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DEVELOPMENT AND IMPLEMENTATION OF A MULTICHANNEL MANAGEMENT SUPPORT SYSTEM FOR PHYSICAL RETAIL STORES BASED ON CUSTOMER'S ONLINE DATA

TESIS PARA OPTAR AL GRADO DE MAGÍSTER EN
GESTIÓN DE OPERACIONES

RENZO ALONSO FUENZALIDA CORREA

PROFESOR GUÍA:
MARCEL G. GOIC FIGUEROA

MIEMBROS DE LA COMISIÓN:
MARCELO O. OLIVARES ACUÑA
DANIEL SCHWARTZ PERLROTH
CARLOS E. NOTON NORAMBUENA

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POR: Renzo Alonso Fuenzalida Correa
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PROFESOR GUÍA: Marcel G. Goic Figueroa

DEVELOPMENT AND TEST OF A MULTICHANNEL MANAGEMENT SUPPORT SYSTEM FOR PHYSICAL RETAIL STORES BASED ON CUSTOMERS ONLINE DATA

Desde la masificación de las plataformas de compra online, los retailers han concebido el funcionamiento de las nuevas tiendas online basándose en lo que ya saben de las tiendas físicas. Hoy por hoy los clientes demuestran un verdadero comportamiento multicanal, usando varios de los canales en diferentes momentos de su proceso de compra. Esto presenta diversas oportunidades de usar la información recolectada en un canal para mejorar la experiencia del cliente en otro. Aunque son varios los flujos de información que pueden explorarse, en este proyecto se utilizan estos datos para informar al nivel operativo de las tiendas físicas, lo que un tema más bien inexplorado. Más específicamente, se analiza la navegación online para identificar tendencias de compra de corto plazo, y se entrega esta información a vendedores de las tiendas físicas en forma de un pronóstico de los productos más populares. Para todo ello, se desarrolla una serie de metodologías para generar reportes semanales, altamente personalizados para cada departamento de las tiendas, basado en el comportamiento de online-offline búsqueda-compra, exhibido por los clientes más relevantes para cada tienda. Luego se procede a entregar estos reportes semanalmente durante 6 semanas, mientras se realizan también encuestas a tanto los vendedores, como a los clientes. Estos datos y los datos de transacciones y ventas en la tienda son analizados para concluir la efectividad de la metodología.

Para evaluar la efectividad de la información entregada a los vendedores, se utiliza un método experimental en el que algunos departamentos reciben una lista con productos menos relevantes a modo de “falso tratamiento”. Para estimar la Venta Incremental se utilizan varias metodologías econométricas, incluyendo Analisis Multinivel y regresiones LASSO (Least Absolute Shrinkage and Selection Operator).

Se encuentra que la metodología propuesta incrementa la venta en tiendas en aproximadamente un 9%, con un potencial incluso mayor cuando se considera la baja participación (non-compliance) observada. No se encuentra evidencia de un efecto significativo entre el tratamiento “vedadero” y el “falso”, lo que sugiere que el marco experimental propuesto no es suficiente para establecer un efecto tan sutil. No se encuentra tampoco evidencia de un cambio en la satisfacción de los clientes o en la confianza y empoderamiento de los vendedores, pero esto se atribuye a efectos psicológicos relacionados con la implementación de esta metodología como un proyecto piloto en las tiendas. Se encuentra evidencia cualitativa sobre la importancia de considerar estos efectos psicológicos en trabajos e implementaciones futuras.

DEVELOPMENT AND TEST OF A MULTICHANNEL MANAGEMENT SUPPORT SYSTEM FOR PHYSICAL RETAIL STORES BASED ON CUSTOMERS ONLINE DATA

Since the massification of online shopping platforms, most retailers have designed the operations of the new online shops based on what they have learned in physical stores. Nowadays, customers are truly having multichannel purchase behavior using several of the available channels at some point of their purchase process. This opens several opportunities to use information collected in one channel to improve customer experience in other channels. Although different information flows can be exploited, in this project we use online data to inform brick and mortar operations which is a rather unexplored topic. More specifically, we analyze online browsing data to identify short-term purchase trends and we give that information to store salespersons to give them a forecast of the most popular items. Thus, we developed a series of methodologies to generate weekly reports, highly customized for each treated department within the store, based on the online-offline-research-shopping behavior by the relevant customers to each store. We then proceed to deliver these reports weekly during 6 weeks, while also conducting surveys on the both employees and customers. This data and the revenue from transactions in the store are then analyzed to conclude on the effectiveness of the methodology.

To evaluate the effectiveness of the given online data to salespeople we use an experimental approach, in which some stores are given a list of less relevant items, as a “false treatment”. To estimate the incremental revenue we apply several econometrical methodologies including the Multilevel Analysis and the Least Absolute Shrinkage and Selection Operator (LASSO).

We found that the proposed methodology increased revenue by approximately 9%, with an even higher potential when considering the non-compliance observed. We didn’t find evidence of a significant effect for the true treatment over the false one, suggesting that the proposed experimental framework is not enough for such subtle effect. We didn’t find evidence of change in customer’s satisfaction or sales workers confidence, but this may be attributed to the psychological effects found around the implementation of this methodology as a pilot project in the store. We did find qualitative evidence on the importance of taking account for these psychological effects on future works and implementations.

This work should conclude my studies in my beloved university, the one that gave me so much. So many friends, precious moments, colleagues to admire, higher goals to pursue and most importantly, the opportunity to see another world and live another life. To this great institution and all the people who are part of it, Thank you.

I would also like to thank Carolina and Magdalena for all their great work during this project. Without their help this document and its conclusions wouldn't be the as good. Thanks to my other colleagues, Alejandra, Loreto, Luis, Daniel and Matias, for their advice, good vibes, and being there during the process. And thanks to my professors, especially Marcel Goic, who has been a mix of inspiration, support, much needed scolds and advice.

Finally I would like to thank my family. For every headache they give me, they have given me ten times the happiness, support, and inspiration. My mother, father, sister, niece, and also my girlfriend Macarena, her parents, brother, and sister. Without all of you I certainly wouldn't be who I am today.

After finishing this work, I start a voyage to the other side of the world. I don't have big expectations or ambitions, I'm just following what so far I've learned is the correct thing to do. From now on, every time I read this lines, I will remember how it felt just before leaving.

"If you want to know the truth of who you are, walk until not a person knows your name. Travel is the great leveler, the great teacher, bitter as medicine, crueler than mirror-glass. A long stretch of road will teach you more about yourself than a hundred years of quiet introspection."

-Patrick Rothfus. The wise man's fear.

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I. INTRODUCTION

I.1 COMPANY DESCRIPTION AND CURRENT SITUATION

This project is sponsored by a joint effort by the University of Chile and a department store in South America. The department store operates in 4 different countries, but we concentrate in the Chilean market where the retailer has a customer base of more than 2 million customers and almost 50 physical stores. In this work we will focus in a time window ranging from September 20th to November 30th of 2016.

Previous work (Palma López, 2015) with the company shows that in the country more than 13% of the active customers exhibit "multichannel" behavior balancing their shopping between the online and physical stores. These customers also account for more than 22% of the total revenue, meaning that these are among the most valuable customers for the firm. Understanding their preferences and needs, and taking proper marketing actions is one of the keystone of the company's multichannel strategy.

These strategies support decision making moves, most commonly using "offline" information in the "online" world, but this flow direction is not unique. Usually, data from transactions in physical stores is available online for financial reasons, this data has been also used in the CRM and Consumer Analytics teams to do customer segmentation and decisions over the product mix and supply in stores. Is only in the recent years that more sophisticated marketing actions have started to take advantage from "online" information, made possible by new technical capabilities to better target particular customers. These more sophisticated actions, based on consumer analytics, are mainly focused on the online channels, like behavior triggered emails, online web personalization, coupons, and others actions that heavily depends on identify a single customer, understand her behavior, and take proper action. This methods has proven themselves over the years, but now the firm is exploring new ways to surpass some of the constraints of this approach and capitalize over the knowledge already available.

We can classify different approaches distinguishing between the source of information and where the action will take place. Considering that most of the transaction still occur in the offline channel, we will consider demographic and long term segmentation information as an offline source.

OFF -> OFF

So far the company has used offline information in the offline world to allocate resources in the different stores, predict demand, and adjust supply to strengthen brand association with socio-economic class.

OFF -> ON

Offline information in the online world is mainly used to create and target specific customer segments with much tailored campaigns and ads in a customized web experience. Its keystone is the capacity to target specific customers, and has seen a rapid growth since the company is continuously investing in new technology and resources for its Consumer Analytics and Marketing areas. Some notorious examples are the distinctions between multi-channel and mono-channel customers, and new categories for highly valuable online customers, a parallel with the classic premium customers. Email campaigns based on demographics, like furniture, baby products, and sports, heavily depends on this information.

On -> On

The success of the efforts made in the online world, along with a highly competitive retail sector, has pushed the company even further, urging them explore more sophisticated ways of taking marketing actions and encouraging the use of online data. Behavior triggered emails and coupons are among the newest marketing actions performed by the firm.

On -> Off

At this point the company has reached the conditions in which exploring the missing flow direction, online to offline, is economically viable and any improvement made is probably as good as any on top of the already made in the other directions.

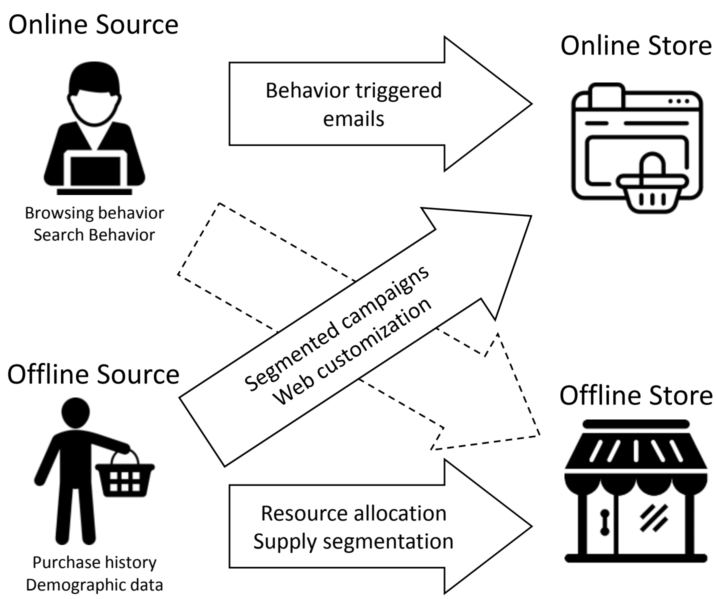

Figure 1: Conceptualization of the different flows of information to marketing action

1.2 Objectives

- Conceptualize and stablish an operational and feasible link between the online information and the physical stores.

- Develop and implement a methodology capable of taking advantage of the previously stablished connection and enable the capture of value from this unexplored flow of information.

- Develop and implement of an experimental design in order to test said methodology and its capabilities to improve revenue, employee's confidence, and customer satisfaction.

II. THEORETICAL AND CONCEPTUAL FRAMEWORKS

II.1 THE CONCEPT OF OMNI-CHANNEL RETAIL

Since late 2000s, the phenomenon of customers using multiple channel during their purchase process has been already documented (Verhoef, et al., 2007). We will use a framework in which the customer's decision to use a specific channel depends not only on the product, but also in relationships between channels. We also acknowledge the fact that one of the most characteristic behaviors in this environment is Online to Offline research shopping.

From a multi-channel approach, in which retailers decide whether include new channel to their existing ones, the new managerial decisions have turned into an omni-channel focus, where the key topics are around how customer's contact points distribute over the many options available. Lately, and with the inclusion of the mobile channel and other new ways to contact the customer, the natural borders between them have started to blurry (Verhoef, et al., 2015). In this context is imperative for the firms to tackle this new scenario with haste, since old barriers like information availability, geography, and customer ignorance are fading fast with the advance of new technologies (Brynjolfsson, et al., 2013). Interactive channels challenge the idea of one-way communication with the customer, and technologies like location-based apps allow brick and mortar stores to offer a whole new mix of products for their visitors without needing them to be actually there. Every major player in the retail sector is currently trying to take advantage or at least cope with this changes.

II.2 FIELD EXPERIMENTS, CONFOUNDERS, INSTRUMENTAL VARIABLES, AND REGRESSIONS

Randomized experiments represent the solution for unobserved confounders and the more transparent way to estimate the effect of a certain treatment. When subjects are assigned in a purely randomized fashion to receive or not to receive a treatment, all the other factors that could be affecting the outcome are equally likely to be present in both groups. This kind of settings provide convincing evidence of causation. Randomized experiments that have in real-world settings are called *field experiments*. When the assumptions of excludability and non-interference are met, the causal effect of a treatment is called Average Treatment Effect (ATE) and it's defined by

$$ATE = \frac{1}{N}\sum_{i=1}^{N}(Y_i(1) - Y_i(0)) = E[Y_i(1)|D_i = 1] - E[Y_i(0)|D_i = 0]$$

where Y_i is the outcome measure for the observation i, and D_i is the assignment to treatment. To estimate the ATE we use a nonbiased estimator of the slope coefficient in a regression where a is equal to $\mu_{Y(0)}$, b is equal to $\mu_{Y(1)} - \mu_{Y(0)}$, and the independent variable d_i is 1 when the observation i is assigned the treatment group.

$$Y_i = a + bd_i + u_i$$

The simplest non-biased estimator is produced by al Ordinary Least Squares (OLS) regression, which also facilitates the incorporation of confounders as extra regressors without biasing or altering the ATE (Gerber & Green, 2012).

When many confounders are to be used, as many as even the number of observations, model overfitting occurs and may not be possible to estimate accurately the ATE. In this case many screening techniques can be applied to reduce the number of regressors before actually calculate the estimators, but a more sophisticated method for both variable selection and regularization is the so called Least Absolute Shrinkage and Selection Operator (LASSO) (Belloni, et al., 2012). This method produces biased estimators, so in order to use it in the ATE estimation context, we use a LASSO regression to select the relevant covariates and then run an OLS regression with just those and the treatment covariate (Belloni, et al., 2014) (Bloniarz, et al., 2016), this methodology is called Two-step LASSO regression.

One last consideration is that sometimes the researcher assigns a subject to the treatment, but the subject partially receives it or doesn't receive it at all. This is called One-Sided Noncompliance and in this case the ATE, as defined previously, does not reflect the real magnitude of the treatment effect. The ATE as if all subjects were compliers is called Local Average Treatment Effect (LATE) and is calculated using an instrumental variable that captures the measure of actual treatment a subject received (Angrist & Imbens, 1995).

II.3 Hawthorne Effect

Hawthorne effect is referred to as a nonspecific effect caused by participation in a study as such rather than by the specific intervention measures taken (Wickström & Bendix, 2000). It is often used to describe the idea that the researchers themselves can be part of the treatment, conditioning the answer towards what the subjects perceive is desired by them. However this conceptions are widely criticized in the sociology and psychology communities because they generally overlook deeper phenomena, which afterwards were considered to be of decisive importance (Wickström & Bendix, 2000). Many factor could explain the increase in productivity, or any other outcome under study, such as receiving positive attention, possibility of influence work procedures, and threat of losing one's job, among others. It has been found that certain key factors seems to influence the magnitude of this effect, such as age, authoritarianism, rural – urban background, and union activity level (Rosen & Sales, Apr 1966).

III. Methodology

III.1 Reports Design

Inspired by the actions already taken by the company towards the online world and the Online to Offline research shopping behavior, we use the customer's product views to approximate her short term preferences. This concept is materialized in a short list of the most viewed products for the last week. These reports are intended to be used by salespersons in the physical store to guide customers.

An important challenge to identify product preferences is that they might be store-specific. Thus, to better capture the preferences for the customers likely to be in the certain store, for each store we restrict our attention to "relevant customers" who are likely to visit said store. To perform the selection we consider two factors: geographical location, and shopping history. The first criteria is simple, if the person lives in the two closest districts to the store, she is eligible. The second criteria rests on firstly rank the stores in which each client has purchased in the last 6 months by number purchases made, drop the online store, and then select the first in the list, which is called "preferred store". For a certain store, if a customer has it as her preferred store or lives nearby, then she is considered a relevant customer to that store.

We then proceed to aggregate the product views made by the relevant costumer base in the last week for every product for each store. This aggregation process also distinguish between sex and two groups of age, namely Young (age less than 35) and Adult. This list of products with views for every segment is the base for the custom report creation. Every department in the stores has its unique disaggregation requirements. For instance, Audio & Video uses the four segments (Young – Adult x Men – Woman) and an extra list just for accessories, while Men Shoes just distinguish between Young and Adult customers. To build the list we also consider the store inventories. While some departments can only sell units that are already in the local inventory, others can rely on the distribution center. Every product that couldn't meet the requirements regarding stock is dropped from the list. All these requirements were previously agreed with the salespersons in each department.

Finally the 10 most viewed products for each specific requirement the department has end up in the report. The document also has simple suggestions for the sales workers on how to use the information. Each product is displayed as it unique SKU, the product name, and the brand. Examples of the final designs can be found in the Appendix.

III.2 Experimental Design

Reports are to be delivered once a week in each treated store, by hand directly in their work area by the researchers, and by email to each immediate superior of the sales workers treated. During the same visit a survey is conducted to verify, among other things, how much the sales representatives used the report in the previous period, if the report reflects customer's preferences observed by themselves, and how much they can influence customer decisions in their own opinion. On a different week day, usually 3 or 4 days after the delivery of reports, the researchers visit the store to survey customers, asking questions about perceived service quality, appropriateness of the sales workers product suggestions, and others.

The “True” treatment is defined as delivering the report as described before. Alternatively there’s a “False” treatment, consisting in exactly the same procedure, but with a report made using a list of items that were not identified as the most popular products. These alternative lists are created selecting a sample from the 10th to the 30th most viewed product instead of the top 10, representing a drop in views of 61%. The idea behind this experimental design is to differentiate between what could be caused purely by a psychological effect of being subjected to this experimental design, and the value of the information in this context. The False treatment is not exactly as bad as no treatment with the psychological effects, but selecting a random sample of every product available would be lead to salesperson to recognize them as non-credible set invalidating the contrast.

Two stores are to be treated, in each of them 9 different departments from the Shoes and Electrics and electronics product lines. During a certain week, each department could be treated with a true treatment (T), a false treatment (T) or being left as a control and not receive a report (C). As a limitation imposed by the company we don’t allow any department to receive a false treatment or control more than 2 times during the studied period. Also two extra stores, considered by the company as the “mirror stores” for the ones intervened, are set to be controls every week.

The experiment takes place during a 6 weeks period, from October 10 to November 30 of 2016. A week zero is used as a control.

Store	**Departments**	**Week 0**	**Week 1**	**Week 2**	**Week 3**	**Week 4**	**Week 5**	**Week 6**
		10/13 10/19	10/20 10/26	10/27 11/02	11/03 11/09	11/10 11/16	11/17 11/23	11/24 11/30
Store 1	Audio & Video	C	T	T	T	T	T	C
	Men Shoes	C	T	T	T	T	C	F
	Women Shoes	C	T	F	T	F	T	T
	Big electric appliances	C	T	T	F	T	T	F
	Computers	C	T	T	T	T	F	T
	Small electric appliances	C	T	T	T	T	F	T
	Smartphones	C	T	T	C	F	T	T
	Videogames	C	T	T	T	T	T	C
	Sport Shoes	C	T	C	F	T	T	T
Store 2	Audio & Video	C	T	F	T	T	C	T
	Men Shoes	C	T	T	F	T	T	C
	Women Shoes	C	T	T	T	T	C	F
	Big electric appliances	C	T	F	T	C	T	T
	Computers	C	T	T	F	T	F	T
	Small electric appliances	C	T	T	T	T	F	T
	Smartphones	C	T	T	T	F	T	F
	Videogames	C	T	F	T	F	T	T
	Sport Shoes	C	C	T	F	T	T	F
Mirror Store 1	*All departments*	C	C	C	C	C	C	C
Mirror Store 2	*All departments*	C	C	C	C	C	C	C

Table 1: Experimental design schedule. (T) True treatment; (F) False treatment; (C) Control.

III.3 Assessments

III.3.1 Incremental Revenue

Each department has different revenue levels, in order to make them comparable we define an average base revenue of T periods for each department in each store d is set as

$$Base\ Revenue: BR_d = \frac{1}{|T|}\sum\nolimits_{i \in T} Daily\ Revenue_{id}$$

The period T is defined between September 20th and October 12th. This dates start right after national independence holidays and finishes right before the start of the treatments, with no significant events in between[1].

Finally the Incremental Revenue is calculated for each department in a store d and for each week w as

$$Incremental\ Revenue: IR_{dw} = \frac{\sum_{t \in w} Daily\ Revenue_{td}}{BR_d}$$

The total of 9 departments, in 4 different stores, during 7 weeks, adds to 252 observations of Incremental Revenue, 76 of which are true treatment, 26 are false treatment, and the remaining 150 are control.

III.3.2 Customer's perception

In regard to the customers, the surveys for them are divided in 2 parts:

- *Perception about the information received*: determine the quality of the information given to the customers by the salespersons.
  - Whether the customer was served by a salesperson, if received information suggestions about products.
  - How accurate or relevant is the information for the customer.
  - Overall satisfaction.
- *Omni-channel behavior*: identify omni-channel behavior among the store customers and between client segmentations.
  - Whether the customer ever made an online purchase in the company.
  - Did the customer search online before coming to the store today, does she have the habit of doing so.
  - Have ever the customer attended to a physical store to then buy online.
  - The main reasons why to buy online.

During the study 202 surveys were performed, 99 were made in one of the stores and, 103 in the other.

[1] Tests with other timespans T resulted in very similar results and conclusions, probing the robustness of the results.

III.3.3 Salespersons perception

The sales workers answered surveys periodically in a similar fashion to the customers, with focus in 3 thematic areas:

- *Use of the report*: monitor el real use of the report.
  - Declared level of utilization and specifically what activities did with the report.
  - Percentage of clients that the sales worker gave information.
- *Perception about the experiment*: identify their perception about the experiment
  - If the information in the report seems to be accurate, how the customers receives it.
  - Their perception on the institutional support that this project gives them.
  - How much affinity they have with the project.
- *Effect on the sales performance*: identify effects that the treatment may have on their sales performance.
  - How much they feel the report does helps them in giving recommendations and closing deals.
  - How much they feel they can influence on the customer's product choice and on their willing to purchase.

A total of 185 surveys were answered, 78 were made in one of the stores, and 107 in the other.

In order to have a better understanding of complex phenomena that won't be captured by the surveys, a 50 minutes long Focus Group was conducted in each of the stores. They both occurred at the end of the experimental period and groups of 5 sales workers were picked at random to join in each case. The conversation was guided around the next topics:

TOPICS	OBJECTIVES	QUESTIONS
The experiment	Emotional perspective: emotional reception to the current intervention	What is the project we have been working on about? Describe its characteristics with your own words. Did you use the given tool (report)? How did you feel when you used the tool?
Pilot projects and interventions in general	Reception of other pilot projects and activities related to KPI improvement.	Have you ever participated in another pilot project? Could you name a few? Did you feel comfortable while engaging in them?
Information channels	Examine the mechanisms by which the sales workers get the information they need about products, stock, and trends on revenue, needed from their job.	How is the information on product stock delivered in the store? How? From who? And how often do you receive information on the pilot projects currently running? Do you use all the information available for the product when closing a deal?
Incentives	Examine the motivations in place to increase revenue.	Do you feel support from the company in you daily labors?
Self-evaluation	Self-critical reflection on their performance on the experiment.	How would you self-evaluate regarding this project? Justify.

TABLE 2: FOCUS GROUP TOPICS AND QUESTIONS

IV. Results

IV.1 Omni-Channel presence

To validate the report's conceptualization we analyze some the results from the customer's surveys, particularly the ones concerning the omni-channel behavior. These results support one of the keystones for this work, since the desired effect depends on the online offline research shopping behavior actually happening.

Firstly is the notion of a given customer being what is considered a "multi-channel customer", where we find that 44% of the surveyed customers declare having made a purchase in the online store at least once before. We don't find statistically significant differences between age segments and gender, but they do exist when comparing the two stores. This diverges from the overall 13% classified as a multi-channel customer using historical transactional data could be explained in two factors. One is the fact that multi-channel customers are in overall better customers, which means they are overrepresented in a sample from customers in a store at any given time. The other that could explain this difference is geographical segmentation, since the two intervened stores are in big metropolitan areas, where more engaged customers also concentrate. These last ideas are supported by the significant difference found between the two stores.

Now we explore the order in which customers use different channels. When asked if they usually research online beforehand going to a store to purchase, 53% of the customers said that they usually did. This proportion does not change significantly between gender and store, but does change when comparing customers older than 50 years old and the rest. This suggests a strong adoption of this omni-channel behavior among customers, which validates some of the assumptions necessary for the reports to work properly. The customers were also asked about this same online offline research purchase behavior, but in the current purchase they were making at the time of the survey. Their answers reveals an expected difference between departments, where more technology oriented and high involvement products seems to propitiate this behavior. This evidence suggests that we should expect variation in the effectiveness of the treatment depending on the department.

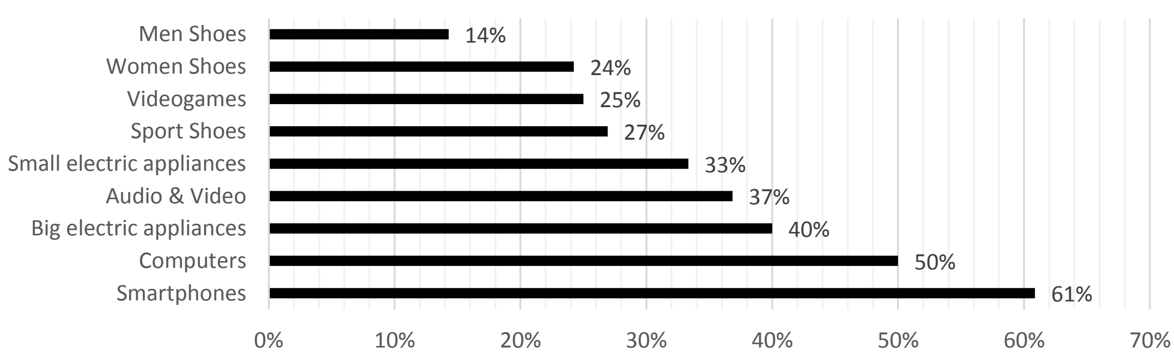

Figure 2: Percentage of customers researching online and shopping offline by department

The alternative direction is offline online research shopping, in which customers attend to the store to gather information on the products they are considering to buy and then proceed to purchase in online channels. We found that 35% of the surveyed customers declared having done this at least once, proving that we are no longer in a multi-channel environment, but in an omni-channel. This finding is relevant because never before the company have had confirmation of this behavior, and although is a lot smaller than its counterpart, reveals a new dimension to explore in future works.

We didn't find evidence of statistically significant differences among gender or between the surveyed stores, but again elderly customers (over 50 years) show less of this behavior. When asked their reasons to do so, customers declare that is because of lower prices in the online counterpart for the same product.

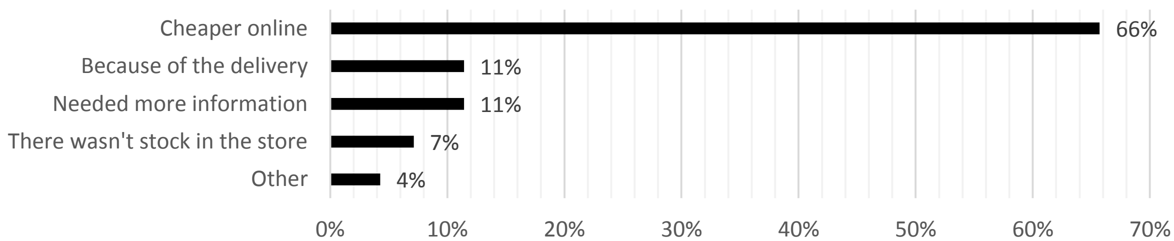

FIGURE 3: REASONS TO RESEARCH OFFLINE AND SHOPPING ONLINE

IV.2 QUANTITATIVE RESULTS ON REVENUE

In this part we review the effect that the treatment has over the Incremental Revenue. This analysis is divided in two main parts: Department level, in which we consider the experimental unit to be a department in a given week, and Sales worker level, in which we estimate the treatment effect on each individual assigned as a sales worker for the given department. In this last case we simply assume that if a department is treated, all its employees also are.

To determinate which employee worked for which department, we implemented a simple rule to assign clerks to department. We start by ranking each employee by its number of transactions in the department, and then look for the biggest gap proportional to the level between two employees. Constraint to that the selected employees represent at least 50% of the total revenue of the given department, that the employee with lowest number of tickets has at least 5 of them, and that this same employee has at least 1% of the tickets that the highest ranked employee in the department has.

	Audio & Video	Big electric appliances	Computers	Men Shoes	Smartphones	Small electric appliances	Sport Shoes	Videogames	Women Shoes
Audio & Video	17	0	5	0	0	0	0	2	0
Big electric appliances	0	14	0	0	0	0	0	0	0
Computers	0	0	14	0	0	0	0	0	0
Men Shoes	0	0	0	7	0	0	0	0	0
Smartphones	0	0	0	0	30	0	0	0	0
Small electric appliances	0	0	0	0	0	3	0	0	0
Sport Shoes	0	0	0	0	0	0	10	0	0
Videogames	0	0	1	0	0	0	0	6	0
Women Shoes	0	0	0	0	0	0	0	0	14

TABLE 3: CONFUSION MATRIX OF THE ALGORITHMIC DEPARTMENT ASSOCIATION

This algorithm is contrasted using known associations for just one of the stores made available by the company. This algorithm, using only transactional data, have an accuracy of the 93.5%. In spite of these results, it is worth mentioning that sales workers often cover for each other during shifts. Additionally, considering that employees are in different shifts regimes, it is important to use actual interaction in each department and not only contractual associations. In other words, employees whose contract is for one department, but her sales are prominently for another or has a shift so short that her sales are minimum, does not go along with the intention of treatment, and thus shouldn't be considered associated with that department.

A more detailed explanation on this algorithm can be found in the Appendix.

IV.2.1 Department Level

We will use a standard OLS regression with covariates in order to estimate the ATE of any kind of treatment, true or false. The list of covariates to be used are:

- Department (categorical): The 9 different kind of departments.
- Week (categorical[2]): 7 possible weeks, including week 0.
- Store (categorical): 4 different stores.
- Males (numerical): % of male sales workers in the department.
- Employees (*)[3] (numerical): total number of employees in the department.
- Age (*) (numerical): mean of the employee's age in the department.
- Time (*) (numerical): mean of the employee's total time since they started to work in their current position.

One of the simplest specifications, which accounts for the possible fixed effect on the many weeks (W) and departments (D), is as follows:

$$IR_{dw} = \beta_0 + \beta_T T_{dw} + \underbrace{\sum_{d' \in D} \beta_{d'} \mathbb{I}_{d'=d}}_{\substack{Department \\ 8\ in\ total}} + \underbrace{\sum_{w' \in W} \beta_{w'} \mathbb{I}_{w'=w}}_{\substack{Week \\ 6\ in\ total}} + \varepsilon$$

In this particular case we get a coefficient β_T for the Treatment (any of the two) equal to 0.045969 with a significance of 0.032374. This result is valid in itself, but we have access to a considerable amount of other covariates. Given the huge amount of possible specifications when we use different combinations of the covariates above, we estimate the ATE for each of the 8192.

In order to summarize these results and give a broad idea of the treatment effect for any of the treatments (true or false) over control, the next table shows the mean of the ATE for the many specifications. The Simple one is just the mean for the specifications in which the β_T coefficient for the treatment is statistically significant with a 90%, 95%, and 99%

[2] We decided to use it as a categorical variable because we want to capture shock effects like the ones produced by special promotional events.

[3] (*) Also we calculated the squared variable and the log of the variable. This allows the variable to reach up to the 3rd power when we later use the first order interactions.

tolerance. Alternatively, the Conservative one is the mean for the individual ATE, but considers them to be zero when the regressor is not statistically significant with a 95% tolerance.

	Simple – 90%	Simple – 95%	Simple – 99%	Conservative
Estimated ATE	0.0934	0.0992	0.1174	0.0257

TABLE 4: ESTIMATED OLS ATE IN DEPARTMENTS

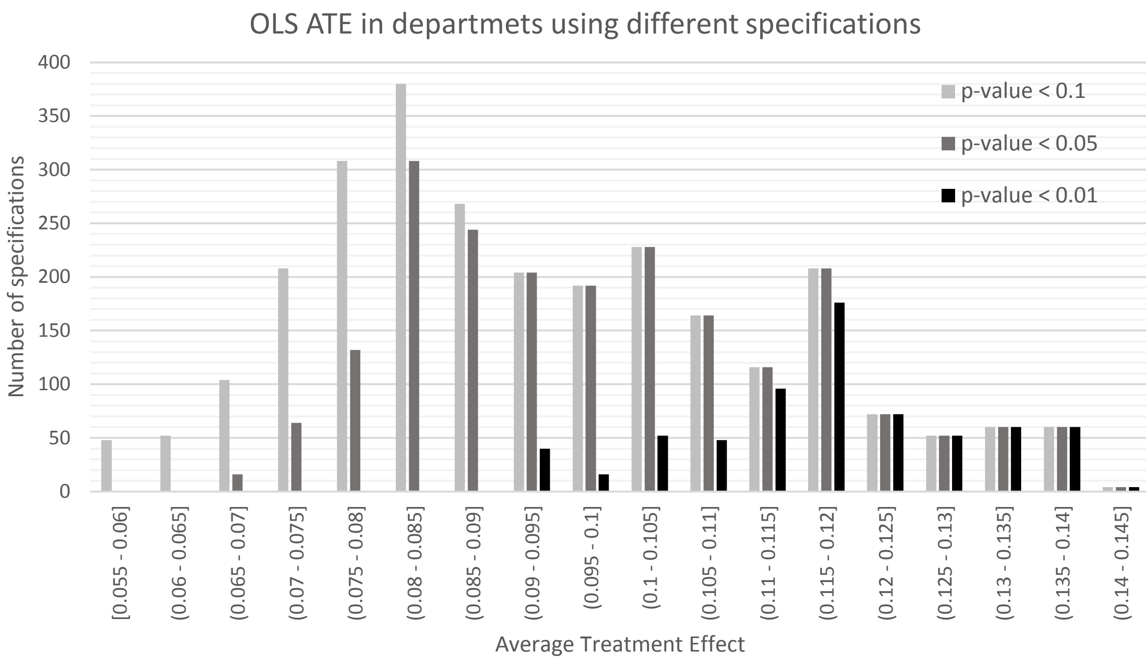

FIGURE 4: HISTOGRAM OF OLS ATE IN DEPARTMENTS FOR SEVERAL SPECIFICATIONS

We can clearly observe that the many combinations of covariates will give us a range of estimations for the ATE, and although they seems to robustly converge around 0.1 when statistically significant, we would like to have a more precise answer for the magnitude of the effect. This is when we could use a two-step LASSO regression to estimate the ATE with an original specification that includes all the covariates, letting the tricky specification selection process to the LASSO method.

With this technique we could even use the first order interactions between all the covariates, a specification with a total of 332 regressors and only 252 observations. This regression, then, consider fixed effects for the week, department, store, and the other available covariates, and its interactions.

	ATE	S.E.	p-value
With all the confounders	0.0564	0.0332	0.0889
With all the confounders and first order interactions	0.0851	0.0258	0.0096

TABLE 5: LASSO ATE IN DEPARTMENTS

Lastly we want to consider the fact that the sales workers may have not complied with the treatment. This non-compliance is usually addressed using the Instrumental Variable technique, with a new variable to be explained by the original treatment assignation (or intention to treat). We use the mean of a self-declared score from 0 (absolutely no use) up to 10 (used it every day in all the instructed ways) that answers to the survey question "*How much did you use the report over the course of the last week?*". This has not been used as a covariate before, since not all the departments have it, because is asked only in the surveyed stores.

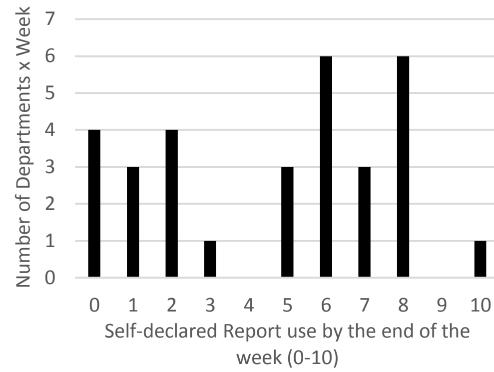

FIGURE 5: SELF-DECLARED LEVEL OF USE (COMPLIANCE)

The following table shows an estimated LATE. Is worth to mention that, since the LATE is the coefficient for the compliance variable, in this case for each "point" of compliance (from 1 to 10), the Incremental Revenue is incremented by the LATE. Currently the mean for this variable in a treated department is 4.5968, which at a LATE of 4.7% would mean a incremental revenue over 20%.

	Simple – 90%	Simple – 95%	Simple – 99%	Conservative
Estimated LATE	0.0469	0.0471	0.0465	0.0156

TABLE 6: ESTIMATED OLS IV LATE IN DEPARTMENTS

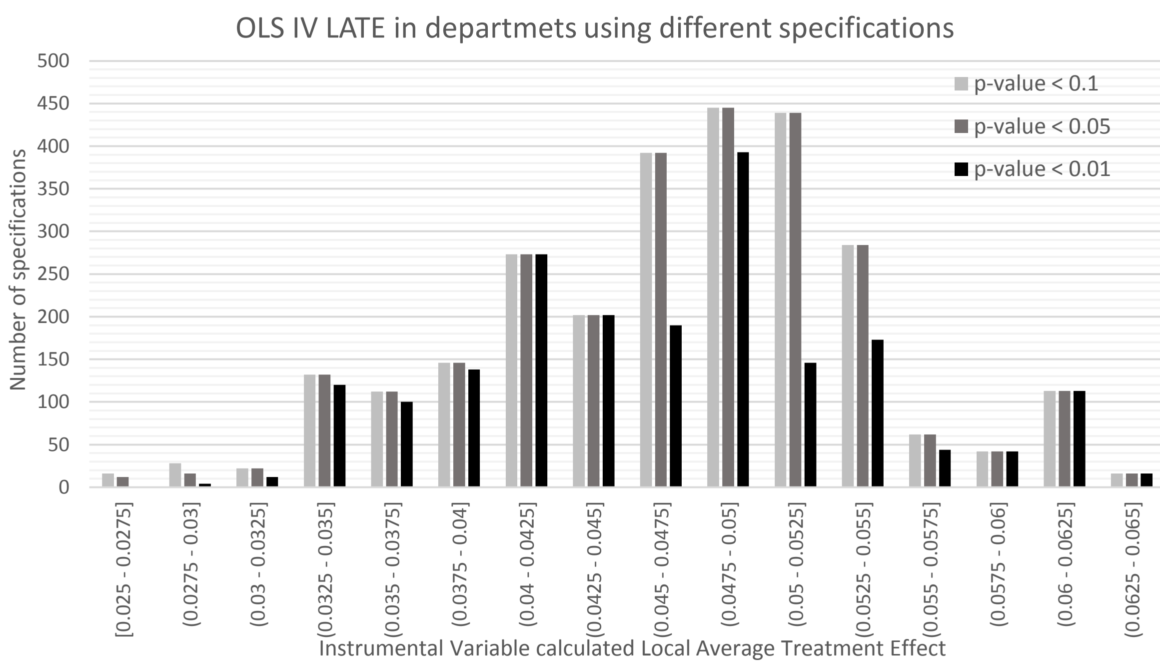

FIGURE 6: HISTOGRAM OF OLS IV LATE IN DEPARTMENTS FOR SEVERAL SPECIFICATIONS

These results suggest a huge treatment effect, improving revenue from 2% up to 11%, with some certainty around 9%, and even over 20% for complier departments. But this is the effect of any of the treatments, true or false, which means is yet not clear how much of it is from treating and how much is because of the information value.

To clarify this point we proceed to repeat the same analysis but now with the true treatment (76 observations) as treated observations and false treatment (26 observations) as control, dropping all the previous control observations.

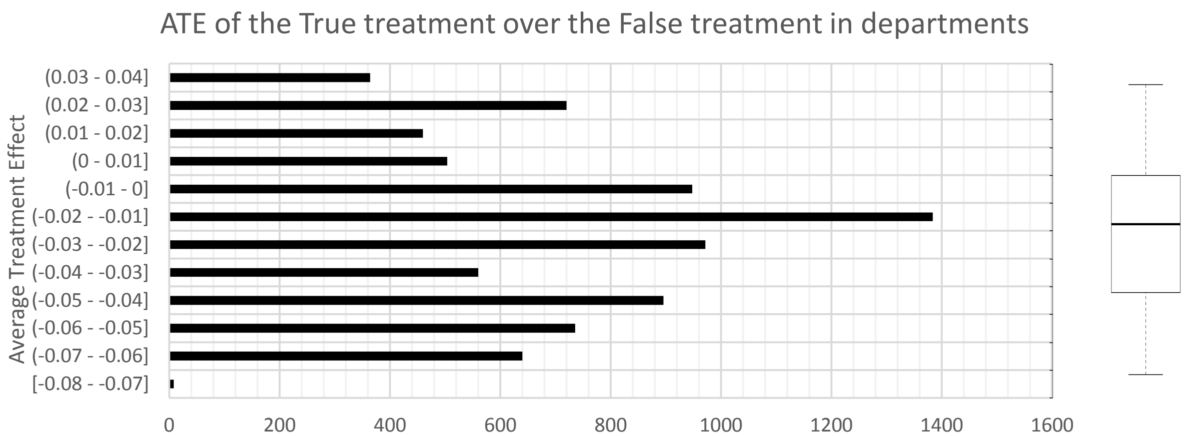

FIGURE 7: OLS ATE ESTIMATES OF THE TRUE TREATMENT OVER THE FALSE TREATMENT IN DEPARTMENTS. NONE SIGNIFICANT

	ATE	S.E.	p-value
With all the confounders	-0.07695	0.06592	0.243
With all the confounders and first order interactions	-0.13965	0.08292	0.0922

TABLE 7: LASSO ATE OF THE TRUE TREATMENT OVER THE FALSE TREATMENT IN DEPARTMENTS

Using the available previous methods, none of the 8192 specifications could find a statistically significant ATE, and the best one has a p-value of 0.3383. Even running the two large specifications for the two-step LASSO method, or running again the 8192 specifications for the IV to estimate the LATE, we don't find a statistically significant treatment effect.

The lack of power to conclude in a statistically significant fashion may be due to the low number of control observations available, suggesting the need for a more extensive analysis of this phenomenon. Within the reach of this work, this last finding suggests that the treatment effect may not be entirely attributed to the content of the reports in the context in which the experiment is developed.

IV.2.2 Sales worker Level

One of the problems with the original experimental design is the small number of observations. One way to deal with this is using a Multilevel approach, in which the old experimental units are disaggregated, and where things affecting the original units, like the treatment, will affect all the smaller ones in the same way. For this purpose we calculate the Incremental Revenue for each sales worker exactly as we did in the department level. Some covariates that use to be aggregated now appear in a granular level, like the employee age, gender, and time in the company. Others, like number of employees, and self-reported use of the report disappear. In this new context we have just 1024 different specifications.

This lower level of aggregation also brings a greater variability for the dependent variable and also some outliers, mainly caused by employee's partial shifts and days off. To cope with this we proceed to exclude the outliers, defined as observations outside 1.5 times the interquartile range above the upper quartile and bellow the lower quartile.

With all this in mind, we proceed in the same way as we did in the department level.

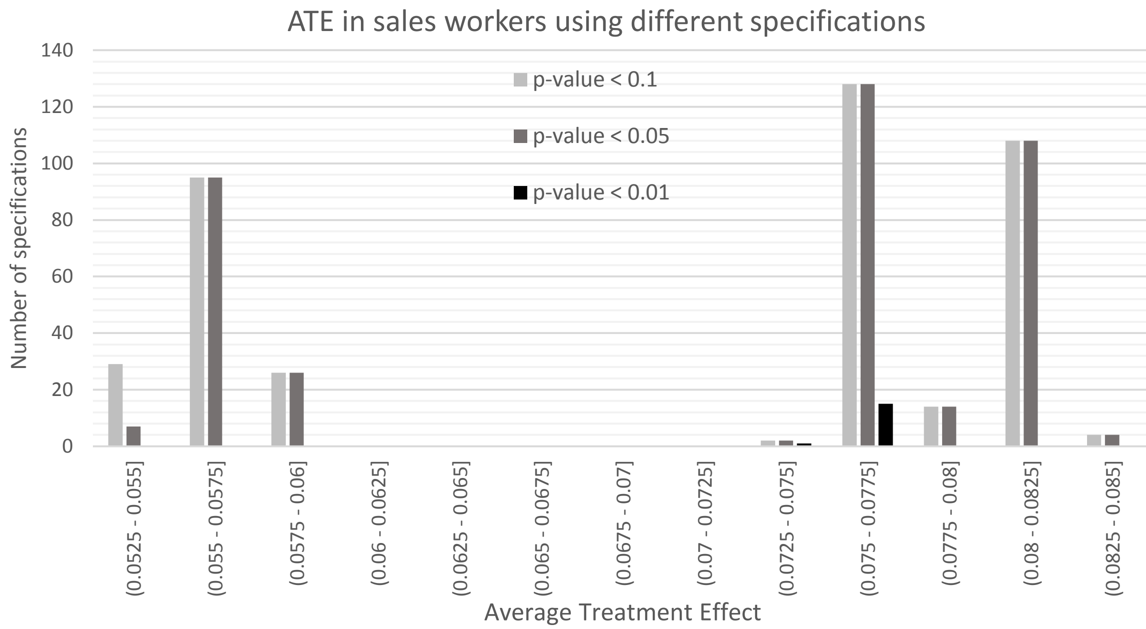

FIGURE 8: HISTOGRAM OF OLS ATE IN SALES WORKERS FOR SEVERAL SPECIFICATIONS

	Simple – 90%	Simple – 95%	Simple – 99%	Conservative
Estimated ATE	0.0708	0.0717	0.0768	0.0269
Estimated ATE Mode 1	0.0564	0.0568		
Estimated ATE Mode 2	0.0792	0.0792	1.2673	

TABLE 8: ESTIMATED OLS ATE IN SALES WORKERS

We again get a treatment effect around 7%, close to the one observed in the department level and a good evidence of robustness in this results. We also find a very particular behavior in the estimated ATE, having two modes depending on the specification. In any case these two modes don't apart from each other too much and still allow us to conclude in the same way about the treatment.

With the confounding serving as an instrumental variable for the treatment no longer available, we can't estimate the LATE, but presumably is even a bigger than the already astonishing results for the simple OLS regressions over the intended treatment.

One last result is the ATE of the true treatment against the false one. In this case we now have a considerably larger number of observations so we would expect to at least have a better understanding of this effect.

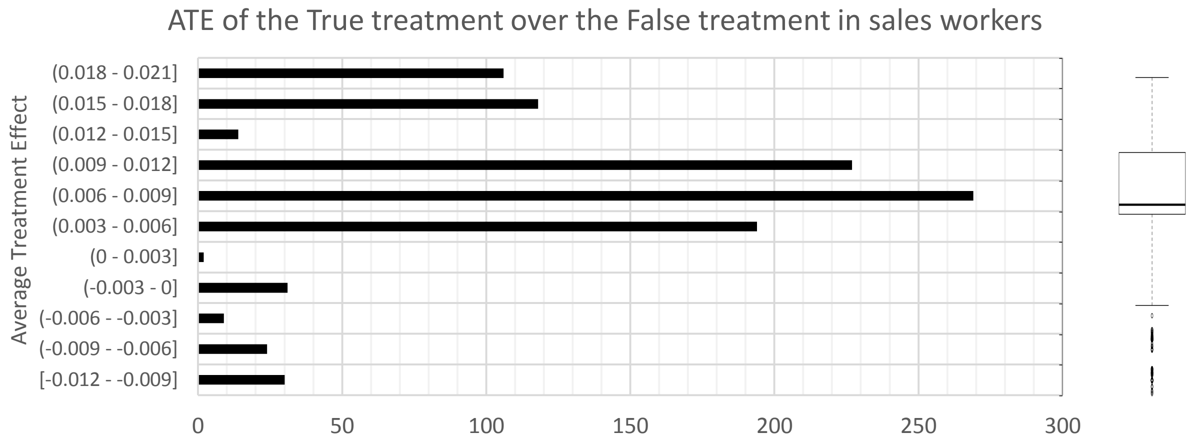

FIGURE 9: OLS ATE ESTIMATES OF THE TRUE TREATMENT OVER THE FALSE TREATMENT IN SALES WORKERS. NONE SIGNIFICANT

	ATE	S.E.	p-value
With all the confounders	-0.02048	0.03685	0.578
With all the confounders and first order interactions	-0.03270	0.07284	0.653

TABLE 9: LASSO ATE ESTIMATES OF THE TRUE TREATMENT OVER THE FALSE TREATMENT IN SALES WORKERS

None of the specifications is statistically significant and the minimum p-value found amongst them is 0.5338. Although the results are not conclusive, with this more detailed analysis we can appreciate a small tendency towards a positive effect. The LASSO ATE estimations need all the covariates to be non-blank, thus using fewer observations and making its results less precise.

After using all the analysis techniques available in the scope of this work, we can't conclude for the value of the information itself over a false treatment. This results may well be attributed to the original experimental design, which, restricted by company policy, didn't assign enough false treatments in the treated stores. Other possible explanation is that the experimental design actually also accounts for the methodology of the reports, thus is also possible that the information is actually valuable, but the reports are not the best way to capitalize said value. Further research is needed to clarify this point.

IV.3 QUALITATIVE RESULTS ON SALES WORKERS AND CUSTOMERS

IV.3.1 SURVEYS

The first thing to explore is the characteristics of the sales employees in the stores where this project went along. We deal with employees ranging from 19 up to 63 years old, some recently employed and some with a history of more than 10 years in the company, with a balance in gender, where female population reaches 53.9%. Within this heterogeneity one should expect a mixed response to the treatment, but since surveys were conducted anonymously their results represent just the general tendency among the employees.

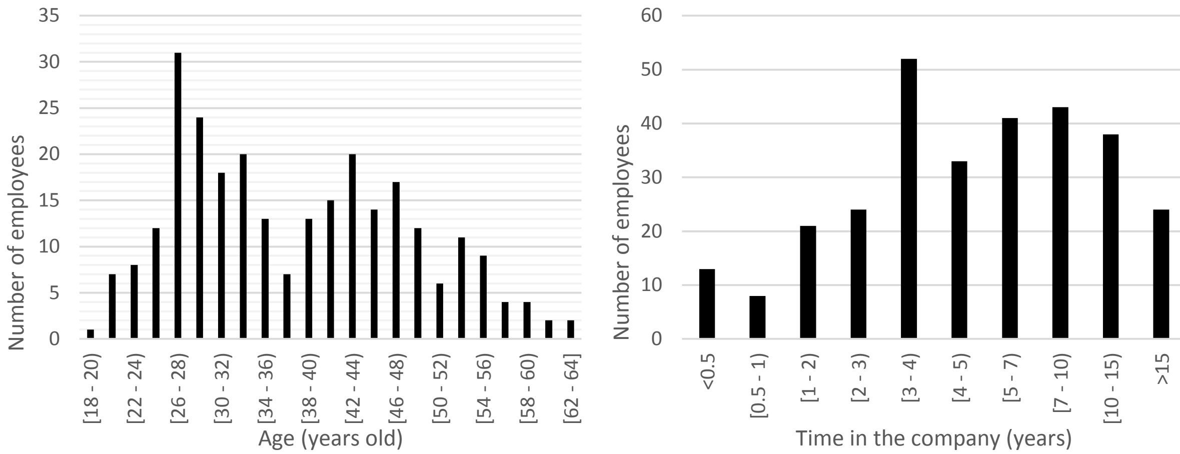

FIGURE 10: AGE (LEFT) AND TIME IN THE COMPANY (RIGHT) FOR THE SALES WORKERS IN THE 4 STORES

One of the first key findings is the generalized low rate of compliance, with a 48% of employees declaring having not received the report at the end of a week when they should have, thus suggesting that the LATE effect may be closer to the real treatment effect in Incremental Revenue.

When observing compliance and usage in the treated stores, we found a deep difference in behavior between them. We also found that this behavior changes over the weeks in a drastic way, with no clear adoption pattern. These two facts suggest a highly unpredictable adoption for this kind of treatment, not responding to a monotonous curve, as in a more traditional adoption process. This unpredictability is possibly influenced by the employees' perception of the research project, the pressure impose by their superiors to comply, group social dynamics within the store, or any other psychological factor.

As for the confidence of the sales workers, we evaluate the amount of recommendations they give to the customers and their self-reported capabilities to influence them.

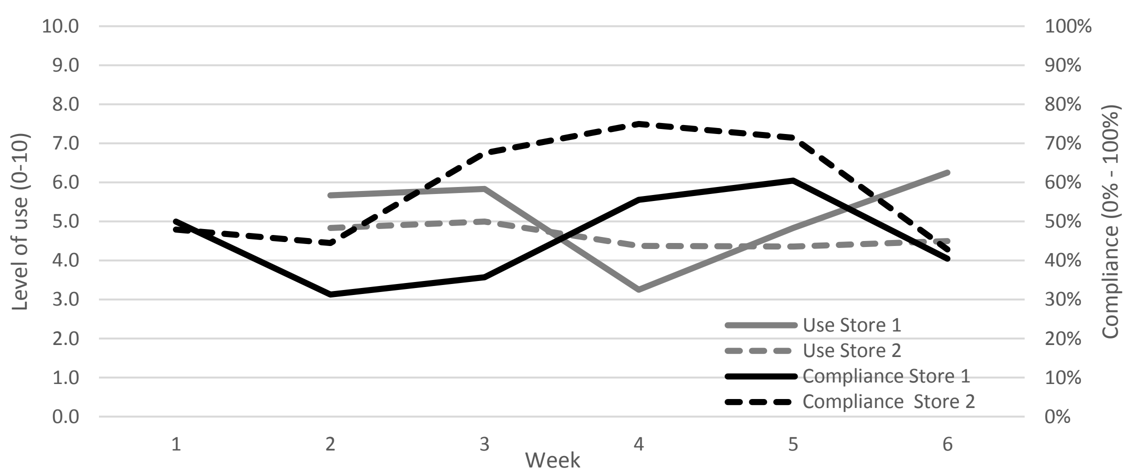

FIGURE 11: USAGE AND COMPLIANCE OVER THE WEEKS

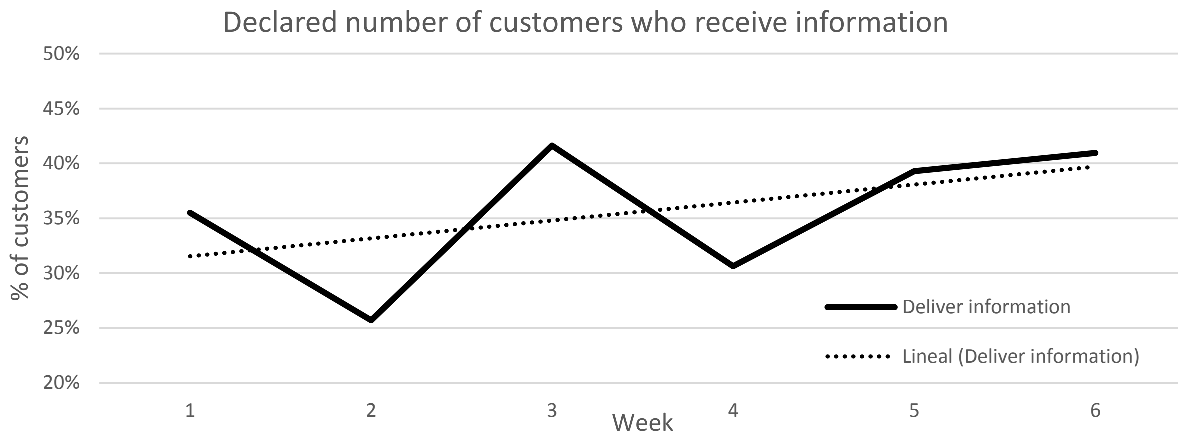

FIGURE 12: NUMBER OF CUSTOMERS WITH INFORMATION DIVIDED BY NUMBER OF CUSTOMERS SERVED OVER THE WEEKS

About how the sales workers give information to the customers, we calculate the percentage of customers who receive information as the declared number of customer to whom the employee gave information based on the report, divided by the declared number of customer served. We run a simple linear regression for this metric explained by the week and found that the direction is positive, meaning that over the weeks the delivering of information was improving, but the coefficient wasn't statistically significant. This results shows a slight change in behavior for the salespersons, but again, not an adoption process as we would have expected.

When asked how much they consider they could influence over the specific product the customer was about to purchase, about the customer actually making a purchase (conversion), or the quality of their product recommendations, we didn't find any significant difference between treatment (any) and control, nor between the true treatment and the false treatment, neither a tendency over time.

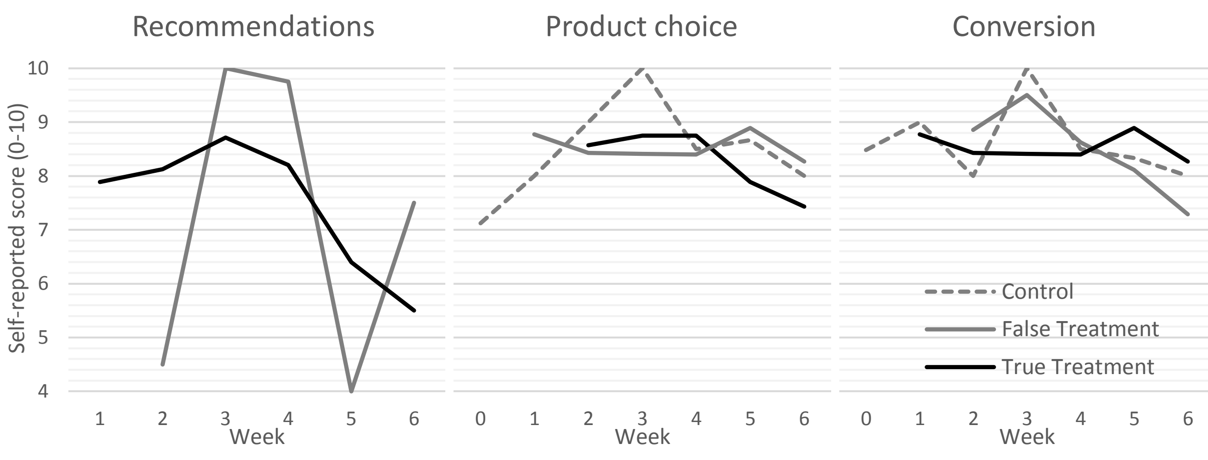

FIGURE 13: SELF-REPORTED QUALITY OF RECOMMENDATIONS (1), INFLUENCE ON PRODUCT CHOICE (2), AND INFLUENCE OVER CONVERSION (3) BY TREATMENT AND WEEK

Finally we asked about how much salesforces felt this project helps them to perform their job in a scale ranging from 0 (insignificant) to 10 (a major part of the institutional help they receive from the company). Here, we found a mean score of 6.95, without significant variants between weeks, treatment or any other variable. Complementary to this information, when asked if they rather receive this report weekly, 58.9% of the answers were affirmative. These findings, and the previous ones, suggest a certain reluctance to this kind of pilot project.

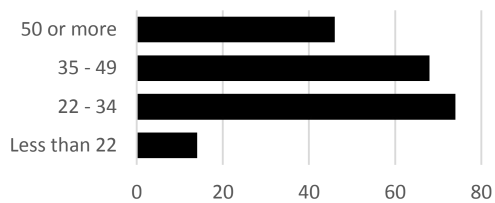

FIGURE 14: CUSTOMER'S OBSERVED AGE SEGMENT

Regarding the 202 costumers surveyed, we also find a heterogeneous environment with a female proportion of exactly 50%. The researchers also classified the respondents in "observed" age segments base on a direct question or based on outlook if the respondent didn't answered.

People were asked if they were served by a sales worker. If they responded affirmatively, they were asked if they were given any kind of information on products. Finally if they responded affirmatively, they were asked if the sales worker give them a specific product recommendation. This funnel is shown below.

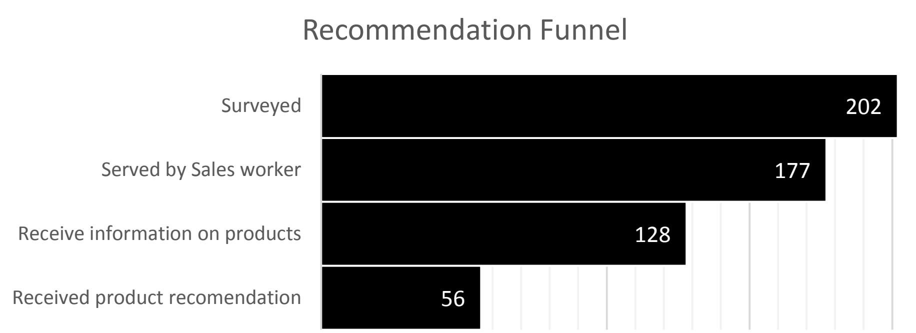

FIGURE 15: RECOMMENDATION FUNNEL DECLARED BY CUSTOMERS

Even though is natural to think that many customers reach a sales employee for a specific doubt or product, or even to ask something not related to a product at all, only 28% of the customers get a product recommendation. We expected that this funnel were a lot less acute. Also is worth mentioning that we didn't find any statistically significant difference in this behavior, for any of the levels, between treated and untreated departments, nor we did between true treatment and false treatment.

We asked the customer who received a specific recommendation, to evaluate how good the recommendation was and how relevant it was for her purchase. Since we have such an unbalanced sample, with 9 observations for customers served by untreated employees, 31 with false treatment and 162 with true treatment, we also use the Mann-Whitney-Wilcoxon Test, which is a non-parametric test that don't need the assumption of an underlying normal distribution and performs better than a t test with unbalanced samples.

	Treated(121) vs Untreated (7)	True Treatment (101) vs False Treatment (20)
How good is the recommendation	Treated: 9.4959 Untreated: 9.8571 t test p-value: 0.0672 MWW test p-value: 0.5568	True Treatment: 9.4059 False Treatment: 9.95 t test p-value: **0.0003** MWW test p-value:**0.0384**
How relevant is to decide to purchase	Treated: 8.9256 Untreated: 9.7143 t test p-value: **0.0444** MWW test p-value: 0.4076	True Treatment: 8.9208 False Treatment: 8.95 t test p-value: 0.9615 MWW test p-value: 0.7949

TABLE 10: CUSTOMER'S PERCEPTION OF THE RECOMMENDATION BY TREATMENT USING MANN-WHITNEY-WILCOXON (MWW) AND T TEST

Mostly because of the small number of untreated observations, we found no conclusive evidence that treating a department would improve the customer's perception about recommendations given by the department sales workers. Another issue with our survey data is a strong response bias, where customers tended to answer extreme values, effectively answering a perfect 10 in most of the cases, and rendering impossible to extract any conclusion on the differences.

When comparing the true treatment against the false one, we expected to see a distinctive improvement in the true treatment, or at least no effect. The result is that in the perceived quality of the recommendation, customers reported significantly better scores for the false treatment. To go deeper, we show the histogram of answers for this question in the next figure, where we can appreciate that the difference, still existing, is not qualitatively strong.

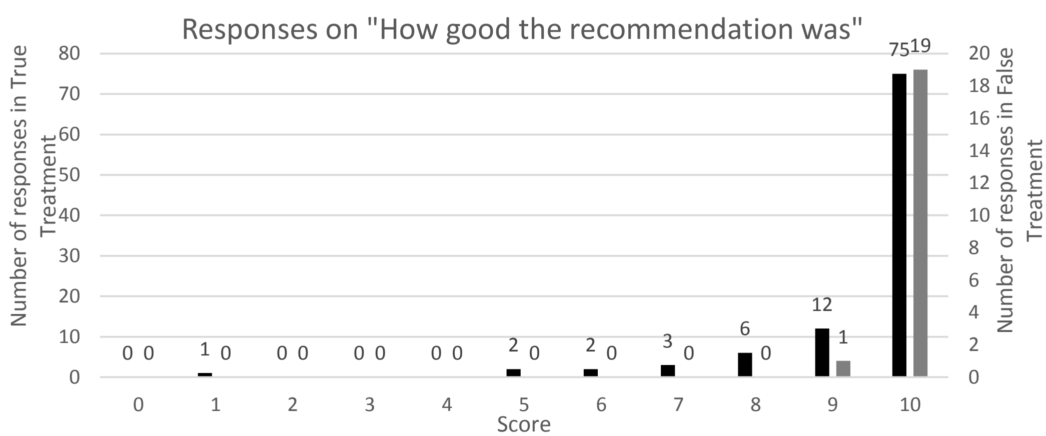

FIGURE 16: HISTOGRAM OF ANSWERS ON THE CUSTOMERS SURVEY ABOUT THE QUALITY OF THE RECOMMENDATION

One final aspect to study is the overall satisfaction the customer declares. Again we didn't find significant differences between the treated and untreated departments, neither did we between departments under true treatment and under false treatment. Interestingly enough, satisfaction varies considerably between departments, as shown in the next figure. We appreciate that the worst ranked departments are also high ranked in Research Online and Purchase Offline behavior (p. 9).

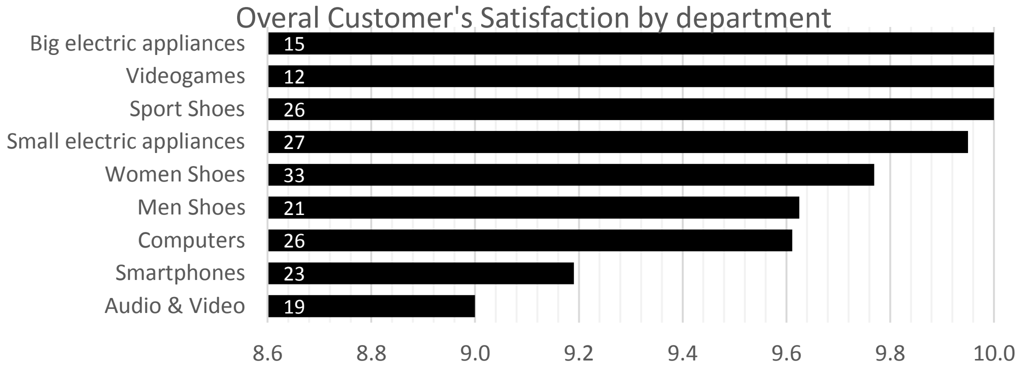

FIGURE 17: OVERALL CUSTOMER'S SATISFACTION BY DEPARTMENT (WITH NUMBER OF RESPONSES)

IV.3.2 FOCUS GROUP

About the project itself, we found that there is a generalized lack of knowledge about it. The sales workers know what the reports are, but they don't know their objective. They have a negative emotional reception, linking this project with the intention to incentivize sales through the online channel, which is a pressure to them. Some even see this project as an attempt to assess the possibility of terminate some of the employees.

Regarding the many interventions of this kind made in the stores, like pilot projects and A/B tests, the employees feel that they require a great amount of effort to perform on top of their regular tasks and usually with no reward. They don't know the final results of the projects they get involved on, and thus they don't find meaning in them. They show little interest in new initiatives.

About the information channels we find that in both intervened stores there wasn't a group transfer of information. The reports were delivered individually, without a complete explanation of its contents and purpose. The employees broadly proclaim that in the face of any kind of doubt they rather seek a peer advice, than going to their superior.

In reference to their vision of the company's efforts towards them, they see little intention from the company to improve their wellbeing. They claim that training sessions, while not scarce, they are usually poor in content and not focused on what they think mostly need to perform better.

The last topic is a self-evaluation. In this the employees show a high level of self-criticism, saying that they have put low effort in the project, partly because their misunderstanding of the project objectives.

In this context the employees had a chance to open up with the researchers, letting us know that the main reason for the low compliance and reception is the fear for their job security, the lack of knowledge about the project due to the poor communication channels, and their overwhelming amount of tasks and KPIs to pay attention to before these new pilot projects. This last part is revealing, as it helps to better understand the low difference between true and false treatment and the almost null effect in behavior and perception captured in the surveys.

V. Discussion, Recommendations and Future Work

Although we did find a conclusive improvement in revenue across the many points of view and specifications, we weren't able to stablish the value of the information being transmitted from the online world to the physical store using the proposed methodology. Based on the previous evidence that the online navigation behavior does have value when actualized in custom campaigns and behavioral triggered marketing actions, we can only ponder this results in the methodology for the information transmission (the reports) and the experimental design around its implementation. Future research should be focused in a deeper understanding of the so far elusive effect that the information on customer's behavior may actually have on the revenue, contrasting a polished version of the proposed methodology with a placebo alternative, and taking account for the response bias in surveys.

Despite the uncertainty on how much exactly this information can impact the revenue using the current methodology, the report scheme was a commercial success. The idea of giving this new tool to the sales workers directly, instead of delivering through the traditional vertical line of communication, proved to be successful and the majority of employees declared that they would rather have this tool. Future efforts to empower the lowest operational plants should consider the current state of the communications channels and target both the employees to whom the effort is supposed to affect and their superiors.

Given the limitations to identify a customer inside a physical store, the short reaction time that a sales worker have to have to answer customer's requests, and the impossibility to allocate considerable amounts of data for a worker to have at hand, the proposed methodology of reports seem to be good enough. Future efforts may be directed to push some of the said boundaries, like the use of geo-localization devices to identify customers entering the store, or give mobile devices to the employees for them to have an easier access to customer's and product data.

The main finding regarding the implementation of the proposed methodology is the friction generated by the lack of information and the poor management of employee's feelings and fears towards new projects. We suggest that future works using field experiments or even long term implementations, should allocate a considerable amount of time and effort towards this topics, since they seem to be key success factors.

VI. Conclusions

In this work we were able to conceptualize a way to capture the potential benefit from an integration between the online data and the physical stores, considering all the operative difficulties and constraints. Some solutions on the tactical level have been previously implemented, like reports to central product planners, but nothing has ever reached the stores or the sales employees directly. This method relies on a key supposition abput the multi-channel behavior of the store's customers, only previously confirmed with transactional data. This supposition was then verified and even deepened, unveiling for the first time for the company the suspected customer's omni-channel behavior.

The methodology to extract relevant information for the specific department, based on customer's online and offline data, and then produce highly customized reports for each one of them, has proven to have a significant impact on revenue. Measurements suggest a robust increased revenue around 9%, varying from department to department and already considering the underlying resistance to comply from employees. Although not perfect, this methodology is operatively feasible, as we were able to implement it with low resources, and effective.

The experimental frame proposed to test this methodology aimed to measure on the one hand the effectiveness of the methodology as a whole, glancing not only to the revenue numbers, but also to the impact it would have on the employees and the customers. And on the other hand made use of a placebo scheme to isolate the effect of the information alone and control in case of something like a Hawthorne effect. This last part had partial success due to the limited budget and company allowance. Despite the possible psychological interactions on the results, this design allowed us to grasp the impact a treatment like this may have in stores, revealing the huge potential on revenue, a low compliance which increase said potential, and a vague effect on customer's perception.

The psychological factor of the sales workers is key to understand the results of this exercise. With a complex and new project showing up from seemingly nowhere, and poor communication channels to made the employees participants and inform them, high rates of non-compliances and a generalized untrusty attitude arose. This same attitude may partially explain the high revenue without a clear distinction between true and false treatment. Again this same rejection may explain the directionally negative and statistically null effects on customer's perception and self-reported confidence. This is supported by the final conversations during the focus group, when sales workers declared having little knowledge about the project, even having participated in it.

This projects findings can be interpreted as an outstanding success in increased revenue or a deep uncertainty on customer's data exploitation methods. In any case these findings show an imperative need to keep exploring the huge potential value that initiatives like this could add. Also a broader approach that considers the psychological factors behind low level employees affected by them is needed in future works. In the end, revenue is just another way to measure employee's performance, and even with the most sophisticated tools at hand, if they are not capacitated or motivated to use them, these tools become by definition useless.

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VIII. APPENDIX

VIII.1 REPORTS

Reporte Semanal 17-11-2016 [redacted]
[redacted] **Arauco Maipú**
Video juegos

Recomendaciones con la lista
1. Leer y revisar los productos de la lista
2. Revisar stock disponible en tienda
3. Revisar si están en oferta

Recomendaciones con productos más visto

4. Recomendar directamente a los clientes algún producto de la lista
5. Buscar darle mayor visibilidad en tienda a algún producto recomendado en la lista

Hombre		
5319266	CONSOLA PS4 500GB SLIM+UNCHARTED 4	SONY
5380385	CONSOLA NES CLASSIC EDITION	NINTENDO
4772975	XBOX ONE 500GB + FIFA 2016	XBOX
4772977	CONSOLA XBOX 360 500GB	XBOX
4786149	Consola Wi U MARIO KART 8	NINTENDO
4795732	CONSOLA PS4 500GB+UNCHARTED	SONY
4949105	PS VITA WIFI SLIM	SONY
5319267	CONSOLA PS4 500GB SLIM+FIFA 2017	SONY
4772976	XB1+KIN+ZOO TYCOON+DC SPOTLIGHT+KS	XBOX
5001823	CONSOLA XBOX ONE 500GB + QB	XBOX

Mujer		
5319266	CONSOLA PS4 500GB SLIM+UNCHARTED 4	SONY
5380385	CONSOLA NES CLASSIC EDITION	NINTENDO
4788098	CONSOLA X360 4GB + FORZA H2	XBOX
4772977	CONSOLA XBOX 360 500GB	XBOX
5259232	BUNDLE HW 3DS SUPER MARIO	NINTENDO
4772976	XB1+KIN+ZOO TYCOON+DC SPOTLIGHT+KS	XBOX
4949105	PS VITA WIFI SLIM	SONY
5045381	CONSOLA PS4 500GB+UNCHARTED4	SONY
4414680	CONSOLA HW 3DS XL NEW BLACK	NINTENDO
4795732	CONSOLA PS4 500GB+UNCHARTED	SONY

Juegos Hombre		
3826779	GRAND THEFT AUTO V PS3	TAKE 2
4270323	GRAND THEFT AUTO V PS4	TAKE 2
5275801	PES 2017 ROLA PS4	SONY
3828094	CALL OF DUTY: GHOST PS3	ACTIVISION
5275805	PES 2017 ROLA PS3	SONY
5287023	FIFA 2017 PS4	EA
5287027	FIFA 2017 X360	EA
3414608	HALO ANNIVERSARY XBOX	MICROSOFT
4735736	PS4 Uncharted Collection	SONY
4757629	STAR WARS BATTLEFRONT PS4	EA

Juegos Mujer		
5275805	PES 2017 ROLA PS3	SONY
4765168	GUITAR HERO LIVE WIIU	ACTIVISION
3885221	ZOO TYCOON XBOX	MICROSOFT
3826781	GRAND THEFT AUTO V XBOX	TAKE 2
5275801	PES 2017 ROLA PS4	SONY
3866015	POKEMON X 3DS	NINTENDO
3478328	NIKE FITNESS KINECT XBOX	MICROSOFT
4757626	NEED FOR SPEED PS4	EA
4991097	WiiU SUPER MARIO 3D WORLD	NINTENDO
4275423	XBOX ONE HALO MC COLLECTION REPLEN	XBOX

Translation:

Weekly Report -date-
-Company name- -Store-
-Department-

Recommendations with the list
1. *Read and check the products on the list*
2. *Check stock in the store*
3. *Check if they are on a special sale*

Recommendations with the most viewed products

4. *Suggest a listed product directly to the customers*
5. *Try to improve visibility in the store for some of the listed products*

Reporte Semanal 24-11-2016 [redacted]
[redacted] **Arauco Maipú**
Audio y Video

Recomendaciones con la lista
1. Leer y revisar los productos de la lista
2. Revisar stock disponible en tienda
3. Revisar si están en oferta

Recomendaciones con productos más visto

4. Recomendar directamente a los clientes algún producto de la lista
5. Buscar darle mayor visibilidad en tienda a algún producto recomendado en la lista

Hombre Joven		
5222220	LED SAMSUNG UN50KU6000	SAMSUNG
5155721	LED SAMSUNG UN55KU6000	SAMSUNG
5331133	LED LG 43LH5730	LG
5267159	LED SAMSUNG UN40K6500	SAMSUNG
5095014	LED SAMSUNG UHD UN40KU6000	SAMSUNG
5155719	LED SAMSUNG UN49KU6500	SAMSUNG
4481715	HOME SAMSUNG HT-J4500K/ZS	SAMSUNG
4087010	MICRO PHILIPS MCM2300/55	PHILIPS
4474042	LED SAMSUNG UN40J5500AGXZS	SAMSUNG
5331974	LED LG 49LH5730	LG

Mujer Joven		
5222220	LED SAMSUNG UN50KU6000	SAMSUNG
5155721	LED SAMSUNG UN55KU6000	SAMSUNG
5331133	LED LG 43LH5730	LG
5155719	LED SAMSUNG UN49KU6500	SAMSUNG
5051910	LED SAMSUNG UN40J52000	SAMSUNG
880608191	LED 32' HD RLED-L32D1620	RECCO
5095020	LED SAMSUNG UHD UN55KU6500	SAMSUNG
5330815	LED LG 55UH6030	LG
5267159	LED SAMSUNG UN40K6500	SAMSUNG
5116860	MINI SONY MHC-V11	SONY

Hombre Adulto		
5222220	LED SAMSUNG UN50KU6000	SAMSUNG
5155721	LED SAMSUNG UN55KU6000	SAMSUNG
4615925	LED SAMSUNG UN32J5500AGXZS	SAMSUNG
5331133	LED LG 43LH5730	LG
5155719	LED SAMSUNG UN49KU6500	SAMSUNG
4474042	LED SAMSUNG UN40J5500AGXZS	SAMSUNG
5116860	MINI SONY MHC-V11	SONY
5330811	LED LG 49UH6030	LG
880608187	LED 21.5' FHD RLED-L22D1620	RECCO
5095014	LED SAMSUNG UHD UN40KU6000	SAMSUNG

Mujer Adulto		
5222220	LED SAMSUNG UN50KU6000	SAMSUNG
5155721	LED SAMSUNG UN55KU6000	SAMSUNG
5331133	LED LG 43LH5730	LG
5155719	LED SAMSUNG UN49KU6500	SAMSUNG
880608191	LED 32' HD RLED-L32D1620	RECCO
5267159	LED SAMSUNG UN40K6500	SAMSUNG
5331974	LED LG 49LH5730	LG
5095020	LED SAMSUNG UHD UN55KU6500	SAMSUNG
3891499	SIST. M SONY CMT-20	SONY
4473991	LED SAMSUNG UN32J4300AGXZS	SAMSUNG

Accesorios		
5152654	GOOGLE CHROMECAST 2DA GENERACION	MACROTEL
3209213	APPLE TV MD199CI/A	APPLE
880426199	SOUNDLINK COLOR BT SPKR BLK US EU	BOSE
4800666	PARLANTE KSES PBT32	KSES
4559666	SOUNDLINK MINI BT SPKR II PRL EU1	BOSE
4955160	AUDIFONO ARTURO VIDAL LW-RMX001AV	LOGIC
4624611	PARLANTE BT25B BLUETOOTH NEGRO	PHILIPS
4245679	AUDIFONO OVERHEAD ZX110 NEGRO	SONY
4624610	AUDIFONO SHB3060BK BLUETOOTH	PHILIPS
4178442	AUDIF BLUETOOTH NEGRO SHB4000	PHILIPS

VIII.2 SALES WORKERS CLASSIFICATION ALGORITHM

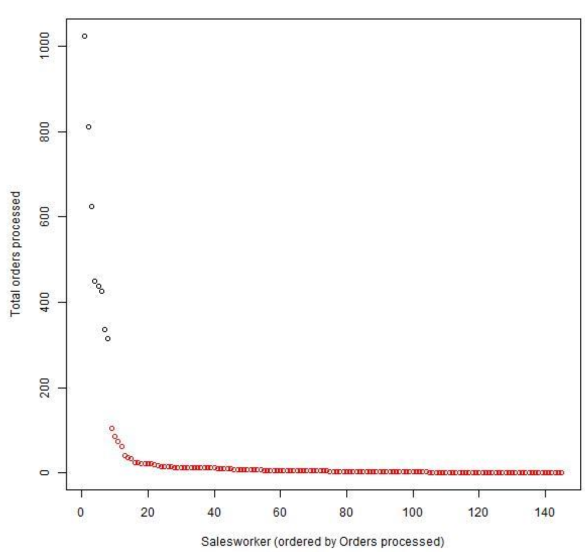
The method for classification uses transactional data from 2 months of purchases in the selected stores. First it classifies the different products sold between the departments in which the sales workers are to be associated with. Secondly it ranks the employees by number of transactions made in which a product from a department is involved. In other words, if a purchase includes two products from Audio & Video and one from Videogames, that sales worker had made one transaction for Audio & Video and one for Videogames.

After having each possible association ranked by the number of transactions, it calculates the differential against the upper sales worker. So if the first one has 100 transactions, and the second one has only 90, its differential is $100 - 90 = 10$. Also it calculates this differential divided by the level, which in this case would be $10/90 = 0.11$.

The method excludes all the employees that makes at least the 50% of the revenue for the specific department, immediately considering them part of the sales workers for that department. On the other extreme, all employees with less than 5 transactions or less than the 1% of the transactions made by the best employee for that department, are immediately considered not to be part of the sales workers for that department.

For the remaining candidate employees, the method searches for the maximum differential divided by level, which represents the maximum relative drop in transactions between one employee and another. This gap represents the limit between sales workers for that department and the rest of employees who are just supporting the sales process.

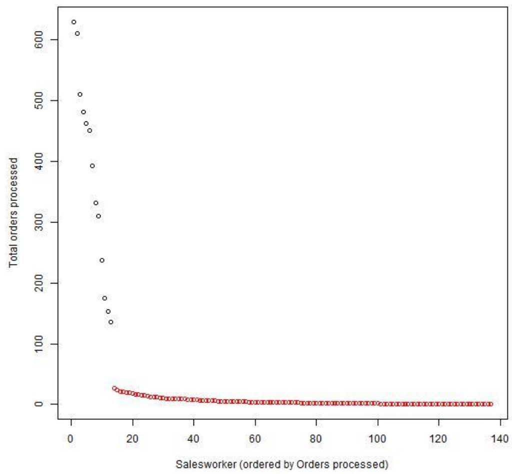
Here we show some examples of the classification results. Employees ranked by number of transactions in a certain department, in red the ones not classified as from that department.



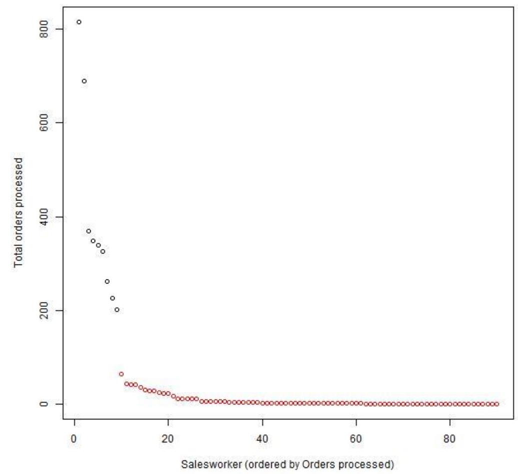
This diagram corresponds to the Sport Shoes for the Store 2.

Each circle is a specific employee who has made a transaction involving a product associated with this department in the time windows used.

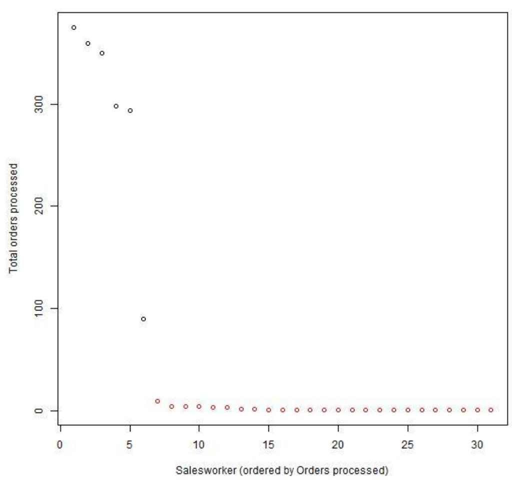
Black circles are classified as sales workers for the Sport Shoes department in the Store 2.



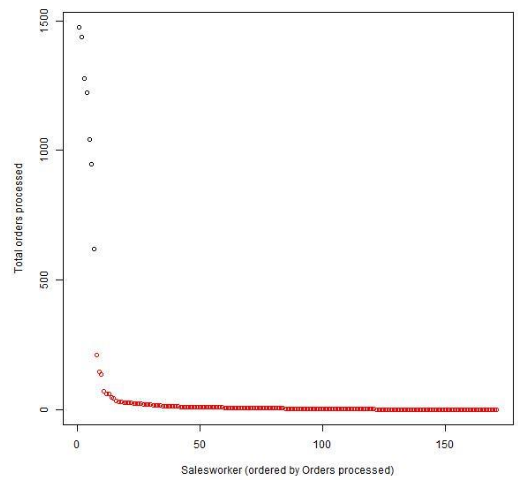
AUDIO & VIDEO – STORE 1



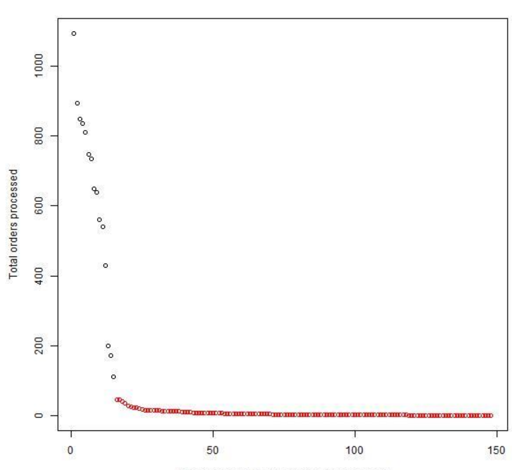
COMPUTERS – STORE 1



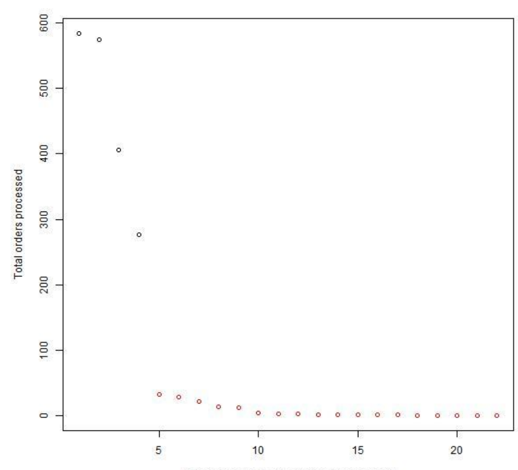
VIDEOGAMES – STORE 2



SMALL ELECTRIC APPLIANCES – STORE 2



SMARTPHONES – MIRROR STORE 1



BIG ELECTRICAL APPLIANCES – MIRROR STORE 2