The agents that are present in the third layer will be designed to be less creditworthy than their downstream buyers, therefore they can benefit from RF. KMV credit risk model as a structural one requires a parameter reflecting the standard deviation of total assets. Given the initial values, simulation is

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run for 200 steps (each step reflecting one day), creating a vector of 200 values for the total asset value of each agent. The first credit rating of agents occurs at step 201 and financing becomes available to the agents of the 3rd layer at this time. From this point forward, we call 3rd layer agents “suppliers” of our model, and 2nd and first layer agents are referred to as manufacturers and retailers, respectively.

Two scenarios are simulated. For the first scenario we assume that in the absence of RF, suppliers can only access short-term financing in the form of bank loans. The interest rate related to this form of financing is calculated by adding a constant margin to the firm’s estimated default probability. In the second scenario, RF is made available to suppliers. Between two options of financing available to agents in the latter scenario, RF has priority over bank loans due to the lower rate of interest imposed on the suppliers.

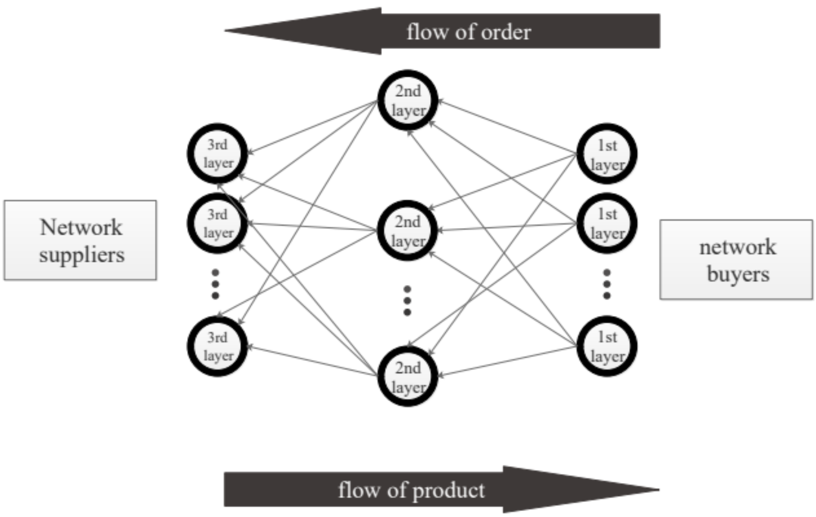

Figure 1. Flows of order and Product in the supply chain under study (arrows represent the cash flows).
Source: Research findings

Welch’s t-test is used to evaluate the effects of RF on the credit risk level of suppliers. Due to the stochastic behavior of the model, for each scenario, the model is simulated 60 times with equal horizons. At the end of each simulation, the average probability of default among all suppliers is extracted. After simulating both scenarios, each for 60 times, there will be a vector of

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average default probability for each scenario. The desired hypothesis test is implemented at this point to test whether RF significantly alleviates credit risk level on a certain layer of a SC or not. Table 1 provides description of model parameters.

3.1 Notation and Parameter Description

Each agent belongs to a certain layer of the supply chain as shown in figure 1. It is also important to differentiate between an agent's state at distinct points in time. Therefore, we design the notation of our model in a manner that presents the value of a certain parameter for a unique agent in a specified layer at a certain point in time. For instance, take X as a parameter. $X_{s.i}(t)$ represents the value of parameter *X* for agent *i* on layer *s* at time *t*. This is the main notation style of the model. Table 1 describes the meaning of parameters. The few parameters that do not follow the mentioned notation style are described explicitly.

3.2 Order and Product Flow

At each step of the simulation, the demand is realized by agents on the first layer. Demand is stochastic and follows an exponential distribution [52] [53], with parameter $\lambda\_D_{1.i}$. Each agent has some cash that is used to provide raw material and also to repay any form of debt. Financial inflows of an agent are also added to its cash value. Any financial transaction that affects cash is carried out at the beginning of each day. As shown in Eq. -(1), daily possible transactions consist of receiving of accounts receivables, payment of accounts payable, and also repayment of a bank loan.

$$Cash_{s.i}(t) = Cash_{s.i}(t-1) + TR_{s.i}(t) - TP_{s.i}(t) - G_{s.i}(t) \quad (1)$$

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Table 1
Parameter description

Parameter	Description	Parameter	Description
$Y_{s.i}(t)$	Amount of order sent upstream	$D_{1.i}(t)$	Total orders received from buyers
$Cash_{s.i}(t)$	Available liquidity	$G_{s.i}(t)$	Repayment amount of a short-term bank loan
$INV_{s.i}(t)$	Inventory value	$TR_{s.i}(t)$	Total accounts receivable value
$FA_{s.i}(t)$	Fixed assets value	$TP_{s.i}(t)$	Total accounts payable value
$AR_{s.i}(t)$	Accounts receivable value	R_f	Yearly risk free interest rate
$AP_{s.i}(t)$	Accounts payable value	$SAR_{s.i}(t)$	Sellable accounts receivable
$CC_{s.i}(t)$	Credit capacity	P_s	Homogeneous unit selling price on layer s
$ST_{s.i}(t)$	Short-term debt	$PT_{s.i}$	Production time
$LT_{s.i}(t)$	Long-term debt	$ML_{s.i}(t)$	Maximum available liquidity
$A_{s.i}(t)$	Total assets	PD	Payment delay term
$L_{s.i}(t)$	Total liabilities	FP	Short-term bank loan maturity
$\gamma_{s.i}(t)$	Short-term bank loan interest rate	FG	Minimum time interval between bank financing
$m_{3.i}$	Profit margin of agent i on layer 3	v_i	Supplier set of agent i
$DD_{s.i}(t)$	Distance to default	b_i	Buyer set of agent i
$Q_{k.i}(t)$	Order quantity of agent k to agent i at time t	$\lambda\_D_{1.i}$	Distribution mean of total orders received from buyers by agent i on layer 1 at time t
α	The ratio of an account receivable discounted by financial institution	t_d	Delivery time of a demand realized at time t to buyers from outside of the network

Source: Research findings

Maximum available liquidity for agents can be calculated using Eq. (2). An agent's maximum available liquidity is the maximum amount it can spend on ordering raw material. As is shown in Eq. (2), maximum available liquidity for suppliers consists of supplier's cash, the amount that can be received as a short-term bank loan ($[CC_{s.i}(t) - ST_{s.i}(t)]$) and the liquidity which can be realized by RF available at the moment ($\propto \cdot SAR_{s.i}(t)$). Sellable accounts receivable of a supplier are those receivables that are demanded from a buyer less risky than the supplier. RF is only made available to suppliers, therefore the only source of financing for other downstream agents is the short-term bank loan.

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$$ML_{s.i}(t) = \begin{cases} Cash_{s.i}(t) + [CC_{s.i}(t) - ST_{s.i}(t)] + \propto \cdot SAR_{s.i}(t) & if\ s = 3 \\ Cash_{s.i}(t) + [CC_{s.i}(t) - ST_{s.i}(t)] & Otherwise \end{cases} \quad (2)$$

Agents' order quantity is bounded by their liquidity. Eq. (3) shows that agents send orders to upstream according to the downstream demand unless they are financially constrained even after seeking all the available financing.

$$Y_{s.i}(t) = \begin{cases} min\left(\frac{ML_{s.i}(t)}{P_{s+1}}.D_{1.i}(t)\right) & if\ s = 1 \\ min\left(\frac{ML_{s.i}(t)}{P_{s+1}}.\sum_{k\in b_i} Q_{k.i}(t)\right) & if\ s = 2 \\ min\left(\frac{ML_{s.i}(t)}{P_s - m_{3.i}}.\sum_{k\in b_i} Q_{k.i}(t)\right) & if\ s = 3 \end{cases} \quad (3)$$

Order flow reaches the SC upstream instantly by the rules already described. In the case of the product flow, a production time is considered for each agent. We assume that an agent only starts producing when it has received all of its ordered products related to an order by a specific buyer from its suppliers. Assume an order is realized by a first layer agent at time *t*, the delivery date of the same order by the same first layer agent is calculated by Eq.(4).

$$t\_d = t + max_{k\in v_j}(PT_{3.k}) + max_{j\in v_i}\left(PT_{2.j}\right) + PT_{1.i} \quad (4)$$

3.3 Payment Delay

After the delivery of products at time *t*, agent *k* (which is the buyer at layer *s−1*) owes its supplier (agent *i* at layer *s*) an amount equal to $P_s \times Q_{k.i}(t)$. It is assumed that the payment of this amount is not carried out instantly but with a delay according to parameter *PD*. During the time interval between *t* and *t+PD*, the mentioned amount is added to the accounts payable and accounts receivable of the buyer and the supplier respectively. Figure 2 shows the process of payment delay.

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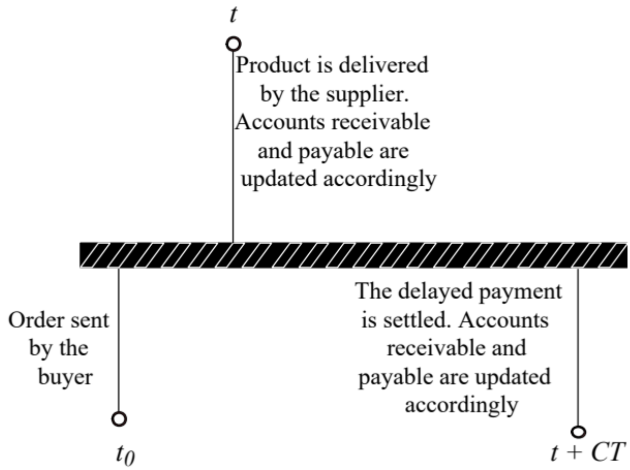

Figure 2. Payment delay mechanism
Source: Research findings

3.4 Inventory Value

Since it takes time for each agent to produce goods according to parameter $PT_{s.i}$, received orders from upstream remain in the ownership of that agent until it is sold to agents downstream as finished product. Inventory value of each agent ($INV_{s.i}(t)$) is calculated as the value of received orders that are still in the ownership of the agent and will be sold downstream after the production time has completed.

3.5 Short-Term Bank Loan

If an agent does not have sufficient cash for its operation, it can provide financing by acquiring a short-term bank loan. A credit capacity equal to fixed asset value is considered for each agent and acts as a ceiling for unsettled bank loans value of each agent. A minimum time distance between two bank financing occasions is required (FG). Loans are fully repaid on a short-term horizon according to parameter FP. The yearly interest rate of a loan ($\gamma_{s.i}(t) + R_f$) is set according to the agent's default probability over the next year plus risk-free interest rate.

3.6 Reverse Factoring

Suppliers are the only agents in the model who have access to RF as an alternative source of financing due to difficulties regarding the credit risk

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calibration of agents. RF is prioritized over bank loans since a lower interest rate is imposed on this scheme. A supplier can receive a ratio (according to $\propto$) of an account receivable discounted by an interest rate related to its more creditworthy buyer's (if any available) credit risk if it finds itself financially constrained.

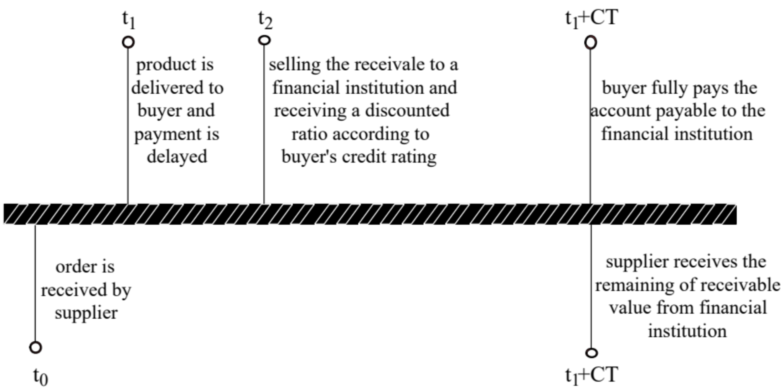

Figure 3. Reverse factoring mechanism
Source: Research findings

Figure 3 represents the RF mechanism implemented in the simulation. Accounts receivable of supplier and accounts payable of the buyer is updated according to the value of products delivered at time t_1. Normally a financial transaction would occur between the buyer and supplier at time $t_1 + PD$. If the supplier needs financing during the period of payment delay, RF can happen. If the supplier decides to sell a receivable in the form of RF at time t_2 (which is after t_1 and before $t_1 + PD$), a ratio of that receivable (defined by the parameter $\propto$) is discounted by the financial institution according to the buyer's default probability. After discounting a ratio of the receivable, the financial institution owns that receivable. At the time $t_1 + PD$, the buyer pays the full amount of the delayed payment to the financial institution and the supplier receives the rest of the receivable value (equal to the ratio of $1-\propto$).

3.7 Agent's Balance Sheet

Each agent has a balance sheet that reflects its financial state. As it can be seen in figure 4, the items in the designed balance sheet are not as many as items presented in a standard balance sheet, but as much as this simulation is

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concerned, they contain key pieces of information that are needed for performing credit rating in the model.

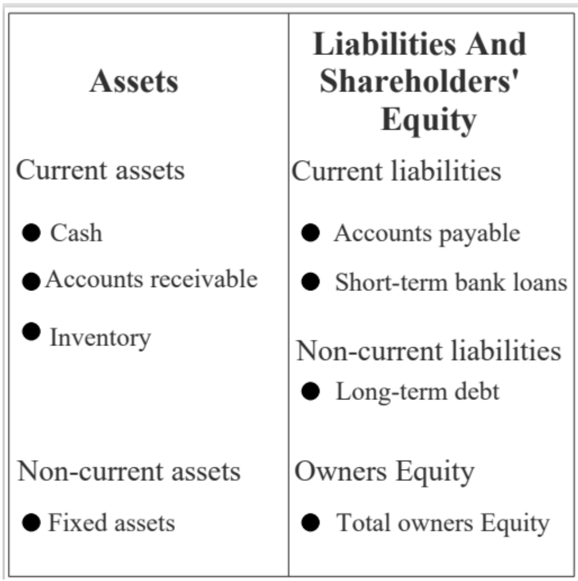

Figure 4. Agents' balance sheet
Source: Research findings

Fixed assets and long-term items of the balance sheet are set at the start of the model and determine the credit risk level of the agent. It is assumed that non-current assets and liabilities do not change during the horizon of simulation. As in a standard balance sheet, the total owner's equity is calculated by the difference between total assets and total liabilities. According to KMV model, Bankruptcy occurs only when the value of the total owner's equity reaches zero.

3.8 Credit Rating

As mentioned before, the structural credit risk model known as KMV model is used to estimate the credit risk levels of agents. Credit rating plays an important role in our model since the interest rate of short-term bank loans are determined based on the estimated default probability. RF is another feature that relies on the credit levels of agents since a supplier can only sell

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receivables that belong to a buyer that has a better credit risk status than the supplier itself.

Define $\sigma_{A_{s.i}}$ as the standard deviation of a firm's total assets. The KMV distance to default for agent *i* at layer *s* at time *t* ($DD_{s.i}(t)$) is calculated by Eq. (5).

$$DD_{s.i}(t) = \frac{A_{s.i}(t) - Default\_point}{\sigma_{A_{s.i}} \cdot A_{s.i}(t)} \tag{5}$$

The choice of Default Point depends on the study, here the value of total short-term debt plus half of the total long-term debt is accepted as the default point. Having estimated the distance to default for an agent, default probability can be calculated by Eq. (6) (*N* is the normal cumulative distribution function).

$$Default\ probability_{s.i}(t) = 1 - N(DD_{s.i}(t)) \tag{6}$$

At first, the model is simulated for 200 steps and the dynamics of total assets are stored for agents. At step 201 a value for $\sigma_{A_{s.i}}$can be calculated, and therefore credit rating and RF begin at this step. This approach estimates credit risk (and consequently interest rates) for a horizon of 200 days.

3.9 Hypothesis Test

The main goal of this study is to investigate the credit risk impacts of RF implementation in a SC. For this purpose, two scenarios are simulated. The only source of financing available in the first scenario for all agents is short-term bank loans. In the second scenario, the suppliers also have access to RF.

The model is simulated 60 times for each scenario and at the end of each individual simulation, the mean default probability of the supplier layer is calculated and stored. After this process is completed, a vector of 60 default probabilities is available for each scenario. A hypothesis test is needed at this point to judge whether RF significantly reduces default risk at the supplier layer or not.

Welch's t-test is used to test the population means. The reason behind choosing this specific test is that population variances do not have to be similar for the test results to be valid. First, a two-tailed version of the test is carried out with hypotheses described in Eq. (7) and then we interpret the result for the one-tailed scenario described in Eq. (8). The test statistic and standard error are presented in Eq. (9) and Eq. (10) respectively. In the following equations, μ represent the average default probability of agents in the same

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layer of supply chain. Furthermore, $\bar{X}_1$, S and n respectively refer to each sample's mean, standard error and size.

$$\begin{cases} H_0: & \mu_{RF} = \mu_{no\_RF} \\ H_1: & \mu_{RF} \neq \mu_{no\_RF} \end{cases} \tag{7}$$

$$\begin{cases} H_0: & \mu_{RF} \geq \mu_{no\_RF} \\ H_1: & \mu_{RF} < \mu_{no\_RF} \end{cases} \tag{8}$$

$$T\_Statistic = \frac{\bar{X}_1 - \bar{X}_2}{SE_{X_1 - X_2}} \tag{9}$$

$$SE_{X_1 - X_2} = \sqrt{\frac{s_1^2}{n_1} + \frac{s_2^2}{n_2}} \tag{10}$$

3.10 Initial Parameter Values

Stochastic demand and random supplier selection behavior cause different behaviors and liquidity pathways for agents within each layer. In other words, simulation is started with homogenous agents and is finished with heterogeneous agents. Initial values of parameters such as inventory value ($INV_{s.i}(t)$), accounts payable value ($AP_{s.i}(t)$), accounts receivable value ($AR_{s.i}(t)$), short-term liability ($ST_{s.i}(t)$) and other unmentioned parameters are set to zero. The rest of the parameter values that need to be set at the start of the simulation are presented in table 2.

Credit capacity of each agent ($CC_{s.i}$) is also set equal to the value of its fixed assets ($FA_{s.i}(0)$) and does not change through the simulation. Calibrating the credit risk level of agents is the main concern behind setting initial parameter values of the simulation. Suppliers are set to be less creditworthy than other agents. Long-term liabilities ($LT_{s.i}(0)$), fixed assets ($FA_{s.i}(0)$) and cash ($Cash_{s.i}(0)$) are key parameters that determine credit risk levels of agents. The maturity of short-term loans ($FP_{s.i}$) are set to be equal to payment delay term (PD) for creating better comparability between RF and bank loan financing and $\propto$ is set to be 0.7 based on previous research [54].

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Table 2
Parameter values

Parameter	$s = 1$	$s = 2$	$s = 3$
$Cash_{s.i}(0)$	6600	6600	500
P_s	1.02	1.01	1.oo
$\lambda\_D_{1.i}$	1000	-	-
$m_{3.i}$	-	-	0.05
R_f	0.05	0.05	0.05
$FP_{s.i}$	10	10	10
$FG_{s.i}$	2	2	2
$PT_{s.i}$	1	1	1
$FA_{s.i}(0)$	60	60	50
PD	10	10	10
$LT_{s.i}(0)$	100	100	200
α	-	-	0.7

Source: Research findings

4 Results

The model is simulated for 500 steps with 5 retailers, 10 manufacturers, and 15 suppliers for each scenario. At first, key resulting differences from the two mentioned scenarios are presented by describing the results of single 500 step simulations of the model. Our main conclusion is drawn based on a hypothesis test performed upon the data extracted from multiple replications of the model due to the stochastic behavior resulted from stochastic demand.

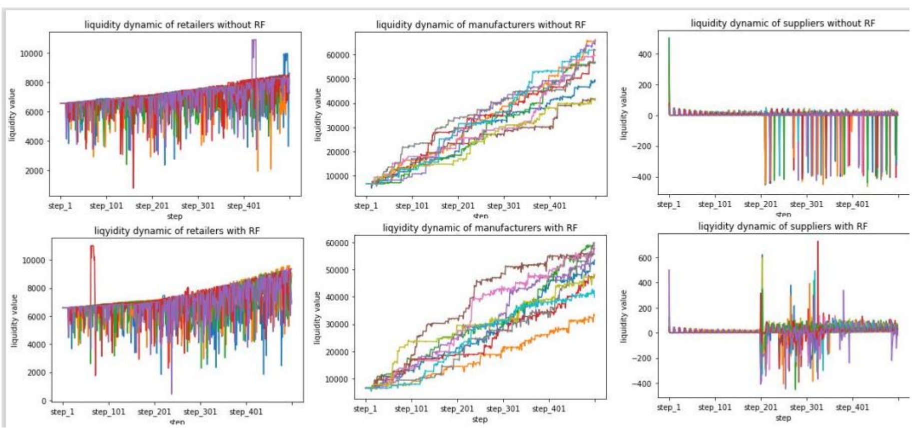

Figure 5. Cash dynamics of agents under each scenario
Source: Research findings

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Cash dynamics of agents at each scenario are projected in figure 5. Retailers and manufacturers start with high levels of cash and get more demand due to less competition relative to suppliers. As it was expected, the cash status of suppliers would change under different financing scenarios. Bank loan repayment value is subtracted from cash due to Eq. (1) and negative values of cash are related to times that the supplier has to pay off a big loan. Negative values of cash do not cause bankruptcy as long as the agent's owner's equity is positive. RF reduces a firm's indebtedness level in the model, hence less debt repayment occasions occur and less negative cash values happen.

Retailers and manufacturers do not rely on financing due to their high levels of cash which is sufficient relative to their demand level. Suppliers on the other side rely heavily on financing since they are set to be financially constrained. Suppliers try to replace bank loans with RF as much as possible, but as figure 6 shows, sometimes RF does not satisfy all the financing needs and short-term bank loans are required.

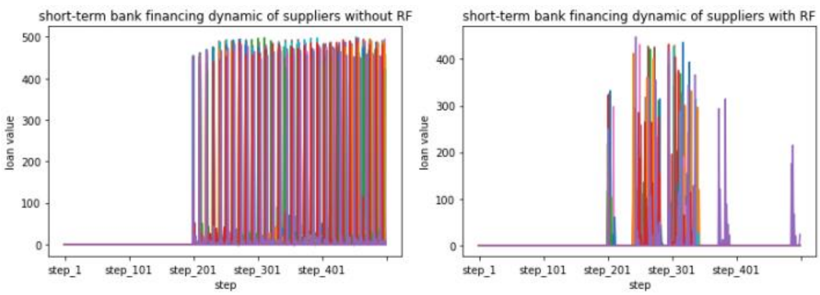

Figure 6. Short-term bank loans sought by agents
Source: Research findings

Credit rating starts from step 200. Since a clear vision of the default probability of both supplier and manufacturer is crucial for RF, the beginning of credit rating also marks the beginning of financing availability in the model. As shown in figure 7, RF has happened multiple times for different agents in the second scenario replacing short-term bank loans.

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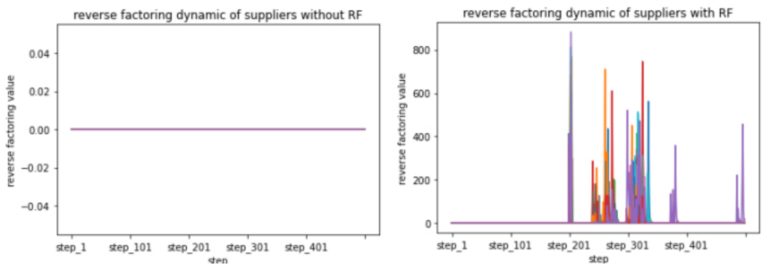

Figure 7. Reverse factoring activated by suppliers
Source: Research findings

Figure 8 shows the credit risk dynamics of agents. Suppliers are set to mostly have higher default probability than other agents in the scenario representing the absence of RF. It can be seen that RF has alleviated the credit risk level of suppliers at the end of the simulation horizon. Comparing default probability of suppliers in the second scenario with their short-term bank financing behavior in figure 6 implies that levels of short-term debt and credit risk of agents have a positive correlation (as expected due to equation 5).

Due to the stochastic behavior of the model, a single simulation run for each scenario is not sufficient to conclude the credit risk effects of RF. Each scenario is simulated 60 times for a horizon of 500 steps and at the end of each replication default probability mean of the third layer is stored as mentioned previously. A hypothesis test is implemented using vectors of default probability means to test whether reverse factoring successfully alleviates the average credit risk of the supplier layer or not.

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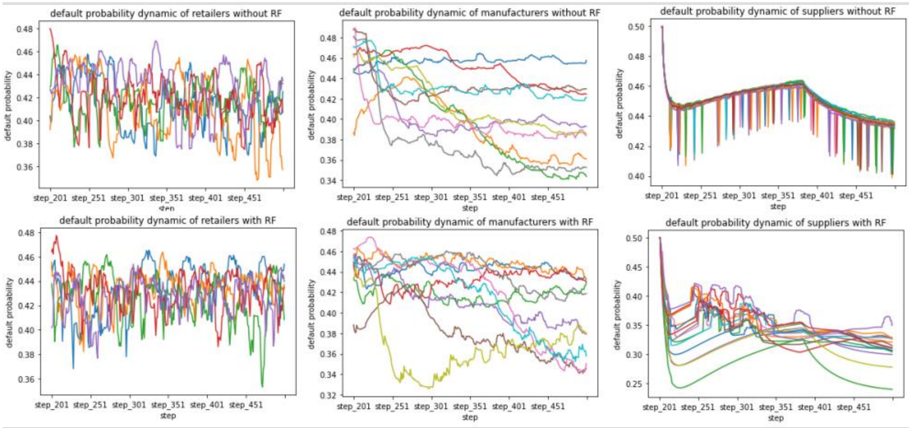

Figure 8. default probability dynamics of agents
Source: Research findings

The hypothesis test is carried out as explained by Eq. (9) and Eq. (10) using scipy.py library in python as a two-tailed hypothesis test according to Eq. (7). To interpret results of the test as a one-tailed test explained in Eq. (8), $\bar{X}_1$ is considered relative to scenario 2 and $\bar{X}_2$ relative to scenario 1. Null hypothesis of Eq. (8) can be rejected if $0.5 \cdot p\_value \leq \alpha$ and $T\_statistic < 0$. Descriptive statistics of default probability vectors and also hypothesis test results are shown in table 3. Descriptive statistics show that the standard deviation of the default probability means of the supplier layer has increased in the second scenario, but the average default probability mean has decreased. The result of the hypothesis test suggests that the implementation of RF has significantly reduced the default probability mean of supplier layer in the model for the chosen time horizon with a confidence level of 95%.

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Table 3
Descriptive statistics and hypothesis test result

Descriptive Statistics			
Scenario 1		**Scenario 2**	
Population number	60	Population number	60
Mean	0.479	Mean	0.335
Standard deviation	0.001	Standard deviation	0.017
Min	0.473	Min	0.293
Max	0.483	Max	0.365
Hypothesis Test			
$\propto$	$T\_Statistic$	$\frac{p\_value}{2}$	Decision
0.05	-64.060	3.30×10^{-57}	Reject null hypothesis

Source: Research findings

5 Conclusion

The main purpose of this study was to investigate the effects of RF implementation on credit risk levels of SC members that benefit from this financing scheme. A three-layer SC was designed for this purpose and the main processes of ordering, delivery, and financing were simulated using an agent-based modeling approach, for agents on different layers. Our model includes 30 agents consisting of 5 retailers, 10 manufacturers, and 15 suppliers. KMV model of credit risk [31] [32] [33] was used to estimate the default probability of agents. Credit ratings were then used for determining interest rates of financing.

Results of this study show that RF significantly reduces the default probability of a collection of agents located on the same layer of a SC with a confidence level of 95%. In other words, RF increases the financial stability of the network. This result is in line with [17] who has pointed out the strategic values of SCF to a core enterprise of a SC. While the hypothesis test shows that the average default probability of suppliers in scenario 2 (with RF) is significantly less than scenario 1 (without RF). An explanation for this result could be that as suppliers receive funds earlier, their liquidity increases and thus, they are less likely to become bankrupt. The standard deviation of suppliers' default probability increases in the case of RF availability due to the diversity of default probability trajectories. It is worth to mention that for the supplier layer, the default probability level of all suppliers is lower in scenario 2 comparing to scenario 1 [8].

As a financing scheme that relies on participation, RF is beneficial for both financially constrained suppliers (in terms of financial stability and interest

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rate reduction) and creditworthy buyers. This research suggests that offering RF to financially constrained suppliers can create a more stable supplier base for a buyer. Results show that RF would also alleviate the destructive effects of rapid price changes and economic uncertainty in an inflated economy such as the Iranian economy.

There are some existing limitations in our model such as simplifications of several behavioral aspects and the rules regarding payment delay and RF. Future research should model the financial interactions more realistically. The results of this study can be validated using a collection of real-world data.

This study can be developed through several approaches. The rules regarding payment delays can be influenced by the rich literature of trade credit. A better determination mechanism for wholesale prices and the determination of trade credit terms based on order quantities are some examples. The benefits of a financially stable supply side to downstream members can be studied since the designed supply chain consists of 3 layers. Financing was made available infinitely to agents which is not basically wrong regarding the whole banking system. Considering a financial institution with finite resources (instead of an infinite banking system) can be the starting point of a study about the effects of participation in SCF on a financial institution.

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