Lisbon School of Economics & Management
Universidade de Lisboa

MASTER OF SCIENCE IN FINANCE

MASTER'S FINAL WORK

DISSERTATION

THE EFFECTS OF AUTOMATION ON RECEIVABLES MANAGEMENT

INÊS DINIZ MORAIS

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ABSTRACT

Globalization has created a necessity to manage efficiently the company’s working capital, more specifically its account receivable. Large international companies have been following this process and have implemented innovative solutions to keep up with this transformation.

In this study, we evaluate the effects of automation (robotization) on receivables management of a multinational company. We use credit management data for the main European markets between February 2019 and December 2020 and evaluate the effect of automation on the order processing time, meaning the time that is spent processing the purchase orders and the consistency of the output, this is, the consistency among the output provided by the credit analysts and the market analysts. We find that the implementation of the robot reduced, in general, the average order processing time, but the biggest impact of this automation was for the markets with higher degree of automation, with an expected reduction on the average order processing time by, approximately, 80% (or 16 days). For the markets with medium and low automation levels, the introduction of the automation was also favourable in reducing the average order processing time, but was not so beneficial as for the group of high automated markets, since we found that for the markets exhibiting medium levels of automation, the implementation of the robot was associated with an increment by, approximately 102% to 117% of the order processing time (an increase of 3 to 4 days), compared to the group of markets with low automation. And also, we found that it is expected a decrease of the order processing time by, approximately, 65% (or 16 days, approximately) if the order is analysed after the implementation of the robot and requested by a market belonging to the group of high automated markets, compared to the markets with low automation. With this we concluded that the group of markets that benefited the most with the implementation of the robot was the markets displaying higher levels of automation, following the markets with low levels of automation, and, finally, the group of markets exhibiting medium levels of automation.

We found that the consistency among the outputs provided by the credit analysts and the market analysts increased with the implementation of automation and we found a negative correlation between credit limit assigned to each customer and if the order is requested by a client with payment agreements approved.

KEYWORDS: Accounts Receivable, Automation, Trade Credit; Working Capital Management.
JEL CODES: G30; O30; 031

RESUMO

A globalização criou a necessidade de gerir de forma eficiente as necessidades de fundo de maneio, mais especificamente nas suas contas a receber. As grandes empresas internacionais têm vindo a acompanhar esse processo e implementando soluções inovadoras para acompanhar essa transformação.

Neste estudo, avaliamos os efeitos da automação (robotização) na gestão de contas a receber de uma empresa multinacional. Utilizamos dados para os principais mercados europeus entre fevereiro de 2019 e dezembro de 2020 e avaliamos o efeito da automação no tempo de processamento das ordens, ou seja, o tempo que é gasto no processamento das ordens de compra e a consistência dos outputs, ou seja, a consistência entre os outputs fornecidas pelos analistas de crédito e analistas de mercado. Verificámos que a implementação do robot reduziu, em geral, o tempo médio de processamento de pedidos, mas o maior impacto dessa automação foi para os mercados com maior grau de automação, com uma redução esperada no tempo médio de processamento de pedidos em, aproximadamente, 80% (ou 16 dias). Para os mercados com níveis de automação médio e baixo, a introdução da automação também foi favorável na redução do tempo médio de processamento de pedidos, mas não foi tão benéfica quanto para o grupo de mercados de alta automatização, uma vez que descobrimos que para os mercados com níveis médios de automação, a implementação do robot está associada a um aumento de, aproximadamente, 102% a 117% do tempo de processamento das ordens (aumento de 3 a 4 dias), em relação ao grupo de mercados com baixa automação. E também, constatamos que se espera uma diminuição do tempo de processamento das ordens em, aproximadamente, 65% (ou 16 dias, aproximadamente) se o pedido for analisado após a implantação do robot e solicitado por um mercado que pertencem ao grupo de mercados altamente automatizados, em comparação com os mercados com baixa automação. Concluímos que o grupo de mercados que mais beneficiou com a implementação do robot foram os mercados com níveis de automatização mais elevados, acompanhando pelos mercados com níveis de automatização baixos e, por último, o grupo de mercados com níveis de automatização médios.

Verificámos que a consistência entre os outputs atribuídos pelos analistas de crédito e analistas de mercado aumentou com a implementação da automação e verificou-se uma correlação negativa entre o limite de crédito atribuído a cada cliente e se o pedido é solicitado por um cliente com acordos de pagamento aprovados.

Palavras-chave: Contas a receber, Automação, Crédito Comercial; Necessidades de Fundo Maneio

Classificação JEL: G30; O30; 031

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LIST OF ABBREVIATIONS

AR – Accounts Receivable

CCC – Cash Conversion Cycle

DSO – Days Sales Outstanding

ISEG – Lisbon School of Economics and Management

JEL – Journal of Economic Literature

OLS – Ordinary Least Squares

ROI – Return on Investment

WCM – Working Capital Management

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1. INTRODUCTION

The introduction of automation processes in firm's operating activities has seen a recent surge in the last years. Due to globalization and technology proliferation, several companies have automatized their accounts receivables and credit management through different systems, for example, process optimization systems, in order to reduce analysis or order processing time; systems for eliminating repetitive or monotonous tasks; and constant information update systems, to support the credit analysts. The automation processes have helped firms to streamline and enhance the efficiency of their accounts receivable management, improve operations and provide a more efficient and faster customer response (Copley, 2015). It has become a necessity to continue to be competitive in the market, enhance profitability and achieve sustainable growth. Companies have decided to automatize their entire accounts receivable management, from credit management to invoicing and accounts reconciliation. Madakam et al. (2019) defends that the costs of processing accounts receivable manually are very high, therefore automation allow firms to improve their efficiency and performance (Corcentric, 2021).

Previous studies suggest that the automation of accounts receivable procedures improves working capital efficiency by reducing the amount of cash allocated to customer's payments, strengthen cash inflows and reducing the days sales outstanding. In addition, the use of automation processes in accounts receivable increases firm value since it reduces the costs of working capital and improves the cost of back-office operations (Mayes & Dyer, 2015).

In this study, we evaluate the effects of automation, more specifically the effects of the introduction of automation robot on firm's daily account receivables activities, on order processing time and output consistency, this is, the time that is spent processing a credit purchase order and the consistency among the credit output provided by the credit analyst and the market analyst. For that purpose, we collect monthly report data from the credit management department of a multinational company. These reports include daily data for the main European countries where the firm operates for the period between 1st February 2019 until 31st December 2020.

We find that automation reduced in general the average order processing time, improving the efficient on the credit management flow. However, when decomposing the results by different levels of automation, we conclude that the implementation of the automation represented a positive impact for all markets, but it was more beneficial for the markets displaying a higher number of automated credit tasks, this is, for the group of markets with high level of automation, in the sense that it is expected a reduction on the average order processing time by, approximately, 16 days (or 80%). Nonetheless, we discover that for the groups of markets with medium and low automation levels, the introduction of the automation in this company was also favourable in reducing the time spent processing the orders, but not as much compared to the group of markets exhibiting high levels of automation. We found that, actually, the markets displaying an hybrid system of manual and automated credit tasks or procedures (group of medium automatized markets) was the one that benefited the least with the implementation of automation. We also found that the consistency among the outputs provided by the credit analysts and the market analysts increased with the implementation of automation and we found a negative correlation between credit limit assigned to each customer and if the order is requested by a client with payment agreements approved.

We contribute to the literature in several ways. First, understanding the effects of automation on the accounts receivable activities is a relatively recent topic. To best of our knowledge, we are the first empirical study to evaluate how the introduction of automation impacts the credit policies on receivables management, namely in terms of order processing time and output consistency, this is, the harmonization of the credit outputs provided by credit analysts and market analysts.

Although the number of studies evaluating the impact of automation on working capital has been increasing, only a few explore theoretically the association between automation and receivables management. In this study, we take advantage of an introduction of a robot within a multinational company to understand whether automation improves receivables management efficiency. Moreover, firms spend a big portion of their time and resources managing working capital and trade credits (Long et al., 1993). Hence, it is important to understand the consequences of introducing automation to effectively manage accounts receivables. Finally, we have access to comprehensive data on daily orders and credit concession for the firm's main markets.

This study is organized in five different sections. In the next section, we review the literature on receivables management and the impact of automated systems in receivables management. We also explore the literature about trade credits, the drivers that justifies the existence of firm's accounts receivables and lean on the literature of working capital management. In Section 3, we present the data that we collect from the multinational company, for the empirical study and the main variables used to conduct our study and the summary descriptive statistics. Section 4 presents our empirical methodology and the results obtained. Finally, in the last section, we provide the final and main conclusions achieved in this research and suggestions for future research.

2. LITERATURE REVIEW

2.1. ACCOUNTS RECEIVABLE AND TRADE CREDIT

Accounts receivable is a process where a company concedes credit to its customers for the acquisition of goods or services, and where it is expected to receive the proceeds or payments from the client's purchases in a later period. Joy (1980) defined accounts receivables as the "debt owed to the firm by its customers arising from sale of goods or services in ordinary course of business" (p. 290). Similarly, Munene (2018) stated that accounts receivable "represents money owed to a business in return for goods already delivered or services already rendered" (p. XI). Ngugi (2014) defends that accounts receivable is the money that a costumer owes to a firm for selling their products or services on credit. The customer must pay to the seller according to the conditions previously established on the agreement, namely, the credit terms that can compromise conditions of payment, prices and delivery. Thus, the procedures of managing accounts receivable starts when the seller decides to sell their goods or services with a deferred payment date. With the offering of credit to their customers, known as trade credits, the firm is building their policy on receivables management, in order words, the firm is creating what is called their trade credit policy (Ngugi, 2014).

Brigham and Houston (2003) defend that the management of account receivables is strongly influenced by the company's credit policies and consequently the collection procedures. It is crucial for firms to establish a good credit policy, namely evaluate the worthiness of customers and adopt a collection procedure responsible to maintain an efficient collection standard, avoid cases of customers that fail their commitments with the company and provide guidelines to resolve uncollectible credits.

For the buyer's side, trade credits are seen as an important source of financing to fulfil their short-term needs (Cuñat and Garcia-Append, 2012; Seifert et al., 2013) particularly for companies, that are facing problems with credit institutions (Petersen and Rajan, 1997). In contrast, from the seller's side, trade credits represent an investment in current assets that have to be financed but also an opportunity to establish better relationships with their customers. Trade credits can be seen as an advantage over third party intermediaries, allowing the sellers to offer credit with a lower interest rate in a long run. Demirgüç-Kunt and Maksimovic (2001) and Rao and Gaglani (2014) argue trade credits give a competitive market advantage for sellers that have access to capital, especially in the case of markets that are not so competitive with others. Similarly, Fabbri and Klapper (2016) defend that supplier's market power is negatively associated with trade credit provision. The authors state that when products are homogenous and there is a lot of competition on the market, if the supplier's bargaining power is low, it means that the supplier is in a weak position to enforce payments and more inclined to allow delayed repayments to attract new customers, or to avoid existing customers from changing to a different supplier (Fisman and Raturi, 2004; Dass et al., 2015).

Chod et al. (2016), defends that the benefit of trade credit given to a customer by his supplier will be better if the greater is the share in the clients' supply expenses. If the supplier takes responsibility for a huge portion of the share clients' purchases, will have a better benefit for the greater portion of credit offered, thus, is better prepared to offer better conditions to that client. Thus, the author implies a positive relationship between the provision of trade credit and the retailer's spending on supplier's share.

However, companies that enable their customers to buy their goods or services by credit, incur in the risk of not paying, so, it is crucial to efficiently manage the level of trade credit and accounts receivables and consequently, the balance between risk and performance (Baker et al., 2020). In the same line, Harris (2005) explains that this balance between risk and performance is related to how accounts receivables are managed in the way that if there is a massive investment in inventories and receivables, it is expected a reduction of the firm's performance and profitability and, in the other hand, if there is not enough allocation of resources for accounts receivables, it will increase the risk of the firm not being able to meet its commitments and profitability goals. Therefore, companies must have an effective and dynamic management of accounts receivables aligned with their business strategy.

According to Mbembe et al. (2017) and Zimon & Zimon (2019), receivables management is one of the most important components of a working capital management (WCM), which has a direct effect on firm's liquidity, profitability and growth. The concept of working capital management is entirely related with the ability of companies to effectively manage their resources and their short-term operational and financial obligations. Deloof (2003) and Ponsian et al. (2014), states that WCM is explained partially by the currents assets that represent a firm's financial resources that can modify the daily life's operations of companies. The other part of WCM is composed by accounts payable that represents the short-term financial obligations that a firm should comply with.

Boisjoly et al. (2020) praises the importance of an efficient management of working capital and states that if companies adopt an aggressive working capital strategy, they can experience consistent cash flows. Furthermore, Boisjoly et al. (2020) find a positive correlation between the components of WCM and shareholder's value. Relatedly, Bendavid et al. (2017), pointed out that working capital management should be invested in long-term in order to enable firms to reach profitability and thus, achieve a high-return asset while ensuring enough liquidity throughout the operating cycle. Sharma and Kumar (2011) and Singh et al., (2017) defend that WCM has high importance in corporate finance and is directly correlated with the management of the company in terms of its investment and short-term financing decisions. In the same vein, Smith (1980), Deloof (2003), Falope and Ajilore (2009) and Gill et al. (2010), highlighted that WCM is one of the most important components of financial management in firms and affirmed that working capital usually has a higher proportion invested with comparison with the total assets held by a company. The authors provide evidence demonstrating that liquidity and profitability are directly influenced by WCM and later on net worth. These measures are vital for companies' growth and their survival since it affects the way they manage their business.

Rao and Gaglani (2014) indicate that one of the main measures to be competitive in the market is to concede credit to the clients, since it increases the retention rate and revenues. Moreover, the same authors also refer that an excess of accounts receivables can increase the costs related with the difficulties in releasing company's funds which will lead to an increase in working capital that will affect negatively firm's value. Haresh (2012) is in line with Rao and Gaglani (2014), by defending that managers can create value for their shareholders by decreasing the number of days of accounts receivable, concluding that there is a negative relationship between firm's profitability and accounts receivable. Haresh (2012) states that firms that present lower levels of profitability should reduce their accounts receivable to have a better liquidity position and diminish their cash gap in the cash conversion cycle, arguing that profitability can be improved if working capital is managed more efficiently.

By the same token, Deloof (2003) defends that managers can increase firm's profitability by decreasing the average collection period. The higher is the number of days in receivables outstanding, the greater will be the probability of the company to misplace its profitability, as a longer average collection period translates into a greater investment in accounts receivable, which will decrease companies' liquidity that is necessary to meet firm's obligations. However, in a different perspective, Abuhommous (2017) pointed out that the investment in accounts receivable has a positive relationship with companies' profitability, defending that firms can increase their profitability by investing on trade credit, and that this association is even stronger when firms have highly volatile demand.

There are many advantages to use trade credit in companies' daily operations. Petersen and Rajan (1997) stated that trade credit enables customers to manage their invoices according to the clients' liquidity, and, at the same time, reduces the cost of paying. Moreover, credit terms established by the suppliers for each client, normally never change with the costumer's credit quality over time. Another advantage is that trade credit can be a useful tool when the buyer has absence of information about the seller. Additionally, trade credit is helpful in reducing costs in terms of the quality of the supplier's goods, controlling the buyer and the residual value of the assets. This is because, if the buyer fails to pay and if the goods are durable, the better collateral the supplier will have, and the better credit is offered (Mian and Smith, 1992; Petersen and Rajan, 1997). The existence of taxes is one of the first motives for the urge of trade credit, because if the buyer and seller have different tax fares, trade credit creates tax shield to protect the highest tax schedule. This is explained by the fact that the seller should record the same portion of taxable income at the same time that is receiving credit from the buyer (Brick and Fung, 1984; Cuñat and Garcia-Append, 2012; Afonso et al., 2021).

Nevertheless, there are a lot of constraints when managing accounts receivables. From the seller's perspective, firms are exposed to the problem of their buyers do not fulfil their payment obligations. If the seller restricts the process of collection, the long-live relationships with the buyer can be destroyed in the long-term. From customer's side, early payments generate unavoidable financial costs (companies tend to rely in short-term debt to finance its short-term needs), leading to a decrease of liquidity (Long et al., 1993). In the same vein, Asselbergh (1999) find that the main problems that companies face when selling on credit are the difficulties arising with asymmetric information. Sellers are exposing themselves to imperfect information, which can later result in transaction costs. This happens because companies do not have complete or perfect information about the clients that they are extending their credits, incurring in the problem of the clients not fulfilling their obligations with them. Moreover, Mbembe et al. (2017) pointed out other difficulties. Some countries, such as China, have internal problems in managing their accounts receivable, mainly due to the manual tasks used for monitoring credit, weak credit policies, the poor management's structure and the collaborators incompetence. Organizations without efficient systems for accounts receivable management faces complications with collection ratios and, consequently, liquidity problems.

Zimon & Zimon (2019) states that an appropriate strategy should be implemented on receivables management to allow firms to reduce the probability of having customers with significant overdues on their accounts. Additionally, Asselbergh (1999) pointed out that companies should have incentives to develop organizational structures responsible to reduce the transactions costs arising in the presence of asymmetric or imperfect information.

2.2. AUTOMATION PROCESS AND ACCOUNTS RECEIVABLE MANAGEMENT

Automation is "the technique of making an apparatus, a process, or a system operate automatically" (Madakam et al., 2019, p. 3) and includes the processing capability of any system to "generate, edit, execute, monitorise and debug an application program for controlling an industrial automation mechanism comprising components of logic, motion and/or process control" (Sadre et al., 1996, p. 29). Automation has begun to be applied to several business process. For the interest of this study, we focus on the effect of automation on credit management.

Recent studies have presented evidence about the impact of the automation on the credit management and its domains. According to Corcentric (2021), accounts receivable automation is the transformation of unwieldly manual accounts receivable processes by "automating and streamlining systems electronically to reduce repetitive and time-consuming (and potentially error-prone) tasks" (p.2). Nonetheless, manual invoicing system is still being used by the majority of the firms, According to Senzu and Ndebugri (2017), 60% of the firms use manual invoicing system, while 40% adopted the automated invoice system.

The adoption of automation on cash management and accounts receivables presents several advantages and it is considered a good practice of working capital management (Brealey et al., 2018). Mugambi et al., (2019) finds that automation avoids problems that can arise when accessing credit in times of liquidity constraints, this is, in times where customers present a low level of liquid assets in comparison to their disposable income or recurring expenses or when individuals have difficulties in borrowing money and are discouraged to applying for credit, directly to their suppliers. On the other hand, the author refers that the adoption of automation is particularly relevant when there is an increase in cash management, avoiding incongruities between the timing of payments and the cash availability. Automation can quickly update cash inflow and outflow, helping the decision process by generating more accurate and reliable information. In fact, Antysheva et al. (2020) suggest that the automation of accounts receivables management improves real-time data acquisition and promotes high speed decision making. Automation also improves time management, by allowing time to be allocated to other projects, thereby increasing their productivity. The automation process ensures task consistency because tasks are performed every day at the same time and in the same way (Madakam et al., 2019).

Camerinelli (2010) suggest that the automation process enhances payment processing and at the same time, facilitates the financial transaction management. With the automation process, companies can reduce the process of time payment, decrease costs and errors, and with this, avoiding fraud problems. In fact, treasurers can get a better control of cash throughout the monitorization of payments. Antysheva et al., (2020) find that automation on account receivables can efficiently determine the maximum amount of credit that a firm should offer to its clients, thereby limiting the risks of non-receipt of funds. Moreover, Senzu and Ndebugri (2017) point out that companies with automated invoicing system present lower cases of disputes in comparison to companies with the manual invoicing system. Hence, it is important for companies to adopt a robust autonomous credit management processes because it allows companies to manage better their operations and reduce bad debts and procedural errors, increase liquidity and reduce the average collection period, and consequently, reduce the cash conversion cycle. To be more efficient, firms should send the invoices to customers through automate invoicing systems.

Optimizing accounts receivable is one of the best practices for an efficient working capital management. In fact, the introduction of automation procedures can reduce exposure potential human errors. The automation of accounts receivable help companies to manage better their resources (Antysheva et al., 2020). For example, it allows firms to reduce the deferral period for accounts receivables by 20%, reduce the overdue as well the amount of accounts receivables by 25% and reduce between 15 to 25% the reserves for doubtful debts (uncollectable credits) and enhance return on investment in two months. However, at the same time, the biggest disadvantages of automatizing receivables management are the large investment necessary for the creation of a feasible automated system and the additional investment in employee's requalification and formation (Antysheva et al., 2020).

3. THE INTRODUCTION OF AUTOMATION IN ACCOUNTS RECEIVABLE BY A MULTINATIONAL FIRM

Before presenting the data and the empirical strategy, we will briefly describe the automation process implemented by a multinational company on their accounts receivable processes. Due to confidentially issues, we cannot disclose the name of the company. The company is a market leader on the food & beverage industry, owning several well-known brands and it is well established all over the world. In 2020, the total sales were approximately 93 billion U.S. dollars, having a higher presence in the American market. The European markets accounts for approximately 16% of the sales, and it will be target of this study.

The company regularly monitors the credit risk profile of its customers by analysing the evolution of credit exposures and monitoring the losses due to uncollectable credits. The company's exposure to credit risk is essentially related to the individual characteristics of each customer and geographic market. The firm defines a credit policy where each new customer is analysed individually from the point of view of its credit risk prior to its acceptance as a customer. After being accepted as a new customer, each market has the responsibility to define a set of credit characteristics to be assigned to the new clients, namely the risk category, credit limit and payment terms, among others. After these conditions are met, a new client can initiate a credit relationship with the company by making new orders. In the situation of a client that does not have any commercial relationship with the company, within one year, the customer credit characteristics must be reviewed. The process of credit decision making is a decentralized process, since it is the credit analyst's that provide the final credit decision for each order, complying always with the company credit policies and procedures.

Before the implementation of the robot, the block orders were analysed according the same policies and procedures, but the analyst did not have the output provided by the robot. The entire analysis was made by the analyst without any feedback or support from the robot. Therefore, the final output only considered the analyst evaluation. According to our data, before the introduction of the robot, the analyst took, on average, 2,07 days, 2,01 and 28,68 to process an order in the groups of markets with low, medium and high automation, respectively.

On 1st October 2019, to streamline the credit management procedures, the firm decided to implement an automation process (also known as robot) in the credit management department. With the introduction of the automatized system in the credit analysis processes, more specifically in order processing, the firm expected a reduction on human errors related to managing and taking credit decisions and more importantly a reduction on the collections period and the order processing time.

To implement the automated robot, the credit management department standardized the final outputs provided to the orders, with the main purpose of the robot making the same type of analysis for all the different markets. Thus, the robot analysis is the same for all the markets, following the same procedures and providing the same outputs accordingly to each customer and order.

The robot evaluates the characteristics of each client, facilitates the collection process and supports the credit decisions and order processing. When an order appears in the system, the robot reviews the costumer's account and assesses his/her credit and payment history. Then, accordingly the robot provides a recommendation to concede or to not concede credit to that order. The robot recommendation is later reviewed by the credit analyst that takes the final credit decision. The credit analyst can follow the recommendation given by the robot or can take an opposite decision. The latter situation can happen since the robot is still in an early stage of the implementation to make a final decision and there still is a small probability that the robot might give an output that is not the most correct. In this situation, the credit analyst should take into consideration the error, report it, and present the correct recommendation according to the current situation of the costumer's account. When the credit analyst is in accordance with the robot recommendation, no other steps are required.

Other domain that the robot is responsible for contacting customers when the net due date is near or when the customer has overdues, also referred as dunning process. The robot will also provide alerts for unexplained deductions[1], unauthorized deductions[2] or other credit deductions. The robot also provides assistance to the collection tool task, by defining a set of actions with the purpose to support credit analysts to perform their daily activities. This assistance includes prioritizing a list of customers to be contacted/analysed according to the previously established market rules, as well as providing every information to the credit analyst about each customer's historic record without the need to resort to other sources. Finally, the robot can be responsible for the statement of account task, representing the sending of account statements to the customers whenever they request it.

[1] Unexplained deductions are deductions where we still do not know the real reason of the deduction.
[2] Unauthorized deductions are deductions where after analysis being made, the decision is that deduction is invalid.

In the next years, the firm intends to expand this automation process to all account receivable activities, since credit concession until the billing process. With this, the firm intends to reduce the cash conversion cycle, by decreasing the client's overdues and to avoid blocked orders.[3]

[3] Usually, an order is blocked mainly when the credit limit is exceeded or when exists overdues on the customer's invoices. When an order is blocked, it requires human intervention to continue the normal flow of credit management.

4. DATA AND DESCRIPTIVE STATISTICS

Our data includes daily purchase orders from 1st February 2019 to 31st December 2020, for a multinational company operating in the food & beverage industry. The data were collected from the credit management department's monthly reports. These reports are organized by geographic locations. Unfortunately, we only have access to data on the European market. We selected the fourteen most important European markets/countries, representing approximately 16% of total sales of the company. Due to data constraints, we were not able to collect data from January 2019 for some markets. For markets 7 and 8, we only have data from February 2019 and for market 11, the observations only starts from March 2019 and, for market 13, we only have observations from May 2019.

In order to assess the level of automation of these fourteen markets, we divided into three different groups: the first group, the less automatized markets, with a level of automation lower than 25%, this is, the credit procedures are highly manual, include the markets 8, 11 and 14; the second group, the medium automatized markets, with a level of automation between 26% and 74%, comprising a hybrid system of automatic and manual tasks, corresponds to the following nine markets: 3, 4, 5, 6, 7, 9, 10,12 and 13; finally, the last group, representing the most automatized markets, has a degree of automation equal or higher than 75%, this is, the tasks are more automatized and human action is almost null, contain only two markets 1 and 2. The less automated markets presents a total observations of 35,45%, the medium automatized markets sums 37,63% of total observations and the higher automatized markets counts with 26,92% of total observations. We can also highlight that the degree of automation, represented in percentage, is measured by the following tasks: Dunning, Statement of Account, Unauthorized Deductions, Unexplained Deductions and Collection Tool.

In Table 1, we show the tasks aggregated by market and the respective level of automation. These tasks support the credit management flow and the credit analysts. It is also possible to see per market and for each task, if it is automated, not automated or if the task is not applicable to the market, due to the existence of other forms of credit procedures. For each market, there is the correspondent percentage of market automation that is obtained simply by dividing the number of automated tasks by the total number of tasks, excluding the tasks that are not applicable to the market.

Table 1: Degree of automation per market

Market	Order Output	Dunning	Statement of Account	Unauthorized Deductions	Unexplained Deductions	Collection Tool	% of Market Automation
1	Yes	Yes	Yes	Yes	Yes	No	80%
2	Yes	Yes	Yes	N/A	No	Yes	75%
3	Yes	Yes	Yes	N/A	No	No	50%
4	Yes	No	Yes	Yes	Yes	No	60%
5	Yes	No	Yes	N/A	No	Yes	50%
6	Yes	No	Yes	N/A	No	Yes	50%
7	Yes	No	Yes	N/A	No	Yes	50%
8	Yes	Yes	No	No	No	No	20%
9	Yes	Yes	No	No	No	Yes	40%
10	Yes	Yes	N/A	No	No	No	25%
11	Yes	No	N/A	No	No	N/A	0%
12	Yes	Yes	N/A	N/A	No	No	33%
13	Yes	No	Yes	No	Yes	No	40%
14	Yes	No	No	No	Yes	No	20%

For our analysis, we decided to compute t-tests (Independent group t-tests) designed to compare the means of our main independent and dependent variables between the three groups of automated markets, before the implementation of automation, which can be seen in Table 2. Table 2 includes observations from February 2019 until September 2019 (before implementation of automation), for all markets except for markets 2, 5, 11 and 13.

Analysing the results from Table 2, the group of high automation markets present a high daily average of order processing time, ascending to 28,68 days. In comparison with markets with a lower and medium automation, this difference is quite significant, since it represents a difference of more 26,61 days and 26,67 days, respectively. The average percentage of consistency is higher in groups of markets with a greater percentage of automation (35%) than in groups with percentages of automation relatively lower (14% and 9%). These results meet our expectations, countries included in the group of more automated markets, have a greater number of more automated tasks, which leads to greater consistency in the output given to each order.

With respect to credit concession, we observe a lower percentage of credit concession in the group of markets with low automation market. For the less automatized markets, the percentage of credit concession is 98%, for the medium automatized markets and high automatized markets is 94% and 74%, respectively. The countries included in the medium automatized markets presents a greater average amount of credit concession and a higher average amount of credit limit assigned to each client, 5.282,71€ and 607.924,10€, respectively. These measures are especially lower in the group of markets with high automation (presenting an average value of 1.730,10€ and 102.943,20€, respectively). This happens probably because the average percentage of clients with low credit risk is only approximately 7% in the group of markets with high automation, while in the other group of markets, medium and low automation, are approximately 16% and 90%, respectively. For this reason, the company is not willing to assign a higher credit limit to each client or a higher amount of credit concession per each order on the group of markets of high automation. The statistics suggests that, in markets where the percentage of automation is higher, customers are more likely to default on their responsibilities, since that group of markets markets presents the lowest percentage of customers with low credit risk[4].

Markets with lower degree of automation, presents a higher number of orders requested per customer and per market (1.098,29€ and 30.649,10€, respectively). On the contrary, markets with higher degree of automation have a larger number of customers (7.007 customers). This means a difference of approximately more 6.190 customers in comparison with the market that has a smaller number of customers, that is, the medium automatized markets. Interestingly, we observe that even though that the group of high automation markets have the higher number of customers, we observe that there are few purchase orders requested per market and per customer comparing with the group of medium automatized markets. Finally, we can observe that, the percentage of retail products[5] sold is higher in medium automatized markets (61%) and lower in high automatized markets (44%).

[4] In our analysis, we considered low credit risk: new customers, customers without risk and low risk customers.
[5] Retail products are the best-selling product category in this company.

Table 2: Differences between the low, medium and high automation market groups before the implementation of the robot

Variable	(1) – (3) N	(2) – (3) N	(1) Low automation	(2) Medium automation	(3) High automation	(1) – (3) Difference	(2) – (3) Difference
Daily average of order processing time (in days)	44380	24974	2,07	2,01	28,68	-26,61***	-26,67***
			(0,00)	(0,00)	(0,13)	(0,08)	(0,13)
Average percentage of consistency	44380	24974	0,09	0,14	0,35	-0,25***	-0,21***
			(0,00)	(0,00)	(0,00)	(0,00)	(0,00)
Average percentage of credit concession	44380	24974	0,98	0,94	0,74	0,24***	0,21***
			(0,00)	(0,00)	(0,00)	(0,00)	(0,00)
Average amount of credit concession (in €)	44380	24974	3995,36	5282,71	1730,10	2265,26***	3552,62***
			(8,64)	(19,59)	(0,00)	(13,50)	(18,94)
Average amount of credit limit (in €)	44380	24974	413157,90	607924,10	102943,20	310214,7***	504980,9***
			(1127,02)	(5842,37)	(0,00)	(1760,01)	(5649,51)
Average percentage of customers with low credit risk	44380	24974	0,90	0,16	0,07	0,83***	0,09***
			(0,00)	(0,00)	(0,00)	(0,00)	(0,00)
Average number of orders requested per customer (in units)	44380	24974	1098,29	104,14	6,87	1091,43***	97,27***
			(11,65)	(1,67)	(0,15)	(18,19)	(1,62)
Average number of orders requested per market (in units)	44380	24974	30649,10	6812,50	12906	17743,1***	-6093,5***
			(19,77)	(32,37)	(0,00)	(30,87)	(31,31)
Number of customers per market (in units)	44380	24974	2477,81	817,98	7007,00	-4529,19***	-6190,016***
			(1,56)	(3,65)	(0,00)	(2,44)	(3,53)
Percentage of retail products sold	44380	24974	0,49	0,61	0,44	0,05***	0,17***
			(0,00)	(0,00)	(0,00)	(0,01)	(0,01)

Table 3 - General Descriptive Statistics

Variable	N	Mean	Std. Dev.
Daily average of order processing time (in days)	244.727	5,14	1,98
Percentage of consistency	244.727	0,20	0,22
Percentage of credit concession	244.727	0,92	0,051
Amount of credit concession (in €)	244.727	5.023,97	3.266,89
Amount of credit limit (in €)	244.727	608.203,73	591.067,50

For the descriptive analysis, our database includes 244.727 observations (purchase orders) divided between ten markets (we excluded markets 2, 5, 11 and 13). However, due to data limitations for the descriptive statistics (Table 3 and 4) we only considered observations after February 2019. In Table 3 it is possible to see the general descriptive statistics about our main dependent and independent variables. The results suggest us that, the daily average of order processing time was 5,14 days, with an output consistency of 20%. This means that the output provided by the credit analyst is exactly the same with the output of the market analyst in about 20% of the requested orders. The average percentage of credit concession was considered high, rounding 92%, with an average amount of released credit of 5.023,97€. The average amount of credit limit assigned to each client was, approximately, 608.203,73€.

Table 4 - Descriptive statistics per market automation group

Market Automation: -1	N	Mean	Std. Dev.
Daily average of order processing time (in days)	94.740	1,89	0,19
Percentage of consistency	94.740	0,13	0,09
Percentage of credit concession	94.740	0,95	0,05
Amount of credit concession (in €)	94.740	4.203,07	2.648,15
Amount of credit limit (in €)	94.740	598.306,37	520.136,72

Market Automation: 0	N	Mean	Std. Dev.
Daily average of order processing time (in days)	74.267	1,92	0,10
Percentage of consistency	74.267	0,31	0,37
Percentage of credit concession	74.267	0,93	0,03
Amount of credit concession (in €)	74.267	8.135,65	3.391,20
Amount of credit limit (in €)	74.267	996.737,43	718.630,80

Market Automation: 1	N	Mean	Std. Dev.
Daily average of order processing time (in days)	75.720	12,35	5,10
Percentage of consistency	75.720	0,17	0,00
Percentage of credit concession	75.720	0,86	0,00
Amount of credit concession (in €)	75.720	2.999,10	0,00
Amount of credit limit (in €)	75.720	239.509,11	0,00

In table 4, we present our descriptive statistics per market automation group. For the less automatized markets, the daily average of order processing time was 1,89 days, being the group with the lower order processing time (compared to 1,92 days, on average, for medium automatized markets and 12,35 days, on average, for high automatized markets). The output consistency is higher in markets where the tasks are both manually and automatically (31%) and lower in markets where the processes are highly manual (13%). The average percentage of credit concession is high in low automatized markets (95%) in comparison to medium and high automatized markets (93% and 86%, respectively). The average amount of credit conceded is higher in medium automatized markets (8.135,65€), in contrast with the groups of low and higher automatized markets (4.203,07 and 2.999,10€, respectively). Finally, the average amount of credit limit assigned to each client is higher where the processes are hybrid, this is, both manual and automatic (996.737,43€), and less where the processes are mainly contributed by the human action (598.306,37€) and where the human action is almost null, this is, the group of high automated markets (239.509,11€).

5. EMPIRICAL METHODOLOGY AND RESULTS

4.1 EMPIRICAL METHODOGY

To evaluate the effects of automation on credit management in a multinational company, we estimate the following equation using the difference-in-difference estimators:[6]

$$Y_{imy} = d + m + y + \alpha Treated_i + \beta Robot_{my} + \gamma Treated_i \times Robot_{my} + \lambda' Controls_{imy} + \epsilon_{imy}$$

Where d denotes day, m is the month, y is the year, i is the market,

We use two dependent variables: $time_{imy}$, measured as the logarithm of the length time (days) for an order to be treated plus one, and $consistency_{imy}$, a dummy variable equalling one if the output provided by the credit analyst is the same as the market analyst and zero otherwise.

The main variable of interest is the interaction term $Treated_i \times Robot_{my}$. *Robot* is a dummy variable equalling one whether an order was received after the implementation of the automation process, namely after 1st October 2019 and zero otherwise. The variable *Treated* takes into consideration the three groups: high, medium and low automated markets. By controlling for differences due to time before and after the introduction of the robot and differences between high, medium, and low automation markets, the empirical strategy allows us to identify the effect of the robot net of any differences due to characteristics of customer or the order.

The vector *Controls* includes several characteristics assigned to the client and to the order that are relevant for credit analysis and order processing. The vector includes dummies for a vector of *credit_terms,* the credit conditions and terms attributed to each customer, including for example the payment terms, payment cycles, credit discounts and due dates. This measure generally follows the industry practices and is defined by each market and the customer's cash collection cycles. The credit terms can change from market to market and can vary from customer to customer and, as well, from order to order, depending on the current credit situation of the client. This variable takes into consideration the financial situation of the client and the credit relationship with the company.

Additionally, we also include the variable *lncredlimit*, measured as the logarithm of the maximum credit that can be attributed to each client. It may vary from customer to customer and

[6] This approach has been widely used in the previous literature. See, for example, Branstetter et al. (2014), Ferreira et al. (2019), Venâncio et al. (2021) and Venâncio and Jorge (2021).

from order to order, depending on the credit situation and relationship with the company, being a primary factor considered for the credit check while a new order is created for each customer. Each customer has a credit limit assigned, accordingly to the credit characteristic mentioned before. However, it does not mean that this limit cannot be exceeded. In fact, in our analysis, there are several customers that exceeded this limit because this type of clients may reunite some special conditions that allow them to exceed those credit limits. Moreover, we decide to include a dummy variable for *agreement_customer* equalling one if the order was requested by a customer that has payment agreements approved. We found interesting to assess this variable, since this is the credit output most attributed to each order and we intend to observe the impact of this variable in this analysis.

We also included thirty-one dummies to account for each day of the month and twelve dummy variables for the month of the year and as well two dummy variables for each year, 2019 and 2020. In the analysis we also considered eleven dummies to account for the different channels/type of products sold in each order. In addition, we included 10 dummy variables to account for the credit risk that can be assigned to each customer. The credit risk can change through time, depending on the financial status and credit conditions of each client. Finally, we also included the fourteen dummy variables representing the countries that requested the orders and we also considered thirty-one dummy variables accounting for the different credit analysts that processed the order. It is important to refer that the credit analysts are the first line of analysis to provide a recommendation, this is, an output for each order received. After this stage the market analysts are later responsible for the final revision and the final credit recommendation (output) to be attributed to each order. This means that the outputs conceded by the credit analysts and market analysts can be the same or different, and this is where we will analyse the consistency of the output (*consistency*).

We include customer and credit analyst fixed effects to further control for unobserved heterogeneity and possible omitted bias.

4.2 EMPIRICAL RESULTS

For the empirical analysis, we use a fixed effects models (by using the within regression estimator). We performed the regressions dividing the empirical analysis into four breakdown models (displayed in four tables). Table 5 comprises observations from the three different market automation groups, being our base model. Table 6 includes the results of the computed regressions for the medium and high automated market groups. Table 7 includes only the results for the medium and low automated market groups and, finally Table 8, contains the results for the high and low automated market groups. We decided to separate the analysis between the groups with different levels of automation to study the differences in our main variables with respect to our dependent variables, mainly differences in the estimated coefficients, variable significance and correlation. Therefore, we found interesting to make this separation and assess the outcomes. We also performed the same regressions for the models but without applying the logarithm to the dependent variable *time*, which can be seen in Appendix section (appendixes 2 to 9).

In Table 5, our base model, we present the results considering the three market automation groups: low, medium and high automation. Columns (1) and (2) presents the results for the dependent variable *time* without and including control variables, respectively.

Table 5 - Empirical results using fixed effects models for the Groups of High, Medium and Low Automation Markets

VARIABLES	Time (1)	Time (2)	Consistency (3)	Consistency (4)
Robot	0.114	0.132	0.296**	0.181
	(0.343)	(0.343)	(0.121)	(0.129)
Mktaut*Robot	-0.655***	-0.667***	-0.048**	0.030*
	(0.111)	(0.117)	(0.022)	(0.018)
Ln(Credit Limit)		2.773		-1.536**
		(1.856)		(0.705)
Agreement Customer		-0.134**		-0.072***
		(0.064)		(0.015)
Constant	6.226***	-30.485	-0.167	16.982**
	(0.556)	(20.331)	(0.126)	(7.676)
Observations	249,463	246,368	244,727	241,799
R-squared	0.343	0.353	0.044	0.523
F-statistics	36.18	.	4.214	.

Columns (1) and (3) do not includes control variables. Columns (2) and (4) includes control variables. Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1. Time measured the logarithm of the length time (days) for an order to be treated plus one.

The coefficient associated with our variable of interest, *mktaut_robot* is statistically significant and negative correlated with the dependent variable *time*. This means that after the implementation of the robot, the time to process an order for the most automated market reduced by, approximately, 48,06%[7] (without considering control variables) and 48,68% (including

[7] Since we applied the logarithm to the dependent variable *time*, the conversion of the coefficient is made through the following calculation: $\left(e^{(-0{,}655)} - 1\right) \times 100 \approx -48{,}06\%$. For further analysis we applied the same calculation according to the respective coefficient.

control variables), or approximately, a reduction of 9 days (Appendix 2, column 1 and 2). This result suggests that if an order is analysed after the introduction of the robot and the higher is the automation level of the issuing market, the shorter will be the time spent analysing an order. The coefficient associated with the variable *robot* is not statistically significant, whether the regression includes or not control variables.

Regarding the control variables (Column 2), we observe that the variable *lncredlimit* is not statistically significant, however the variable *agreement_customer* is statistically significant at a confidence level of 5%. This means that the credit limit assigned to each client is not statistically significant to explain the order processing time, but if the client has payment agreements approved, we expect a decrease on the order processing time by 12,54%.

Columns (4) and (5) of Table 5 presents the regression results for the dependent variable *consistency* without and including control variables, respectively. The coefficients associated with variables *robot* and *mktaut_robot* are statistically significant, at a 5% confidence interval, to explain the consistency among the outputs provided by the credit analysts and the market analysts. More precisely, the variable *robot* presents a positive correlation with the dependent variable *consistency*, meaning that if the order is analysed after the introduction of the robot, the will be an higher harmonization between the final output provided by the credit analysts and the market analysts (increase of, approximately, 0,296 points) which is in accordance with our expectations. Additionally, the interaction variable *mktaut_robot* besides being statistically significant at a confidence level of 5%, presents a negative association with the dependent variable *consistency*, presenting a negative coefficient of -0,048. This is quite interesting since the results are suggesting that if an order is analysed after the introduction of the robot and the issuing market belong to a group of high automation markets, the output consistency among the credit analysts and markets analysts will be lower.

However, if we consider the column 4 of Table 5, the results mentioned above for the dependent variable *consistency* do not stand if we use in the regression with control variables, since the variable *robot* and the interaction term variable *mktaut_robot*[8] are no longer statistically significant to explain the dependent variable *consistency*. However, the control variables *lncredlimit* and *agreement_customer* are statistically significant at a 5% and 1% confidence level, respectively. With respect to the credit limit, we found a negative association with the dependent

[8] In our analysis, we only consider a variable to be statistically significant at a 5% confidence level or lower. Accordingly, since in the results of the Table 5, the variable *mktaut_robot* is only statistically significant at a 10% confidence level, we do not consider this variable statistically significant for our analysis.

variable, insofar that there is empirical evidence implying that if the credit limit assigned to each client increases by 1%, it is estimated a decrease of output consistency by -0,015[9] units. This means that the higher is the credit limit assigned to each customer, the lower will be the consistency among the output provided by the credit analysts and the output provided by the market analysts. This is not unexpected, since the higher is the credit limit attributed to each client, the higher can be the divergence among the opinions of the credit analysts and the market analysts towards the most appropriated output to be assigned to each order requested by a costumer. The variable *agreement_customer* presents a negative correlation with the variable *consistency*, insofar that if it is a costumer with payment agreement approved the output consistency will decrease by 0,072 units, although presenting a low impact.

Another important conclusion is that the regression presented in the column 1 (Table 5) presents an R^2 of 0,343, meaning that the variables *robot* and *mktaut_robot* explain by themselves, approximately, 34,3% of the variation in the dependent variable *time.* When adding the control variables, *lncredlimit* and *agreement_customer* to the regression, there was, in fact, an increase of the R-squared but was a minimal increase, since the R^2 increase only to 0,353. This means that the control variables did not provide significant explanatory power to the variations in the dependent variable *time*. However, when considering the dependent variable *consistency* (column 3 and 4, Table 5) we notice that if we do not consider the control variables mentioned above, the variables *robot* and *mktaut_robot* only explain about 4,4% of the variations of the dependent variable *consistency,* but when adding for the control variables, the R^2 increases to 0,523, meaning that all the variables combined explain about 52,3% of the variations on the dependent variable *consistency,* adding much more explanatory power to the model.

In Table 6, we present the regression results considering the high and medium automated market groups, where the group of high automated markets assume the value of one and the group of medium automated markets assumes the value of zero. In this analysis, we notice some differences. First, the variable *robot* is now statistically significant to explain the dependent variable *time,* compared to our base model, presenting as well a positive relationship with the dependent variable. This suggest that if the order is analysed after the introduction of the robot we will observe an increment of order processing time by 265,1% or 279,62%, whether not using

[9] Since the variable *lncredlimit* is measure as the logarithm of the maximum limit credit to each client, the coefficient needs to be converted through the following calculation: $-1{,}536 \times \ln(1 + 0{,}01) \approx -0{,}015$ or $\frac{-1{,}536}{100} \approx -0{,}015.$

(column 1) or using (column 2) control variables, respectively, which represents a significant increase of, approximately, 9 days (Appendix 3, columns 1 and 2).

However, having a look to the variable of interest, *mktaut_robot*, we observe another interesting evidence. The results exhibit a statistically significant negative correlation with the dependent variable *time* (column 1 and 2), same as the results obtained in our base model (Table 5), though presenting a higher negative impact in this association with the dependent variable. Likewise, there is statistical evidence suggesting that if an order is processed after the introduction of the robot and if it is issued by a market that belongs to the group of high automated markets, there will be a decrease of 80,23% (without considering control variables) or an decrease of 80,72% (considering control variables) on the time spent processing an order, which represents a reduction on the time spent processing an order of, approximately, 16 days (Appendix 3, column 1 and 2). Thus, the combined effect of the order being treated after the introduction of the robot and if the order is issued by a market that belongs to the group of markets with high automation, the lower will be the time consumed to process the orders. This is one of the first important conclusions of this investigation, since it is suggesting that the implementation of the robot had a positive impact in reducing the average order processing time in the group of markets with high automation.

Curiously, having in mind the groups of medium or high automatized market groups (Table 6), if we consider the control variables *agreement_customer* the outcomes are quite different compared to our base model, since now the variable is not statistically significant to describe the dependent variable *time*. Nonetheless, the variable is also statistically significant to explain the output consistency (*consistency*), demonstrating the same correlation as our base model (Table 5), but exhibiting an higher impact on the dependent variable, since it is likely to see a decrease of 0,116 units on the output consistency if the order was requested by a client with payment agreements approved.

Table 6- Empirical results using fixed effects models for the Groups of High and Medium Automation Markets

VARIABLES	Time (1)	Time (2)	Consistency (3)	Consistency (4)
Robot	1.295***	1.334***	0.481***	0.262*
	(0.406)	(0.412)	(0.123)	(0.147)
Mktaut*Robot	-1.621***	-1.646***	-0.119***	-0.008
	(0.168)	(0.169)	(0.038)	(0.031)
Ln(Credit Limit)				
Agreement Customer		0.220		-0.116***
		(0.383)		(0.043)
Constant	-0.349	-0.261	-0.371**	0.337***
	(0.379)	(0.440)	(0.156)	(0.110)
Observations	151,048	149,275	149,987	148,250
R-squared	0.434	0.442	0.080	0.518
F-statistics	63.61	.	4.752	.

Columns (1) and (3) do not includes control variables. Columns (2) and (4) includes control variables. Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1. Time measured the logarithm of the length time (days) for an order to be treated plus one.

With respect to our dependent variable *consistency*, we can fairly say that comparing with our base case, the variable *robot* is still statistically significant (now at a confidence level of 1%), suggesting that it is expected an increase of 0,481 units on the output consistency if the order is treated after the implementation of the robot (not assuming control variables on the regression, column 3). However, if we assume control variables, the variable *robot* is no longer statistically significant to explain the output consistency, yet, presenting a positive correlation. In addition, the previous conclusions for the interaction effects variable *mktaut_robot* towards the variable *consistency* remain the same, only considering the group of markets with medium and high automation (Table 6). There is empirical evidence (column 3, assuming no control variables) stating that if the order is treated after the introduction of the robot and if the order was issued by the group of markets with high automation, it is expected a decrease of 0,119 units on the output consistency.

In Table 7, we can find below the results obtained for the regressions in analysis for the groups of medium and low automatized markets. In this model, the group of medium automatized markets assumes the value of one and the group of low automated markets assumes value of zero. We found some interesting differences compared with the previous models. First, the variable *robot* presents a negative correlation with the dependent variable *time* (whether considering or not considering control variables, column 1 and 2), although not being statistically significant. Thus, there is evidence suggesting that it does not matter whether or not the order was processed after the introduction of the robot to explain the time spent to analyse an order, for the groups of medium and low automatized markets.

However, with respect to the variable of interest, *mktaut_robot,* we found out some differences that have not been observed so far. Despite the results suggesting that the variable is statistically significant at a 1% confidence level (column 1 and 2, Table 7), the association with the dependent variable *time* is positive. Such evidence is proposing that if an order is treated after the implementation of the robot and if it is issued by a market that belongs to the group of medium automatized markets it is expected an increase of 101,98% (column 1) and 116,63% (column 2) on the time spent processing the orders, translating into an increase of, approximately, 3 days (Appendix 4, column 1 and 2). This is another important evidence of this work because it means that the effects of the order being treated after the introduction of the robot and if the issuing market belongs to the groups of medium automated markets it is expect an increment of the time that it takes to process an order, compared to the group of markets with low automation. Thus, this is another important of our work, because it is suggesting that the implementation of the robot was more favourable to the markets exhibiting low levels of automation than the markets displaying medium levels of automation

Concerning the control variables, the results are implying a positive correlation between the variable *lncredlimit* with the dependent variable *time*, however not statistically, and a statistically significant negative correlation between the variable *agreement_customer* and *time*. Accordingly, there is evidence indicating that for the groups of medium and low automated markets (Table 7), what it matters the most to explain the time consumed processing an order, in terms of control variables, is if the order was requested by a customer with payment agreements approved. In line, it expected a decrease of the time that it takes to process an order of 13,76%, if the order was requested by a client with payment agreements approved.

Table 7- Empirical results using fixed effects models for the Groups of Medium and Low Automation Markets

VARIABLES	Time (1)	Time (2)	Consistency (3)	Consistency (4)
Robot	-0.105	-0.176	-0.091	-0.076
	(0.167)	(0.178)	(0.060)	(0.058)
Mktaut*Robot	0.703***	0.773***	0.052	0.067*
	(0.160)	(0.161)	(0.037)	(0.036)
Ln(Credit Limit)		3.081*		-0.857
		(1.787)		(0.694)
Agreement Customer		-0.148***		-0.077***
		(0.048)		(0.017)
Constant	-2.237***	-37.402*	0.268***	10.349
	(0.598)	(20.360)	(0.089)	(7.999)
Observations	173,721	171,132	169,007	166,585
R-squared	0.095	0.123	0.023	0.439
F-statistics	3.468	.	1.641	.

Columns (1) and (3) do not includes control variables. Columns (2) and (4) includes control variables. Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1. Time measured the logarithm of the length time (days) for an order to be treated plus one.

Regarding to the dependent variable *consistency* we found out that for the groups of medium and low automated markets, either the variable *robot* and the interaction term variable *mktaut_robot* are not statistically significant to explain the output consistency among the credit and market analysts, even considering or not considering control variables in the regressions. In the previous two models studied, both variables were considered statistically significant to explain the dependent variable *consistency* (not assuming control variables), however, for this model (Table 7), the implementation of the robot does not seems to have any significant impact in improving the output consistency among the opinion of the credit and market analysts. In fact, the only variable that is statistically significant to explain the dependent variable *consistency* is if the client has payment agreements approved (*agreement_customer*), however presenting a negative correlation, insofar that it is expected a decrease of 0,077 units if the order was requested by a client with payment agreements approved.

It is worth mentioning that this model, using only the groups of medium and low automated markets, is the one where the regressions have the lowest explanatory power to describe both dependent variable *time*, across the 4 models in analysis. Having a look to Table 7, column 1 presents an R^2 of 0,095 which means that the variables *robot* and *mktaut_robot,* by themselves, only explain 9,5% of the variations on the dependent variable *time* (not considering control variables), which is way lower compared to the other models. We estimate an increase of R^2 to 0,123 when considering the control variables, but still the explanatory power of this variables is much lower again compared to the other three models. This might suggest that for the group of medium and low automated markets, the implementation of the robot did not have that much impact compared to the models including the group of markets with high automation (Table 6 and 8).

Finally, our last model, only considers observations from the groups of markets with high and low automation and can be seen in Table 8, where the group of high automated markets assumes the value of one and the group of low automated markets equals to zero. We must highlight some differences that were not observed so far in the previous models. First, the variable *robot* is not statistically significant to explain the dependent variable *time* displaying a negative association with the dependent variable, which is in line with the results of Table 7.

However, if we consider the interaction term *mktaut_robot,* we observe a statistically significant negative correlation with the variable *time* (valid whether using and not using control variables, column 1 and 2, respectively). Therefore, there is statistical evidence suggesting that it is expected a substantial decrease of the order processing time by 65,13% or 64,73% (whether not using or using control variables, respectively) if the order is analysed after the implementation of the robot and if the order is requested by a market displaying high levels of automation, thus, representing a reduction of, approximately, 16 days (Appendix 5, column 1 and 2). Therefore, this is another major conclusion in this study, since there is statistical evidence suggesting that comparing with markets with low automation, there is a significant reduction of the average order processing time if the order is processed after the implementation of automation and if it is issued by markets exhibiting high levels of automation. Comparing to the previous results of Table 6 and 7, we can observe that the group of automated markets that benefited the most with the implementation of the robot was the markets displaying higher levels of automation, following the markets with low levels of automation, and, finally, the group of markets exhibiting medium levels of automation.

Similarly to the results of Table 5 and 7, the control variable *agreement_customer* presents a statistically significant negative correlation with the dependent variable *time*, denoting that if the order is requested by a costumer with payment agreements approved there will be a decrease on the time spent to analyze an order by 17,72%, considering the group of high and low automatized markets. We also found a positive association between the variable *lncredlimit* and the dependent variable *time*, yet not statistically significant.

Table 8- Empirical results using fixed effects models for the Groups of High and Low Automation Markets

VARIABLES	Time (1)	Time (2)	Consistency (3)	Consistency (4)
Robot	-0.559	-0.557	0.311**	0.238*
	(0.376)	(0.372)	(0.122)	(0.141)
Mktaut*Robot	-1.035***	-1.042***	0.078*	-0.066*
	(0.220)	(0.239)	(0.044)	(0.038)
Ln(Credit Limit)		1.722		-2.237***
		(1.973)		(0.765)
Agreement Customer		-0.195***		-0.059***
		(0.058)		(0.014)
Constant	6.263***	-17.407	-0.345**	24.365***
	(0.588)	(21.637)	(0.157)	(8.244)
Observations	174,157	172,329	170,460	168,763
R-squared	0.404	0.414	0.063	0.597
F-statistics	44.96	.	5.206	.

Columns (1) and (3) do not includes control variables. Columns (2) and (4) includes control variables. Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1. Time measured the logarithm of the length time (days) for an order to be treated plus one.

Finally, considering the variable dependent *consistency* we observe that the variable *robot* is statistically significant to explain the dependent variable, obtaining similar results as in Table 5 and 6, and presenting a positive correlation. This demonstrates that it is expected an increase of 0,311 units in the output consistency if the order is analysed after the introduction of the robot, for the groups of high and low automated markets (column 1). However, when assessing the impact of the interaction variable *mktaut_robot* we observe that is no longer statistically significant[10] to explain the output consistency, same as the results of the previous model (Table 7), either considering or not considering control variables (Table 8, columns 3 and 4).

Having a look in the control variables, we found comparable results as the ones obtained in our base model (Table 5), since for both control variables *lncredlimit* and *agreement_customer* we found a statistically significant negative correlation with the dependent variable *consistency*. With this it is expected a higher divergence between the opinion of the market analysts and credit analysts when the order was requested by a customer with payment agreement approved and when the higher is the credit limit assigned to each client , for the group of high and low automated markets.

[10] In our analysis we consider a threshold of 0,05 (5%) for the p-value when we are assessing the significance of the explanatory variables. Any value above 5% for the p-value is discard in terms of significance in our analysis.

We also find it interesting to analyze the results considering observations from all markets without exempting any of them from the analysis. However, in order to do so and due to data limitations, for the following models and regressions we are only considering all observations from May 2019 onwards. The results are displayed in the same way as the previous analysis, decomposing the results into four models: Table 9, with the results for the Groups of High, Medium and Low automated markets; Table 10 comprising the results for the Groups of High and Medium automated markets; Table 11 displaying the results for the Groups of Medium and Low automated markets and, finally Table 12 exhibiting the results for the Groups of High and Low automated markets. In general, we observe very good consistency across all the new results obtained in the following models compared to the previous respective analysis and models, which provides more robustness to the conclusions achieved so far. Therefore, we will point out the main differences obtained in this analysis.

In Table 9, there are some differences worth to mention. Compared to the base model of the previous analysis (Table 5), the results suggest that the variable *robot* is no longer statistically significant to explain the dependent variable *consistency* (not considering control variables), which means that it does not matter whether or not the order was analyzed after the introduction of the robot to explain the output consistency, this is, the harmony between the output provided from the credit analysts and the market analysts (Table 9, column 3).

Table 9- Empirical results using fixed effects models for the Groups of High, Medium and Low Automation Markets (Robustness using only observations since May 2019 onwards)

VARIABLES	Time (1)	Time (2)	Consistency (3)	Consistency (4)
Robot	-0.071	0.085	0.200*	0.151
	(0.296)	(0.288)	(0.111)	(0.114)
Mktaut*Robot	-0.751***	-0.751***	-0.054**	0.026
	(0.099)	(0.104)	(0.021)	(0.016)
Ln(Credit Limit)		-0.783		-0.043
		(0.585)		(0.066)
Agreement Customer		-0.135*		-0.076***
		(0.071)		(0.017)
Constant	0.104	7.386	0.096	0.556
	(0.298)	(6.477)	(0.136)	(0.805)
Observations	271,275	268,094	271,275	268,094
R-squared	0.282	0.301	0.031	0.525
F-statistics	29.20	.	2.991	.

Columns (1) and (3) do not includes control variables. Columns (2) and (4) includes control variables. Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1. Time measured the logarithm of the length time (days) for an order to be treated plus one.

Moreover, with respect to the variable *lncredlimit*, we found that the variable is now not statistically significant to explain the dependent variable consistency (considering control variables, column 4). Although presenting a negative correlation as the previous model (Table 5) the credit limit assigned to each customer does not matter to explain the output consistency. Moreover, we denote another change when comparing the control variable *agreement_customer* with the dependent variable *time,* since it is no longer statistically significant to explain the dependent variable, although presenting a negative correlation, as the base case of the previous model (Table 5, column 2). The remaining results are in line with the base model presented before in Table 5, which provides more consistency and robustness to the mentioned conclusions.

It is possible to visualize in Table 10 the results for the groups of High and Medium automated markets. There were no substantial differences between the estimated results and the results obtained in the previous model in Table 6. However, we can mention that with respect to the variable *robot* we observe a lower impact in the dependent variable *time*, compared to the results of the previous model, in the sense that in this results, it is expected an increase of the order processing time by 112,55% (column 1) or 157,02% (column 2) if the order was process after the implementation of automation and issued by a market with levels of high automation. With respect to the remaining results we observe very good consistency with the previous results obtained in Table 6.

Table 10- Empirical results using fixed effects models for the Groups of High and Medium Automation Markets (Robustness using only observations since May 2019 onwards)

VARIABLES	Time (1)	Time (2)	Consistency (3)	Consistency (4)
Robot	0.754**	0.944***	0.320***	0.219*
	(0.348)	(0.343)	(0.118)	(0.128)
Mktaut*Robot	-1.608***	-1.570***	-0.112***	-0.015
	(0.169)	(0.181)	(0.037)	(0.025)
Ln(Credit Limit)		0.107		0.014
		(0.499)		(0.063)
Agreement Customer		-0.143		-0.083***
		(0.111)		(0.027)
Constant	0.011	5.523	-0.603***	0.183
	(0.319)	(5.482)	(0.220)	(0.737)
Observations	182,491	180,325	182,491	180,325
R-squared	0.343	0.362	0.055	0.543
F-statistics	40.80	35.85	3.307	208.0

Columns (1) and (3) do not includes control variables. Columns (2) and (4) includes control variables. Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1. Time measured the logarithm of the length time (days) for an order to be treated plus one.

In Table 11, it is exhibiting the results for the group of medium and low automated markets. The main differences observed is that the variable *robot* is now statistically significant to explain the variable *consistency* (column 3 and 4), presenting a negative correlation. Therefore, the results are indicating that for the group of medium an low automated markets, if the order is treated after the introduction of the robot it is expected a decrease on the output consistency by 0,092 units (not considering control variables) or a decrease of 0,086 units (considering control variables), comparing with the results obtained for this variable in Table 7 (column 3 and 4), that were not statistically significant. This means that for the markets displaying low and medium levels of automation, the output consistency diminished after the introduction of automation.

Table 11- Empirical results using fixed effects models for the Groups of Medium and Low Automation Markets (Robustness using only observations since May 2019 onwards)

VARIABLES	Time (1)	Time (2)	Consistency (3)	Consistency (4)
Robot	-0.150	-0.127	-0.092**	-0.086**
	(0.154)	(0.168)	(0.043)	(0.043)
Mktaut*Robot	0.446***	0.479**	0.033	0.090***
	(0.173)	(0.191)	(0.034)	(0.030)
Ln(Credit Limit)		-0.745		-0.079
		(0.752)		(0.076)
Agreement Customer		-0.277***		-0.083***
		(0.079)		(0.016)
Constant	-1.926***	12.445	0.278**	1.289
	(0.416)	(8.810)	(0.109)	(0.908)
Observations	193,409	190,743	193,409	190,743
R-squared	0.087	0.109	0.013	0.453
F-statistics	4.067	.	1.516	.

Columns (1) and (3) do not includes control variables. Columns (2) and (4) includes control variables. Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1. Time measured the logarithm of the length time (days) for an order to be treated plus one.

In addition, we verify that the variable *lncredlimit,* although not being statistically significant to explain the dependent variable *time* (column 2, Table 11), is negatively correlated. The remaining results suggest the same empirical conclusions as the comparative model displayed in Table 7, providing more robustness to our analysis.

Finally, in Table 12, it is possible to observe the results for the groups of high and medium automatized markets. As it is possible to see, there was no significant differences worth to mention, remaining the same conclusions of the previous comparative model in Table 8.

Therefore, we observe very consistent results which enable us to conclude with more robustness and reliability.

Table 12- Empirical results using fixed effects models for the Groups of High and Low Automation Markets (Robustness using only observations since May 2019 onwards)

VARIABLES	Time (1)	Time (2)	Consistency (3)	Consistency (4)
Robot	-0.605	-0.585	0.295**	0.231*
	(0.368)	(0.364)	(0.124)	(0.139)
Mktaut*Robot	-1.012***	-1.015***	0.075*	-0.067**
	(0.211)	(0.229)	(0.041)	(0.033)
Agreement Customer		-0.167***		-0.064***
		(0.061)		(0.014)
Constant	6.541***	6.343***	-0.266*	0.287***
	(0.623)	(0.493)	(0.147)	(0.055)
Observations	166,650	165,120	166,650	165,120
R-squared	0.402	0.412	0.059	0.577
F-statistics	43.67	.	5.181	.

Columns (1) and (3) do not includes control variables. Columns (2) and (4) includes control variables. Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1. Time measured the logarithm of the length time (days) for an order to be treated plus one.

6. CONCLUSION

The extreme competitiveness in the markets forces companies to be increasingly efficient in terms of resources used and more productive to compete and to have a sustainable position in the markets. The automation of accounts receivables is one of the multiple measures for a firm to become more efficient, be more productive and to be better prepared to promote a sustainable growth.

The aim of this research was to analyse the impact of the automation on accounts receivables in a multinational company, more precisely to study the effects of the introduction of automated systems on the order processing time and consistency between the credit and market analysts, highlighting the importance of introducing automated systems to streamline the general credit management procedures and to ensure a more efficient credit management flow.

In our study, we performed different analyses using fixed effects models (by using the within regression estimator). In a first stage we computed the regressions using all observations from February 2019 onwards from the three groups of automated markets: high, medium and low automation. Then, we decided to decompose these results across the three different levels of automation, firstly, computing the regressions with observations from the groups of high and medium automated markets; secondly, the groups of medium an low automated markets and, finally, the groups of high and low automated markets.

Regarding to the time spent processing the purchase orders, the results obtained lead us to conclude that, in general, if the order is processed after the introduction of the robot it is expected a decrease on the average order processing time in, approximately, between 12% to 14%, representing a decrease of, approximately, 1 day, according to our base model, yet not being statistically significant. Moreover, considering our base model and including observations from all the group automation markets, if the order is processed after the implementation of automation and the higher is the market automation levels, we estimate a reduction on the order processing time of 48% to 53% (approximately, 9 to 11 days), according to the base model and robustness models, respectively. This is an important conclusion of this research since it is suggesting that if an order is analysed after the introduction of the robot and the higher is the automation level of the issuing market, the shorter will be the time spent processing an order.

With respect to the output consistency, and considering the general results for the three groups of automated markets, we found a positive correlation with the order being treated after the introduction of the robot, meaning that it is expected an increase on the consistency among the outputs provided by the credit analysts and the market analysts when the order is analysed after the introduction of the robot, especially for the markets displaying high and low levels of automation. Moreover, we conclude that the higher is credit limit assigned to each customer and if the order is requested by a client with payment agreements approved, the lower will be the consistency among the output provided by the credit analysts and the output provided by the market analysts. This is not unexpected, since the higher is the credit limit attributed to each client, the higher can be the divergence among the opinions of the credit analysts and the market analysts towards the most appropriated output to be assigned to each order requested by a costumer.

Interestingly, when we decomposed the results into the three different groups of automated markets, we found revealing evidences and some differences comparing with our base model. First, we conclude that with respect to the group of markets with high automation, the implementation of the robot had a positive impact in reducing the average order processing time by, approximately 80% (or 16 days, approximately) representing a greater impact of the implementation of the robot for the markets with high automation comparing with our base model. Nevertheless, when we observed the independent results for the groups of medium and later low automation markets, the differences are quite significant.

We found that for the markets exhibiting medium levels of automation, if the order was treated after the introduction of the robot it is expect an increment on the time that it takes to process an order by, approximately, between 102% to 117% (without considering and considering control variables, respectively), this is, an increase of approximately 3 to 4 days, compared to the group of markets with low automation. This means that the introduction of the robot was more favourable in reducing the average time of order processing for the group of low automatized markets. Finally, we found statistical evidence suggesting that it is expected a decrease of the order processing time by, approximately 65% (or 16 days, approximately) if the order is analysed after the implementation of the robot and requested by a market belonging to the group of high automated markets, compared with the group of low automated markets which means that the introduction of the robot promoted higher benefits in reducing the average order processing time for the markets with more automated task (higher levels of automation).

Therefore, one of the major conclusions of our work is that the introduction of the automation had in general a positive impact for all groups of market automation, whether high, medium and low, in the sense that it is expected a reduction on the average order processing time with the implementation of the robot. Nonetheless, we discover that for the groups of markets with medium and low automation levels, the introduction of the robot was also favourable in reducing the time spent processing the orders, but were not that benefited compared to the markets exhibiting high levels of automation. In fact, we conclude that the group displaying a hybrid system of automated tasks and manual task (markets with medium levels of automation) was the one that benefited the least with the implementation of the robot. In conclusion, we believe that credit tasks and procedures should be more automated for all markets in order to benefit from the synergies promoted by the implementation of automation systems.

This study has, however, some limitations especially when it comes to the data that was used for this research. Unfortunately, we were not able to collect observations from months and years prior to 2019 for all the markets and for January 2019, which lead us to exclude some markets from the regressions. However, we believe that we overcome this problem including the observations from all markets since May 2019 onwards for the regressions that were computed for robustness purposes. Unfortunately, was not possible to collect information concerning the time that a client takes to pay their credit orders or if there were clients with uncollectable credits. Moreover, some markets maybe not be fully comparable due to their own characteristics.

For future research, we believe that it could be interesting to analyse other drivers that influence the orders processing time and output consistency among credit analysts and credit markets, and also other factors that contribute to streamline the credit management practices and improve company’s accounts receivables.

REFERENCES

Abuhommous, A. (2017). The Impact of Offering Trade Credit on Firms' Profitability. Journal of Corporate Accounting & Finance.

Afonso, A., Jalles, J. & Venâncio, A. (2021). Taxation and public spending efficiency: An international comparison, *Comparative Economic Studies, 63(3)*, 356-383.

Antysheva, E., Prishutova, T. & Frolova, V. (2020). Accounts receivable management in Digital transformation. International Scientific Conference "Digital Transformation on Manufacturing, Infrastructure and Service"- November 18-19, 2020. Congress center of Peter the Great St. Petersburg Polytechnic University.

Asselbergh, G. (1999). A Strategic Approach on Organizing Accounts Receivable Management: Some Empirical Evidence. Journal of Management and Governance 3: 1–29,

Baker, H. K., Pattnaik, D., Kumar, S. (2020). Trade credit and firm profitability: Empirical evidence from India. International Journal of Finance & Economics.

Bendavid, I., Herer, Y. T., Yücesan, E. (2017). Inventory management under working capital constraints. Journal of Simulation. 11, 62–74.

Biais, B. & Gollier, C. (1997). Trade Credit and Credit Rationing. The Review of Financial Studies. 10 (4), 903-937.

Boisjoly, R. P., Conine Jr, T. E. & McDonald IV, M. B. (2020). Working capital management: Financial and valuation impacts. Journal of Business Research. 108, 1-8.

Branstetter, L., Lima, F. Taylor, L. J. & Venâncio, A. (2014). Do entry regulations deter entrepreneurship and job creation? Evidence from recent reforms in Portugal, Economic Journal, 124(577), 805-832.

Brick, I. E., & Fung. W. K. H. (1984). The Effect of Taxes on the Trade Credit Decision. Financial Management. 13(2), 24–31.

Brigham, E. and Houston, J. (2003) Fundamentals of Financial Management. Thomson Southwestern, Cincinnati.

Camerinelli, E. (2010). Trends in cash, liquidity and working capital management automation: The
role of technology. Journal of Corporate Treasury Management 3 (2), 141–148.

Chod, J., Lyandres, E. & Yang, S. A. (2019). Trade credit and supplier competition. Journal of Financial Economics. 131, 484–505.

Copley, S. (2015). “What is Systems Analysis?”. IGCSE ICR. Retrieved 27th May 2021. https://www.igcseict.info/theory/8/what/index.html

Corcentric (2021). Accounts receivable automation software. Retrieved 27th May 2021. https://www.corcentric.com/order-to-cash/accounts-receivable-automation/

Cuñat, V. & Garcia-Appendini, E. (2012). Trade credit and its role in entrepreneurial finance. Oxford Handbook of Entrepreneurial Finance. Oxford University Press. 526-557.

Dass, N., Kale, J.R. & Nanda, V. (2015). Trade credit, relationship-specific investment, and product market power. Review of Finance. 19 (5), 1867-1923.

Deloof, M. (2003). Does Working Capital Management Affect Profitability of Belgian Firms?. Journal of Business Finance & Accounting. 30 (3-4), 573-588.

Demirgüç-Kunt, A. & Maksimovic, V. (2001). Firms as Financial Intermediaries: Evidence from Trade Credit Data. Policy Research Working Paper. World Bank. 2696.

Fabbri, D. & Klapper, L. F. (2016). Bargaining power and trade credit. Journal of Corporate Finance. 41, 66–80.

Falope, O. & Ajilore, T. (2009). Working Capital Management and Corporate Profitability: Evidence from Panel Data Analysis of Selected Quoted Companies in Nigeria. Research Journal of Business Management. 3, 73-84.

Ferreira, M., Santos, J. & Venâncio, A. (2021). Collateral value and entrepreneurship: Evidence from a property tax reform. SSRN Working paper 3544706.

Fisman, R. & Raturi, M. (2004). Does Competition Encourage Credit Provision? Evidence from African Trade Credit Relationships. The Review of Economics and Statistics. 86(1), 345-352

Gill, A., Biger, N. & Mathur, N. (2010). The Relationship Between Working Capital Management And Profitability: Evidence From The United States. Business and Economics Journal. 1-9.

Haresh, B. (2012). Working Capital Management and Profitability: Evidence from India - An Empirical Study. Ganpat University - Faculty of Management Studies Journal of Management and Research. 5.

Harris, A. (2005). Working capital management: difficult but rewarding. Financial Executive, 21(4), 52-54.

Joy, O. M. (1978). Introduction to financial management. Irwin (Richard D.) Inc., U.S.

Lee, C. H. & Rhee, B.-D. (2011). Trade credit for supply chain coordination. European Journal of Operational Research. 214, 136–146.

Long, M. S., Malitz, I. B. & Ravid, S. A. (1993). Trade Credit, Quality Guarantees, and Product Marketability. Financial Management. 22 (4).

Madakam, S., Holmukhe, R. M. & Jaiswal D. K. (2019). The future digital work force: Robotic Process Automation (RPA). Journal of Information Systems and Technology Management. 16.

Mayes, C. & Dyer, J. N. (2015). SMB Automation of Accounts Payable and Accounts Receivable. International Journal of Business Research. 15 (3), 37-54.

Mbembe, S. M., Mutegi, D. & Were, E. (2017). Factors affecting accounts receivables management: A case study of selected pharmaceutical distributors in Nairobi County. International Journal of Business Management & Finance. 1 (21), 347-368.

Mian, S. & Smith Jr, C. W. (1992). Accounts Receivable Management Policy: Theory and Evidence. The Journal of Finance. 47(1),169–201.

Mugambi, B. M., Gichohi, P. & Kambura, S. (2019). Effect of cash management automation on financial management in Meru County Government. International Journal of Finance. 4 (1), 1-10.

Munene, F. (2018). Accounts receivable management and financial performance of Embu water and sanitation company limited, Embu County, Kenya [Published Master Thesis of Business Administration - Finance]. Kenyatta University. Kenyatta University Institutional Repository. Retrieved 9th June 2021. https://ir-library.ku.ac.ke/handle/123456789/19512

Ngugi, S. K. (2014). Determinants of Accounts Receivables Management in the Hotel Industry in Kenya [Published Doctoral Thesis of Business Administration]. Jomo Kenyatta University of Agriculture and Technology. Digital Repository of United States International University-Africa. Retrieved 9th June 2021. http://erepo.usiu.ac.ke/handle/11732/502;jsessionid=E197C1F3B9521BC4DFAE5466C315CB2E

Petersen, M. A. & Rajan, R. G. (1995). The Effect of Credit Market Competition on Lending Relationships. The Quarterly Journal of Economics. 110 (2), 407-443.

Petersen, M. A. & Rajan, R. G. (1997). Trade Credit: Theories and Evidence. The Review of Financial Studies. 10 (3), 661-691.

Ponsian, N., Chrispina, K., Tago, G. & Mkiibi, H. (2014). The effect of working capital management on profitability. International Journal of Economics, Finance and Management Sciences. 2 (6), 347-355.

Rao, S., Gaglani, H. (2014). Impact of receivables management on working capital: a study on select cement companies. International Journal of Management Research & Review. 4 (6), 651-659.

Sadre, A., Baechtel, D. F., & Graber, M. S. (1996). U.S. Patent Number 5.485.620. Washington, DC: U.S. Patent and Trademark Office.

Seifert, D., Seifert, R. W. & Protopappa-Sieke, M. (2013). A review of trade credit literature: Opportunities for research in operations. European Journal of Operational Research. 231 (2), 245-256.

Senzu, E. T. & Ndebugri, H. (2017). Account receivable management across Industrial sectors in Ghana; analyzing the economic effectiveness and efficiency. SSRN Electronic Journal.

Sharma, A., & Kumar, S. (2011). Effect of Working Capital Management on Firm Profitability. Global Business Review. 12(1), 159-173.

Singh, H. P., Kumar, S. & Colombage, S. (2017). Working capital management and firm profitability: a meta-analysis. Qualitative Research in Financial Markets. 9 (1), 34-47.

Venâncio, A. & Jorge, J. (2021). The role of accelerator programmes on the capital structure of start-ups, Small Business Economics.

Venâncio, A., Barros, V. & Raposo, C. (2020). Corporate taxes and high-quality entrepreneurship, Small Business Economics

Yazdinejad, E. A. & Jokar H. (2019). Discovering determinants of trade credit demand: Evidence from top managers insight. Cogent Economics & Finance. 7 (1).

Zimon, G. & Zimon D. (2019). An assessment of the influence of nominalized quality management systems on the level of receivables in enterprises operating in branch group purchasing organizations. Quality access to success. 20 (169).

APPENDIX A – ADDITIONAL TABLES

Table A 1 - Variable Description

Variable name	Variable designation	Description
Country	*country*	Represents the market in which the order was requested.
Customer	*customer*	Represents the customer's number account that requested the order.
Credit terms	*credit_terms*	This variable provides the correspondent credit terms that is assigned to each customer that requested an order.
Released credit value	*released_credit*	Represents the value of credit that is conceded per order requested.
Output	*output*	Represents the possible output that is attributed to each order by the credit analyst.
Output by market	*output_market*	Represents the possible output that is attributed to each order by the market analyst.
Credit analyst name	*analyst_name*	This variable shows who was the credit analyst that was responsible to analyze the order.
Market analyst name	*analyst_market*	This variable shows who was the market analyst that was responsible to analyze the order.
Payment agreement customer	*agreement_customer*	Represents a dummy variable equaling one if the order was requested by a customer with payment agreements approved.
Credit limit	*lncredlimit*	It represents the logarithm of the maximum amount of credit that can be assigned to a customer.
Credit exposure	*credit_exposure*	It represents the amount of credit that a customer owes to the company at the moment.
Credit limit used (%)	*credit_used*	It is the ratio between the credit exposure and the credit limit. It represents the percentage of credit already used by a costumer from the limit initially assigned for him.
Distribution channel	*dist_channel*	Represents the type of product that was sold in the purchase order.
Risk category	*risk_category*	It represents the credit risk attributed to each client. It may vary from 1 to 10, depending on the type of customer.
Robot	*robot*	It is a dummy variable equaling one if the order appeared after the implementation of the automation process (robot) and zero otherwise.

Order treatment period	*Time*	Is the logarithm of the length time, measured in days, for an order to be treated or finished. Before applying the logarithm, this variable is obtained by subtracting the date that the order was finally treated (released) minus the date that the order was introduced in the system to be analyzed.

Table A 2 - Empirical results using fixed effects models for the Groups of High, Medium and Low Automation Markets

VARIABLES	Time (1)	Time (2)	Consistency (3)	Consistency (4)
Robot	-1.044	-0.928	0.296**	0.181
	(2.745)	(2.757)	(0.121)	(0.129)
Mktaut*Robot	-9.099***	-9.317***	-0.048**	0.030*
	(1.130)	(1.186)	(0.022)	(0.018)
Ln(Credit Limit)		6.007		-1.536**
		(18.118)		(0.705)
Agreement Customer		-0.759		-0.072***
		(1.032)		(0.015)
Constant	7.340**	-51.111	-0.167	16.982**
	(2.888)	(199.899)	(0.126)	(7.676)
Observations	244,727	241,799	244,727	241,799
R-squared	0.520	0.537	0.044	0.523
F-statistics	33.33	.	4.214	.

Columns (1) and (3) do not includes control variables. Columns (2) and (4) includes control variables.
Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table A 3- Empirical results using fixed effects models for the Groups of High and Medium Automation Markets

VARIABLES	Time (1)	Time (2)	Consistency (3)	Consistency (4)
Robot	9.266***	9.423**	0.481***	0.262*
	(3.590)	(3.720)	(0.123)	(0.147)
Mktaut*Robot	-15.994***	-16.147***	-0.119***	-0.008
	(2.350)	(2.444)	(0.038)	(0.031)
Ln(Credit Limit)				
Agreement Customer		14.198**		-0.116***
		(6.663)		(0.043)
Constant	-19.485***	86.052***	-0.371**	0.337***
	(4.968)	(5.107)	(0.156)	(0.110)
Observations	149,987	148,250	149,987	148,250
R-squared	0.631	0.638	0.080	0.518
F-statistics	57.93	.	4.752	.

Columns (1) and (3) do not includes control variables. Columns (2) and (4) includes control variables.
Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table A 4 - Empirical results using fixed effects models for the Groups of Medium and Low Automation Markets

VARIABLES	Time (1)	Time (2)	Consistency (3)	Consistency (4)
Robot	1.294	0.541	-0.091	-0.076
	(1.941)	(2.008)	(0.060)	(0.058)
Mktaut*Robot	3.130**	3.572***	0.052	0.067*
	(1.246)	(1.369)	(0.037)	(0.036)
Ln(Credit Limit)		-27.584		-0.857
		(19.201)		(0.694)
Agreement Customer		-0.706***		-0.077***
		(0.271)		(0.017)
Constant	-12.645***	328.369	0.268***	10.349
	(3.925)	(222.483)	(0.089)	(7.999)
Observations	169,007	166,585	169,007	166,585
R-squared	0.121	0.166	0.023	0.439
F-statistics	1.557	.	1.641	.

Columns (1) and (3) do not includes control variables. Columns (2) and (4) includes control variables.
Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table A 5 - Empirical results using fixed effects models for the Groups of High and Low Automation Markets

VARIABLES	Time (1)	Time (2)	Consistency (3)	Consistency (4)
Robot	-10.697***	-10.619***	0.311**	0.238*
	(3.079)	(3.081)	(0.122)	(0.141)
Mktaut*Robot	-15.468***	-15.748***	0.078*	-0.066*
	(2.433)	(2.616)	(0.044)	(0.038)
Ln(Credit Limit)		3.690		-2.237***
		(21.983)		(0.765)
Agreement Customer		-2.385***		-0.059***
		(0.654)		(0.014)
Constant	-28.588***	-61.107	-0.345**	24.365***
	(5.239)	(239.534)	(0.157)	(8.244)
Observations	170,460	168,763	170,460	168,763
R-squared	0.574	0.591	0.063	0.597
F-statistics	41.15	.	5.206	.

Columns (1) and (3) do not includes control variables. Columns (2) and (4) includes control variables.
Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table A 6 - Empirical results using fixed effects models for the Groups of High, Medium and Low Automation Markets (Robustness using only observations since May 2019 onwards)

VARIABLES	Time (1)	Time (2)	Consistency (3)	Consistency (4)
Robot	-3.454	-1.745	0.200*	0.151
	(2.680)	(2.377)	(0.111)	(0.114)
Mktaut*Robot	-10.881***	-10.928***	-0.054**	0.026
	(1.096)	(1.109)	(0.021)	(0.016)
Ln(Credit Limit)		-10.838***		-0.043
		(3.935)		(0.066)
Agreement Customer		0.549		-0.076***
		(0.694)		(0.017)
Constant	29.468***	157.822***	0.096	0.556
	(3.933)	(44.067)	(0.136)	(0.805)
Observations	271,275	268,094	271,275	268,094
R-squared	0.409	0.434	0.031	0.525
F-statistics	20.50	.	2.991	.

Columns (1) and (3) do not includes control variables. Columns (2) and (4) includes control variables.
Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table A 7 - Empirical results using fixed effects models for the Groups of High and Medium Automation Markets (Robustness using only observations since May 2019 onwards)

VARIABLES	Time (1)	Time (2)	Consistency (3)	Consistency (4)
Robot	5.421	7.106**	0.320***	0.219*
	(3.396)	(3.008)	(0.118)	(0.128)
Mktaut*Robot	-20.102***	-19.308***	-0.112***	-0.015
	(2.264)	(2.197)	(0.037)	(0.025)
Ln(Credit Limit)		-1.270		0.014
		(3.641)		(0.063)
Agreement Customer		2.183**		-0.083***
		(1.049)		(0.027)
Constant	-44.428***	39.845	-0.603***	0.183
	(8.080)	(39.977)	(0.220)	(0.737)
Observations	182,491	180,325	182,491	180,325
R-squared	0.479	0.496	0.055	0.543
F-statistics	27.00	26.61	3.307	208.0

Columns (1) and (3) do not includes control variables. Columns (2) and (4) includes control variables.
Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table A 8 - Empirical results using fixed effects models for the Groups of Medium and Low Automation Markets (Robustness using only observations since May 2019 onwards)

VARIABLES	Time (1)	Time (2)	Consistency (3)	Consistency (4)
Robot	0.223	0.266	-0.092**	-0.086**
	(1.394)	(1.517)	(0.043)	(0.043)
Mktaut*Robot	2.095**	2.261*	0.033	0.090***
	(1.058)	(1.175)	(0.034)	(0.030)
Ln(Credit Limit)		-10.731		-0.079
		(8.003)		(0.076)
Agreement Customer		-0.837*		-0.083***
		(0.485)		(0.016)
Constant	21.160***	130.942	0.278**	1.289
	(3.717)	(93.493)	(0.109)	(0.908)
Observations	193,409	190,743	193,409	190,743
R-squared	0.073	0.106	0.013	0.453
F-statistics	2.118	.	1.516	.

Columns (1) and (3) do not includes control variables. Columns (2) and (4) includes control variables.
Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table A 9 - Empirical results using fixed effects models for the Groups of High and Low Automation Markets (Robustness using only observations since May 2019 onwards)

VARIABLES	Time (1)	Time (2)	Consistency (3)	Consistency (4)
Robot	-11.102***	-10.840***	0.295**	0.231*
	(3.038)	(3.044)	(0.124)	(0.139)
Mktaut*Robot	15.098***	15.284***	0.075*	-0.067**
	(2.324)	(2.495)	(0.041)	(0.033)
Agreement Customer		-2.195***		-0.064***
		(0.632)		(0.014)
Constant	-18.805***	83.969***	-0.266*	0.287***
	(4.818)	(5.302)	(0.147)	(0.055)
Observations	166,650	165,120	166,650	165,120
R-squared	0.566	0.584	0.059	0.577
F-statistics	37.33	.	5.181	.

Columns (1) and (3) do not includes control variables. Columns (2) and (4) includes control variables.
Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1