The Impact of Trade Credits in Nanostore Distribution

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ABSTRACT

In developing countries, small mom-and-pop grocery stores called nanostores are one of the main grocery market channels. Cash constraints are a severe issue that affects these small businesses, preventing them from buying enough inventory to meet client demand, and forcing them to reject orders from suppliers due to a lack of cash to pay the supplier on delivery. These cash constraints also impose challenges for the suppliers of these stores, by extending the duration of individual visits to nanostores as a result of cash handling, increasing product rejections and reducing the service level consumers experience. Our research explores the effects of relieving these cash constraints via trade credits, using historical data from the sponsor company and a variety of econometric techniques. Our analysis indicates that a supplier trade credit policy, where nanostores are granted short-term deferral for product payments, can significantly boost revenue and generate logistics cost savings. As a result, the return on investment of this policy is positive as early as the first month of implementation. In addition to the clear benefits for the business, this policy can help the traditional nanostore grocery channel remain competitive in developing countries.

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We would further like to acknowledge MOLISAC for enabling this project. The availability of data and information about the company's operations were what facilitated the insights generated by this capstone, and we hope that the company finds this project as compelling as we have working on it.

Blake would like to especially thank his parents, Jamie and Dan, for their steadfast love, support, and belief in him. He also wants to send his deep appreciation to his siblings, Brianna, Cassandra, Chad, and Samantha, all of whom he had the privilege to spend quality time with over the past year and who continue to help me grow as a person.

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1 INTRODUCTION

While much focus in the retail food supply chain today is on larger chains and grocery stores, many communities are still primarily served by "nanostores." These are defined as "very small, family-owned and operated stores" (Fransoo et al., 2018). They typically employ just a handful of people to serve their local communities, with whom they likely have personal relationships. Nanostores keep a limited stock-keeping unit (SKU) assortment offering a couple of options in each category. According to the Passport Grocery Retailing in Latin America report (Euromonitor, 2018), the traditional (nanostore) grocery retail market accounted for 51% of the total grocery market share in the region in 2017. This trend is projected to continue, with McKinsey reporting a 70% growth rate over a recent five-year period (Mejia-Argueta, 2017).

As such, the channel represents significant opportunity for Consumer Packaged Goods (CPG) companies. While nanostores have greater supply chain complexities, they also offer higher margins. Since the stores are small and can offer limited shelf space, winners in the space need to invest in delivery capabilities or create partnerships to ensure their product reaches customers.

1.1 PROBLEM STATEMENT

Throughout the world, the suppliers of nanostores typically require cash on delivery of goods, since these stores are informal and thus have limited access to bank accounts and digital payments. However, nanostores frequently face cash shortages, disrupting suppliers' delivery routes and reducing sales revenues for those routes. The International Finance Corporation estimates that 40% of such stores in Latin America and the Caribbean are "partially or fully financially constrained" (Casanova, 2019). This can be attributed to a variety of causes. It could simply be that the store has not sold enough products to generate cash for the following order. It may also be in part due to the informal credit system they offer to customers within their neighborhood. Indeed, relying on the strength of personal relationships, the store owner may allow individuals days or weeks to pay, limiting cash on hand.

This lack of cash results in commercial and operational inefficiencies for the distribution companies operating in this space. A primary concern is lost sales due to the store's inability to finance inventory to meet demand. Simply put, if a nanostore proprietor does not have cash on hand, they cannot receive goods, and therefore cannot sell goods. This constraint may manifest as lower order totals, or as complete or partial order rejection on the day of delivery. In this case, the rejection itself also results in lost time, as the driver often will have already unloaded the goods and brought them to the store before learning of the cash deficiency. More time might be consumed in the case of a partial order delivery, as the driver and the store operator determine which products can be delivered at that time. Additionally, the process of counting and handling cash with each store increases the duration of the route.

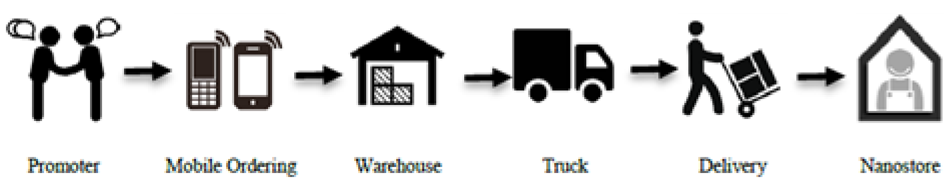
These scenarios come at a significant detriment to suppliers in this space. Lost sales impact the bottom line, and extra time spent on the route contributes to higher operational costs. To address this issue, some distribution companies have opted to implement a trade credit policy. For example, the likes of AB InBev and Coca Cola have partnered with a financing product called Tienda Pago in recent years in both Peru (2014) and Mexico (2016) to help nanostores purchase goods with a loan (Casanova, n.d.). In theory, by enabling nanostores to obtain product without needing cash on hand the distribution company can realize better revenue and create a more profitable business model.

1.2 RESEARCH QUESTIONS

This paper quantifies the potential commercial and operational benefits of implementing a trade credit policy for a supplier to nanostores. Specifically, we evaluate whether the implementation of a trade credit policy in a supply chain with cash-constrained customers leads to increased sales (as measured by goods ordered and received, as well as the purchased assortment size) and decreased rejections. We also explore whether the credit leads to reduced time at particular stops along a distribution route due to greater operational efficiency. Next, we extrapolate the increased revenue and operational savings from these improvements based on our results to display the return on investment (ROI) resulting from such a credit policy. This is explored in different scenarios reflecting varying extents of credit issuance. Finally, the project deduces key managerial insights from the study to contextualize the results and help similar companies decide on the optimal policy to implement.

To explore these research questions, we work with a sponsor company in Lima, Peru, called MOLISAC. MOLISAC is a distributor of grocery retail products to approximately 20,000 nanostores. The company operates a "presales" model, as described by Boulaksil & Belkora (2017) as a strategy that works well in dense urban areas. In this scenario a sales representative visits each store prior to its delivery to record its orders via a smartphone application. The sales representative visits each store weekly to understand its needs. If the store places an order, MOLISAC delivers the goods the following day and receives cash in exchange. This arrangement is like the one shown in Figure 1.

Figure 1
How the presales model works



Note. Originally adapted from Tenoli.org.

To mitigate issues related to cash constraints, MOLISAC selectively offers its clients credit as an alternative to cash on delivery. Initially, a new customer must buy in cash as per standard operating policy. However, after about a month they can request credit from the sales representative. Assuming a good relationship, MOLISAC will enable their representatives to offer the client a credit in an amount approximately reflecting their respective average order size. Most stores that are offered the credit utilize it. Nonetheless, the overall issuance remains low due to the limitations of credit lines offered by MOLISAC per representative (varying based on their route). The credit is due within a one-week timeframe and the sales representative is responsible for both allocating the credits across customers and collecting the cash. Although an extension may be arranged if a client does not pay within the allotted period, the credit policy is withdrawn if deadlines are not met. The sales representative assumes debt if completely unpaid by the client.

The company has done preliminary research to show that there may be a relationship between the credit policy and improvement in operational efficiencies and sales measures. The project works with the sponsor company to address the research questions at hand.

1.3 SUMMARY OF INSIGHTS AND CONTRIBUTIONS

Inefficiencies related to the cash-constrained nature of nanostore distribution networks are a widespread issue. This is especially true in emerging markets, particularly in Latin America, Africa, and Asia. This capstone provides key takeaways in three areas related to the implementation of trade credit policies in these environments. First, the paper shows the trade credit policy's effect on sales and rejections. In this regard we find that introducing the credit to an order results in about a 60% increase in sales and 33% increase in SKU variety. We also find a nearly 40% decrease in rejections. Second, it shows how the trade credit policy affects time spent on routes. For stops in which the credit is used, we find the duration of the stop to be decreased by about 20%. Finally, the paper summarizes the benefits of the trade credit policy overall and shows its relative merit compared to the drawbacks it introduces. In a scenario we model with a credit usage rate of 100% of customers, we find that the potential return on investment is 78% per month. However, it can be considered that most suppliers will be hesitant to implement such a widespread program at the outset. Even with a more modest view of credit adoption at 10-20%, we still find a 50% return on investment.

The case for suppliers to utilize trade credits is straightforward, as the ROI findings indicate. However, just as interesting are the potential implications for nanostores themselves and the communities they serve. Many nanostore proprietors operate their stores as methods of subsistence, and this intervention offers a path to more stable financial situations. By keeping nanostores stocked, distributors can help to improve their survival rate, supporting family-owned businesses and ensuring future business partners. The implications of these findings extrapolated to the nanostore environment across just Latin America are vast, considering the commonplace cash constraints in the region. There are also positive effects for society at large. For example, by reducing route time and avoiding rejections, we can extrapolate a reduction in carbon emissions within communities. Additionally, better in-stock conditions and improved operations can provide end-consumers – numbering in the millions or perhaps the billions – with more consistent product availability at a lower cost.

2 LITERATURE REVIEW

In this capstone project we determine whether the implementation of a credit policy is a good tool for nanostore suppliers to increase sales and SKU variety, reduce order rejections, and save time. We also analyze the trade-off between the financial cost of a policy of this kind and the benefits achieved expressed in terms of savings in the total logistics cost and increase in revenue. To inform our business understanding and subsequent analytical work, we reviewed literature pertaining to nanostore operations, nanostore logistics, and the use of credits. These topics are relevant to help us define the relationship between a credit policy and benefits, ultimately creating a view of ROI and different scenarios where credit should be applied.

2.1 NANOSTORE OPERATIONS

Understanding the operational ecosystem of nanostores helps to contextualize the data from the project sponsor. Through the work of Fransoo et al. (2018), we understand common characteristics that define nanostores, such as their modest scale (in terms of footprint and line-item ordering), limited category and SKU depth, and relatively low numbers of customers served (often with close relationships to the store operator). Importantly, the work also highlights the causes and outcomes of financial constraints of such stores. The cash-based system is the main culprit identified, inhibiting growth and leading to lost sales. The stores, characteristically in high-density urban areas, generally incur high cost-to-serve. This is exacerbated for more rural stores, which face similar challenges but at lower route density. These costs mean that prices must be raised to maintain margins, resulting in product premiums for the predominantly poor customer base of the stores. While credits are briefly discussed as an antidote to these problems, it is noted that there is reluctance amongst manufacturers and distributors to grant them broadly. This is primarily because of default risk on the outstanding credit, inhibiting overall credit adoption.

It is also relevant to understand different distribution strategies that suppliers use to serve nanostores. These strategies could have an impact on the effectiveness of the trade credit implementation. Boulaksil & Belkora (2017) discuss two sales strategies: van sales and presales. The presales model is the one that MOLISAC currently uses, where an independent sales representative visits each store to collect orders prior to delivery. Another option is van sales, a more holistic approach in which drivers "drive, park, negotiate sales, sell, unload products, take back expired products, and collect money for sale". While this approach requires less labor, it is typically inefficient and results in fewer sales. The presales model may be more conducive to the success of the credit implementation, leveraging the expertise of the sales representatives and supporting the delivery of larger orders with a better planning horizon.

2.2 NANOSTORE LOGISTICS

Our project considers logistics costs as a potential factor in assessing the effectiveness of the credit policy. Some work has been done to understand nanostore logistics to date. Castañon (2018) investigates how the survival of nanostores can affect the logistics costs of Consumer Packaged Goods (CPG) companies or distributors. The authors find that it is more expensive to deliver to new stores, rather than to existing customers. This is shown to be largely driven by the time needed to locate new stores and their relatively smaller drop size. This research indicates the importance to distributors of taking measures to improve nanostore survival rate, especially in relation to incurred logistics costs in their service network.

Escamilla et al. (2020) study trade credits' effects on logistics efficiency at MOLISAC, the Latin American distribution firm sponsoring our project. Using an econometric analysis, they find that the implementation of such credits reduces both order rejection rates and route duration. Specifically, the study indicates that total route time could be reduced by as much as 26.4%. They further find that rejections may be almost eliminated if the effect is extrapolated to the portions of the route previously not treated with credit. Our project is an extension of the findings in this paper, and we take some direction from the further research suggested by the authors.

2.3 TRADE CREDITS AND NANOSTORE CREDITS

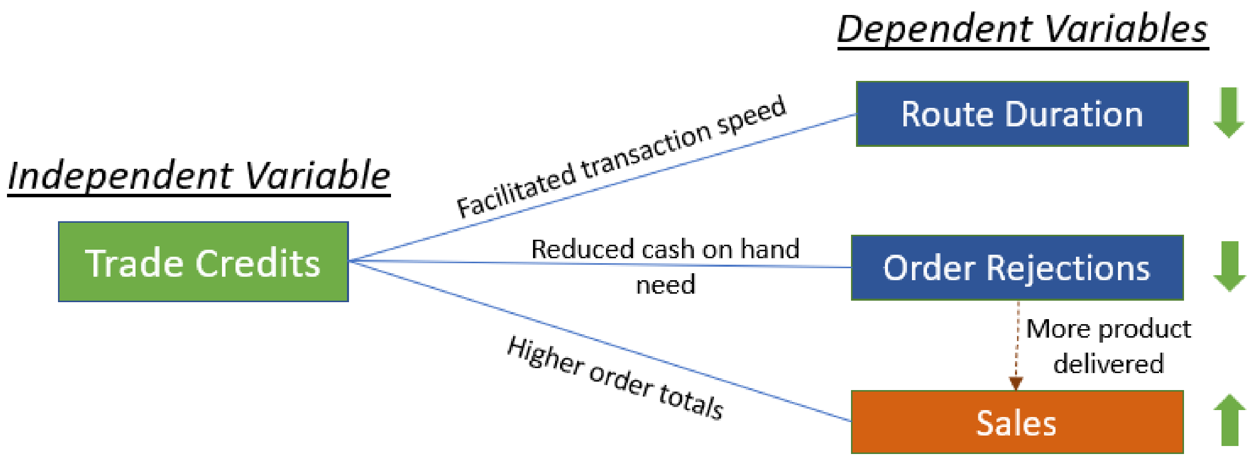
As a concept, providing credits to alleviate cash constraints has existed for many years. This intervention has been primarily aimed at poverty alleviation, with the prevailing theory being that greater access to finance will provide more equitable opportunities. This idea is explored through a 2015 Critical Literature Survey from the IEG/World Bank Group, reviewing microfinance literature from the preceding ten years. The author finds that there has not been clear evidence to-date that microcredits are effective at the individual or firm level and the overall result remains ambiguous. However, they do recognize that “tailored credit and insurance interventions for specific groups with well-identified needs and opportunities…might be a promising way forward.” This provides an indication that more targeted research in the area is still needed.

Perhaps most critically, it is important to understand extant work related to trade credits’ application in nanostore distribution. The field is relatively new and credit effects are still uncertain. As such, seeing initial outcomes can help us better create expectations for our analysis outputs. Boulaksil & van Wijk (2018) explore the conditions under which a distributor should offer credit to a customer, and their incentives to do so. They state that although greater risk is incurred by offering expanded trade credits, the practice ultimately proves beneficial to the supplier under most circumstances. This is due to increased sales, higher service level, and greater profitability in the long-term. The caveat, however, that it is not recommended to offer a credit if the nanostore is run poorly independently of the credit. This is because trade credits have an “amplifying” effect: they strengthen even modestly successful nanostores on one hand but can further compound losses for unprofitable stores on the other. The paper also describes the relevancy of the risk of nanostore bankruptcy to a supplier. The authors conclude that this factor is less important than perceived, only negatively affecting the supplier in the short-term as they lose any outstanding loans. Otherwise, the expected long-run benefits are likely worth it to the supplier. This study provides first indication of the overall benefits of a credit policy.

2.4 CONCEPTUAL MODEL

Given the research questions we intend to address, along with key learnings derived from a review of the literature, we can develop a conceptual model and corresponding hypotheses. The overall conceptual model for how each of the relevant variables is expected to be impacted by the trade credit policy is presented in Figure 2.

Figure 2
Trade Credits impact conceptual model



Our conceptual model is based on industry knowledge and findings from the literature. Our first hypothesis regards the effect of trade credits on sales and SKU variety, and logically follows when considering the impact of cash constraints. Nanostores will not typically order more than they think they can reasonably anticipate paying for. This means that there could be unmet demand or that customers may be drawn to more well-stocked competition. By alleviating the need for cash, we allow stores to place larger orders reflective of actual demand.

H1: The use of a trade credit will increase the total sales revenue for the supplier and expand the variety of ordered SKUs.

Our next hypothesis concerns the effect of trade credits on order rejections. We expect to have similar directional findings as Escamilla et al. (2020) regarding order rejections. That is, rejections should be lower as cash is no longer required to receive an order. It remains possible that physical space considerations and other factors can lead to rejection of goods.

H2: The use of a trade credit will reduce the amount of rejected goods for the supplier.

The third hypothesis examines route duration in the presence of trade credits. We again draw upon initial work by Escamilla et al. (2020) that indicates a reduction in route time. This is driven through an elimination of cash handling at each stop, and the minimization of goods movement from the truck that would typically not be delivered to the store in the presence of cash constraints.

H3: The use of a trade credit for will reduce the transaction times for the supplier.

In total, we hypothesize that the combined commercial and operational benefits of the implementation of a trade credit policy in a cash-constrained system will be robust. Since time spent on routes is a variable cost driver of MOLISAC's operations, implementing the credit will help to reduce expenses. A reduction of rejections, which cause operational complexity, should also contribute to lower expenses. Meanwhile, the first hypothesis points towards an overall increase in delivered product, thereby boosting revenue. These hypotheses in conjunction allow us to predict a positive ROI for the supplier that offers credit to nanostores. Nonetheless, we must consider the "investment" portion of the ROI. Companies which offer credit are inevitably exposed to costs such as loan defaults and the cost of capital outlaid for the initiative. While these factors are specific to the context of each supplier, we hypothesize that in most cases the benefits will be substantial enough to outweigh the costs associated with the policy.

H4: For nanostore suppliers, the benefits of trade credits are greater than the costs and therefore result in a positive ROI.

Consideration of these four hypotheses composes the remainder of our project. We next collect data with which to explore these hypotheses.

3 DATA

This project utilizes empirical data to determine relationships between an independent variable, trade credits, and several dependent variables: sales (in total volume and number of SKUs), order rejections, and stop duration. The research determines whether the benefits of the trade credit outweigh negative effects and thus result in a positive ROI for the sponsor company. This process relies on sets of data from the sponsor company: particularly granular order and sales data, route-by-route GPS traces data, and data around transportation costs. After cleaning and organizing this data, we explore our initial hypotheses as detailed in our conceptual model.

3.1 DATA MODEL

The sponsor company works with several databases housing inventory, client, accounts, and distribution information. These databases were interrelated in various SQL query scripts to obtain a comprehensive dataset with sales transaction data. This dataset contains information regarding transactional sales records and order rejections in monetary units, weight, and volume; sale condition, in cash or credit; and payback time. Information about this dataset can be found in Table 1.

Table 1
Sales transaction dataset information

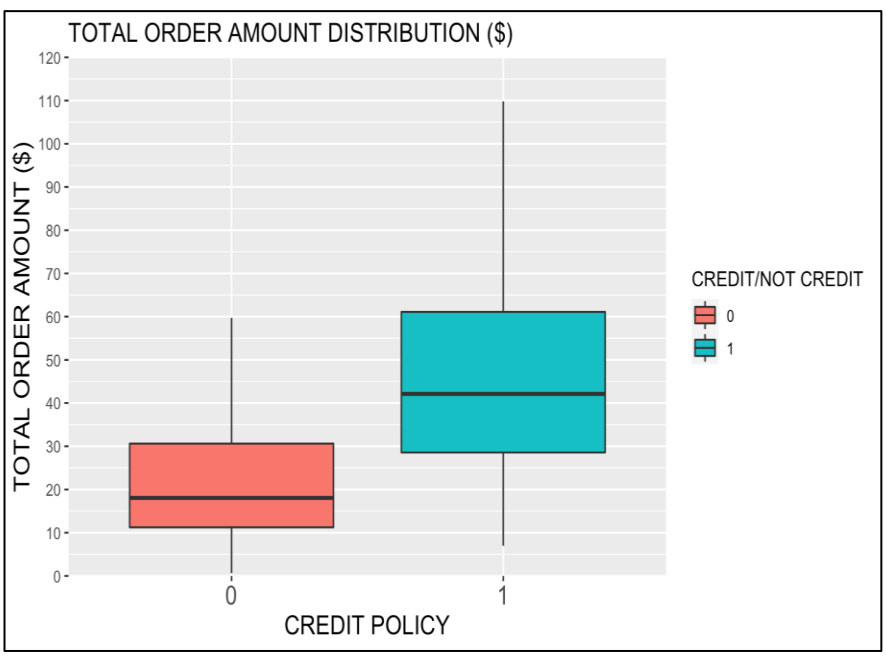
Records	837,140
Stores	14,264
Beg. Date	May 1, 2018
End. Date	Dec. 31, 2019
Periods	87 weeks

The GPS dataset contains all geographical position traces collected in January through June of 2019 for 13 trucks. The dataset contains registers for important events that occurred during the dispatch route. These registers include indications of when the truck engine turned on and off, and when the truck was stopped for more than 3 minutes. Additionally, the sponsor company provided financial information regarding its transportation costs. Labor, fuel, and depreciation were the major components of the total transportation cost. This data required extensive preparation for further analysis. For example, we removed null and irregular values, merged files, and changed datatypes. After finishing the data cleaning process, we can conduct a descriptive analysis to start looking for important trends in datasets.

3.2 DESCRIPTIVE ANALYSIS

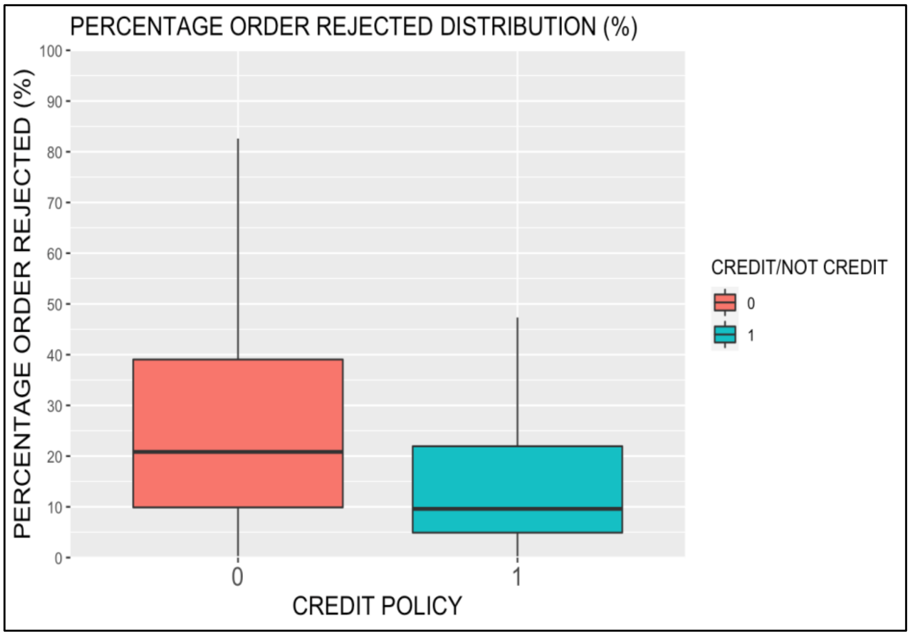
By exploring our data at a high level, we can better understand how our initial hypotheses compare to the sponsor company's reality. To do so, we compare the performance of stores across relevant measures when they used the trade credit and when they did not, considering only stores that have both types of observations. We first compare the total order amount for customers that use cash and for those that use the credit (as shown in Figure 3). Results suggest an initial inclination towards the effectiveness of the trade credit in bolstering store sales.

Figure 3
Total order amount by credit variable



We next look to evaluate the percentage of rejected orders and the relationship with trade credit, as reflected in Figure 4. The result of this process gives us information regarding how stores who use trade credit reduce the percentage of orders rejected in comparison with stores using cash.

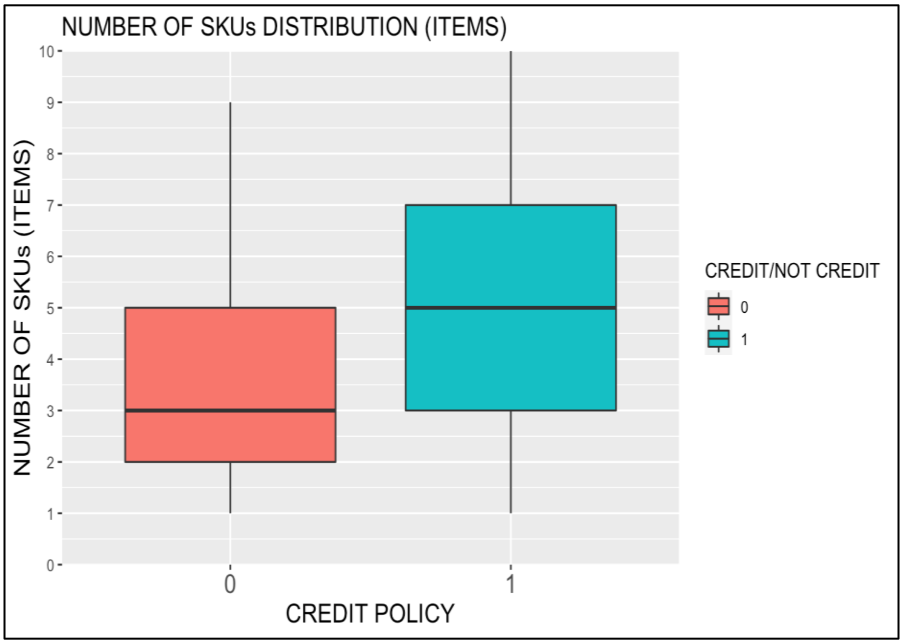
Figure 4
Percentage of order rejection by credit variable



Finally, we also find a positive correlation between trade credit and the number of stock-keeping units (SKUs) a store buys from the sponsor company, suggesting that stores that use credit more perform better in terms of product variety. This is observed in the number of SKUs ordered using trade credit and using cash (Figure 5). While not explicitly part of our initial hypothesis, this reflects the ability of the credit to help nanostores better serve customer demand.

Figure 5

Average order SKUs by store size and credit variable



Overall, this descriptive analysis provides strong indications that our hypotheses are on the right track. Not included here is exploration of the duration hypothesis, as it requires a more extensive analysis. Although not definitive, this exercise allows us a quick way to better understand the relationship between the credit variable and relevant outcomes for our sponsor company.

4 METHODOLOGY

As per stated hypotheses, this study seeks to determine relationships between an independent variable (trade credits) and five dependent variables: ordered goods, received goods, SKU variety, order rejections, and stop duration. These dependent variables are related to the overall commercial and logistics operations of the supplier. However, because the stores were not randomly assigned to receive a credit, there are endogeneity concerns that need to be addressed in our empirical analysis. These arise mainly from selection bias, meaning there might be confounding differences in the treatment and control group. To minimize the concerns of such confounders affecting our insights, we apply a difference-in-differences to a set of comparable treatment and control groups derived through a nearest-neighbor matching procedure.

4.1 POISSON FIXED-EFFECTS PANEL DATA REGRESSION

Since our project deals with panel data measurements over a period of almost two years, we are able to further include store fixed effects to deal with endogeneity. We use a Poisson Fixed-Effects estimator to capture the effect of the credit solution.

A previous study conducted in conjunction with the sponsor company, Escamilla et al. (2020), also uses a series of Fixed-Effects regressions to analyze route time and order rejections, which have the following structure shown in Equation 1.

$$E(y_{it}|x_{it}, c_i) = c_i \exp{(x_{it}\beta)} \tag{1}$$

They use Poisson Fixed-Effects because of the nature of the data, containing strictly non-negative continuous variables. Since we are working with the same company, we build on and extend that analysis in this paper with a similar approach. Like the previous work, we leverage the panel structure of our dataset and conduct a series of Poisson Fixed-Effects regressions. However, we extend their analysis by leveraging a detailed, store-level dataset that allows us to better capture the dynamics at play, as opposed to their route-level analysis. The detailed nature of our dataset further allows us to address selection bias through matching and to include a control group, through a difference-in-differences approach.

4.2 MATCHING AND DIFFERENCE-IN-DIFFERENCES FOR COMMERCIAL MEASURES

In the matching method, we seek to approximate random selection by measuring store performance prior to any treatment is applied and identifying similar stores over the same period with which to compare post-treatment. We first determine which stores will be considered as the treatment group – in other words, those that we expect to have had materially different outcomes because of the credit. For this group, we need to create parameters to ensure that each store had sufficient usage of the credit to expect to see results, but also that the store began using the credit late enough such that there would be data surrounding its performance pre-implementation. Additionally, these parameters exclude certain types of transactions which might reflect a biased deployment of the credit. For instance, sales agents may sometimes grant "on-the-spot" credit to avoid having an order rejected. They may also selectively increase their granting of credits towards the end of incentive periods to reach sales targets. These types of situations would unduly influence the results and therefore should be removed from consideration.

Using data provided by the company, we engineer new features that focus on stores' characteristics regarding credit usage. Specifically, we aggregate available data surrounding sales, rejections, and the use of credit for each store. We further incorporate features around the earliest and latest dates of credit usage, and the maximum amount of consecutive orders for which credit was used.

With these data in hand, we can more deliberately dictate which stores we believe could expect to see a benefit from the credit. These stores compose the treatment group for our matching process. Among stores that had any credit orders, we selected those with the following criteria:

- > 2 credit orders in the timespan of the dataset
- > 30% and < 70% of orders which used credit between the first and last credit transactions
- First utilized credit after the first 3 months of data

With a treatment group of 387 stores defined, we iterate on historical data for these stores prior to credit implementation to collect relevant monthly (4-week period) information for the matching process – namely, amount of transactions, order amounts, and rejection amounts.

Likewise, this iterative process is completed for the control group of stores, which act as candidates to be matched to the treatment group. Using a nearest-neighbor matching algorithm, we compare treated stores' performance prior to receiving the credit to control group candidates most similar in the key performance measures stated above. This algorithm utilizes StandardScaler and NearestNeighbors methods from SciKitLearn and is deployed in Python.

The output of the algorithm is a list of treatment stores and a list of identical length with one control group candidate matched to each treated store. This method uses matching with replacement, so that it is possible for one control store to be matched to multiple treatment stores.

Next, we compare the two groups' performance across similar time periods around the implementation of the credit for the treatment group. In this way, we can nearly simulate a randomized controlled trial using historical data. For this comparison, we use the difference-in-differences method. In this method, we consider the difference of a post-treatment store with its pre-treatment self, but also the difference observed in the control group over the same period. By contrasting these two "differences" we can assess the actual effect of the treatment. As explained by Angrist & Pischke (2005), "the divergence of a post-treatment path from the trend established by a comparison group may signal a treatment effect." Using this method, we look to compare two groups of clients that have similar transaction behavior during a certain period and that differ only on the adoption of trade credit. To do so, we create a dataset which includes both the treatment and control groups' data around the credit implementation. This dataset retains relevant performance measures on a store-week basis for the timespan captured. Additionally, it contains an indicator as to whether a store was an "active" credit user at that time (i.e., the period between the first and last credit transaction). This dataset also included dummy variables for each week of the year to control for time fixed effects.

We then proceed to estimate this difference-in-differences model through a series of Poisson Fixed-Effects regressions, with our variables of interest as dependent on the use of the credit.

4.3 REGRESSION MODELS FOR COMMERCIAL MEASURES

We initially explore the effects of the trade credit policy on ordered goods, received goods, SKU count, and order rejections. We conduct a Poisson Fixed-Effects regression and difference-in-differences model to measure the impact of the credit policy on these variables. For that reason, we develop individual regression models for each dependent variable. Since we apply the same approach across the board, we can generalize our model, as shown in Equation 2.

$$E(Z_{it}) = \exp(h_i + \alpha_t + \tau X_{it} + \beta After_{it} Credit_i + \epsilon_{it}) \quad (2)$$

In this model, Z_{it} represents the relevant dependent variable for nanostore *i* in week *t,* h_i represents the store's heterogeneity term, and α_t stands for weekly fixed effects. The *After* term is an indicator of whether period *t* occurs before or after the credit implementation, and the *Credit* term indicates whether the store is a credit user. The *X* term represents control variables included in the model. The first three models estimating ordered goods, received goods and SKU count contain those dependent variables as their respective *Z* terms, with the number of weekly transactions as a control variable. We conduct these estimations to measure not only if the order amounts are increasing, but also if the credit is affecting the actual amount of goods and variety of products received by the store. The fourth model is again similar but considers rejected order amounts as the dependent variable and includes ordered goods as a control variable in addition to weekly transactions.

These regression models result in coefficients that point towards how much of an impact the presence of credit makes on ordered goods, received goods, SKU variety, and order rejections. These components have an ultimate impact on the profitability of the sponsor company and are explored in our final analysis of the policy.

4.4 GPS ANALYSIS

Careful analysis is needed in attempting to understand the effect of credits on route time, a driver of logistics costs. Specifically, we seek to evaluate whether the presence of a credit for an order reduces the amount of time spent to complete that transaction. Simply applying regression to aggregated route data lacks the nuance that is present in actual route interactions. Instead, GPS traces from each of the truck/route/date combination are retrieved. This information gives us a fuller picture of the step-by-step actions taken and associated time spent during delivery.

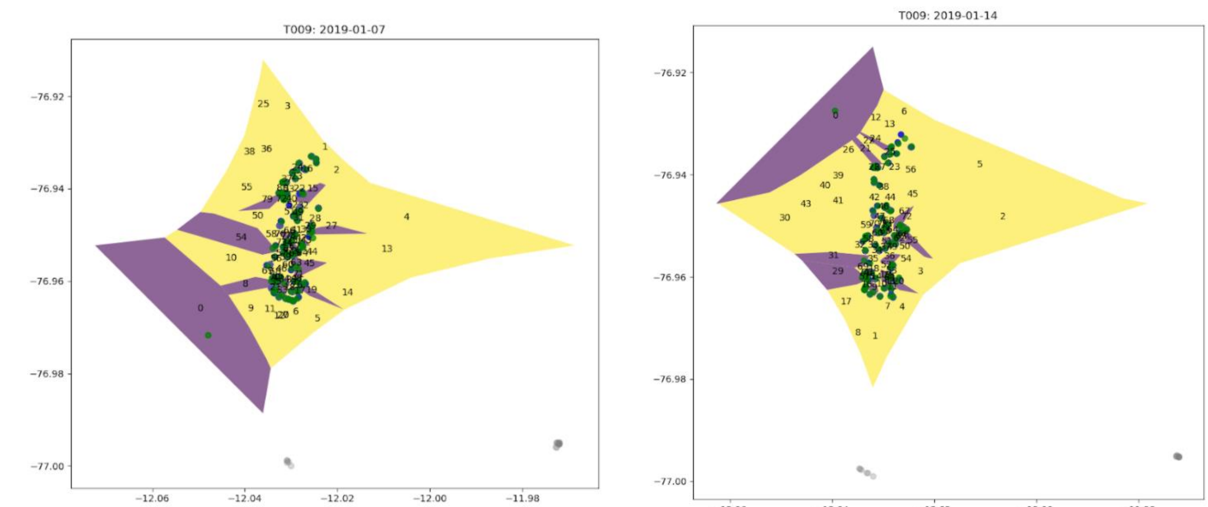
For this analysis we include location information from each customer in the customer data, and each stop in the stop data as derived from the GPS traces. By iterating on each truck/day combination in the customer data, we compute clusters for stores within 20 meters of each other. After this, we obtain a set of coordinates with which to build Voronoi polygons for each cluster by utilizing a scipy spatial package. This maximizes the space assigned to each cluster such that an entire map area is filled and assigned. Once the polygons are plotted, we can again iterate over the customers and identify which polygon they belong to.

The next step is to create a subset of stops for each specific truck/date combination. To remove non-relevant GPS traces, we only retain GPS entries related to vehicle stops and to ignition-on and ignition-off events in the correct sequence. We also retain only stops within polygons. To ensure confidence in the data, we exclude truck/day combinations where there is a two-hour or more gap and include an indication of instances where the first and last events are separated by less than four hours.

We are then able to review which customers were visited by examining the stops; those customer polygons that were visited are “assigned” to themselves. The others, meaning those that were not visited, are assigned to the nearest stop identified. This assumes that delivery teams leverage the closest stop to visit each customer. The results of this exercise are reflected in the polygons in Figure 6.

Figure 6

Output polygons from GPS analysis



Note. Polygons represent the same truck in subsequent weeks. Yellow areas were visited, while purple were not. Green dots represent stores, while gray dots represent stops.

Then, we compute the sequence and duration of the stops, ignoring stops that erroneously registered as zero seconds. We iterate through each polygon and allocate the duration of the visit among all customers served in that stop by proportional order volume. We now have data that show which customers were being visited by each truck on each day, and for how long. The output of the GPS analysis process is a dataset more closely reflecting time per stop along with associated store characteristics. For analysis purposes, we decide to retain only stops in which there is a single customer assigned, increasing confidence in the data accuracy. This information is subsequently analyzed in a regression model to find what drives store delivery time, and therefore route time, under certain credit conditions. The model is represented in Equation 3.

$$E(D_{int}) = \exp(h_i + Weekday_{int} + \tau NumberOrders_{int} + \gamma OrderVolume_{int} + \beta Credit_{int} + \epsilon_{int}) \qquad (3)$$

In this model, D_{int} represents the duration of a stop *n* at nanostore *i* in week *t,* and h_i represents the store's heterogeneity term. The $Weekday_{int}$ term is an indicator of which day the stop occurs on, and the $Credit_{int}$ term indicates whether a credit was given for that transaction. Included as control variables are the number of orders and the overall order volume for the stop.

As with the matching process, we confine the analysis to stores which we believed would truly benefit from the credit. In addition to the initial filtering of GPS traces, this excluded, for example, stores for which a one-off credit might have been received – this situation may actually *increase* time spent at a store (due to the irregularity of the transaction and negotiation/documentation of credit). Specifically, we look for customers who had at least two consecutive credit orders, and an overall credit usage ratio of at least 30%, but no more than 70%.

4.5 TRANSPORTATION COSTS METHODOLOGY

In the delivery cost model, route duration is the main driver for delivery cost. To calculate the logistic cost saving benefits obtained by the reduction of route time, we consider as elements of the total transportation cost the following components: labor cost, fuel consumption and vehicle depreciation.

We carry out a cost analysis considering a base scenario that assumes 100% trade credit. However, this scenario is not realistic considering the implementation challenges and associated default risks. Therefore, we also consider that the sponsor company could implement the credit policy under three different trade credit rate scenarios: 10%, 20% and 40%. Then, we apportion total cost savings according to those scenarios.

4.5.1 DELIVERY COST MODEL

Our delivery cost model assigns a monthly total delivery cost and considers the major components of the total delivery cost and time as the cost driver.

For labor cost we first determine the total amount of money paid to workers on each truck. With this information we obtain a ratio of labor cost per hour based on the working hours assigned to each truck. As time determines the total delivery cost, we take the total labor cost across all trucks by multiplying both the hourly labor cost by the total number of hours worked per month. For fuel consumption cost, we use the total amount of money spent monthly in all trucks of the company. With this information we get the ratio of cost per hour. Similarly, as time is the driver which determines the total delivery cost, we obtain the total fuel consumption cost by multiplying both numbers. Finally, depreciation cost is determined by the total lifetime value of the assets used on the delivery. We consider a total lifetime of 60 months for delivery trucks. With this information we achieve the cost of depreciation per hour and the total depreciation cost.

To build the model, we use the regression coefficient achieved in the panel data regression model built with the route dataset. This coefficient is a key input of the simulation model that is needed for emulating the potential benefits of the credit policy.

4.6 RETURN ON INVESTMENT METHODOLOGY

Trade credits can help to reduce nanostore cash constraints and thus help suppliers to achieve more revenue, reduce the number of orders rejected and obtain logistics cost savings. Implementing a trade credit policy involves several costs associated with implementing the trade credit policy. The most relevant is the financial cost. The sponsor company is in Peru, and it has a cost of capital of 8% according to the average current 2020 interest rate in the Peruvian financial system. We also consider IT management additional cost that will be necessary to implement if the trade credit policy is offered. Since the sponsor company use the salesforce to collect the money paybacks, it is necessary to increase the number of sales representatives to take charge of this task.

To analyze the total return on investment of the project we aggregate the following: the benefits obtained by the increased revenue and the logistic cost savings according to sales and rejection regression model, and the logistic cost savings generated by the reduced route time according to the route time regression model. The benefits and logistics cost savings are obtained by applying the regression coefficient in a simulation analysis.

With all this information we conduct a return-on-investment analysis that considers the total cost of the investment and the monetary benefits that the project will generate during the implementation. The formula of this analysis is shown in Equation 4.

$$ROI = (Current\ value\ of\ investment - Cost\ of\ investment)\ \div Cost\ of\ investment \qquad (4)$$

The current default rate at the sponsor company is 0.5% for year 2019. The company constantly controls and manages collection of receivables documents. The context in which the company operates is particularly hard since most of nanostores do not have credit history in formal financial institutions. We assume that the company could implement the credit policy considering three different trade credit rate scenarios: 10%, 20% and 40%. These scenarios could be implemented and controlled in an efficient way. We apportion total sales revenue increment according to those scenarios and project those numbers for five years. We accrue this along with the revenue generated for the reduced number of orders rejected and the delivery cost savings.

5 RESULTS AND ANALYSIS

An examination of the results of our analyses will help us to determine the accuracy of our hypotheses. Specifically, we explore the results of the regressions, determine transportation cost savings, and calculate ROI based on our findings. We then conduct a sensitivity analysis to understand how various default rates affect the ROI.

5.1 REGRESSION RESULTS

As described in the methodology in Chapter 4, we run a Poisson Fixed-Effects regression on the sales (as represented by orders and receipts in monetary terms), SKU variety, and rejections, derived from the matching and difference-in-differences techniques. We additionally run a Poisson Fixed-Effects regression on stop time as derived from the GPS analysis described in the methodology. The results of these analyses are shown in Table 2.

Table 2
*Regression results for relevant dependent variables (***=p<0.001, **=p<0.01, *=p<0.05)*

	Ordered	**Received**	**SKUs**	**Rejections**	**Stop Duration**
Credit Coefficient	0.46***	0.47***	0.29***	-0.47***	-0.24*
Credit Effect	57.68%	59.4%	33.07%	-37.46%	-21.18%
Observations	45046	45046	45046	34931	6467
Groups	745	745	745	545	1546
95% Conf. Low	0.40	0.41	0.24	-0.73	-0.46
95% Conf. High	0.51	0.52	0.34	-0.21	-0.02
Store Fixed-Effects	Yes	Yes	Yes	Yes	Yes
Week Fixed-Effects	Yes	Yes	Yes	Yes	Yes

To understand the effect of the credit, the coefficients associated with the credit must be transformed exponentially due to the nature of the regression. This transformation yields an explanatory percentage by which we can understand in clear terms how the credit changes the dependent variable in each respective analysis (as seen in the “Credit Effect” row in Table 2). We find that sales are increased by about 60%, rejections are decreased by almost 40%, and stop duration is reduced by about 20% in the presence of the credit. The findings confirm our initial hypotheses, and we can use them to extrapolate benefits and costs savings to determine ROI. We also observe a 33% increase in SKU variety because of the credit solution, providing us with a qualitative measure of nanostore success. Critically, the results are statistically significant and point towards a generalizable credit implementation model for other nanostore suppliers.

5.2 TRANSPORTATION COSTS RESULTS

To determine labor cost, we first consider the daily labor cost amount, which is represented by the amount of money paid to the truck driver and two assistants for a shift of eight hours. Dividing the daily labor cost by eight we get the ratio cost per hour. We multiply this ratio by the total monthly number of hours to get the total labor cost. The monthly labor cost is determined by multiplying this number by the total number of vehicles. Applying the route time coefficient, we get the new total cost and the total cost savings related to labor, as reflected in Table 3.

Table 3
Labor savings calculations

	DAILY LABOR COST	NUMBER HOURS WORKED DAILY	RATIO COST/HOUR	MONTHLY NUMBER HOURS	TOTAL LABOR COST	ROUTE TIME COEFFICIENT	NEW COST	COST SAVINGS
LABOR COST	160	8	20	2496	49920	0.212	39337	10583

For fuel consumption, we first consider the total monthly number of hours used to deliver orders in 12 trucks. The sponsor company use a fuel consumption ratio of cost per hour. To get the total fuel cost, we multiply these numbers. Applying the route time coefficient, we get the new total cost and the total saving cost related to labor. This is shown in Table 4.

Table 4
Fuel savings calculations

	MONTHLY NUMBER HOURS	RATIO COST/HOUR	TOTAL FUEL COST	ROUTE TIME COEFFICIENT	NEW COST	SAVING COST
FUEL CONSUMPTION	2496	6.25	15600	0.212	12292.8	3307

We start to measure depreciation by obtaining the total annual value of the vehicle fleet. The company estimates the expected total number of hours trucks can operate. This number is based on eight hours daily and the number of days in five years of delivery operations. We get the ratio of depreciation by dividing the total annual value by the total number of operating hours. From this, we get the total depreciation value for a month. Applying the route time coefficient, we get the total depreciation savings, as seen in Table 5.

Table 5
Depreciation savings calculations

DEPRECIATION	
TRUCKS	**12**
ANNUAL VALUE	**1,200,000**
NUMBER OPERATING HOURS	**1,040**
RATIO DEPREC/HOUR	**1,154**
DEPRECIATION	**240,000**
COEFFICIENT	**0.212**
SAVING COST	**4,240**

5.3 RETURN ON INVESTMENT RESULTS

We take coefficients from the sales regression model to determine the increasing revenue and the logistics cost savings. The sales regression coefficient indicates that after implementing a credit policy for all clients, the sponsor company's revenue would increase annually by 59.4%. Table 6 represents the potential captured profits for the company considering this finding.

Table 6
Total potential profits in different credit scenarios

MONTHLY CREDIT SCENARIO	100%	10%	20%	40%
Base	2,500,000	250,000	500,000	1,000,000
Sales Regression Coefficient	59.4%	59.4%	59.4%	59.4%
Increased Sales	1,485,000	148,500	297,000	594,000
Cost Of Goods (90%)	1,336,500	133,650	267,300	534,600
Profit (10%)	148,500	14,850	29,700	59,400

Default rate is an important factor to consider when implementing a trade credit policy since it implies an outright loss of money. For this reason, we include the default rate as a cost associated with the total cost of the project. We also include additional IT management costs representing the investment the company needs to make to manage credit receivables from a larger number of clients. This cost was derived as a proportional value of the current account solution of the company. We finally include additional salesforce costs reflective of the number of people that would be necessary to hire to handle collections. This cost is based on the current labor costs seen in the company and the number of receivables that each representative currently handles. Table 7 represents these costs as compared to the total benefit to determine potential ROI in different credit scenarios.

Table 7

Total potential benefits and ROI in different credit scenarios

MONTHLY CREDIT SCENARIO	100%	10%	20%	40%
Additional Profit	148,500	14,850	29,700	59,400
Cost Saving	37,223	3,722	7,445	14,889
Total Benefit	185,723	18,572	37,145	74,289
Financial Cost	50,000	5,000	10,000	20,000
IT Management	20,000	4,000	8,000	10,000
Additional Salesforce Cost	30,000	3,000	6,000	12,000
Default Rate	0.5%	0.5%	0.5%	0.5%
Total Cost	104,167	12,417	24,833	43,667
ROI	**78%**	**50%**	**50%**	**70%**

We can observe that the biggest cost for the project is the financial cost associated with the amount of money required to offer credit to all customers. However, even after considering all relevant costs, the results still indicate a positive ROI.

5.4 SENSITIVITY ANALYSIS

We use the company's historical default rate as a cost of the trade credit policy to evaluate the return on investment of the project. However, it is essential to think about how the default rate can influence the net benefits obtained from the implementation of the trade credit policy.

The main concern for the sponsor company as it considers implementing the trade credit policy is a potential increase in the default rate, since this can lead to financial loss. The benefits of implementing the policy for a larger group of nanostores are clear, however it is intuitively true that this could lead to higher default rates. For this reason, it is important to evaluate different scenarios with higher default rates and compare the results obtained in the event this happens. These scenarios are explored in Table 8 (detailed analysis included in Appendix).

Table 8
Sensitivity analysis displaying ROI considering variable default and credit rates

MONTHLY CREDIT SCENARIO DEFAULT RATE	100%	10%	20%	40%
2.5%	54%	32%	32%	48%
5.0%	31%	15%	15%	27%
7.5%	14%	2%	2%	11%

After conducting further analysis using 2.5%, 5% and 7.5% as default rates, we observe that a default rate higher than 7.5% leads to a negative return on investment and could lead to financial loss for the sponsor company. Therefore, it is critical for any nanostore supplier to manage the default rate level when considering implementing a trade credit policy.

6 DISCUSSION

This paper shows significant findings that should be of interest to nanostore suppliers. First, we establish the effectiveness of the implementation of a trade credit in relation to commercial measures of orders, receipts, and rejections. We find that for stores using credit, the order size and amount received is predicted to increase by nearly 60% over those that do not. The variety of SKUs is also increased by 33%. Further, the amount rejected decreases by about 40%. These results show how restrictive cash constraints are for nanostores and point towards opportunity for mutual growth between them and their suppliers via credit utilization. Second, we establish the relationship between trade credits and the duration of stops along a route. We find that for a stop serving a store which is using a credit, time spent is reduced by about 20%. This should be of particular interest to suppliers, which incur numerous costs relative to time in their supply chain operations.

6.1 MANAGERIAL INSIGHTS

Although the analysis is robust and the results are impressive, we must consider that our data are empirical and not experimental. Therefore, there are caveats that might be applied when interpreting our findings. For example, our results find a 59.4% increase in goods received when the credit is applied. How might this be explained outside of the credits' effects? There are a few possibilities, especially considering the Conditional Independence Assumption upon which the matching process works. This method presumes that the model captures all relevant covariates in dealing with selection bias in the treatment group. However, this may not be the case for our analysis given the lack of detailed data around other plausible factors. For example, physical space considerations are also omnipresent for nanostores; perhaps the empirical data reflects credit usage by large stores that can take in more inventory and the effect would not be replicable with smaller stores. Another explanation is that stores with credit might get more attention from salesmen, who are more confident in the ability of the store to convert orders to receipts.

Other mechanisms may also play a role in influencing our results. Nanostores might order from multiple suppliers in a normal setting but consolidate their orders to one supplier that offers them credit, thus inflating perceived improvements. Store and population density could also be a factor if some stores can capture market share from competition by leveraging the credit for greater in-stock conditions. Ultimately, the nanostore market is rife with complexity that is difficult to sift through when evaluating historical data. We anticipate further experimental research being done to explore these possibilities in the future.

The question remains of what action or implementation may be taken in review of our analysis. We believe that despite the caveats listed above, there is strong promise shown in our results, and that the sponsor company and others like it should consider methodically deploying the credit.

The first recommendation offered is to begin with a small credit initiative. Although the greatest returns were shown in conjunction with the highest amount of credit offered, there are unknowns in any system. It is likely prudent to begin with no greater than 10-20% issuance of credit in relation to the entire client base. Additionally, it would be sensible to attempt to identify stores which have physical space to accommodate extra goods as candidates for the initial credit offering. It is further worth considering that larger orders from stores which are already served may incur more operational costs (e.g., labor, trucks, etc.). Beginning with limited credit issuance may help suppliers to understand the magnitude of added cost for the stores that they serve before expanding the credit program.

The sponsor company specifically could apply the trade credit policy to increase the variety of SKUs allocated in the stores. This could help to open an opportunity for the development of new categories and special types of products. New categories of products from CPG companies are usually limited to supermarket channel, and it is difficult to place them in nanostores because of the lack of cash of these stores have to invest on new products. The credit initiative could provide an opportunity in this regard.

In the end, the traditional grocery market is one of low margins. To survive, nanostore suppliers must always look for efficiency. By offering a trade credit, they could increase their profit margins in a fast way while also developing their customer base. This action can help to develop strong relationships between suppliers and clients that can reap benefits for the whole channel on the long-term.

7 CONCLUSION

Nanostores are a vital part of the economies and daily lives of billions of people across the globe. This number only figures to rise as more of the population moves towards urban environments. Thus, the area represents significant economic opportunity, especially for those companies which distribute to nanostores. A significant challenge in this space is the presence of cash constraints, which inhibit commercial and operational effectiveness.

This project finds that by using a credit to alleviate this constraint, suppliers to nanostores can increase sales, decrease rejections, and reduce route time. This results in a ROI that supports the potential of the implementation of a credit policy in a cash-constrained nanostore supply chain. While the benefits seen will primarily be reaped by suppliers, there are significant implications for the overall nanostore ecosystem. As stated, this traditional grocery channel is the most important in Latin America. It is also a source of work for millions of business owners who struggle to thrive in difficult economic conditions. By facilitating shared growth and driving cost out of the system, credits can support store survival, increase item availability, and reduce costs. Ultimately, as stores increase their productivity, they can invest in new technologies and further improve the way they serve their customers. It is our hope that our findings contribute to the continued study of this area for the benefit of all.

REFERENCES

Angrist, J.D., & Pischke, J. (2015). Mastering 'Metrics: The Path from Cause to Effect. Princeton University Press.

Boulaksil, Y., & Belkora, M. J. (2017). Distribution Strategies Toward Nanostores in Emerging Markets: The Valencia Case. Interfaces, 47(6), 505–517. doi:10.1287/inte.2017.0914

Boulaksil, Y., & van Wijk, A. C. C. (2018). A cash-constrained stochastic inventory model with consumer loans and supplier credits: The case of nanostores in emerging markets. *International Journal of Production Research*, 56(15), 4983–5004. https://doi.org/10.1080/00207543.2018.1424368

Beck, T. (2015). Microfinance-A Critical Literature Survey. Retrieved from http://documents1.worldbank.org/curated/en/588931467993754857/pdf/Microfinance-a-critical-literature-survey.pdf

Casanova, M. (2019). Credit to Merchants: Tienda Pago's Digital Solution for Fast-Moving Consumer Goods (Rep.). International Finance Corporation.

Castañon, X. (2018*).* The hidden impact of micro retailers' survival rate on the logistics cost of consumer-packaged goods companies (Thesis). Massachusetts Institute of Technology. Retrieved from https://dspace.mit.edu/bitstream/handle/1721.1/118117/Castañon_2018_Capstone.pdf?sequence=1&isAllowed=y

Escamilla, R., Mogollon M., & Fransoo, J. (2020, March). The impact of credits on the efficiency in the distribution to the nanostores. 2020 MIT SCALE Latin American Conference.

Euromonitor International. (2018). Grocery Retailing in Latin America (p. 46). Passport.

Fransoo, J. C., Blanco, E. E., & Mejia-Argueta, C. (2018) Reaching 50 Million Nanostores: Retail Distribution in Emerging Megacities. CreateSpace Independent Publisher Platform.

Mejia-Argueta, C. (2017, December 06). The unlikely success of nanostore retailing. Retrieved April 19, 2021, from https://www.scmr.com/article/the_unlikely_success_of_nanostore_retailing

APPENDIX

Table 9
Cost benefit analysis considering a default rate of 2.50%.

COST BENEFIT ANALYSIS	100%	10%	20%	40%
ADDITIONAL PROFIT	148500	14850	29700	59400
COST SAVING	37223	3722	7445	14889
TOTAL BENEFIT	185723	18572	37145	74289
FINANCIAL COST	50000	5000	10000	20000
IT MANAGEMENT	20000	4000	8000	10000
ADDITIONAL SALESFORCE COST	30000	3000	6000	12000
DEFAULT RATE	2.50%	2.50%	2.50%	2.50%
TOTAL COST	120833	14083	28167	50333
ROI	54%	32%	32%	48%

Table 10
Cost benefit analysis considering a default rate of 5.00%.

COST BENEFIT ANALYSIS	100%	10%	20%	40%
ADDITIONAL PROFIT	148500	14850	29700	59400
COST SAVING	37223	3722	7445	14889
TOTAL BENEFIT	185723	18572	37145	74289
FINANCIAL COST	50000	5000	10000	20000
IT MANAGEMENT	20000	4000	8000	10000
ADDITIONAL SALESFORCE COST	30000	3000	6000	12000
DEFAULT RATE	5.00%	5.00%	5.00%	5.00%
TOTAL COST	141667	16167	32333	58667

ROI	31%	15%	15%	27%

Table 11

Cost benefit analysis considering a default rate of 7.50%.

COST BENEFIT ANALYSIS	**100%**	**10%**	**20%**	**40%**
ADDITIONAL PROFIT	148500	14850	29700	59400
COST SAVING	37223	3722	7445	14889
TOTAL BENEFIT	185723	18572	37145	74289
FINANCIAL COST	50000	5000	10000	20000
IT MANAGEMENT	20000	4000	8000	10000
ADDITIONAL SALESFORCE COST	30000	3000	6000	12000
DEFAULT RATE	7.50%	7.50%	7.50%	7.50%
TOTAL COST	162500	18250	36500	67000
ROI	14%	2%	2%	11%