Applicability of ARIMA models for investigating the effects of Technology spillover on Car Manufacturing Companies' performance

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Abstract

The present study seeks to investigate the effects of technology spillover on the performance of automobile companies. In short, technology spillover is an opportunity to transfer and exploit and obtain information, technology or technical know-how, without prior planning. One of the most important indicators in evaluation of cars' manufacturing companies' performance is sales; hence, this study focused on sales variable and took it as a representative of Technology spillover. To this aim, the sales data were collected from the domestic car manufacturing companies. For this mean, sales' pattern during ten years is recognized using Seasonal ARIMA (S-ARIMA) model. Akaike Information Criterion (AIC) and Schwarz Bayesian Information Criterion(BIC) were used to select the most appropriate model. It is found that the selected model can be applied to forecast the sales with Mean Absolute Percentage Error (MAPE) in the range of 6%. This research also confirmed the idea, if Foreign Direct Investment (FDI) is taking place in developing countries, with regards to the necessary conditions and infrastructures, technology spillover occurs, and meaningful changes in factory performance would happen. Also, the proposed forecasting model can help senior managers of domestic companies in mid-term and long-term planning.

Keywords
Technology spillover, Foreign Direct Investment, Host Company, ARIMA models

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1. Introduction

The increasing growth of information and the diversity of technologies are driving communities to optimal use of technology. One of the new approaches to technology is technology spillover, which is an involuntary result of the technology. In other words, technology spillover is an opportunity for exchange and utilization of information, technology-based knowledge, and ideas (Marshall, 1920). Of course, some recent studies have shown that technology spillover is difficult to distinguish in technology transfer due to its complexity (John Kou, 2005). One of the ways to take advantage of technology spillover is moving along FDI. Collaboration between international and domestic companies facilitates the access to foreign information resources and results in the facilitation of the process and facilitates the process of absorbing technology for the Host Company. Policy makers in developing countries consider foreign investment as an opportunity for an economic boost. Research carried out in Spain showed that the outflow of foreign direct investment was only for factories with a good level of absorption capacity (Strobl, Barrios, 2002). Unfortunately, the subject of technology spillover in Iran has been neglected, and domestic industries and companies have been reluctant to utilize this particular approach. This paper attempts to demonstrate the positive impact of technology spillover from foreign investment in the automotive industry.

The occurrence of technology spillover depends on various factors of human, finance, and so on. An important advancement in theoretical studies in recent years is the idea that the spillover effects are not uniformly distributed, but rather change based on the characteristics of the domestic factory. Accordingly, scientists have investigated the impact of special trends, ownership structure, and size of factories, (Sinani, 2004, Meyer). Factories with very high or very low absorption capacity may not benefit from the spillover process (Girma, 2005). The logic that lies behind this proposition is that a company with very low absorption capacity does not have the minimum knowledge required to absorb foreign technology. On the other hand, a company with a very high absorption capacity is moving ahead of the technology boundaries, and there is little information that can be learned from the foreign factory (Haskel, 2002).

In this paper, sales variable was used for the analysis using ARIMA models and considering the chief knowledge officers' and experts' recommendations to investigate technology spillover and its impact on the performance of car manufacturing companies. From the contributions of this article, we can mention using time series analysis for technology spillover and prediction of the impact of technology spillover on company performance. The rest of the paper is organized as follows: section two describes the background and related studies, then section three includes data collection and methodology, section four presents forecasting and validation of the model, and finally, section five presents the results and discussion. The paper is concluded in section six with a detail description of future research directions.

2.Background

2.1 Technology Spillover

Theoretical fundamentals of research or the concept of technology spillover has roots in human history, and any learning and adaptation are considered as a form of technology spillover. However, the scientific study of the relationship between technology spillover and foreign investment dates back to the 1960s. The first concept of technological spillover was introduced in the late nineteenth century (Marshall, 1890). The Spillover is a situation in which industries or companies benefit from the knowledge, technology, markets, skilled staff and innovation of others, without spending direct costs to gain it. To describe more precisely, knowledge and technology spillovers occur when a company by communicating with other companies with a similar or dissimilar activity, at no cost or much lower cost than the company, which possess the technology, reaches the same revenue. As a result, what causes an unintended profit of a company is technology spillover (John Kou, 2005).

Important features of technology spillover include being affected, incompatibility with the characteristics of the primary technology and uncontrollability. In other words, technology spillover is somewhat similar to social processes, and therefore is not completely predictable; however, how much and how the spillover occurs, ultimately, cannot be predicted exactly. As a result, technology spillover is an opportunity for the companies which want to advance and make use of the experience of strong companies. In fact, in the process of formation, consistency, and durability of technology, developing companies must obtain the conditions necessary for maximum utilization, by understanding the situation (Roohian, zamiri, 1393)

The first researches on the impact of foreign investment on the spillover has examined the cost-benefit of foreign private investment in the welfare and real income of the host country (McDougal, 1960). Generally, in a competitive

environment in which the law governs, and the conditions for foreign investment and global trade exist, technology spillover is more likely to occur (Sabirianova, 2005).
Research showed that companies operating in supportive or exclusive markets suffer from a loss of productivity, and no spillover occurs in such areas. For example, research conducted in China and Indonesia showed that technology spillover has only occurred in areas where competition exists (Blalok, Gertler, 2006).
Researchers show that different companies have different reactions to market liberalization. For example, highly technologic companies are encouraged to invest in other sectors. Generally, in a competitive and non-exclusive market, technology spillover may have different impacts. One of the factors affecting the type and amount of spillover is the distance between native and world-leading technology (Aghion, 2005).
Scientists believe that spillover is non-voluntary as well as informal and occur without the voluntary cooperation of foreign companies. In other words, domestic factories can imitate the technology of foreign companies without any help. Indeed, studies show that, even with formal mechanisms, knowledge transfer is very difficult (McDermott & Corredoira, 2010).

2.2 ARIMA models

The ARIMA models represent a general class of models that can be used effectively in time series' modeling. An assumption in these models is that the conditions under which the data is collected remain constant. The box and Jenkins models include four major components: The Autoregressive models (AR), the Moving Average process (MA), the Autoregressive Moving Average (ARMA) and the Auto-Regressive Integrated Moving Average (ARIMA) (Montgomery, 2015).
Autoregressive models (AR): In this process, a dependent variable such as Z is obtained by a multiple regression of its variables in the past. Hence, it called Autoregressive.

$$z_t = \varphi_1 z_{t-1} + \cdots + \varphi_p z_{t-p} + a_t$$

According to the equation above Z is an AR (p) process where p is the order of the process, and it is white noise.
Moving Average process (MA): This process has events' immediate impact and lasts for a short time. The Zt process is called the Moving Average whenever the following equation is established.

$$z_t = a_t - \theta_1 a_{t-1} - \theta_2 a_{t-2} - \cdots - \theta_q a_{t-q}$$

In this equation, q is the order of the process; it is white noise and θ_is are the coefficients of the equation.
Autoregressive Moving Average (ARMA): It refers to a series of processes that combines the two previous processes. In other words, the random variable Zt is said to be ARMA (p, q) if it applies to the equation below.

$$z_t = \varphi_1 z_{t-1} + \cdots + \varphi_p z_{t-p} - \theta_1 a_{t-1} - \theta_2 a_{t-2} - \cdots - \theta_q a_{t-q} + a_t$$

In the above equation, p and q are process orders and a_t is white noise.
Autoregressive Integrated Moving Average (ARIMA): The three previous processes were based on the stationarity assumption. In other words, the variance-covariance matrix remains constant over time, which results in a constant mean and variance for the process. However, if the process is non-stationary, it transforms into a stationary one by using first-order differentiation and repeating it four times. Finally, this process modeled with the aid of an ARMA model. These processes are represented by ARIMA (p, d, and q), where p is the autoregressive order, q is the order of moving average and d is the number of differentiation (Box, George EP, et al., 2015).
Predicting sales related- time series quantities is very important for companies in the various sectors of the industry. In the automotive industry, the automotive market behavior is of interest since it would be used to express the changes in the economy precisely (Findley, Monsell, 1998). (Brühl, Hülsmann et al., 2009) proposed an ARIMA model for the German automotive market that consists of additive components: trend, seasonal calendar and error component, and they showed that the model has given better results than other models like Principle Component Analysis. (Sana Prasanth Shakti, Mohan Kamal Hassan et al., 2017) used the ARIMA model for predicting the number of tractor sales for a time-series data and checked its performance by plotting the graph for the confusion matrix and visualization of the result of an ARIMA classification algorithm. Obtained results showed that ARIMA model performs better for prediction of the next following years' sales.
Despite the use of ARIMA models to forecast sales, its applicability in investigating technology spillover in car companies hasn't been studied which is the main contribution of this research. ARIMA models forecast future values of the desired variable by using historic data and assuming that other parameters and external variables, which are effective in technology spillover, remain constant while another modeling technique usually uses values of independent variables to forecast the value of the intended variable. Time series models don't require side information about the sales, so they are the suitable models to forecast. These forecasts can help the companies ensure the satisfaction rate of their customers for the products, and be more confident in their strategic and short-term planning.

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3. Material and Methodology

3.1 Data Collection

In this research, investigating spillover technology and its impact on the sales of the car manufacturing companies, we collected the time series data of the total cars sold per month in one of the domestic companies between 2006 and 2016, which has international and cross-border interactions with Chinese car manufacturing companies. The following chart shows the time series data of the monthly sales from Mar-2006 to November-2016 is shown in Figure 1.

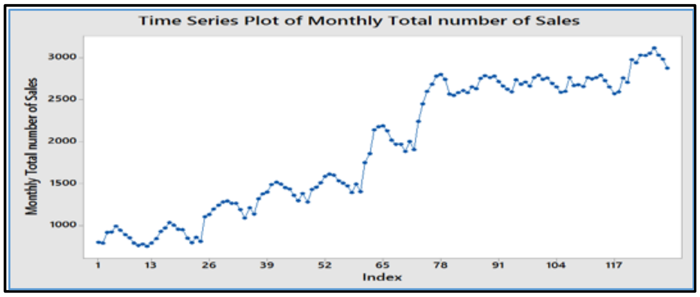

Figure 1. Time series data of the total cars sold per month

3.2 Methodology

To determine the process of technology spillover in Iranian car manufacturing companies, after modeling, the situation of the company regarding total sales of cars was predicted if the current conditions are almost constant in the winter of 2016. In the analysis using Box and Jenkins models, one-variable time series are forecasted with statistical modeling. Forecasting with Box and Jenkins models includes the following steps presented in Figure 2 (Montgomery, Douglas C., Cheryl L. Jennings, and Murat Kulahci, 2015).

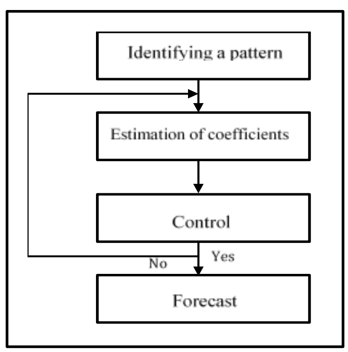

Figure 2. Box and Jenkins forecasting methodology

Identification phase includes determining the appropriate values for p and q by using ACF and PACF plot and then Estimation of coefficients of the identified model done. After construction of the model, it should be controlled by diagnostic checking of its residuals if they are white noise. By ensuring the validity of the model, it can be used to forecast the desired variable for next periods of time in the Forecasting phase.

4. Forecasting Model

4.1 Pattern identification

In this section, 80% of all data were used to identify the pattern and the rest were left for the validation phase. If the process is stationary, the values for p, q and d were specified by observing the pattern in the monthly sales data of the company. For this purpose, process Autocorrelation Function chart (ACF) and Partial Autocorrelation Function chart (PACF) are used. In fact, if the process is non-stationary, then there will be a need for differencing to achieve a stationary process. As shown in Figure1, the time series data are not stationary because the average of the process has increased over time. Also, the sales' slumps over the 12-month period indicate that there is a seasonal trend in the data. Figure 3 shows sales data after the first-order and seasonal differencing. As observed, the mean is fixed.

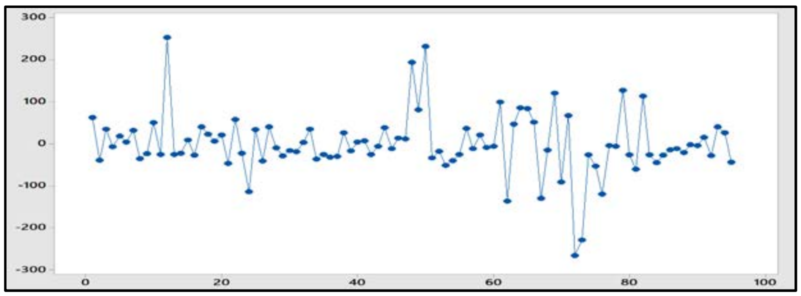

Figure 3. Stationary time series of car sales

The ACF and PACF charts are as follows.

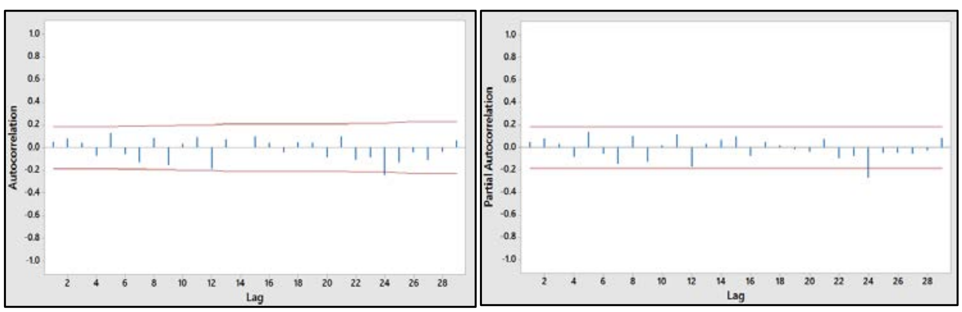

Figure4. ACF and PACF of stationary time series

As shown in Figure 4, with various lags over the course of time, the data have a sinusoidal trend and are within the control limits and not cut off. Therefore, it can be concluded that in the non-seasonal part, p=0 and q=0.
Considering the amounts associated with lags 12, 24, 36, etc. in ACF and PACF graphs, we noticed that determining the degree of process is harder in seasonal parts because, in both graphs, the amount of lag 12 is very close to the controlling limit and is out of control in lag 24. So it is better to use the software to fit the assumed models and then compare the coefficients for the correctness of each model. Table 1 represents the result for each assumed model.

Table1. Examining possible models regarding fitting to the models

	Assumed Model	The result of model
1	SARIMA (0,1,0) × $(0,1,0)_{12}$	According to the ACF and PACF charts, it is not a suitable model.
2	SARIMA (0,1,0) × $(0,1,1)_{12}$	According to the ACF and PACF charts, outsiders from the limits can be seen.
3	SARIMA (0,1,0) × $(0,1,2)_{12}$	**It can be a good model and needs to be a further inspection on the residuals.**
4	SARIMA (0,1,0) × $(1,1,0)_{12}$	The ACF and PACF charts are inappropriate.

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5	SARIMA (0,1,0) × $(1,1,1)_{12}$	The P-value of a coefficient is large.
6	SARIMA (0,1,0) × $(1,1,2)_{12}$	The P-value of a coefficient is large.
7	SARIMA (0,1,0) × $(2,1,0)_{12}$	**The ACF, PACF charts and the coefficients are appropriate. It Needs more investigation than others.**
8	SARIMA (0,1,0) × $(2,1,1)_{12}$	**It Needs more investigation than others.**
9	SARIMA (0,1,0) × $(2,1,2)_{12}$	The ACF and PACF charts are inappropriate, and the model is not suitable.

We considered three models that require further examination and obtained the values of the AIC and BIC (SIC) indices from the SAS software.
According to Table 2, the first model has better results than others in both indicators. Therefore, the appropriate model will be SARIMA (0,1,0) × (0,1,2).

Table2. AIC and BIC indicators

BIC	AIC	Assumed Model
1317	**1301**	SARIMA (0,1,0) × $(0,1,2)_{12}$
1331	1309	SARIMA (0,1,0) × $(2,1,0)_{12}$
1330	1305	SARIMA (0,1,0) × $(2,1,1)_{12}$

4.2 Estimation of the coefficients

Using SAS software output, the coefficients of the SARIMA $(0,1,0)\times(0,1,2)_{12}$ are obtained, and the equation is as follows.

$$\Phi^*(B^s)\ \Phi\ (B)\ (1-B^s)^D\ (1-B)^d\ y_t = \delta + \ \Theta^*(B^s)\ \Theta\ (B)\varepsilon_t$$
$$(1-B^{12})^1\ (1-B)^1\ y_t = \delta + (1-\theta^* B^{12})^2 \varepsilon_t$$
$$(1-0.01973B^1 + 0.11668B^{12} - 0.10652B^{13})\ y_t = 1.575292 + (1-0.28383\ B^{12} - 0.41962B^{24})\ \varepsilon_t$$

4.3 Model Control

To determine the performance of the proposed model in the previous step, its coefficients are derived from the graphs of the residual values. The respective charts on the distribution of residual values regarding normality, residual graphs of fitted values, residual dispersion charts, and residual graphs for different data periods are shown in Figure 5.

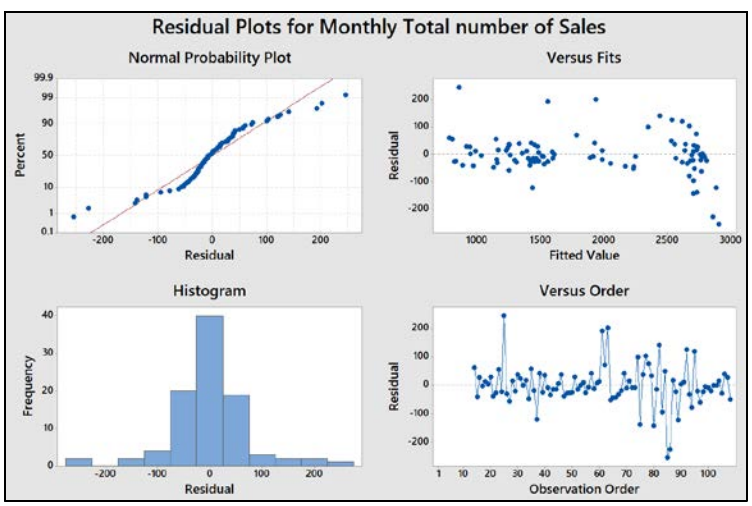

Figure 5. Charts of residual values for the selected model

It could be understood from the graphs that the remainders are almost normal except the initial and final values. Also, the graph of the residual versus the original data values is shown in the second graph, which indicates the proper distribution and good dispersion of the remaining values. The dispersal pattern of the residuals resembles a bell curve, indicating that the distribution of residuals is normal. The remainder chart of different months of the period is scattered almost randomly and has an acceptable dispersion.

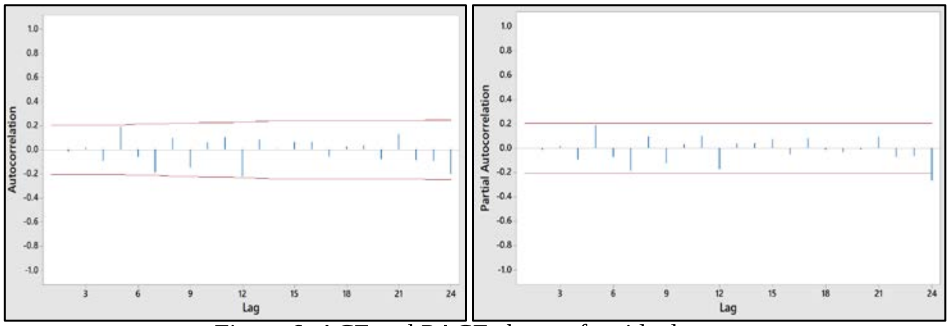

Figure 6. ACF and PACF charts of residuals

The graphs for ACF and PACF residuals in Figure 6 indicate the stationarity of the values. The Durbin-Watson test is used to ensure that these residual values are not correlated with each other.

$$\begin{cases} H_0 : & \phi = 0 \\ H_1 : & \phi > 0 \end{cases}$$

$$d = \frac{\sum_{t=2}^{t=115}(e_t - e_{t-1})^2}{\sum_{t=1}^{t=115}(e_t)^2} = \frac{710290.83}{392562.9} = 1.809$$

At 5% confidence level, and concerning$d_L = 1.65$ $d_U = 1.69$, since $d_U < 1.809$, H_0 is accepted thus there is no correlation among the remainders. Therefore, the proposed model is the most suitable time series model that can be obtained for the original data.
Figure 7 shows the fitted and original data values.

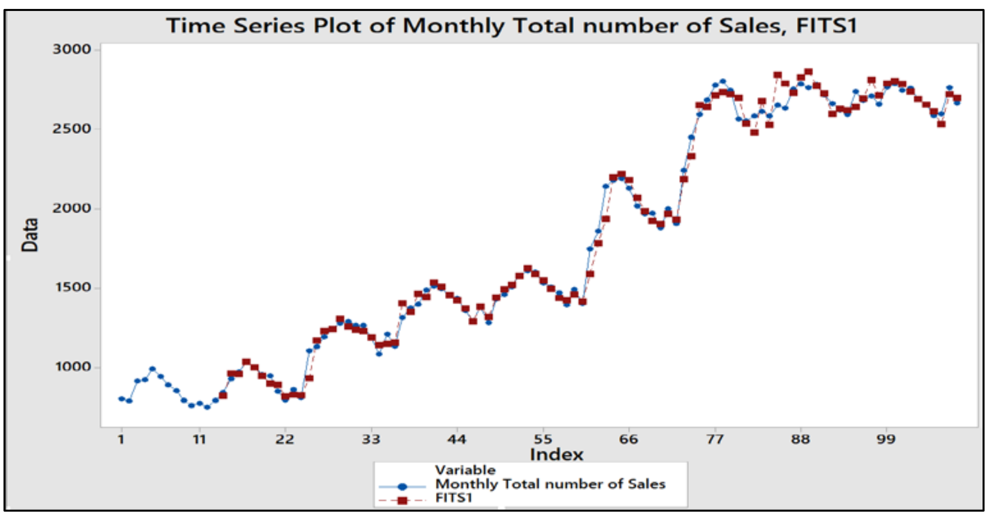

Figure7. Fitted and original values chart

As seen in Figure 7, the resulting model performs very well and can be used for forecasting.

4.4 Forecasting Step and Model Validation

To validate the proposed model, the model was tested using sales data from May-2015 to November-2016. The accuracy is calculated based on the MAPE which was in the range of 6%. The results and calculation of MAPE are presented in Table 3. The obtained value shows that the proposed model is highly efficient in forecasting the sales amount for next periods.

Table3. Forecasted Values obtained from SARIMA (0,1,0) × (0,1,2).

Period	**Actual**	**Forecast**	**APE**	**Period**	**Actual**	**Forecast**	**APE**
Mar-15	2678	2799.4	4.53286	Feb-16	2706	2838.5	4.89727
Apr-15	2657	2825.3	6.33572	Mar-16	2979	3005.8	0.90097
May-15	2765	2934.0	6.11139	Apr-16	2943	3048.9	3.59837
Jun-15	2751	2976.6	8.20102	May-16	3032	3165.8	4.41392
Jul-15	2764	2983.6	7.94320	Jun-16	3024	3213.7	6.27447
Aug-15	2791	2987.9	7.05446	Jul-16	3054	3234.2	5.90046
Sep-15	2726	2924.4	7.27806	Aug-16	3119	3230.8	3.58448
Oct-15	2653	2865.5	8.00942	Sep-16	3031	3167.6	4.50676
Nov-15	2575	2809.9	9.12039	Oct-16	2984	3109.6	4.21046
Dec-15	2596	2802.4	7.94954	Nov-16	2878	3062.2	6.39993
Jan-16	2758	2919.8	5.86512				$\frac{1}{21}\sum \mathbf{APE = 5.8613}$

Using the proposed model, we will forecast the next three periods. The Minitab software provides us with some useful features which are suitable for forecasting process. Table 4 shows forecasted values, upper limits and lower limits for the next three months.

Table4. Forecast of sales for the next three months

Lower Limit	Forecast	Upper Limit	
2742.95	2858.79	2974.64	Dcember-2016
2820.46	2984.29	3148.12	January-2017
2730.36	2931.01	3131.66	February-2017

Considering the integrity, we have 2859, 2984 and 2931.

5. **Discussion**

According to the study of the company over a period of ten years, this was a historical period for the company, in which significant changes occurred. All of these changes have been the result of true strategic decisions. During this period, foreign direct investment has had an undeniable direct impact on the company. These decisions were the improvement of collaborations in the discipline of Research and Development (R&D), Organization structure and Engineering.

One of the factors that played an important role in improving the performance of the company is the improvement of the R&D sector. The data and statistical analysis show that in the sixth year, the R&D team in the design section lead to an increase in the sales amount and the productivity of the organization.

To improve the organizational structure in the sixth year, the supply chain issues were diagnosed and resolved.

In the process of studying the factory, it was found that due to numerous violations in the supply chain of the company, in many cases, orders were not delivered on time. Also, due to the fact that the automation system is not integrated into many sectors, a delay of production occurred. For example, in some cases, the companies which were cooperating with the main company to supply the components were dissatisfied with the interaction with that company (lack of coordination between the sales and finance department has caused dissatisfaction with the manufacturer of the parts and resulted in a delay of production). Applying integrated systems meaningfully increased compatibility and interoperability.

According to the data chart and reports of CKO, in the 7th year of the company's joint activity, a relationship between the technicians and engineers of the Iranian and Chinese companies was formed. Applying the advice from Chinese engineers and technicians has led to significant revenue growth this year. Also, during the intervals in which this

connection has been cut off for any reason, the growth rate of sales has declined. Constructive and continuous collaboration with the manufacturing companies can be a good solution for the spillover of the technology.
This year, after beginning a collaborative cooperation to strengthen the engineering department, some experienced staffs in the production and management sectors were added to the team which resulted in and improvement in the production automation system. Therefore, a positive impact on the factory's performance was observed.

6. **Conclusion**

Technology spillover is a situation which a company or organization can benefit from knowledge, market, specialist staff and innovations. In Iran, enough attention has not been paid to this subject and its impact on the progress of companies both economically and technologically. The purpose of this research is to clarify the influence of technology spillover in domestic companies in Iran to make suggestions to increase the resulting benefits.
In this study, the sales of one of the car manufacturing companies, which absorbed foreign capital, is considered and the companies' time series data were modeled by the well-known ARIMA model which has not been applied previously and is the novelty of the paper. The proposed model satisfactorily met the criteria of modeling accuracy with the MAPE in the range of 6%. Therefore, it can be used to forecast the sales of companies and help the managers of the companies in their planning to improve the corporate performance by the spillover approach. In fact, moving towards the realization of spillover in the production processes and the attempts to control the market share are among the advantages of this forecasting model. As a result of moving along the technology spillover, company's products can surpass other domestic companies that do not have external connections and gain more market share. In the case of occurrence, the technology spillover, other domestic companies will also take advantage of foreign investment and technology.
This article showed that even when many of the necessary infrastructures are not available, foreign direct investment and the approach of technology spillover can make significant changes.
This article is well illustrated by the effects of some parameters that may not seem very important at first glance. In this study, there were significant leaps in the company's sales chart at times when certain changes occurred. All jumps in the graph have been accompanied by serious changes in the factory situation. We have witnessed a leap in the factory sales, precisely at the points where the R & D department has been activated and its outputs have been made available to the plant.
Also, solving the structural problems of the factory and establishing continuous communication with domestic and foreign technicians also triggered a sales leak. These tips can also be solved for other factories operating in similar environments.
Investigating the impact of existing infrastructures in automotive companies on spillover and providing solutions to enhance technology spillover can be some topics of relevance for future researches. Also, the applicability of multivariate time series' analysis may be of interest to feature studies in technology spillover.

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