UNIVERSIDAD DE CHILE
FACULTAD DE CIENCIAS FÍSICAS Y MATEMÁTICAS
DEPARTAMENTO DE INGENIERÍA INDUSTRIAL

# EMPIRICAL STUDY OF DURATION AND NATURE IN PRICE DISCREPANCIES IN SUPERMARKETS OF CHILE

TESIS PARA OPTAR AL GRADO DE MAGÍSTER EN GESTIÓN DE OPERACIONES

MEMORIA PARA OPTAR AL TÍTULO DE INGENIERO CIVIL INDUSTRIAL

VÍCTOR ALBERTO SALDÍAS FIGUEROA

PROFESOR GUÍA:
MARCEL GOIC FIGUEROA

MIEMBROS DE LA COMISIÓN:
MARCELO OLIVARES ACUÑA
ALEJANDRA PUENTE CHANDIA

This research has been funded by Centro de Estudios del Retail

SANTIAGO OF CHILE
MAY 2020

ABSTRACT THESIS TO OPT THE
GRADUATE DEGREE IN OPERATIONS MANAGEMENT
BY: VÍCTOR ALBERTO SALDÍAS FIGUEROA
DATE: MAY 2020
PROFESSOR: MARCEL GOIC FIGUEROA

EMPIRICAL STUDY OF DURATION AND NATURE IN PRICE DISCREPANCIES IN SUPERMARKETS OF CHILE

Since the implementation of price scanners, there has been concern about the accuracy of the charges, which can generate consumer dissatisfaction. For example, according to the Servicio Nacional del Consumidor, it is identified that among the claims made in the year 2015, 21 % corresponds to bad price collection by the large supermarket chains in Chile.

This work studies the precision with which digital scanning systems reflect the prices reported on supermarket shelves together with the perception of the price to pay that the clients have; and pursues three main objectives: (1) determine the nature of price discrepancies, (2) characterize the discrepancies and ( 3) explore the mechanisms after their duration. From the sample collected in supermarkets in the Metropolitan Region carried out in 28 rooms, in a period of 18 weeks the existence of three types of natures was identified (1) shelf-label discrepancy, (2) product discrepancy and (3) discrepancy discount not attributable to the shelf-label. They have different repercussions for consumers, reflecting the lack of proper product management and the loss of opportunity to obtain brand loyalty.

Regarding the level of discrepancies observed, 4.3 % is a favorable charge for the supermarket and 10.4 % favors the customer, obtaining an accuracy in collections of 85.3 %. With which, it is presented that despite the existence of erroneous charges, the client is usually favored, contradicting the initial assumption. Incidence is studied depending on factors such as the day, the promotion, the geographical area and supermarket studied, having differences in performance depending on that.

In order to describe the duration of the discrepancies, a second sampling was carried out, carried out in a particular room. Where, in the 28-day period, the shelf-label price of 76 products was recorded daily, so by crossing with the information provided by a transactional database, the price charged to customers could be obtained, therefore, the precision rate was 78.0 %, with consumer-friendly charges again dominating with 89.0 % of total discrepancies. Then, it is empirically proved that the charges that favor the supermarket are corrected much quicker than when they favor the consumers, which is validated by adjusting according to duration models in discrete time and counting.

With what has been studied, it is presented that the level of collection precision is well below international standards, which raises the implications for consumers and supermarkets, together with waiting for the application of regulatory protocols that allow reversing the situation and making a monitoring their evolution.

RESUMEN DE LA TESIS PARA OPTAR AL GRADO DE MAGISTER EN GESTION DE OPERACIONES
POR: VÍCTOR ALBERTO SALDÍAS FIGUEROA
FECHA: MAYO 2020
PROF. GUÍA: MARCEL GOIC FIGUEROA

# ESTUDIO EMPIRICO DE DURACIÓN Y NATURALEZA DE DISCREPANCIAS EN PRECION EN SUPERMERCADOS DE CHILE

Desde la implementación del uso de scanners de precios ha existido preocupación sobre la precisión de los cobros, que pueden generar insatisfacción de los consumidores. Por ejemplo, de acuerdo al Servicio Nacional del Consumidor se identifica que entre los reclamos efectuados en el año 2015, el 21 % corresponde a mal cobro de precios por parte de las grandes cadenas de supermercados en Chile.

En este trabajo se estudia la precisión con que los sistemas de escaneo digital reflejan los precios avisados en las góndolas de los supermercados junto con la percepción del precio a pagar que tienen los clientes; y persigue tres objetivos principales: (1) Determinar la naturaleza de las discrepancias de precios, (2) caracterizar las discrepancias y (3) explorarlos mecanismos tras la duración de ellas. A partir de la muestra recogida en supermercados de la Región Metropolitana realizada en 28 salas, en un periodo de 18 semanas se identificó la existencia de tres tipos de naturalezas (1) discrepancia de fleje, (2) discrepancia de producto y (3) discrepancia de descuento no atribuible al fleje. Aquellas tienen distintas repercusiones para los consumidores, reflejando la falta de manejo adecuado de los productos y pérdida de oportunidad de obtener lealtad de marca.

En cuanto al nivel de discrepancias observado, se tiene que en un 4,3 % es un cobro favorable para el supermercado y en un 10,4 % favorece al cliente, obteniendo una precisión en los cobros de un 85.3 %. Con lo cual, se presenta que pese a la existencia de cobros errados, se suele favorecer al cliente, contradiciendo la suposición inicial. Se estudia la incidencia dependiendo de factores tales como el día, la promoción, la zona geográfica y supermercado estudiado, teniendo que existen diferencias en los desempeños dependiendo de aquello.

Con el propósito de describir las duraciones de las discrepancias se desarrolló un segundo muestreo, realizado en una sala en particular. En donde, en el periodo de 28 días se registró diariamente el precio de fleje de 76 productos, con lo cual al cruzar con la información provista por una base de datos transaccional se pudo obtener el precio cobrado a los clientes, obteniendo que la tasa de precisión es del 78,0 %, predominando nuevamente los cobros favorables para los consumidores con un 89.0 % del total de discrepancias. Luego, se prueba empíricamente que los cobros que favorecen al supermercado se corrijen mucho más rápido que cuando favorecen a los consumidores, lo cual se valida al ajustar según modelos de duración en tiempo discreto y de conteo.

Con lo estudiado, se presenta que el nivel de precisión de cobros está muy por debajo de estándares internacionales, con lo que se plantean las implicancias para los consumidores y supermercados, junto con esperar la aplicación de protocolos regulatorios que permitan revertir la situación y hacer un seguimiento en su evolución.

*Unos llegan, otros se van, al final quedan los de siempre.*

*Gracias a ti por estar conmigo.*

# Agradecimientos

En primer lugar agradezco a mi familia, a mis padres Sandra y Víctor, por el incansable trabajo que han hecho para que yo pueda cumplir mis sueños, sé que sin ellos, no hubiese llegado hasta aquí y nunca dejaré de dar las gracias por el esfuerzo hecho. Por los desvelos ayudándome con los trabajos del colegio, con los almuerzos y desayunos que me prepararon por años, y por sobre todo por la inmensa preocupación por mi.

Agradezco a mi hermano Sebastián por los innumerables momentos de juegos, peleas y risas que hemos vivido juntos, de los partidos de fútbol que teniamos, de jugar FIFA, o simplemente ver cualquier programa juntos. Siempre estaré feliz de tu compañía y sé que siempre nos tendremos el uno con el otro.

No puedo dejar de agradecer a mis abuelos y tíos, quienes de una u otra forma han sido parte de mi proceso de formación educacional y obviamente personal, me han ayudado cuando más los he necesitado. Me han dado muchas palabras de aliento que me han motivado a seguir esforzándome para hacerlos sentir orgullosos.

A lo largo de los años he conocido mucha gente a los cuales también me gustaría agradecer porque pese a no estar en contacto actualmente, les agradezco los momentos que compartimos.

Gracias a los amigos que he hecho en el colegio, a Cristóbal, Martín, Pablo, Gonzalo y Enzo, junto a ustedes compartí muchas experiencias y confidencias.

Gracias a los amigos de la Universidad, al Piño, Alonso, Diego, Pablo, Rodrigo, Paz, Edgar, Ignacio, Morales y Marcela por todas las tardes de estudio en la oficina, los asados, los partidos y chistes que vivimos juntos.

Gracias a la bandita MGO, Felipe, Pablo, Sebastián e Ignasi, por todo el apoyo para que esos ramos tan duros se hicieran más amenos.

Gracias a los profesores que he tenido en mi vida por sus enseñanzas de vida, que son las que más valoro, en especial a los profesores que apoyaron este trabajo Marcel Goic, Marcelo Olivares y Alejandra Puente.

Finalmente, gracias a mi polola Javiera por siempre apoyarme y darme palabras de aliento cuando más desanimado me sentía, por su cariño y amor que me motivan a superarme. Sé que la vida nos depara muchas cosas juntos y agradezco a la vida por eso.

# Table of Content

# List of Tables

# List of Figures

# Chapter 1

# Introduction & literature review.

## 1.1. History of price scanners

At age 14, Clarence Saunders dropped out of school, and until age 20 he worked in various jobs linked to commerce. At the age of 21, he founded his first wholesale store, which helped him to understand the problems that affected this type of business. These were the costs related to personnel. In 1916 he founded the first supermarket in Memphis, called *Piggly Wiggly*, which was a self-service store, which presented as main innovations, the fact that customers had to go through the aisles and collect the products that they wanted, without the need for the supermarket staff to deliver them, to finally pay them to the cashier, which meant that the time they spent making their purchases would be much less than they usually used under the old flexibility, which Saunders it placed customers at the pinnacle of importance; and focused the business on them.

The innovation allowed him to reduce costs in personnel and to expand these stores throughout the United States, due to the good acceptance by the customers, who appreciated that the time needed to buy were reduced, along with the fact that this type of ordering implied an improvement in supermarket facilities, providing better lighting and cleaning.

Over the years and the adoption of the customer-centric approach by retail stores, they expanded exponentially throughout the world, allowing the time needed to obtain products from customers to be reduced. It is in this way that the problem became another: given the high number of different products that should be handled in inventory, there were problems of control of these, accentuated by the enormous expenses that had to be incurred in order to improve that situation. The above caused errors in the collections of the products, together with the fact that the waiting times in the checkout were very high as a result of the increase in the flow of customers that circulated in them.

The Universal Product Coding (UPC) were introduced in 1970 in the supermarket industry to make purchase processes more efficient by the six largest chains assembled in The National Association of Food Chains (NAFC). UPC's are composed of particular digits indexed to manufacturers and product that would standardize the codes of items sold in supermarkets and provide information on product characteristics such as size and weight, along with information on its corresponding producer, and that later could be read by scanner's being possible to include information from the stores.

However, there was a certain concern on the producers because the creation of a universal code would imply a change in their production processes, in terms of the internal coding of their products. Finally, seven US companies agreed and with the development by RCA an 18-month trial period was launched at the Kroger store in Cincinnati during 1972. It is in that way that at Marsh's Supermarket in Troy, Ohio, at 08.01 a.m. on June 26, 1974, Clyde Dawson made the first purchase using this technology being taken care of by Sharon Buchanan, acquiring a pack of 10 Wrigley's chewing gums, that package along with the receipt are displayed in the Smithsonian Institute.

After 10 years since its implementation, it was estimated that one third of the grocery stores had these devices, while by 2004, according to Fortune Magazine, between 80 and 90 % of the 500 leading US companies use codes of bar, exemplifying its acceptance by the industry.

## 1.2. Supermarkets in Chile

In 1957, in Providencia, the first supermarket in Latin America, "Almac", was born, which would lay the foundation for the subsequent decades, gradually, to be extended in Chile. This is how in 1991, the bar code and laser readers debuted, being the architects of the best in the inventory and supply processes, together with the reduction in costs.

Regarding their participation in the national economy, considering the declarations issued by the four major chains of this industry in June 2011, they had sales of 4,305 million USD so that in June 2016 there was a growth of 57.8 %, generating sales around 6,795 million USD. Which means that the contribution of this industry to the Gross Domestic Product (GDP) of Chile corresponds to approximately 5.0 %, according to the information provided by the Central Bank of Chile.

Despite its constant growth, the supermarket industry faces a number of challenges. From the consumer's satisfaction point of view, it is important to track the number of nature of customer complaints. For example, Servicio Nacional del Consumidor (SERNAC), an organization that keep vigil over the rights of consumers, there is a large number of complaints in relation to a wrong charges of prices in supermarkets, being estimated that 15 % of the total claims correspond to this problem.

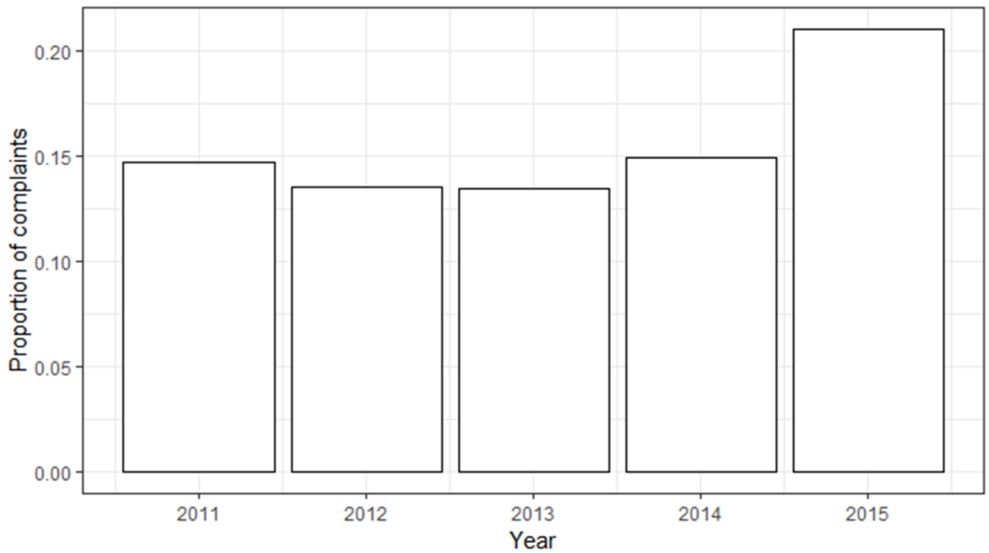


Fig. 1.1: Evolution of proportion of complaints about incorrect charges

Figure 1.1 shows the evolution of the rate of claims received by SERNAC on the existence of erroneous charges in supermarkets, this is how since 2013 the proportion is rising, reaching 21.0 % for the year 2015. These statistics question the proper handling of shelf-label prices by supermarkets, and they seem to indicate that consumers are more active in requiring a higher quality of service, identifying erroneous charges, which can cause loss of confidence, having negative repercussions for the industry. While the feeling of systemic damage is generated for customers.

Therefore, considering that this industry receives large amounts of daily transactions, and that incorrect charges have been identified by consumers, the Centro de Estudios del Retail (CERET) conducts a study to measure the perception and attitudes of customers regarding price discrepancies. It was obtained that 48.0 % of the respondents almost always check that the shelf-label price and the price charged coincide, 16.0 % do it on certain occasions depending on the product and if the purchase is large, and 36.0 % never make. Then, when asked about who they believe favor the wrong charges, 65.0 % said they favor the supermarket, 25.0 % that there is no trend, while only 10.0 % believe that the customer is mostly favored [Estudio de inconsistencias de precios en la industria supermercadista, CERET, 2018].

With what was obtained in that research, the importance of studying the existence of price discrepancies and determining the duration of them in the supermarkets of the Chilean industry is supported. It is presented that a significant proportion of consumers do not review the invoices, together with unveiling asymmetric behavior when detecting a discrepancy, depending on who favors. This allows to assume that the persistence time of the erroneous charges is different, having a negative impact on both the customer and the supermarket.

## 1.3. Literature review

This study is related to two streams of research. The first corresponds to determine the impact of the use of price scanners in retail operations, while the second, studies the influence that information on inaccuracies can have in stores and in particular in customer satisfaction.

With regard to determining the impact on operations, the introduction of price scanners led to the elimination of the need to label each of the products with their respective price, so the amount of personnel required was reduced along with inducing a reduction in the rate of errors in price collections from 12.0 %, when using the manual collection method to 4.0 % after its implementation. Additionally, it was predicted that the use of scanners would imply faster checkout times and bills with more information and detail [Pommer, Berkowitz and Walton, 1980]. However, there were already some complaints about the difficulty that consumers would have in detecting erroneous charges because they would be complex to remember the price of the shelf label [Cutter and Rowe, 1990].In particular, it was claimed that 64 % of consumers believed that the use of these devices would provide a more efficient purchasing environment, 15 % believed that prices would be right, while 20 % of them thought otherwise [Langher and Robinson, 1979].

Particularly, in Chile no studies have been carried out that seek to identify the level of precision that supermarkets have in terms of price accuracy, that is, the consistency in the price displayed in the shelf-label with which it is subsequently charged at checkout. However, corroborating these types of situations is relevant, because these problems persist in supermarkets. In addition, it is important to determine whether favorable supermarket charges are more likely to occur for products with high prices than for low price products such as groceries [Grewall and Compeau, 1999].

In the 1990s the accuracy of charges using price scanners was extensively studied, nonetheless, these researches have ceased, explaining that the standards achieved in the countries under investigation, together with the measures imposed by government entities, allowed to increase accuracy to adequate levels.

This is how a series of publications made by government agencies and academics are identified, mainly trying to determine the operational impact of UPC. Thus, in 1988, the New Jersey Division of Consumer Affairs showed that the presence of favorable charges for the supermarket was almost double that favorable for the customer, along with the fact that the associated costs for consumers were three times that the consequent savings of undercharges [Welch and Massey, 1988]. Then, the Virginia Office of Weights and Measures conducted a study of more than 38,000 products, in 1000 stores in different areas of that state. Obtaining that in grocery stores a level of precision of 96.24 % is reached, having the undercharges in this type of stores were 1.93 %, while for stores of other type, the precision was 93.81 %, where again the favorable charges for customers were higher [Virginia Office of Weights and Measures, 1990].

In New York City, inspectors from the Department of Consumer Affairs visited 21 grocery stores for 3 days, to assess the price charged on promotional products. This is how they identified that in 10.0 % of the products, there were overcharges. In addition, it could be evidenced that half of the stores evaluated did not present such discrepancies, highlighting that in three stores no errors were detected. [Department of Consumer Affairs, 1991].

Subsequently, the Department of Food and Agriculture, Division of Measurement Standards conducted a study in different stores in the state of California, checking the price of 30 products, of which 50.0 % of them had some type of promotion. It is in that way that a level of discrepancies of 4.13 % was detected, being lower for grocery stores with 3.14 % compared to 5.24 % for stores of other types. However, favorable discrepancies for the supermarket prevail for both groups, with 2.11 % of overcharges and 1.03 % undercharges for grocery stores and 2.96 % and 2.28 %, respectively, for other stores. Despite this, 62.7 % of grocery stores and 46.5 % did not show overcharges. In Michigan in 1993, a similar study was conducted that identified an error rate of 9.0 %, of which 83.0 % of them were favorable discrepancies for the supermarket. [Holyfield, 1993].

The unit of Weights and Measures of the Department of Public Service of the state of Minnesota, evaluated the performance of 159 stores, where it was obtained that the accuracy rate was 96.2 %. Grocery stores reach they have a correct charge rate of 96.5 % and stores of other types 95.7 %. However, this study shows that the undercharges are higher than the overcharges, so on average, there is 2.3 % of positive charges for the customer and 1.5 % when not [Blacik, 1994].

The Department of Finance in Seattle, Washington conducted an inspection of the use of price scanners between 1994 and 1996, visiting 259 stores, obtaining as a result that the proportion of stores that did not have overcharges from 12.5 % in 1994 to 38.7 % in 1996. Despite this improvement, the number of stores that did not pass the evaluation, that is, obtained a level of accuracy below 98 % reached 45.4 % for grocery stores and 21.1 % for other stores in 1996 [Leisy, 1996].

On the other hand, in a study carried out in Tennessee, an error rate of 6.64 % was obtained, where 47.47 % of them corresponded to favorable charges for consumers. This research was conducted in 173 stores, checking the price of 13,475 items [Williams, 1996].

Previously, the effect of UPC had been studied exclusively by State, so the Federal Trade Commission (FTC) led a national study, considering the participation of the states of Florida, Massachusetts, Michigan, Missouri, Tennessee, Vermont and Wisconsin to assess price accuracy. For which the standards provided by the National Conference of Weights and Measures (NCWM) were used. Thus, 294 stores were evaluated along with 17,298 products. The results obtained reflect that for grocery stores, the percentage of errors reaches 3.47 %, of which 55.29 % are overcharges; and in store of other types, 5.54 % of the products reviewed have a incorrect charge, of which 43.61 % is a charge that benefits the supermarket. Similarly, it was established that 66 (22.45 %) stores accomplished an accuracy level of 100 %, while 98 % accuracy was achieved by 132 (44.90 %) of the stores.

The previous studies differ with this investigation in the measurement method and the consequent definition of what we consider a price discrepancy. In this , in this case, the shelf-label price is the price that the consumer considers that he will pay for the product, which is different from the performance of audits, where it is verified the SKU code is the same. This approach allows to know the existence of other problems that have not been previously studied, such as poor product disposition or unclear strips.

The above is important to note because under this methodology it is prioritized to know the perceptions that consumers have about the prices to be paid, assuming that in their purchase process, consumers are not responsible for checking the correspondence between the SKUs. Additionally, the existence of other natures of undocumented inaccuracies allows us to identify shortcomings by the supermarket operation, which can cause a decrease in customer satisfaction.

Additionally, considering that supermarkets are customer-centric, that those who are not able to recognize the price they pay for their products, would indicate not only operational and product replacement failures, but also that interest has also been lost in user experience

With respect to academic research, in the 70s and 80s, the perception that consumers had about the use of price scanners was studied, seeking to elucidate if they perceived improvements, however, they did not see great benefits in terms of precision in price charges [Harris and Mills 1980]. In relation to the above, it was wanted to confirm if customers were able to remember the price of the products they bought, which determined that at the time of going through the checkout they no longer remembered them [Gylling, 1976]. Complementing the fact that customers do not compare the prices charged with the shelf label prices [Dickson and Sawyer, 1990].

It is in this way that the first corresponds to that made by Welch and Massey (1988) in which 205 trips were made in 6 large chain stores in New Jersey, from which it was identified that errors are more common to be overcharges. While in New Zealand, Garland (1992) verified the accuracy of prices in grocery stores, obtaining an error rate of 4.29 %. The proportion of undercharges was 2.39 % and 1.65 % for overcharges, contradicting previously done.

Goodstein (1994) studies performance in terms of overcharges and undercharges, through trips to supermarkets from the two most important chains in the United States that use the scanner system. This is how it was identified that in products that do not present promotions, 4.77 % present undercharges, and in 3.58 % overcharges, while in the presence of promotions, the values become 1.75 % and 7.25 % respectively . The fact that there are favorable charges for the supermarket in the presence of promotions is relevant to study because they increase traffic in the store [Kumar and Leone, 1988] and the sales volume of the products [Sethuraman and Tellis, 1991].

For its part, Clodfelter (1997) during 1994, studied the accuracy of prices in 1,700 items from 21 different stores, so when analyzing the results an error rate of 7.88 % was found, where overcharges correspond to 4.29 % and undercharges at 3.59 %, which again presents a tendency to favor the retailer. In addition, 5 of the stores achieved an accuracy level greater than 98 %. Then, the same author, Clodfelter (1998) analyzed the accuracy in charges in 9 states that adhered to use the protocols and procedures provided by the NCWM, being these Alaska, Delaware, Georgia, Kansas, North Carolina, New Hampshire, Carolina South, Washington and West Virginia, over a 36-month period. It is in this way that 146,518 items were checked in 2,388 stores, obtaining that in 5,663 (3.87 %) products there was an erroneous charge of the price, where 2,423 (1.65 %) of them had an undercharges and 3,240 (2.21 %) overcharges. When evaluating the behavior according to the type of store, it has to in grocery stores, the error rate reaches 2.74 % with 1.27 % for overcharges and 1.47 % for undercharges, while for stores of other types, the incorrect charges are 6.01 %, along with a favorable charge for the retailer at 2.38 % and 3.62 % favorable for consumers.

More recently, Pickering and Gaur (2009) mentioned that although this issue was considered 'dead', the existence of overcharges still persisted. This is how they conducted an exploratory study in New Zealand to determine the opinion of consumers about these types of situations. It was obtained that more than half of the respondents said they verify their bill after buying, and of them 96.0 % believe that the supermarket usually makes mistakes in the charges. Finally, 48 % of the respondents affirm that given the existence of discrepancies, they would choose to change stores.

Similarly, Hardesty et al. (2014) refloated the investigations of accuracy in prices, for which they used two large samples. For the first, the Federal Trade Commission organized a study in 36 states, during a three-month period to obtain information about the charges of 107,096 products from 737 stores of different types. An error rate of 3.16 % was obtained, with 1.94 % for undercharges and 1.22 % for overcharges for products without promotion. In addition to identifying that the deviation from the price charged is greater for charges that favor consumers. However, for products with promotion the proportion of overcharges is 2.28 % and for undercharges it is 1.28 %, in addition to the fact that the price deviation is greater when the supermarket is favored. It was also possible to identify that the proportion of overcharges is lower in grocery and mass merchandise stores, while undercharges are lower in grocery stores and drug stores. Finally, it is obtained that for higher prices, the ratio of overcharges to undercharges declines.

On the other hand, using the information collected by the State of Washington's Consumer Affairs Unit from 1996 to 2010, the performance of 231,760 products was obtained, with an error level of 4.08 %, with 1.75 % for overcharges and 2.33 % for undercharges Analyzing the characteristics of the stores and their impact on the existence of inconsistencies, it was observed that in more regulated industries, the errors were smaller, which also occurs in chains with more stores than in those with less quantity. Finally, it was obtained that the temporary price reduction reduced the probability of presenting a discrepancy, while the effect of promotions had the opposite effect.

Again, these studies focused on elucidating the existence of discrepancies by conducting audits and not a costumer-based study and its perceptions. Likewise, it has not been considered to determine the time it takes for an erroneous charge to be rectified, nor to know the patterns that influence that, which reaffirms the contribution of this study.

Other researches have sought to determine the economic damage that consumers have in relation to overcharges, being 2.5 billion USD [Bartholomew, 1992], and subsequently it was estimated that annual losses would be of the order of 1 billion USD [O'Connell, 1993 ]. This allows to know the great impact that incorrect charges have on the economy of people, and how it affects large profits for retailers.

Table 1.1 presents a summary of the studies carried out previously, highlighting the results obtained in terms of accuracy and error percentages disaggregated according to the type of incidence detected. It is noted that the proportion of discrepancies that favor the customer is greater than those that favor the retailer.

Table 1.1: Summary of studies related

| **Study** | **Year** | **Governments** | **Academic** | **Undercharges** | **Overcharges** | **Acuracy** |
|---|---|---|---|---|---|---|
| Virginia Office of Weights and Measures | 1990 | x | | 2.47 % | 2.37 % | 95.16 % |
| Department of Food and Agriculture of California | 1993 | x | | 1.62 % | 2.51 % | 95.87 % |
| State of Michigan | 1993 | x | | 1.53 % | 7.47 % | 91.00 % |
| Department of Public Service of Minnesota | 1994 | x | | 2.30 % | 1.50 % | 96.20 % |
| Federal Trade Commission | 1994 | x | | 2.58 % | 2.24 % | 95.18 % |
| State of Tennesse | 1996 | x | | 3.40 % | 3.06 % | 93.54 % |
| Garland | 1992 | | x | 2.39 % | 1.65 % | 95.71 % |
| Goodstein | 1994 | | x | 3.40 % | 5.59 % | 91.3 % |
| Clodfelter | 1997 | | x | 3.59 % | 4.29 % | 92.12 % |
| Clodfelter | 1998 | | x | 3.24 % | 2.42 % | 96.13 % |
| Hardesty | 2014 | | x | 1.94 % | 1.22 % | 96.84 % |

From the aforementioned studies, it can be seen that price accuracy has been studied extensively through the use of the scanner, using samples essentially in small stores and on reduced occasions in supermarkets. Taking into account that in smaller stores less items are handled in the inventory, control over them is easier with respect to larger stores, such as supermarkets. In addition, it is noted that studies of this nature have been interrupted in the last 15 years, as a result of which in the countries where they were carried out, regulatory measures were introduced that encouraged retailers to provide accurate prices.

Despite this, the time it takes to correct a discrepancy has not been studied, nor has the phenomenon been modeled with any mathematical specification that makes it possible to distinguish how quickly retailers can eliminate these problems depending on who favors the event. In addition, it seeks to confirm the incidence of the section to which it belongs and the shelf-label price, as was done in Hardesty et al. (2014), so it proceed to incorporate the day the product was sold to determine if there are seasonalities in this phenomenon.

Finally, bringing to the forefront the investigation of price accuracy allows to confirm whether access to new technologies by stores and supermarkets has provided more robust tools that facilitate the proper handling of shelf-label prices, in addition of permitting to have a centralized system of prices computationally efficient. Along with determining if customers are more active at the time of detecting erroneous charges since they are 'armed' with their cell phones [Grewall et al., 2012], being able to viralize the problem, leading to a large proportion of the retailer. In addition, to elucidate the current state of the Chilean industry, can lead to more rigorous inspections and the adoption of policies with a view to protecting consumers against wrong charges and to the detriment of them.

# Chapter 2

# A costumer-based evaluation of price inaccuracies in the supermarket industry

## 2.1. Data collection

The main objective of our evaluation is to measure price inaccuracies from a customer perspective. Therefore in our data collection procedure, we focus on comparing prices charged by the cashier against perceived prices.

Thus, the process was developed in an 18-week time window in Santiago, Chile. The selected supermarkets by participating costumers correspond to those belonging to the four chains with the largest market share in the national industry. The supermarkets are Unimarc from SMU, Tottus and Tottus Express from Falabella, Lider and Lider Express from Walmart, and Jumbo and Santa Isabel from Cencosud.

With the participation of 22 costumers, who, at the time of making their purchases, using the cameras of their mobile devices photographed the price they would think they would pay. Subsequently, after paying for the products, the bill was photographed, and later, the images were sent to the persons in charge of the investigation, who manually encoded the information and independently reviewed it to ensure its correctness. Also no product from the supermarket was restricted. The images received with information on the prices reported on the shelf-label and bills allow the contrast between the price that consumers thought they would pay, and finally the price paid by them. This characteristic of the study is distinctive from the previous ones, since the emphasis is placed on what consumers believe they will pay, which allows us to visualize discrepancies that in other contexts are not possible to achieve. In this way, our study focuses on the beliefs and perceptions of consumers.


Fig. 2.1: Examples of data obtained

It is in this way that a database was formed with 2,124 prices of products obtained from 28 stores in the Metropolitan Region, which are summarized in the table 2.1. In addition to what has already been explained, a variable is presented that details the date on which the price tag was printed and placed on the shelf-label, which, however, in 67.0 % of the data, did not exist. Additionally, the percentage deviation of the prices charged in cash with respect to the price that consumers observed in the shelf-label was calculated.

Our evaluation does not only provide a different metric than previously reported in the literature, but it also allow us to identify different sources of inaccuracies. It is understood by a discrepancy in price, to the difference between the price informed by the supermarket in the shelf-label and the price finally charged, which appears on the bill. That incorrect charge may be favorable for the customer or favorable for the supermarket, stating as follows:

- **Undercharge or favorable discrepancy for the customer**: It occurs when the price charged is lower than the shelf-label price, so it is a favorable situation for the customer, but harmful for the supermarket.

$$Price_{shelf} > Price_{charged} \tag{2.1}$$

- **Overcharge or favorable discrepancy for the supermarket**: In this case, the price charged is higher than the shelf-label price, so it is a favorable situation for the supermarket, but harmful for the customer.

$$Price_{shelf} < Price_{charged} \tag{2.2}$$

Recalling that in the case of undercharges, the supermarket incurs monetary losses that cannot be determined since it did not capture the price that the customer was finally willing to pay for the product, along with causing improper handling of their promotions, as a result of the erroneous existing assignment. While the overcharges, generate in the consumers dissatisfaction and insecurity about the reliability of their transactions, which can have an impact on legal actions or loss as a client of the affected. [Pickering and Gaur, 2009]

Table 2.1: Distribution of supermarkets

| **Chain** | **Supermarket** | **Format** | **Stores** | **Items** | **Discrepancies** |
|---|---|---|---|---|---|
| Walmart | Hiper Líder | Hyper | 7 | 420 | 47 |
| Walmart | Express de Líder | Traditional | 5 | 216 | 36 |
| Cencosud | Jumbo | Hyper | 7 | 325 | 35 |
| Cencosud | Santa Isabel | Traditional | 3 | 123 | 12 |
| Falabella | Tottus | Hyper | 2 | 449 | 53 |
| Falabella | Tottus Express | Traditional | 1 | 325 | 59 |
| SMU | Unimarc | Traditional | 3 | 266 | 71 |
| **Total** | | | 28 | 2124 | 313 |

In order to show an example of the data obtained in Figure 2.1, the photographs that allow determining the existence of discrepancies are presented, noting that the price of the shelf label and the price charged to them differs, being the same product in question .

## 2.2. Analysis

### 2.2.1. Discrepancy levels and directions

The first study seeks to identify whether overcharge are more likely than undercharges. Additionally, we analyze how these prices inaccuracies vary depending on product category, day of the week and the existence of promotional activities.

To start, an analysis of the proportion of discrepancies carried out is presented in Figure 2.2, which shows the existence of 92 (4.3 %) overcharges, 221 (10.4 %), undercharges and 1811 (85.3 %) products with no errors in their payment. Therefore, the level of price discrepancies corresponds to 14.7 %, which implies that there is an erroneous charge in approximately 3 out of 20 products.

Of the total discrepancies, 70.6 % is favorable for the customer (p-value $= 10^{-13} < 0.05$), which is more likely that, if there is a discrepancy, it favors the customer, contradicting the assumption raised.

On the other hand, we proceed to analyze the magnitude of the deviation from the price charged, where this value is 16.4 %. When disaggregating according to the type of discrepancy,

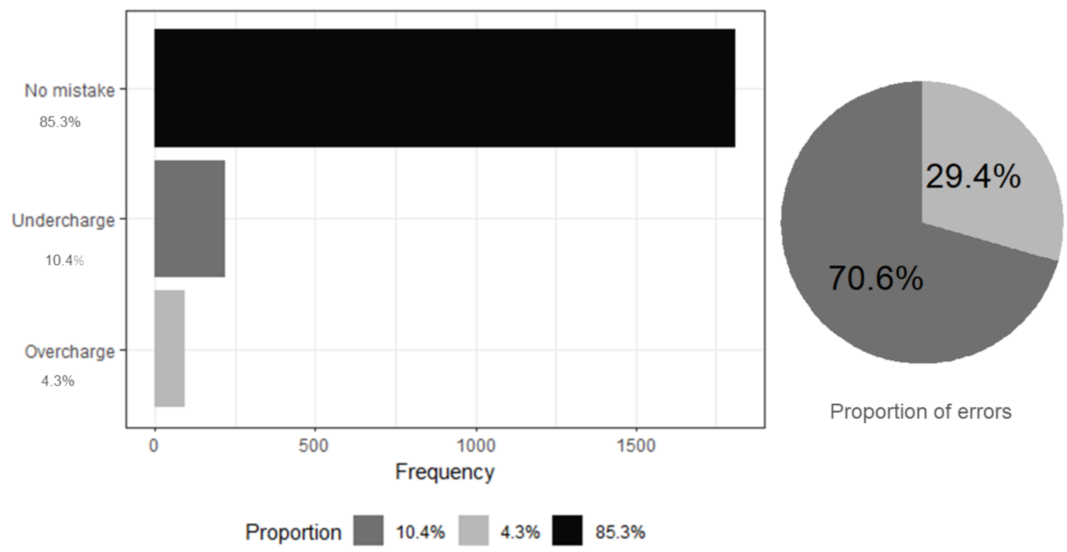


Fig. 2.2: Proportion of discrepancies

it has to the following: if the discrepancy is favorable for the customer, it has a magnitude of 17.90 %, that is, when buying a product of 1,000 CLP (1.25 USD), the consumer will be paying 821 CLP (1.03 USD), CLP 179 (0.22 USD less). While, if the discrepancy is favorable for the supermarket, the magnitude of the deviation is 12.77 %, that is, buying the same product, the customer will pay 1,127.7 CLP (1.41 USD), 127.7 CLP (0.16 USD more). Which realizes that in case of discrepancies in prices, the customer benefits more than the supermarket from incorrect charges.

### 2.2.2. Classification by types

The first analysis aims to determine the nature of the discrepancies, because it has only been established that these occur because the shelf-label price does not match the price that is finally charged to the customer. However, the way in which these errors are obtained has not been investigated. Taking into account that the study is costumer-based it is possible to elucidate the ways in which they identify the prices they will pay.

Reviewing each of the data obtained through the images collected from the shelf-label price and the bill, corroborating the reason why they were classified as a discrepancy. It was possible to identify three types of these origins, the first corresponds to what has been widely documented in the literature, which was called: shelf-label discrepancy, since there is a difference between the price presented in the shelf-label and charged on the bill, being the same product (equal SKU) and in the absence of promotions. That is the most problematic discrepancy, since it is the result of a slow price update with respect to centralized information.

Secondly, the existence of product discrepancies was identified, attributable to the fact that the customer see a price corresponding to that of another product as a shelf-label price, that is to say that the shelf product is not the same as that of the bill (different SKU) what confuses to clients and leads them to consider that they are in the presence of a discrepancy. This is a sign of poor handling of the shelf-label, being exposed carelessly, causing the consumer to be confused and find it difficult to know the price of the products that they want to buy.

Finally, there is a third reason to describe the origin of a discrepancy, this corresponds to a price discount not attributable to the shelf-label, which means that the price on the bill has a discount that is not reflected in a change there and, therefore, the customer does not perceive it as the price they will be charged. This occurs when there is a promotion that is not exposed in the shelf-label, so the customer is unaware of its existence. This does not allow the supermarket to show the customer that the prices charged are low, losing the opportunity to increase customer loyalty.

In the sample, 67.74 % of the discrepancies corresponded to shelf-label discrepancies, 9.90 % to product discrepancies and 22.36 % to price discounts not attributable to the shelf-label.

With that in mind, we proceed to analyze how the proportion of inaccuracies varies without including some type of nature described above. When discrepancies of discounts not attributable to the shelf-label are not considered, the proportion drops from 14.7 % to 13.3 %, of which 60.0 % are favorable discrepancies for the consumer (p-value = 0.002 <0.05). On the other hand, when product discrepancies are not included, the error rate drops to 11.4 %, splitting by 69.1 % in cases favorable to the customer, and 30.9 % for cases favorable to the supermarket (p-value = 0.00 <0.05). And when only consider the discrepancies that correspond to the shelf-label, the level of precision reaches 90.0 %, of which 60.8 % of these are undercharges (p-value = 0.002 <0.05).

This section shows the existence of two new natures of price discrepancies, in addition to that already extensively documented. This allows to show that there is not only a problem in the handling of shelf-label updates, but also that there is a bad disposition of these, which tend to confuse the customers about the price of the product they is buying. Which, despite not being an erroneous charge as such, results in a reduction the satisfaction generated by the customer to go to buy in said store, which in the long term entails damages similar to the existence of a wrong charge .

The other type of source of discrepancies has a close relationship with the application of discounts that the customer does not see on the shelf-label or explicitly on the bill, which,

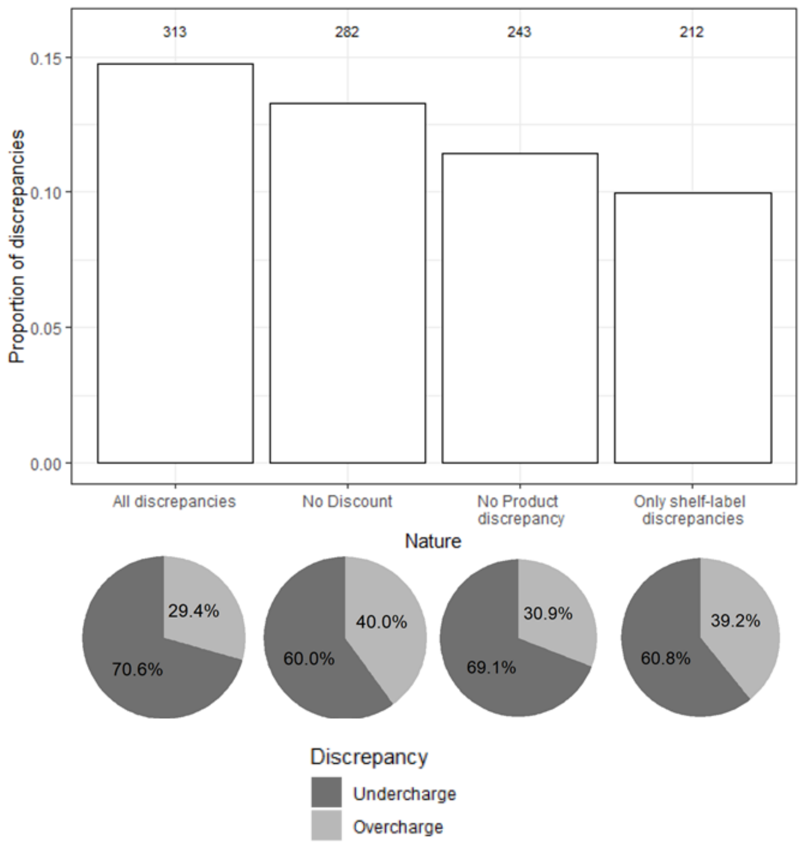


Fig. 2.3: Discrepancies according to nature

while not bad for the customer, is an opportunity not used by supermarkets to show their clients that prices are lower than they were going to pay at the beginning, being able to obtain a benefit if that were known.

#### 2.2.2.1. Accuracy by category

To assess whether the situation is transversal in the different categories available in the sample, together with identifying those in which the eventuality is more exacerbated and more attenuated, it proceed to study the proportions of discrepancies in them.

Through the different categories it is obtained that on average there is 15.2 % discrepancies. In particular, a favorable charge for the customer is presented in 10.3 % of the observations and a 4.9 % favorable for the supermarket. In turn, there is a tendency that the percentage of overcharges are lower than undercharges, however, the exception is in the categories corresponding to meats, alcoholic beverages and fruits, in which the proportion of overcharges are higher, being 71.4 %, 66.7 % and 60.0 %; while the proportion of undercharges are 28.6 % (p-value = 0.257 >0.05)[1], 33.3 % (p-value = 0.563 >0.05) and 40.0 % (p-value = 0.655 >0.05) respectively, however, it cannot be concluded that the foregoing is statistically significant.

Thus, the category with the highest proportion of discrepancies corresponds to that of fish and shellfish, where it is possible to find that in 1 of every 5 products there is a incorrect charge (20.0 %). Conversely, the category with the least errors is that of alcoholic beverages where 1 out of every 11 products has an inconsistency (8.57 %).

Finally, when studying how the behavior of the percentage deviation of the price charged is, the tonic is that the magnitude is greater for undercharges, having that in 66.0 % of the categories. Consequently, the greatest deviation is observed in the category of alcoholic beverages with 27.8 %, which is composed of a percentage deviation of 40.0 % for overcharges and 2.0 % for undercharges. In counterpart is the section of fish and shellfish where the magnitude rises to 7.0 % (6.4 % favorable customer and 10.1 % favorable supermarket). What it realizes, that there is a tendency to have an advantage on the part of consumers in the presence of erroneous charges.

#### 2.2.2.2. Accuracy by day of the week

Understanding that in the supermarket industry there are certain seasonalities during the week, since sales increase considerably as the weekend approaches, so it is important to study the behavior of discrepancies according to the day of purchase, to identify the existence of

[1]The test used for proportions is a Chi-square test

some tendency, or pattern.

It is in this way that it is appreciated that there is no marked effect of differentiation of discrepancies according to the day, however, it can be seen that on Tuesday it has the highest proportion of discrepancies with respect to the number of purchases made on that day, with 19.2 %, where 73.0 % (p-value $= 0.005 < 0.05$) of these are undercharge, while on Sunday the proportion is the lowest with 10.3 %, with 86.8 % (p-value $= 10^{-6} < 0.05$) of them favorable for the costumers. Every day of the week the quantity of undercharges are greater than the overcharges.

On the other hand, the proportion of overcharges is higher on Saturday with 44.7 % (p-value $= 0.46 > 0.05$), which indicates that the null hypothesis cannot be rejected, whereupon, statistically on Saturdays the proportion of discrepancies of each type have a similar value.

It can be seen in Figure 2.4 that from Thursday to Sunday, the level of discrepancies decreases and then increases on Mondays and Tuesdays, dramatically decreasing on Wednesday, which indicates that taking into account that on weekends the number of customers attending to the stores increases with respect on business days, there is a greater concern to offer a good service, so the supermarket managers seek to have the shelf-label updated.

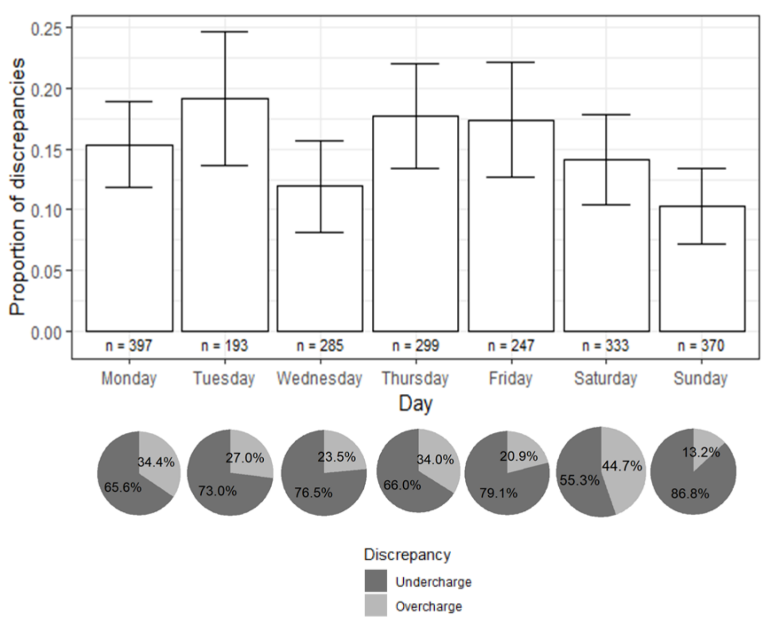


Fig. 2.4: Discrepancies according to the day

#### 2.2.2.3. Accuracy by chain & supermarket

Among the four chains with the highest market share in the national industry, there is a disparity in their performance at the time of having consistency in the prices shown on the shelf-label and the prices finally charged at checkout, with an average discrepancy rate of 16.2 %, where SMU has the worst performance with a proportion of 26.7 %, of which 67.6 % (p-value $= 0.003 < 0.05$) are undercharges. On the opposite side, with the best performance, is the Cencosud chain, which has an erroneous charge rate of 10.5 %, so that 66.0 % (p-value $= 0.029 < 0.05$) corresponds to the favorable discrepancies for the customers, thus, statistically, the proportions of the type of discrepancy are different.

The previous study denotes that there is a substantial difference in the performance of the chains, however, it dominates the existence of favorable discrepancies for the customers over the negative ones for them.

When referring to the chain with the highest proportion of overcharges, SMU is found, where 8.65 % of the cases correspond to the aforementioned, and in contrast, the lowest proportion is owned by Walmart with 3.46 %. In turn, in this last chain, 73.5 % (p-value $= 10^{-5} < 0.05$) of the total discrepancies correspond to undercharges.

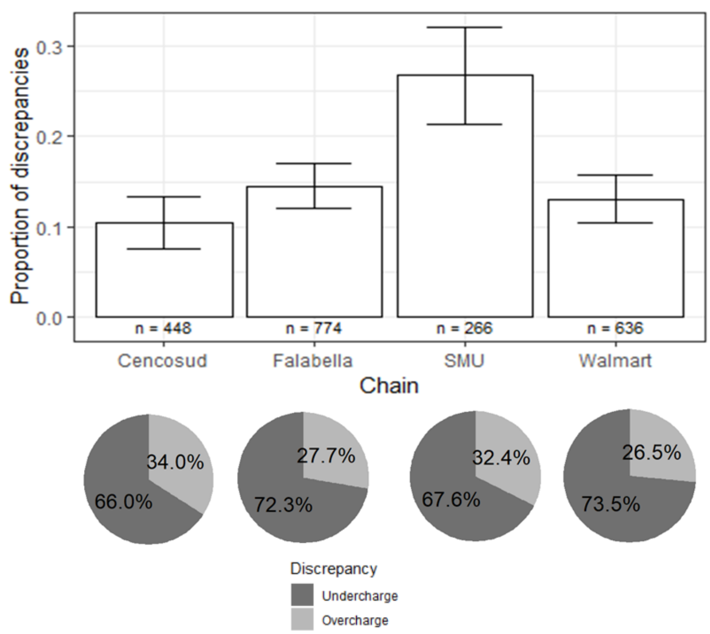


Fig. 2.5: Discrepancies according to chain

Analyzing the performance through the magnitude of the percentage deviation of the price charged, the Cencosud chain has the highest value with 22.2 %, decomposing in 26.9 % in cases favorable to the customer and in 12.9 % when not. While SMU has the lowest value with 11.1 % and is also the only chain where the deviation of prices in overcharges are higher with 13.1 % compared to 11.2 % for undercharges.

Disaggregating by supermarket, where with 26.69 %, Unimarc, belonging to the SMU group, is the supermarket with the highest level of discrepancies, of which 67.6 % (p-value = 0.003 <0.05) of them are undercharges. The supermarkets with the best performance correspond to Santa Isabel and Jumbo, both belonging to the Cencosud group, with accuracy levels of 90.24 % and 89.23 %. However, to this, Santa Isabel has a higher proportion of overcharges with 58.3 % (p-value = 0.564>0.05) so there is no evidence to reject that in this supermarket there is an inclination towards a type of discrepancy, and it is possible to say that there is a high percentage of favorable charges for the supermarket.

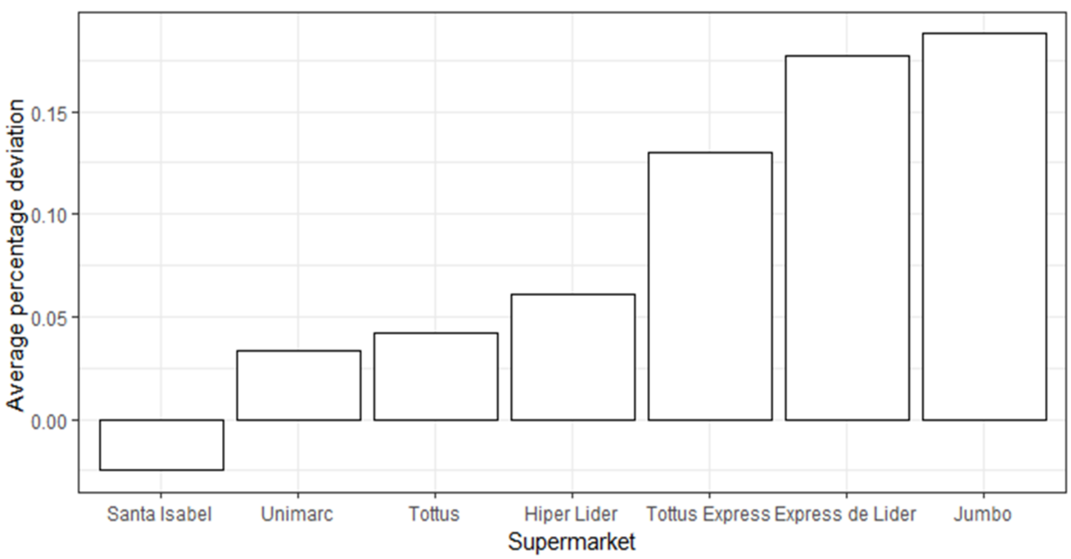


Fig. 2.6: Deviation of the price charged according to the supermarket

Finally, Figure 2.6 shows the average percentage deviation of the price charged, where it can be seen that there is a tendency to favor the customer, given that the values are positive, which implies that, on average, the price deviations when it is an undercharge are greater than when they are overcharges. However, the exception corresponds to the Santa Isabel supermarket, in which the value is negative, realizing that deviations from discrepancies are greater for cases favorable to the supermarket.

#### 2.2.2.4. Accuracy by geographical area

To facilitate the study, the Metropolitan Region was divided into three distinct geographical areas, differentiated by the socioeconomic level of its inhabitants, where the east zone corresponds to the segment with higher incomes and the south/periphery zone to those with lower incomes. Figure 2.7 shows graphically the distribution of zones doing in this study, also is presented the socio demographics characteristics of the inhabitants from Metropolitan Region.

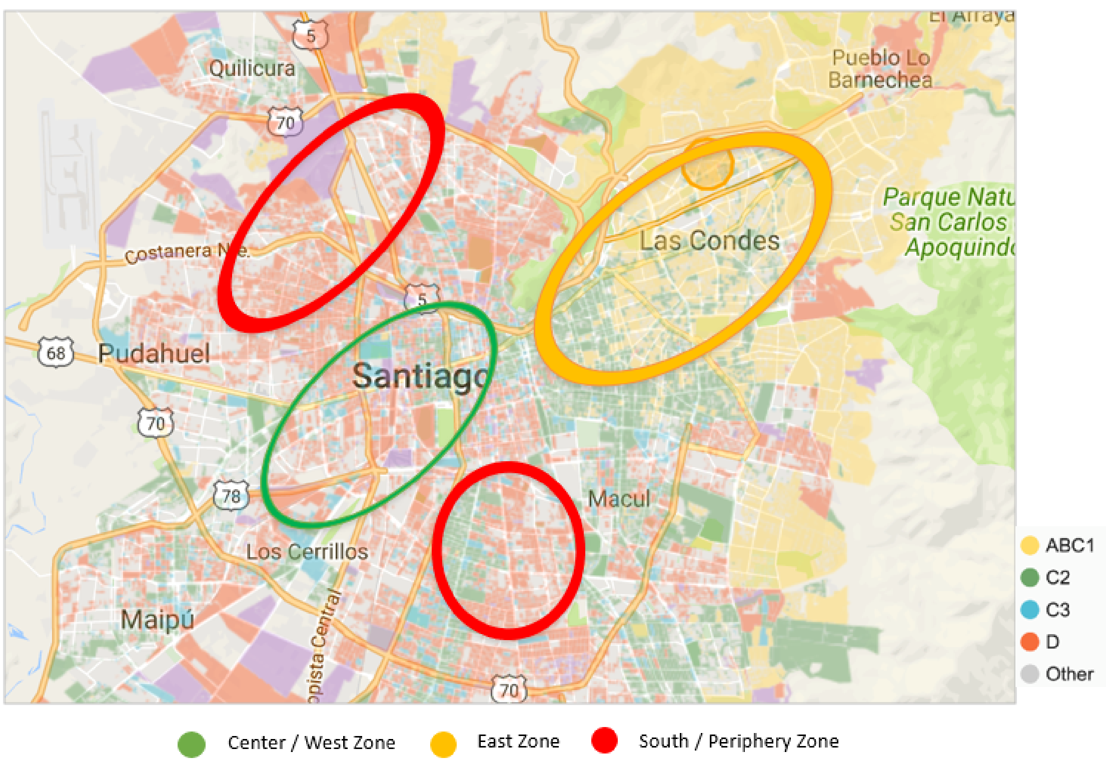


Fig. 2.7: Geographic areas developed in the Metropolitan Region

Therefore, it is possible to identify that the south / periphery zone is the one with the highest percentage of discrepancies with 20.44 %, and when disaggregated according to the type of incorrect charge detected, it was obtained that 74.1 % (p-value = $10^{-6}$ <0.05) corresponds to undercharges. While the east zone has the lowest level of errors with a proportion of 10.56 %, of which 63.2 % (p-value = 0.105>0.05) are favorable for customers.

The central / west zone has a discrepancy level of 11.45 %, where, as in the other areas, undercharge predominate, in this case being 67.9 % (p-value = $10^{-4}$<0.05) of the total erroneous charges. That can be visualized in Figure 2.8.

In relation to the percentage deviation of the prices charged, it has that in the south / periphery it has an average value of 17.2 %. For this same location, for undercharges the

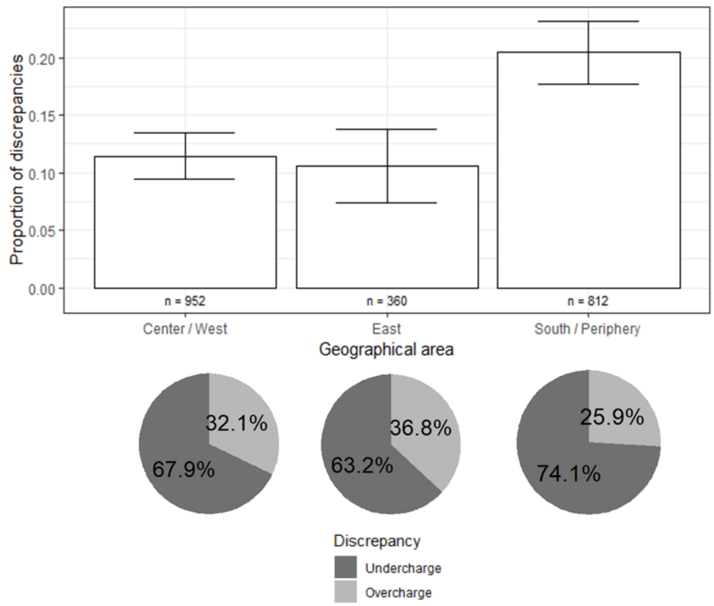


Fig. 2.8: Discrepancies according to zone

average deviation is 19.7 % and 10.1 % for overcharges. In contrast, in the east zone there is the lowest average percentage deviation with a value of 15.0 %, but when it is disaggregated according to the type of discrepancy identified, it is appreciated that the price deviation in the case of being a favorable charge for the supermarket it is 17.9 %, being greater than the percentage deviation when it is a favorable for customers, which has a value of 13.3 %.

Finally, with the information provided in Figure 2.9, it is seen that the average percentage deviation of the price charged for the east zone is slightly positive, as opposed to the south / periphery zone, in which it is of the order of 12.5 % which indicates that, on average, price deviations due to discrepancies tend to favor the customer regardless of the area.

#### 2.2.2.5. Effect of promotions

Of the total products sampled, 343 of them have some kind of promotion. This is how 28.9 % of these articles have a wrong charge, being 86.9 % (p-value = 0.000 <0.05) of them, undercharges. The foregoing indicates that in a 25.1 % of the products with promotion there is a favorable charge for consumers. As for products without promotion, there is an error rate of 12.0 %, with 7.6 % being overcharges and 4.4 % being undercharges, with which in case of an inconsistency 63.1 % (p-value = 0.000 <0.05) will be undercharge. Figure 2.10 graphs as described above.

With respect to the deviation of the price charged, when there is a promotion, there is an average of 21.0 %, which is broken down by a deviation of 25.7 % when it is an undercharge, that is, that a product with a shelf-label price of 1,000 CLP - 1.25 USD, on average 743 CLP - 0.93 USD will be charged, while for overcharges there is a deviation of 10.5 %, so when

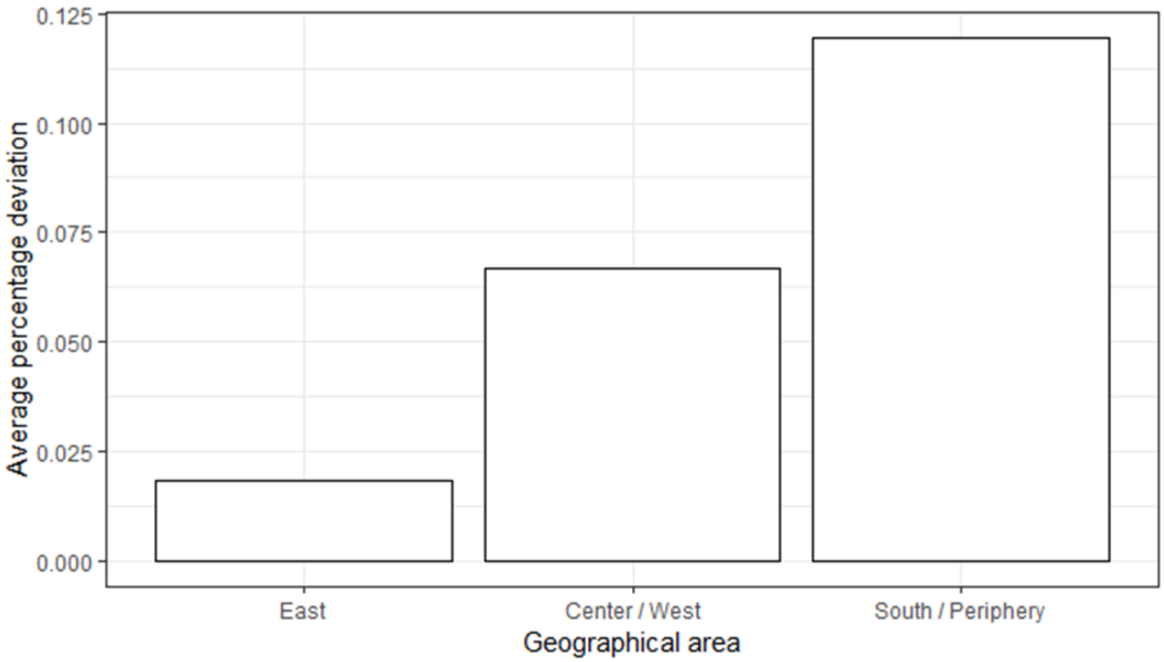


Fig. 2.9: Deviation of the price charged according to the area

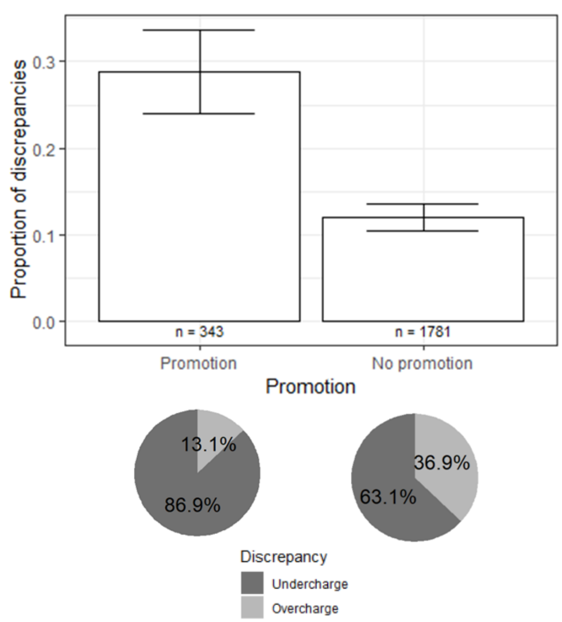


Fig. 2.10: Discrepancies according to the effect of promotions

considering the product of the previous example, 1,105 CLP - 1.38 USD will be charged. When the product has no promotion, the average deviation is 3.3 %, with 12.9 % for favorable discrepancies for consumers and 13.2 % when it is favorable for the supermarket.

This shows that the presence of promotions increases the existence of discrepancies, being essentially undercharges, which has a greater deviation from the price. Meanwhile, since there are no promotions, price deviations tend to favor the supermarket, which means that the expenses incurred by consumers are greater than the savings obtained as a result of the erroneous charges.

It is in this way that the effect of promotions increases the amount of undercharges would indicate that there is an inadequate handling in short-term promotions, that is, the price is updated to a lower one (with discount), however, it is not updated with promptly the price shown in the strapping. Which triggers the customer to see a higher price than he will cancel.

So, in next chapter we will further explore the role of promotions in creating price discrepancies.

#### 2.2.2.6. Accuracy by price segment

The prices of the products considered in this study range from 100 CLP (0.13 USD) to 21,990 CLP (27.49 USD), with an average of 1,459 CLP (1.82 USD). In order to simplify the analysis and understanding of the results, it was grouped into three price segments: low prices, with values between 100 CLP (0.13 USD) and 709 CLP (0.88 USD), regular prices, between 709 CLP (0.88 USD) and 1,419 CLP (1.77 USD) and high prices, between 1,419 CLP (1.77 USD) and 21,990 CLP (27.49 USD).

Considering that products with higher prices have a higher display, one would expect them to have a lower percentage of discrepancies with respect to those with lower prices. Along these same lines, consumers would pay more attention to higher priced products, so retailers would take care to keep prices with the correct shelf-label.

Figure 2.11 shows that as the shelf-label price of the product increases, so does the discrepancy rate, from 12.8 % in the low price segment, 14.3 % in regular prices up to 17.0 % in high prices. In other words, for higher prices, price control is less rigorous.

For the low price segment, 66.3 % (p-value = 0.002 <0.05) of the discrepancies are undercharges, while for the regular price segment the proportion corresponds to 70.3 % (p-value = 0.000 <0.05) and in that of high prices, at 74.0 % (p-value = 0.000 <0.05).

Finally, the deviation of the price charged in the first segment has an average of 3.8 %, being 14.4 % for undercharges and 16.9 % for overcharges. In the second segment there is an

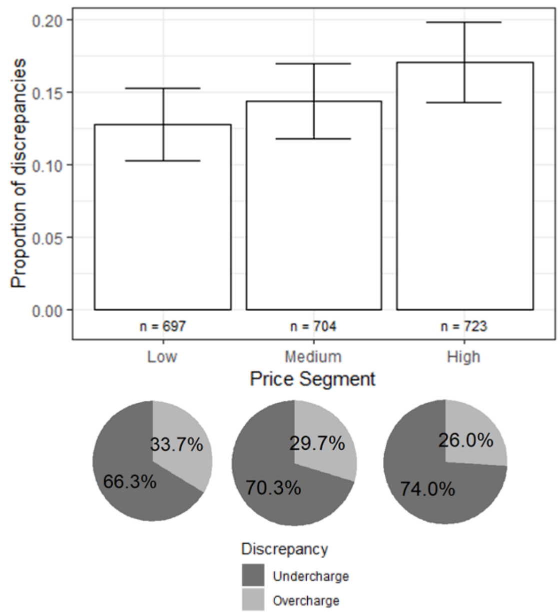


Fig. 2.11: Discrepancies according to the price segment

average of 10.3 % where for the favorable discrepancies for consumers, the deviation is 20.3 % and 13.5 % for the favorable receipts for the supermarket. While in the third segment, the average deviation is 11.4 %, with 18.3 % for undercharges and 8.3 % for overcharges.

The results obtained show that in higher value prices, charges for erroneous prices are made in a greater proportion, being mainly favorable to the customer, so that the interaction with the existence of promotions is seen.

It was obtained, that when including the promotion, the proportion of products of the high segment with discrepancies increased to 32.3 %, being 82.9 % undercharges, similar situation with the segments of low and regular prices which increase to 26.0 % and 28.0 % respectively.

Additionally, it is important to note that the deviation of the price charged for the products of the third segment is low, which would imply that the difference paid "more", seems insignificant to consumers, despite being counter intuitive with what should matter for the supermarket, since they should ensure a correct price on products in which their marketing value is high. However, the discrepancies for this segment continue to prevail, being explained by the above, unlike what would happen with low price products.

The above reaffirms the low concern in maintaining prices, and how the existences of promotions increase the effect described previously.

## 2.3. Overview of price accuracy in the Chilean supermarket industry

From the previous analysis, it was possible to refute the assumption raised, because it was evidenced that since there is a price discrepancy, this is usually an undercharge, together with the fact that, on average, the percentage deviation of the price charged is less when it is a favorable discrepancy for the supermarket, implying that the amount paid 'more' with respect to the amount paid 'less', is of a lesser magnitude, so that the consumer is systematically obtaining 'benefits' from incorrect charges.

Table 2.2: Price accuracy by supermarkets

| **Chain** | **Supermarket** | **Format** | **Accuracy** | **Undercharges** | **Overcharges** |
|---|---|---|---|---|---|
| Walmart | Hiper Líder | Hyper | 88.8 % | 7.6 % | 3.6 % |
| Walmart | Express de Líder | Traditional | 83.3 % | 13.4 % | 3.2 % |
| Cencosud | Jumbo | Hyper | 89.2 % | 8.0 % | 2.8 % |
| Cencosud | Santa Isabel | Traditional | 90.2 % | 4.1 % | 5.7 % |
| Falabella | Tottus | Hyper | 88.2 % | 7.8 % | 4.0 % |
| Falabella | Tottus Express | Traditional | 81.8 % | 14.2 % | 4.0 % |
| SMU | Unimarc | Traditional | 73.3 % | 18.1 % | 8.7 % |
| | | Total | 85.3 % | 10.4 % | 4.3 % |

However, if the price accuracy level of the studied supermarkets is compared, which is summarized in the Table 2.2, it can be seen that the best performance is achieved by the Santa Isabel supermarket, where approximately 1 of every 10 products have an incorrect charge, while Unimarc has a precision level of 73.3 %, realizing that approximately 3 out of 10 products the price charged was not right. And if these supermarkets were evaluated by the standards proposed by The National Conference on Weights and Measures (NCWM) established in the United States, which dictate that for a store to pass an inspection, the level of price accuracy must be greater than 98.0 % , situation that does not happen in the Chilean supermarket industry. Which is an alarm indicator, with respect to the concern that is being given to that, which increases with the high percentage of overcharges being on average, of the order of 4.0 %.

In addition, the level of price accuracy is dependent on the existence of promotions, which have an effect of increase the discrepancy rate. Similarly, the day on which the purchase is made has an impact on the erroneous charges, as a result of the periodicity of the shelf label updates. Finally, the price of the product seems to indicate that their handling is different, which indicates that there are different motivations for supermarket managers.

# Chapter 3

# Underlying mechanism for price inaccuracies

In the previous chapter was studied the level of accuracy of charges of a general sample carried out in the Metropolitan Region, which showed a low percentage of consistency by the industry, therefore a second study was carried out. In this study we want to determine the durations of the discrepancies, so it must constantly monitor the products.

## 3.1. Motivation

In the literature, the accuracy of prices has been studied extensively in the 90's, trying to identify the incidence of this phenomenon, along with determining who favors the discrepancy, retail or consumers. However, the time taken for a discrepancy to be corrected has not been studied, which is of vital importance when deciding the actions to be taken to reverse the problem, considering that if a discrepancy is persistent over time it will reflect a decline concern for rectifying the error. Therefore it is essential to study the mechanisms that influence durations.

This research seeks to understand under which characteristics the time of permanence of a discrepancy is more exacerbated, such as the section to which the product belongs, the price value itself, the presence of promotions and the day of the week in which the purchase was carried out. This can help to detect products that have a poor management of the price update allowing decision makers to anticipate the problem, increasing the level of precision present, which in the long term will lead to an improvement in the quality of service provided to customers along with having adequate control of profits and costs. Additionally, ensuring a high level will provide the opportunity to know the true effect of promotions and price changes on products.

Understanding that there are two types of discrepancies, depending on who favors the incorrect charge, either to the customer or to the supermarket, it is sought to know which type of inconsistency has the longest persistence time, along with determining which one is corrected with greater speed and promptness. It is expected that depending on the type of discrepancy, the duration would be different, conditioned on the variables that could induce it, such as price, category and presence of promotions.

## 3.2. Data collection

The study was carried out by the Centro de Estudios del Retail (CERET), in which a group of people were recruited who, during a period of 28 days, from November 3 to 30, 2016, were assigned the task of registering the shelf-label of 76 products admitted for the study. Those belong to sections of mass consumption such as groceries or dairy products, as cleaning products, in addition to having diversified prices. To do this they had to photograph the shelf label and write down the SKU code and price observed. Those items were selected, seeking to characterize the usual purchases of consumers in a supermarket, for which products of various sections and prices were included. It is important to underline that the sample was collected from a particular supermarket room, unlike the previous study, in which information was collected from various rooms. The advantage of this sampling is that the behavior of the products is tracked daily.

After the participants of the study had registered the shelf-label prices, a cross was made with the transactional information of those items provided by the supermarket, with which it could visualize the price that the product presented on the shelf label and the price that was charged to the customers, being able to verify if they coincided or that there was a discrepancy in the price. This allowed continuous monitoring over time of the prices at which the products were charged.

It should be noted that the process was remunerated by the research participants, with whom it was finally possible to collect 75,565 valid data in said time interval.

## 3.3. Results

As a first analysis, the level of discrepancies presented by the studied supermarket is described, obtaining that it corresponds to 78.0 % (58,908 transactions), that is, in that proportion the products were consistently charged. While the discrepancies have a proportion of 19.6 % (14,822 transactions) when they are undercharges and 2.4 % (1,835 transactions) when they are overcharges. It is in this way that in approximately 1 of every 5 products the price charged does not correspond to the shelf-label price.

On the other hand, when analyzing the proportion of discrepancies according to their type, in the case of existing, in a 89.0 % (p-value= $10^{-10}$ <0.05) is favorable for the client. What refutes the assumption raised above, which stated that if there is a discrepancy, it is more likely to be a overcharge that a undercharge. This is similar to what was obtained in the previous study, however, the proportion of errors is higher, corresponding mainly to undercharges.

Studying the values of the percentage deviations of the price charged, it has a value of 12.0 % which shows that in a product with a price of 1,000 CLP (1.25 USD) with discrepancy it will have a price between 880 CLP (1.10 USD) and 1,120 CLP (1.40 USD). While when is an undercharge, the price deviation is also 12.0 % and if is an overcharge, the value is 11.6 % . Again, exemplifying with a product of 1,000 CLP (1.25 USD), when a undercharge occurs, the price charged on average is 880 CLP (1.10 USD), while, when it is a overcharge the price charged on average is 1,116 CLP (1.40 USD) which realizes that, in this supermarket, in terms of price deviations, the situation is favorable for customers. Again, the values are similar to the previous investigation, being slightly lower, indicating that the price deviates to a lesser extent.

### 3.3.1. Accuracy by section

Similarly to the previous section, in Figure 3.1 the situation observed in this sample is presented. In spite of observing similar patterns, we consider worth reporting detailed results for this data set.

Talking about the proportion of discrepancies, the section with the highest rate corresponds to the cookies section, together with the cleaning section, in which 45.3 % and 45.0 % of the products present an error in the charge. The foregoing realizes that, in approximately 1 of every 2 products of these sections, the price displayed on the shelf-label will be different from the price charged to the customer. In contrast, the sections of drinks and grocery, have inconsistency ratios of 11.7 % and 19.3 %, therefore, when buying products belonging to drinks section, 1 in 10 will present an error, and when grocery items are purchased, almost 2 in 10 will have it.

It is presented that the existence of favorable discrepancies to the costumers prevails, highlighting the fact that on average the proportion of undercharges is 92.3 % (p-value = 0.000 <0.05). In particular, it can be seen that, in the section corresponding to cookies, 100 % (p-value = 0.000 <0.05) of the discrepancies favor the customer, a situation similar to that which occurs in the section of the drinks where 99.4 % of discrepancies are undercharges.

The section with the lowest proportion of this type of discrepancies corresponds to the dairy section, in which a proportion of 83.6 % is reached (p-value = 0.000 <0.05).

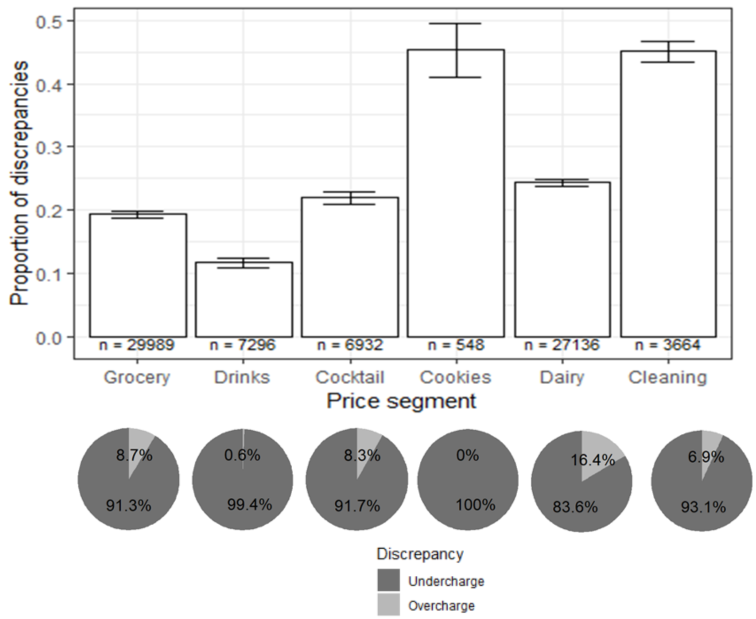


Fig. 3.1: Discrepancies according to the product section

When the percentage deviation of the price charged is studied, it has to the greatest deviation occurs in the cookies section with 28.2 % followed by the cleaning section with 24.0 %. Therefore, considering a product with a price of 1,000 CLP (1.25 USD), the price charged on average would be in the range of 718 CLP (0.90 USD) and 1,282 CLP (1.60 USD) for cookies section; and between 760 CLP (0.95 USD) and 1,240 CLP (1.55 USD) for products in the cleaning section. While with 8.9 %, the grocery section has the smallest deviation from the price, realizing that if there is a discrepancy in a product displayed with a price of 1,000 CLP (1.25 USD) the price charged at checkout will fluctuate between 991 CLP (1.24 USD) and 1,089 CLP (1.36 USD).

When disaggregating the price deviation according to the type of discrepancy detected, there is no clear trend, given that for half of the sections the deviation is greater for undercharges. That is why, in the presence of favorable discrepancies for the customer, the cleaning section has the highest value with 25.0 % against 10.0 % for the opposite case. And when studying for overcharges, the drinks section reaches the highest value with 43.8 % versus 9.24 % for overcharges. From the above, it is claimed that there is a difference in the behavior of discrepancies depending on the section to which the product belongs.

### 3.3.2. Accuracy by day

At this point it is in which there is the greatest differentiation with respect to the anterior study, remembering that previously there was no clear pattern in the discrepancies according to the day. Considering that the information was collected in a temporary window, it proceed to graph the proportion of discrepancies identified as a function of time, which can be seen in Figure 3.2. It can be clearly seen that there is seasonality, in particular with Monday, in which the proportion of discrepancies skyrockets considerably, in relation to the rest of the days. In addition, it is possible to identify that both the week of November 7 and November 14 as the weekend approaches, the discrepancy rate is reduced. While, on the last weekend of the month, discrepancies increase.

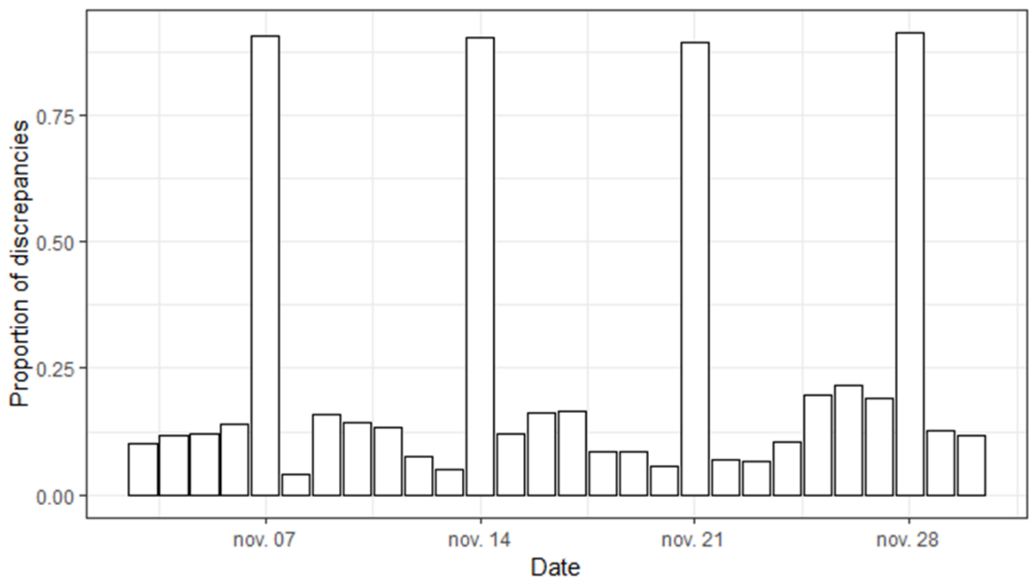


Fig. 3.2: Time series of proportion of discrepancies

So when studying the behavior of the discrepancies according to the day of the week, we find out that on Monday 90.3 % of the products present an incorrect charge, while for Tuesday it corresponds to 9.3 %. Similarly, for the rest of the days, the proportion of inconsistencies does not rise to more than 13.3 % as it does on Thursday. Finally, the days corresponding to the weekend have error rates of 13.0 % and 11.4 % for Saturday and Sunday.

Then, analyzing what type of discrepancy prevails, it should be taken into account that, although Monday presents the highest level of inconsistencies; of the total of them, 99.16 % (p-value = 0.000 <0.05) are undercharges, a situation similar to the one that happens the rest of the days, where the proportion of favorable charges for the client is greater than the favorable for the supermarket. In particular, on Sunday, it has the lowest proportion of undercharges, with 62.9 % (p-value = 0.000 <0.05). It can be distinguished that for both Saturday and Sunday, the proportion of favorable discrepancies for the supermarket increases and decreases considerably on Mondays and Fridays. That can be visualized in the Figure 3.3.

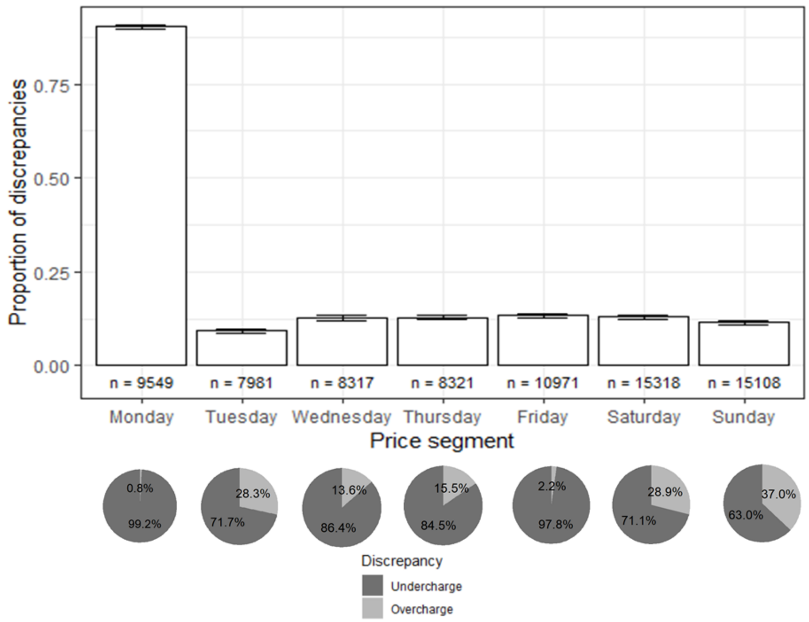


Fig. 3.3: Discrepancies according to the day

The absolute deviation of the price charged presents the highest average on Fridays, where it reaches 21.1 % which translates into an average of a product of 1,000 CLP (1.25 USD), when presenting a discrepancy, the price charged will fluctuate between 789 CLP (0.99 USD) and 1,211 CLP (1.51 USD). On the other hand, on Monday, the lowest value is obtained, being 7.0 %, which implies that, on average, a product of 1,000 CLP (1.25 USD) that has a discrepancy, has a price in the range of 930 CLP (1.16 USD) to 1,070 CLP (1.34 USD). It is important to note that on Friday there is the greatest deviation when disaggregating according to the type of discrepancy, if that is an undercharge the value is 21.0 %, that is, the price charged on average of a product of 1,000 CLP (1.25 USD) is from 790 CLP (0.99 USD); and if it is an overcharge it is 24.9 %, so that on average, a product of 1,000 CLP (1.25 USD) with that type of inconsistency will be charged at 1,249 CLP (1.56 USD).

### 3.3.3. Effect of promotions

Among the transactions made, we observe a large presence of promotions, so it is interesting to verify if they have any impact on the occurrence of discrepancies. This is how 18.4 % (13940) of the transactions present some type of promotion, and of those, 97.1 % present some kind of discrepancy, while in those products that do not present promotion, 5.1 % presents a wrong charge, which can be seen in Figure 3.4. This presents a substantial increase in the incidence of promotions in the proportion of discrepancies in relation to what was shown in the previous section, and motivates to delve into the repercussions of this situation and dilution causes of the fact.

Additionally, it is considered that there is a mismatch on Mondays that it is necessary to analyze in greater depth, which is directly related to the presence of promotions, so in later sections it will be seen in greater detail, emulating the main analyzes with the inclusion and exclusion of discrepancies that day.

Of the discrepancies that occur in products with promotion, 97.5 % corresponds to undercharges (p-value = 0.000 <0.05). On the other hand, when the product does not present any type of promotion, 51.9 % (p-value = 0.036 <0.05) are. It is evident that the existence of promotions has a greater probability of the existence of a discrepancy, than when it does not exist. And this is a big issue considering the relevance of promotions in store traffic.

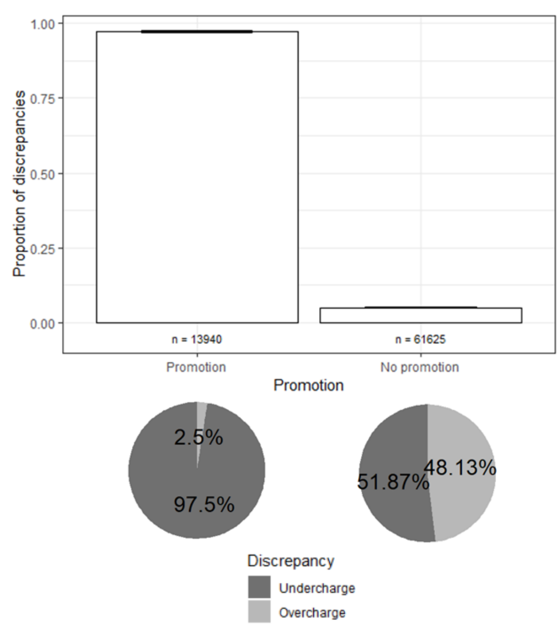


Fig. 3.4: Discrepancies in the presence of promotions

The average absolute deviation of the price charged in the presence of promotions is 11.8 %, also being 11.8 % when it is an undercharge and 10.4 % when it is an overcharge. While when there is no promotion, the average absolute deviation is 13.0 %, which is made up of 14.1 % when it is favorable for the customer and 11.8 % when it is not. That is why, regardless of the effect of promotions, when there is a discrepancy, the deviation is convenient for the consumer.

The situation presented, allows us to assume that this supermarket room constantly carries out short-term promotions, for which it does not update the shelf-label price, which leads the customer to see a higher price displayed than will be paid at the cash. This situation shows the low concern about properly informing about the price of the products, which in the long term will cause the client to stop paying attention to those, given that consistency is rarely presented, which is harmful for the consumer, since they will stop complaining for wrong charges, and they will be less informed about the amounts that they pay.

In addition, that products are constantly under promotions, and are displayed with a fictitious price and higher than what will be charged at the cash , can be considered a practice exercised by supermarkets to imply that their prices are much lower than those client believed that he would pay, which in certain people can be taken as something positive (i.e. I always have lower prices than I thought I would pay) being considered as some kind of marketing strategy.

Another important study corresponds to determining the level of discrepancies, when purchases made on Mondays are not considered. Thus, in 92.5 % of the products with promotions, these present an incorrect price, while when it has no promotion, this proportion amounts to 5.1 %.

This allows to infer that the behavior patterns are maintained by excluding the transactions made on Monday, however, on that day the existence of discrepancies increases. This situation seems to indicate the effect of short-term promotions, which correspond to price discounts that do not reach to be updated in the shelf-label, so the price of the shelf has a higher price than the consumer will finally be charged, which translates into an undercharge.

### 3.3.4. Accuracy by price levels

The shelf-label price exhibited in the products ranges from 269 CLP (0.34 USD) to 13,699 CLP (17.12 USD), with an average of 1,388 CLP (1.74 USD). To facilitate subsequent analysis and understanding of the results, it is decided to group the prices into three categories, being these, low prices in the range of 269 CLP (0.34 USD) to 859 CLP (1.07 USD), regular prices in the range of 869 CLP (1.07 USD) to 1,399 CLP (1.75 USD) and high prices, which correspond to products whose values are between 1,399 CLP (1.75 USD) and 13,699 CLP (17.12 USD). Each of these segments has 32.5 %, 31.5 % and 36.0 % of the observations.

The proportion of existing discrepancies for each of the proposed price segments is presented in Figure 3.5, which highlights that, for products with high prices, the proportion is the highest with 26.0 %, followed by the segment of low prices with 22.3 %, and lastly is the segment with products with regular prices, where 17.4 % presents a discrepancy. The obtained is consistent with the previously expressed, showing that higher price leads to a greater proportion of discrepancies, being mainly undercharges.

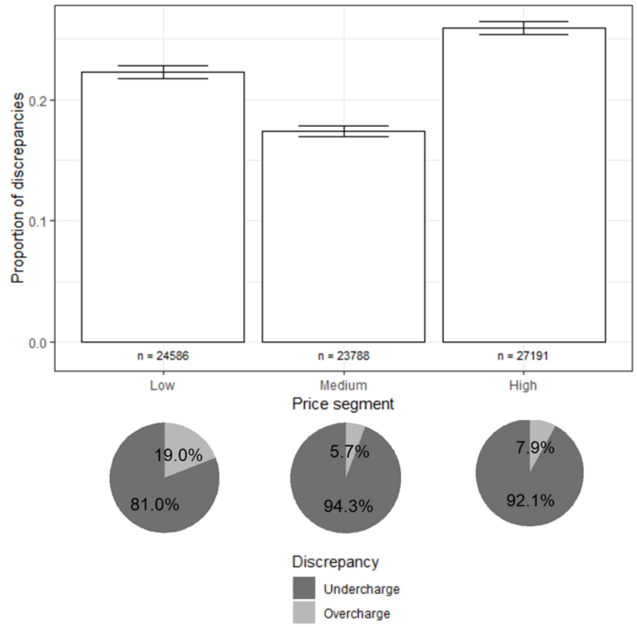


Fig. 3.5: Discrepancies according to the price of the product

Regarding the type of discrepancy that each segment presents, it was obtained that, through the segments, the undercharges predominate. Thus, in the low price segment there is the highest proportion of erroneous charges that favor the supermarket with 19.0 % (p-value = 0.000 <0.05) and in the segment with regular prices there is the lowest proportion with a 5.7 % (p-value = 0.000 <0.05).

In both the low price segment and the regular price segment, the average absolute deviation of the price charged is greater when the it is an overcharge with 9.0 % versus 11.6 % for undercharges in the first segment, and 9.32 % versus 13.7 % for the second. The foregoing indicates that for lower prices (i.e. low price and regular price segment), in case of an overcharge, the price deviation will be higher than if that discrepancy had been an undercharge. In contrast is the segment of products with high prices, where the average price deviation is greater for the favorable case for customers with 15.8 % versus 10.6 % for when it is positive for the supermarket.

### 3.3.5. Overview of the results

From the above, it can be seen that there is a high proportion of discrepancies detected, of which the majority favor consumers. In addition it is evident that there is different behavior depending on the section to which the product belongs, in the same way, it is observed for products with high prices the discrepancy rate is higher than for regular price products.

On the other hand, it was detected that the existence of promotions affects a substantial increase in discrepancies, while it is observed that on Monday there is a substantial increase in erroneous charges with respect to the rest of the days.

The foregoing accounts for the influence of short-term promotions, which together with a slow handling of the shelf-label price update causes consumers to visualize a higher price than they would actually pay given the discount. This situation shows that promotions of this type do not allow to have the prices updated in real time, without having to incur large personnel costs that are dedicated to updating the prices. Thus, it is usual that in the supermarket studied, on Monday a large number of short-term promotions are made, while on the rest of the days they are carried out in a smaller proportion, presenting the same problem.

Finally, most of the insights derived in our first study are replicated in this second study. A key difference is that in this new dataset we observe a large number of price discrepancies on Mondays. These discrepancies are short-lived and they are largely associated to weekly promotions. As we consider them as being a different nature, in our analysis we evaluate if their inclusion changes our results.

## 3.4. Duration of discrepancies

As mentioned in the motivation of this study, there is no research in the literature that addresses the duration of price discrepancies, so this work has the purpose of determine what type of incorrect charge is corrected faster, along with being able to identify the effect of variables such as the section, the price and the presence of promotions.

### 3.4.1. Hypothesis

Considering the investigation conducted by Goic and Troncoso (2017), Medición de la Calidad Servicio en la Industria del Supermercadista Retail to understand what actions consumers take when noticing that the price charged to them is higher than the one reported, to which 66.0 % would give notice during checkout regardless of the amount, 24.0 % would do so if the difference is substantial, while 10.0 % would not. Of those who would give notice, they were asked if they would alert what happened in other channels, having 11.0 % make a claim to SERNAC, 37.5 % would tell the situation to their family and friends, 10.9 % would publish what happened on social networks, 9.8 % would report in other supermarket units (web, customer service, etc.) and 40.0 % would not report in other ways. In the same way, it was inquired about the actions they would take if the price charged was lower than the one shown on the shelf label, this is how, 37.0 % would give notice regardless of the amount, 16.0 % would do it if the difference were substantial and 47.0 % would not. So, in this section the following is hypothesized:

*'Overcharges are corrected faster than undercharges'.*

The above is based on the results presented previously, when a customer is in the presence of a discrepancy that is not favorable, he will claim and therefore alert the administrators that there is an error in the prices displayed in the shelf-label, which will imply that the problem will be solved. Otherwise, when the customer encounters a discrepancy that is favorable to him, he will not alert to that, before which the error will persist until a new shelf-label is assigned or that those responsible for replacing the products realize that there is a wrong price, correcting it.

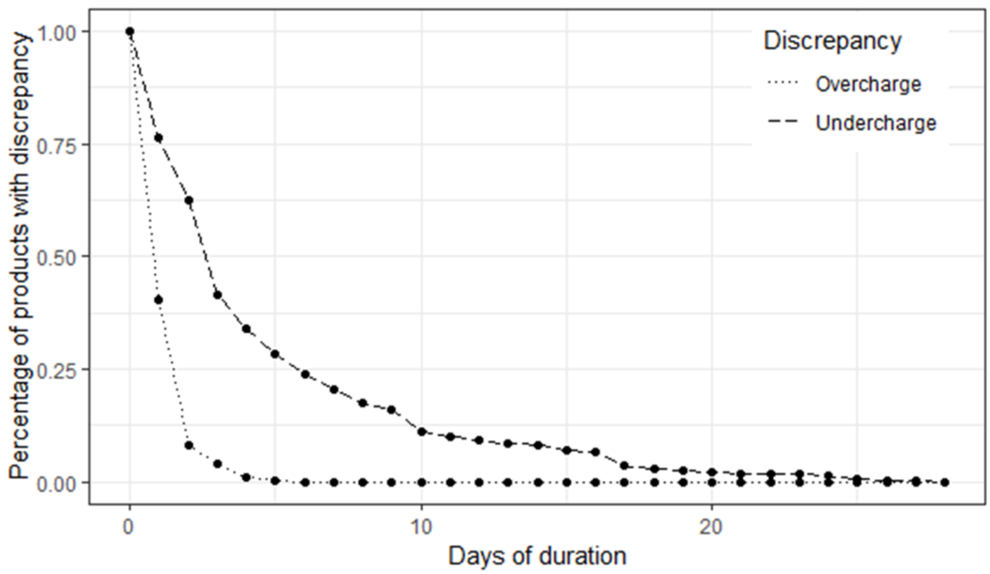


Fig. 3.6: Comparison of products with discrepancies according to type

To corroborate that, we proceed to plot the behavior of the durations according to the type of discrepancy, so that the percentage of products in which the discrepancy persists as the days progress. In the graph of Figure 3.6, it is visualized that the overcharges are corrected faster than undercharges, that is, as in 6 days all incidents of incorrect charges have been resolved when it is favorable to the supermarket, while in 28 days there are no more products with favorable charges for customers.

In the following sections, various models that seek to adjust the previous situation will be studied, with the purpose of describing the factors that lie in their duration, together with corroborating that the speed of correction of undercharges are less than overcharges.

### 3.4.2. Linear regression approach

As a first approach to determine the incidence of different factors in the duration of the discrepancies, linear regression models are used, which are developed in overcharges, undercharges and in discrepancies in general. For that, variables such as, promotion effect, day on which the transaction occurred, section to which the product belongs, along with the price are proposed.

The data construction begins with the creation of the promotion variable coding it in binary form, that is, 1 indicates that it does exist, while 0 indicates it does not. Subsequently, again binary form the variables linked to the price were elaborated, being the segment s1, the one of low prices, the segment $s_2$, of regular prices and finally the segment $s_3$ of high prices, its composition is detailed in section 3.3.4. Then, the variables corresponding to the product section were created, where a 1 indicates that this is the case. Similarly, the variables associated to the day of the week in which the product was traded were developed.

The inclusion of the variables described is based on exploratory analyzes developed previously, since those show variability in the behavior of the discrepancies, at which it is presumable that directly influence the duration of these. Likewise, similar studies have included variables linked to the promotion, product section and price, however, there were no components related to the day on which the purchase occurred, and remembering the high variability detected according to the day, it is important to include.

Finally, the independent variable *"duration"* is measured in days, indicating the number of consecutive periods in which the product $i$ has had discrepancies. Therefore the model proposed correspond to:

$$
\begin{aligned}
\mathrm{d}uration_{\mathrm{i}} = \beta_0 + & \\
& \beta_{favorcostumer} \cdot favorcostumer_{\mathrm{i}} + \\
& \beta_{promotion} \cdot promotion_{\mathrm{i}} + \\
& \sum_j \beta_{\mathrm{price}_j} \cdot \mathrm{price}_{\mathrm{i}} + \\
& \sum_k \beta_{\mathrm{section}_j} \cdot \mathrm{section}_{\mathrm{i}} + \\
& \sum_l \beta_{\mathrm{day}_j} \cdot \mathrm{day}_{\mathrm{i}}
\end{aligned}
\tag{3.1}
$$

Where $j$ is in $\{s1, s2, s3\}$, $k$ is in $\{Grocery, Drinks, Cocktail, Cookies, Dairy, Cleaning\}$ and $l$ is in $\{Monday, Tuesday, Wednesday, Thursday, Friday, Saturday, Sunday\}$. For the general model, which contains both undercharges and overcharges, there is the $favorcostumer$ coefficient, while for models containing only undercharges or overcharges, that coefficient is not used.

A model was also tested in which the dependent variable corresponded to *"log (duration)"*, but did not improve the fit achieved with the model without the logarithm. The results of that model are found in the appendix section.

Table 3.1: Results of regression models

| | **General** | **Overcharges** | **Undercharges** |
|---|---|---|---|
| Intercept | 0.962 (0.151)* | 1.185 (0.167)* | 4.901 (0.164)* |
| Favor customer | 3.870 (0.135)* | | |
| **Promotion** | | | |
| Promotion | 0.272 (0.116)* | 0.135 (0.068)* | 0.175 (0.134) |
| **Price segment** | | | |
| s1 | | | |
| s2 | -1.917 (0.109)* | -0.490 (0.126)* | -1.922 (0.117)* |
| s3 | -1.480 (0.089)* | -0.415 (0.112)* | -1.418 (0.097)* |
| **Product section** | | | |
| Grocery | | | |
| Drinks | -0.879 (0.157)* | -0.320 (0.294) | -0.890 (0.167)* |
| Cocktail | 2.790 (0.126)* | 1.146 (0.077)* | 2.930 (0.139)* |
| Cookies | -0.960 (0.280)* | | -0.911 (0.296)* |
| Dairy | -1.011 (0.089)* | -0.092 (0.117) | -1.091 (0.097)* |
| Cleaning | 6.893 (0.132)* | 0.561 (0.085)* | 7.367 (0.147)* |
| **Day** | | | |
| Monday | | | |
| Tuesday | 0.672 (0.170)* | 0.313 (0.113)* | 0.770 (0.201)* |
| Wednesday | 1.088 (0.150)* | 0.794 (0.120)* | 0.957 (0.168)* |
| Thursday | 2.409 (0.143)* | 0.264 (0.109)* | 2.637 (0.163)* |
| Friday | 1.114 (0.128)* | 2.033 (0.149)* | 0.989 (0.138)* |
| Saturday | 1.437 (0.115)* | 0.875 (0.098)* | 1.143 (0.132)* |
| Sunday | 1.009 (0.124)* | 0.074 (0.097) | 0.859 (0.149)* |
| **Adjusted** $R_2$ | 0.288 | 0.339 | 0.266 |
| Observations | 16657 | 1835 | 14822 |

From the Table 3.1, it can be seen that the existence of promotions increases the duration of the discrepancy, regardless of the sign of that. Additionally, the price influence behaves similarly between overcharges and undercharges, so that when the price is regular or high, the duration decreases with respect to low price products, increasing this effect for articles of the first mentioned segment.

As for the sections, it is possible to appreciate that the cleaning and cocktail products have a longer duration than those of grocery, while the products of the drinks, dairy and cookies sections have a shorter persistence time of the discrepancy.

In relation to the day on which the transaction is made, taking as reference the purchases made on Monday, a purchase must be made on any of the other days implies on a rise in duration, being higher on Friday for overcharges and Thursday for undercharges.

Finally, in the model that groups the discrepancies the coefficient associated with the type of inconsistency, it is observed that if it is a favorable error for the customer, the duration increases considerably with respect to a favorable charge for the supermarket.

The above accounts for the difference in behavior in the duration of the discrepancies, which is closely related to the variables developed.

### 3.4.3. Discrete time duration models

Considering that the durations are measured in days, which are positive units, a discrete time duration model is carried out with the purpose of fit the durations of the discrepancies according to their type.

#### 3.4.3.1. Shifted geometric model

The first model presented corresponds to a shifted geometric, which describes the probability $\theta$ of correcting the discrepancy for any of the products, due to homogeneity. Therefore, being $T$ the random variable that describes the periods of duration, it has:

- $\mathbb{P}(T = t \mid \theta) = \theta \cdot (1-\theta)^{t-1}$ is the probability that the discrepancy is corrected at time t.
- $\mathbb{P}(T > t \mid \theta) = (1-\theta)^{t}$ is the probability that the discrepancy is corrected in a time after t.

Thus, it is obtained that, in the case of undercharges, the probability of correction is 0.199 (0.002), while when it is an overcharge, the probability becomes 0.651 (0.09). The foregoing indicates that when the discrepancy is favorable for the customer, its probability of correction is considerably less than the probability of correction, if it had been favorable for the supermarket.

#### 3.4.3.2. Beta-Geometric model

Then, it is proposed to include continuous heterogeneity in the geometric model, since each product has different characteristics, so it makes sense to assume that each of them has different probability of correction. Therefore the situation is fitted using the Beta-Geometric model.

Recalling that the expected value of the beta distribution corresponds to $\frac{\alpha}{\alpha+\beta}$, while the variance is given by $\frac{\alpha\cdot\beta}{(\alpha+\beta)^2\cdot(\alpha+\beta+1)}$. For undercharges, it has to that $\alpha = 5{,}226$ (0.295) and

$\beta = 17{,}138$ (1,132), with which $\bar{\theta} = 0.234$ and standard deviation 0.088. While when the discrepancies are overcharges, $\bar{\theta} = 0{,}651$ and standard deviation 0.013. With which, again, the probability that the discrepancy is resolved is greater when it is favorable for the supermarket.

#### 3.4.3.3. Geometric and Beta-Geometric Regression

Finally, it is proposed to include observable heterogeneity based on a vector of features $x$ , with some component varying over time, to the previous models discussed, so the model considering is the Geometric Regression. The $x$ vectors of proposed characteristics are composed of information corresponding to the existence of promotions, price segment to which it belongs with the categorization explained previously, section and day in which the transaction occurred.

The second heterogeneous model proposed corresponds to Beta-Geometric Regression, which considers observable heterogeneity, related to the vector of characteristics of the products, as not observable, intrinsic associations of them.

Table 3.2: Results of geometric models

| | Overcharges | | Undercharges | |
|---|---|---|---|---|
| | **Geometric Regression** | **Beta Geometric Regression** | **Geometric Regression** | **Beta Geometric Regression** |
| $\alpha$ | | 1.159 (0.229)* | | 90.078 (42.500)* |
| $\beta$ | | 0.039 (0.011)* | | 113.877 (54.817)* |
| $\theta_0$ | 0.874 (0.010)* | | 0.437 (0.011)* | |
| **Promotion** | | | | |
| Promotion | -0.458 (0.427) | -2.348 (0.346)* | -0.131 (0.043)* | 0.127 (0.043)* |
| **Price segment** | | | | |
| S1 | | | | |
| S2 | 19.446 (105.816) | -5.100 (0.601)* | 1.045 (0.063)* | -1.032 (0.063)* |
| S3 | 36.622 (112.312) | 0.099 (0.470) | 0.666 (0.056)* | -0.656 (0.055)* |
| **Product section** | | | | |
| Grocery | | | | |
| Drinks | -1.193 (4193.580) | -6.505 (17.650) | 0.660 (0.116)* | -0.646 (0.115)* |
| Cocktail | -19.657 (105.815) | 6.251 (0.521)* | -1.179 (0.058)* | 1.175 (0.058)* |
| Cookies | | | 0.396 (0.150)* | -0.382 (0.148)* |
| Dairy | 5.771 (0.850)* | -2.407 (0.387)* | 0.478 (0.048)* | -0.468 (0.048)* |
| Cleaning | -30.978 (112.304) | -0.992 (0.320)* | -1.609 (0.062)* | 1.605 (0.062)* |
| **Day** | | | | |
| Monday | | | | |
| Tuesday | 0.546 (0.508) | -0.866 (0.434)* | -0.357 (0.082)* | 0.364 (0.082)* |
| Wednesday | -5.594 (0.867)* | -0.676 (0.502) | -0.514 (0.069)* | 0.522 (0.069)* |
| Thursday | -6.238 (0.878)* | -15.384 (16.727) | -0.945 (0.057)* | 0.953 (0.057)* |
| Friday | -6.351 (0.890)* | 2.704 (0.451)* | -0.446 (0.049)* | 0.456 (0.049)* |
| Saturday | -5.530 (0.854)* | 2.310 (0.389)* | -0.450 (0.049)* | 0.458 (0.049) * |
| Sunday | -0.598 (0.527) | -0.636 (0.397) | -0.362 (0.054)* | 0.370 (0.054)* |
| **LL** | -1512 | -1491 | -35251 | -35253 |
| **AIC** | 3649 | 3012 | 70531 | 70537 |
| **BIC** | 3128 | 3094 | 70645 | 70659 |
| **MAE** | 95.93 | 106.25 | 619.82 | 530.32 |
| **MAPE** | 0.86 | 11.39 | 0.71 | 0.61 |

The results of the Geometric Regression and Beta Geometric Regression models are summarized in Table 3.2.

For overcharges, in the Geometric Regression model the presence of promotions affects the reduction in the probability of correction with a coefficient of -0.458 (t value = 1.073). This is related to the fact that if the product is in promotion, the customer will not detect the discrepancy, while the supermarket fails to rectify the price promptly, so the erroneous charge is maintained for longer. As the price increases, the likelihood of correction also does so, which is closely related to the customer being more concerned that expensive products are well charged, so if there are discrepancies, it will alert. While if the product belongs to the drinks, cocktail and cleaning section, with respect to the groceries section, the probability of correction decreases, which is attributable to the fact that the products of said sections are not usually purchased by the customer. Therefore, they pay attention to the price that they will pay on them, making sure they are charged properly. While if the product is from the dairy section, the probability increases given that the associated coefficient is 5.771 (t value = 6.789), which is explained in which products of that section are of great importance in the consumption of people , being able to remember the usual prices, recognizing discrepancies in its charges.

When analyzing the influence of the day of the transaction on the probability of correction of the discrepancies, it is appreciated that, with respect to Monday, if the product is purchased on Tuesday, its probability increases, while for the rest of the days, it decreases being greater the effect if purchases are made on Thursday and Friday given the associated coefficients, -6.238 (t value = -7.105) and -6.351 (t value = 7.136) respectively, which is explained by the supermarket attendants in those days, they are people looking to save on their purchases, so they review and verify well the price they will pay, so if the price disagree, they will claim.

With respect to the Beta-Geometric Regression model, when the product presents a promotion, the probability of correction increases given the coefficient -2.348 (t value = 6.786), which seems to indicate that consumers are more attentive to the price when there is a promotion,therefore, when the wrong charge does not favor them, they promptly alert the supermarket, which corrects it to avoid future problems with other customers.

In relation to the price of the product, when the price is regular, the probability of rectification increases (t value = 8.486), while for a high price, it slightly decreases with respect to low prices (t value = 0.211). The foregoing seems to indicate that consumers remember products with very low or very high prices to a lesser extent than regular prices, so it possible for them claim and alert the wrong charge.

The drinks (t value = 0.369), dairy (t value = 6.219) and cleaning (t value = 3.100) sections increase the probability that the discrepancy will be resolved while the cocktail section decreases it with respect to grocery products. In drinks and dairy sections, customers are able to detect errors since they consume them in large quantities, for cleaning products, remember the price since it is something unusual and buy based on the price, so they are attentive to the price to pay . While cocktail products are purchased occasionally, so they do not have an association on the correct price to be cashed.

Finally, when analyzing the incidence of the day of the transaction, it is obtained that if the purchase is a Friday (t value = 5.996) or Saturday (t value = 5.938), the probability decreases. It can be associated with what in those days consumers make weekly (or monthly) purchases so they are not able to remember the large number of products they buy.

The model with the best performance considering AIC and BIC corresponds to the Beta-Geometric Regression, while considering the MAE the best fit is for the Geometric model, which have an average deviation of 40.15 products for period. Finally, talking about the best model when taking into count the MAPE, the Geometric Regression model is the best because it errs in average in a 86.0 % with respect to the real quantity of products that have a certain duration. The different models are shown in Figure 3.7 where it can see the fit of each one.

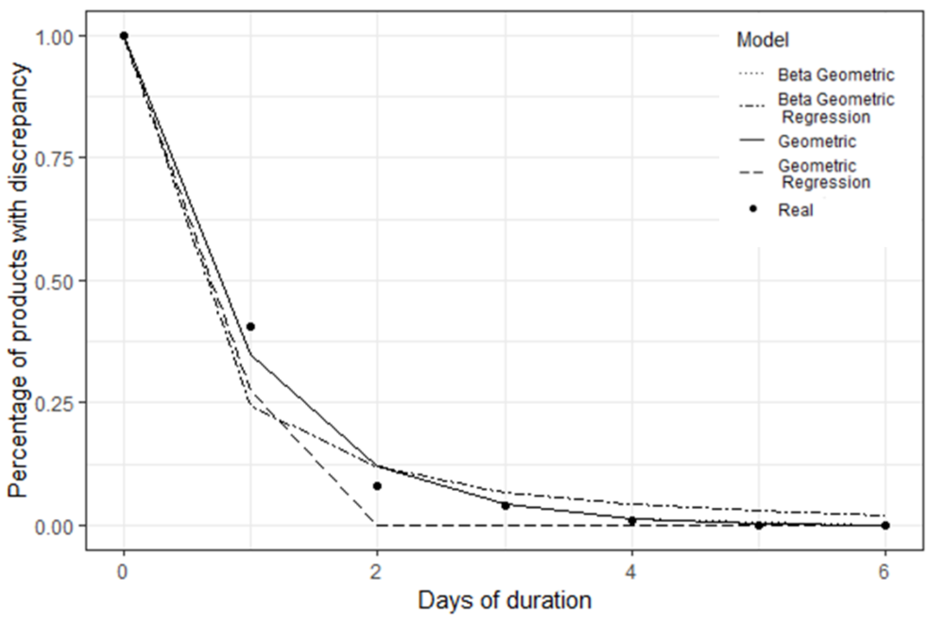


Fig. 3.7: Fit for discrete time duration models for overcharges

In the case of undercharges, for the Geometric Regression model the existence of promotions has a negative effect on the probability with a coefficient of -0.131 (t value = -3.047). That is possible to explain with which the supermarket when making promotions, does not have the ability to update the shelf-label what triggers the discrepancy to extend over time.

In relation to the influence of the price, when the product has a regular price, the probability increases with respect to those of low prices, given the associated coefficient of $\beta_{s2} = 1.045$ (t value = 16587.302), situation similar occurs for products with high prices, however, to a lesser extent with a value of 0.666 (t value = 11.89), which is explained by the fact that the supermarket must pay greater attention to the consistency of charges on high-priced and high-consumption products (which are commonly priced regularly) since errors in them can cause negative consequences both in quality of service as in possible legal actions..

The effect of the section to which the product belongs on the probability that the discrepancy, in comparison with grocery products, is that the drinks, cookies and dairy sections increase it, since they have high-consumption products, so It is relevant to ensure consistent prices by the supermarket While the cocktail and cleaning sections reduce it, what is explained is that there are limited capacities to update the shelf-label, so there is less concern for those sections since they are sold in smaller quantities

In relation to the day on which the product is purchased, considering Monday as the base level, it has to that if the transaction is carried out on any of the remaining days, the probability that the discrepancies are resolved decreases. In particular, on Thursday, it presents the largest decrease with a coefficient of -0.945 (t value = 16.579). The aforementioned, it is explained that on Monday the shelf-label updates are usually made, so when customers go to a supermarket store on the other days, it is expected that the discrepancy persists longer.

For the Beta-Geometric Regression model, the effects of the coefficients are similar to those presented previously. Which accounts for the consistency of this approach to measure the duration of discrepancies.

The geometric model is one that has the lowest MAPE value with a 0.32, which implies that on average it errs by 32.0 %. While considering, the value of MAE, the best performance is obtained by the Beta Geometric model, which is wrong in approximately 182.23 articles. The different models are shown in the Figure 3.8.

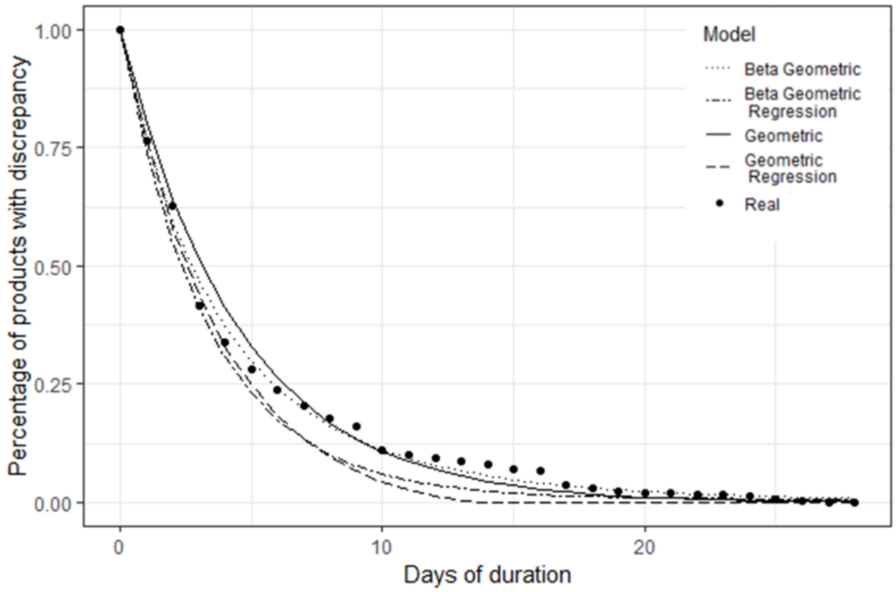


Fig. 3.8: Fit for discrete time duration models for undercharges

In the Geometric Regression model, for undercharges the probability that the discrepancy is rectified is 0.238 (0.076) and for overcharges is 0.729 (0.202). Thus, when carrying out a test of means with a null hypothesis such that the average probabilities are equal, and with an alternative hypothesis that states that the average probability of favorable discrepancies to the supermarket is greater than that of the favorable discrepancies to consumers.In this way, it has t = 202.24, which rejects the null hypothesis, therefore, it can be ensured with a confidence level of 99.0 % that overcharges are corrected faster than undercharges.

While in the Beta-Geometric Regression model, in the case of undercharges the probability of correction is 0.139 (0.097) and 0.624 (0.357) for overcharges, so that a value of t = 131.09 is obtained through a means test. Based on the above, it is confirmed that under this type of specification, the speed with which the discrepancies are corrected is different depending on the type, having for overcharges is greater, which is expected because consumers would give notice of the situation at checkout, while when it does not favor them they would not.

## 3.5. Impact of "short-term"promotions on inaccuracies

Given what has been done previously, it is clear that the duration of the discrepancies is greater when it favors the client than when it does not, and that this can be described by the detailed variables. In relation to that, it was obtained that if there is a promotion 97.1 % of the products, presents a discrepancy, which seems to indicate that there is no adequate handling of the strapping updates when the products are changed. Another interesting pattern is that expressed in Figure 3.2, from which it is possible to visualize that the discrepancy rate of the products purchased on Monday is considerably higher than the rest of the days,

Similarly, intuition seems to indicate that the situation is caused by the use of short-term promotions, that is, those with a duration of a day or two, for which the shelf-label price cannot be updated, which triggers that the consumer visualize a higher price than the one he will actually pay, thus generating an undercharge, which is observed to predominate.

To corroborate this, we proceed to study the duration of the promotions, in order to validate the existence of short-term promotions, which have a high number of discrepancies. It is in this way that 72.3 % of them lasts only one day, and 82.2 % lasts less than two. This is how 96.5 % of short-term promotions have some kind of discrepancy, of which 97.1 % favors the customer, while in longer-term promotions, 99.9 % have discrepancies, of which 99.7 % favors the customer.

The foregoing allows two situations to be indicated, the first one corresponds to the large number of existing short-term promotions, which have a high number of discrepancies, due to the difficulty to handle them quickly, and the second corresponds to the promotions of longer duration are handled worse, because the capacity seems to aim to prioritize short-term promotions (i.e. duration less than two days) so that for longer duration promotions the correction of the strap is displaced by first correcting those of short term.

Thus, it is corroborated that the high number of short-term promotions causes a high number of discrepancies, which usually favor the consumer, that is a serious problem, since the costumer does not know the price he will pay since there is no capacity operational to keep the shelf-label up to date.

When analyzing the duration of the promotions, with the purpose of determining the influence of the short-term ones, it was obtained that 82.5 % of the promotions that last one day occur on Mondays, that would help explain the rate hikes of discrepancies that were detected for these days, realizing that when making short-term promotions, they do not have the ability to update the prices of shelf-label, generating confusion in the price that will finally be paid. On the other hand, if you study the duration of price inconsistencies, of those that persist for a day, 61.3 % occur on Mondays. These findings indicate the incidence of short-term promotions on discrepancy rates, and finally the direct influence of price declines that take place on Mondays.

Noting that there is an abnormal behavior in the discrepancies that occur on Monday, it is decided to replicate the previous analyzes but this time without including the discrepancies that start on Monday, those that correspond to 19.6 % of the total discrepancies identified, being in a 98.4 % of undercharges cases.

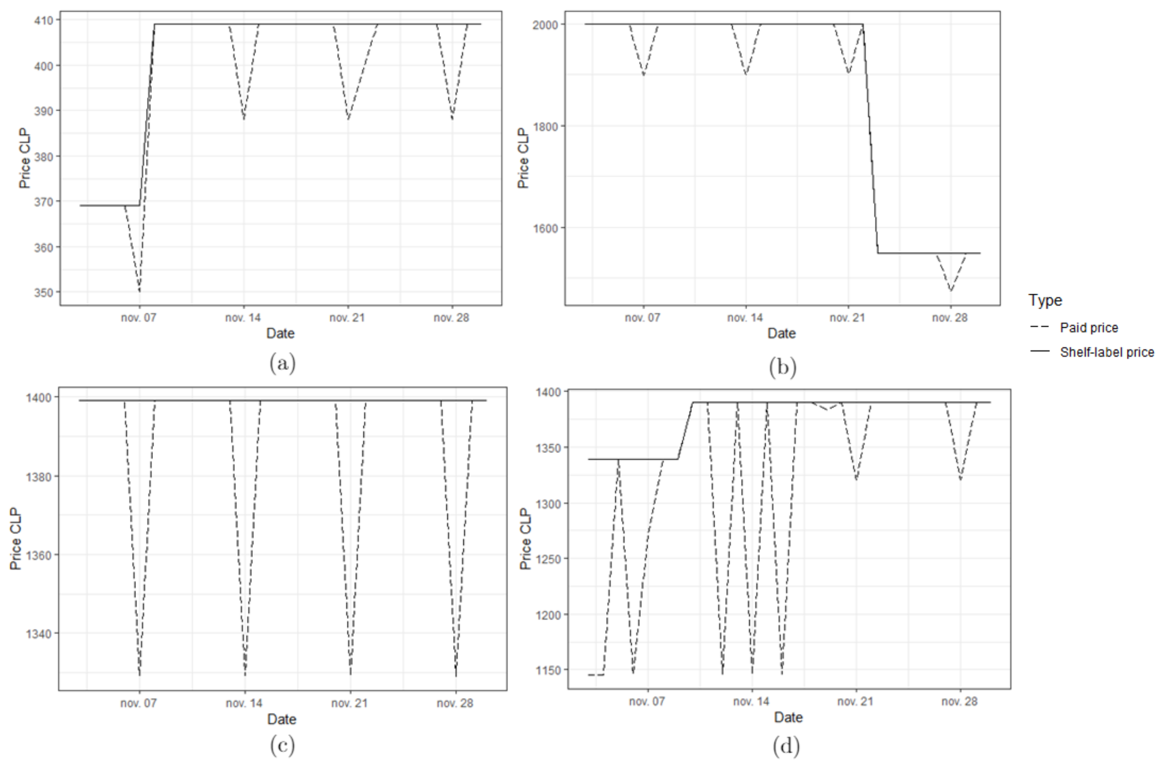


Fig. 3.9: Examples of behavior in prices

In order to visualize that, examples of how prices vary are presented in Figure 3.9, so in a) the behavior is shown when the price goes up for a product, which is displayed in the shelf price -label, and on Monday there are decreases in prices, while in b) it is shown when the product has a decrease in its price, persisting the considerable decreases for Monday. On the other hand, in c) the behavior pattern of a product that keeps its price constant it is presented, and on Mondays it presents discounts. Finally, in d) a pattern of abnormal behavior is shown, corresponding to a product of the cocktail section, it can be seen that it has constant low prices, without updating the shelf.

Table 3.3: Results of regression models without discrepancies started on Mondays

| | **General** | **Overcharges** | **Undercharges** |
|---|---|---|---|
| Intercept | 1.519 (0.174)* | 1.590 (0.205)* | 5.592 (0.194)* |
| Favor customer | 4.031 (0.148)* | | |
| **Promotion** | | | |
| Promotion | 0.185 (0.130) | 0.191 (0.071)* | 0.121 (0.153) |
| **Price segment** | | | |
| s1 | | | |
| s2 | -2.128 (0.131)* | -0.530 (0.132)* | -2.131 (0.142)* |
| s3 | -1.676 (0.109)* | -0.467 (0.112)* | -1.595 (0.122)* |
| **Product section** | | | |
| Grocery | | | |
| Drinks | -0.912 (0.182)* | -0.429 (0.333) | -0.930 (0.196)* |
| Cocktail | 3.017 (0.145)* | 1.126 (0.078)* | 3.199 (0.162)* |
| Cookies | -0.967 (0.319)* | | -0.918 (0.343)* |
| Dairy | -1.356 (0.110)* | -0.096 (0.123) | -1.494 (0.122)* |
| Cleaning | 6.674 (0.144)* | 0.566 (0.086)* | 7.113 (0.164)* |
| **Day** | | | |
| Monday | | | |
| Tuesday | 0.130 (0.206) | -0.047 (0.157) | 0.133 (0.257)* |
| Wednesday | 0.698 (0.176)* | 0.423 (0.165)* | 0.533 (0.202)* |
| Thursday | 2.318 (0.168)* | -0.128 (0.159) | 2.665 (0.198)* |
| Friday | 0.798 (0.144)* | 1.647 (0.189)* | 0.665 (0.157)* |
| Saturday | 1.220 (0.129)* | 0.480 (0.153)* | 0.915 (0.151)* |
| Sunday | 0.717 (0.136)* | -0.323 (0.152) | 0.542 (0.163)* |
| **Adjusted** $R_2$ | 0.288 | 0.336 | 0.266 |
| Observations | 13387 | 1784 | 11603 |

Table 3.3 shows the results obtained when performing linear regression models, in which the dependent variable is the duration of the discrepancies, which are consistent with those shown in Table 3.1. However, it is important to highlight that in the models that cover all the discrepancies and undercharges, the effect of the existence of promotions is minor, which shows that the problem is increased on Mondays; while the influence of promotions is greater for the overcharges model, indicating that there is a more inappropriate handling of promotions that do not start on Mondays.

Then, it is proposed to study the behavior of those discrepancies that start on Mondays, which is presented in the Table 3.4. It is noted that in the case of overcharges, there are 51 products that meet that condition, where for all of them the duration of the discrepancies is one day, being mainly items with promotion of the dairy section (92.1 %). For the general model, the effect of the existence of promotions increases the duration in 1.183 days, that is, an increase of 336.5 % with respect to the model that includes the inconsistencies of prices initiated on any day (see Table 3.1). While for undercharges the increase is 602.9 %, going from an effect of 0.175 to one of 1.230 when only the erroneous charges that start on a Monday are considered.

Table 3.4: Results of regression models with only discrepancies started on Mondays

| | **General** | **Overcharges** | **Undercharges** |
|---|---|---|---|
| Intercept | -0.963 (0.496) | - | 1.297 (0.344)* |
| Favor customer | 2.301 (0.383)* | - | |
| **Promotion** | | - | |
| Promotion | 1.183 (0.313)* | - | 1.230 (0.320)* |
| **Price segment** | | - | |
| s1 | | - | |
| s2 | -0.259 (0.118)* | - | -1.235 (0.154)* |
| s3 | -0.963 (0.496) | - | -0.269 (0.119)* |
| **Product section** | | - | |
| Grocery | | - | |
| Drinks | -0.895 (0.244)* | - | -0.906 (0.247)* |
| Cocktail | 1.716 (0.207)* | - | 1.734 (0.209)* |
| Cookies | -0.897 (0.480) | - | -0.893 (0.484)* |
| Dairy | 1.119 (0.126)* | - | 1.126 (0.127)* |
| Cleaning | - | - | - |
| **Day** | | - | |
| Monday | | - | |
| Tuesday | 1.952 (0.226)* | - | 1.954 (0.228)* |
| Wednesday | 1.424 (0.226)* | - | 1.431 (0.227)* |
| Thursday | 0.689 (0.217)* | - | 0.686 (0.218)* |
| Friday | 0.144 (0.275) | - | 0.143 (0.277)* |
| Saturday | -1.082 (0.273)* | - | -1.084 (0.275)* |
| Sunday | -0.372 (0.621) | - | -0.371 (0.626)* |
| **Adjusted** $R_2$ | 0.152 | 0 | 0.147 |
| Observations | 3270 | 51 | 3219 |

When making the models of duration in discrete time, it was obtained that for the geometric model of undercharges, the probability of correction corresponded to 0.180 (0.002) and for overcharges of 0.645 (0.009), which is consistent with the results obtained previously, noting that by excluding discrepancies initiated on Mondays, both probabilities decreased.

In the case of the specification using a Beta-Geometric model, in the case of undercharges the value of $\bar{\theta}$ is 0.200 and for overcharges of 0.645, for which, again, the results presented are maintained when all discrepancies are included.

Table 3.5: Results of geometric models without discrepancies started on Mondays

| | Overcharges | | Undercharges | |
|---|---|---|---|---|
| | **Geometric Regression** | **Beta Geometric Regression** | **Geometric Regression** | **Beta Geometric Regression** |
| $\alpha$ | | 1.179 (0.234)* | | 245.740 (95.186)* |
| $\beta$ | | 0.041 (0.012)* | | 423.734 (165.622)* |
| $\theta_0$ | 0.796 (0.010)* | | 0.275 (0.003)* | |
| **Promotion** | | | | |
| Promotion | -0.799 (0.601) | -2.302 (0.352)* | 0.107 (0.059) | 0.102 (0.052)* |
| **Price segment** | | | | |
| S1 | | | | |
| S2 | 27.766 (823.515) | -5.026 (0.605)* | 7.743 (4.997) | -1.175 (0.097)* |
| S3 | 30.676 (1046.337) | 0.127 (0.470) | 8.901 (5.008) | -0.895 (0.110)* |
| **Product section** | | | | |
| Grocery | | | | |
| Drinks | -3.933 (2478.619) | -11.995 (275.965) | 2.542 (17.846) | -0.645 (0.163)* |
| Cocktail | -9.473 (6769.378) | 6.221 (0.522)* | -8.071 (4.998) | 1.311 (0.086)* |
| Cookies | | | -6.712 (5.031) | -0.286 (0.195) |
| Dairy | 10.142 (40.995) | -2.336 (0.394)* | 1.877 (0.164)* | -0.777 (0.088)* |
| Cleaning | -20.607 (1047.338) | -0.967 (0.323)* | -9.727 (5.008)* | 1.755 (0.107)* |
| **Day** | | | | |
| Monday | | | | |
| Tuesday | 8.040 (1041.498) | -0.913 (0.434)* | -0.128 (0.155) | 0.066 (0.111) |
| Wednesday | -9.822 (40.995) | -0.711 (0.503) | -0.157 (0.128) | 0.223 (0.095)* |
| Thursday | -10.447 (40.996) | -21.518 (387.764) | -0.484 (0.098)* | 0.867 (0.070)* |
| Friday | -10.590 (40.995) | 2.636 (0.455)* | -0.111 (0.080) | 0.287 (0.059)* |
| Saturday | -9.678 (40.995) | 2.236 (0.395)* | -0.142 (0.077) | 0.334 (0.057) * |
| Sunday | 5.209 (119.434) | -0.699 (0.400) | -0.041 (0.081) | 0.213 (0.062)* |
| **LL** | -1614 | -1489 | -28939 | -28956 |
| **AIC** | 3255 | 3007 | 57908 | 57943 |
| **BIC** | 3332 | 3089 | 58018 | 58061 |
| **MAE** | 86.79 | 106.31 | 479.55 | 560.95 |
| **MAPE** | 0.85 | 11.39 | 3.65 | 0.58 |

In the Table 3.5 the geometric and Beta-Geometric regression models are presented, which show similar behavior patterns to those detailed in the Table 3.2, except that in the geometric model for undercharges , the influence of promotions is to increase the probability of correction, implying that the durations persist for a shorter amount of time, however the coefficient is not significant. Additionally, in the Beta-Geometric model for this same type of discrepancy, the negative effect of promotions is less. On the other hand, in the case of overcharges, it is observed that in the geometric regression model the negative influence of promotions is increased. Thus, for undercharges, when discrepancies with promotions started on Mondays are not considered, the effect of the promotion has an effect on the duration being shorter than in the case that includes all erroneous charges, while for overcharges, it has an effect of diminishing the probability of price inconsistencies being solved, that is, the durations are longer.

Finally, when comparing the correction probabilities under these specifications, in the case of geometric regression, for undercharges it has a value of 0.216 (0.072) and 0.692 (0.157) for overcharges; As for the Beta-Geometric regression model, the values are 0.120 (0.082) and 0.613 (0.357) respectively.

This section concludes that the effects of the variables studied in the duration of the discrepancies are maintained when the discrepancies initiated on Monday are excluded, increasing the influence of the existence of promotions for overcharges. Similarly, when only discrepancies started on Monday are considered, the previous results are maintained, however, the incidence of promotions increases significantly for undercharges and overcharges.

# Conclusion and Discussion

Thanks to the approach used in this study, which took into account the customer's perception of the price they would pay, unlike the usual performance of auditing prices, it was possible to determine the existence of three types of discrepancies. They can have different repercussions for consumers and supermarkets. In the event of a wrong charge associated with the fact that the shelf-label price is different from the price charged at checkout, the repercussions with substantially negative for the supermarket, since it denotes a low concern and control of the products, generating distrust in consumers, leading to that consumers want to change the supermarket in their next purchases [Pickering and Gaur, 2009]. Additionally, consumers can initiate claims to government entities, which can potentially end in lawsuits. With respect to product discrepancies, this shows a deficiency in the ordering of the shelves, reducing the shopping experience for customers. Finally, when the discrepancy is a consequence of a discount not attributable to the shelf-label, the supermarket loses the opportunity to introduce consumers, that their prices are low, also losing the chance to delight their customers. The described corresponds to one of the main contributions of this research, since it deepens in understanding the reasons why discrepancies occur, which is achieved by focusing on the consumer.

Then, when analyzing the level of precision presented in the supermarkets of the Chilean industry, it was evidenced that they have a poor handling of the shelf-label prices. Thus, on average 85.30 % accuracy is reached, with 4.30 % of charges that are unfavorable to consumers, with the best performance 90.24 % accuracy. In addition, if the levels reached by these supermarkets are compared with international standards, their performance would entail penalties and fines, together with economic losses due to the reimbursement of the money of the item purchased with an erroneous price [Garland, 1992].

When analyzing the discrepancy rate based on various factors, it was obtained that the proper handling of prices differs according to the geographical area of the store, which indicates that precision is prioritized in higher income areas (East zone). On the other hand, the existence of promotions triggers a substantial increase in the proportion of errors, and considering that the presence of promotions induces greater traffic to the stores, it is important to verify that the prices displayed are charged correctly.

From the above it is observed that the errors in the collections exist in large quantities in the Chilean industry, which is why it becomes relevant to implement public policies that allocate resources to control. Those measures have had significant effects in reducing errors in the countries where they have been implemented, such as the United States, New Zealand and Canada. An example is the elaborated by The Retail Council of Canada, which developed a program called the Scanner Price Accuracy Voluntary Code, where when the consumer identifies an overcharge, if the price is less than 10 dollars, the product is free, and if is greater, they get a discount of 10 dollars on their purchase.

The second study corresponded to analyze and model the duration of the discrepancies, for which a sampling was carried out for 28 continuous days in a particular room. To adjust it, we started with a linear regression model, from which it was obtained that transversely the existence of promotions has a positive impact on the duration. Additionally, the duration is shorter for products of regular prices, since they are products of mass consumption and the clients have notion of the approximate price that they pay for them. As for the sections, if the product is a cocktail, the duration is estimated to be longer, realizing that they are products for which the supermarket makes less efforts to keep prices updated, as opposed to dairy or grocery products, which are highly traded. Finally, the day on which the purchase is made has an impact on the duration, this is how if the product is traded on a Monday it is expected to persist for less time, which is closely related to the short-term promotions carried out those days, while for overcharges, if a Friday is transacted a longer duration is expected and for undercharges that happens if it is transacted on Thursdays.

Later, the duration were adjusted according to discrete and counting time models. It was obtained that undercharges are rectified at a lower rate than overcharges, considering a geometric approach, the probability to correct an undercharge is about 0.20, while for overcharges is 0.65. The previously mentioned is related to the customers when noticing a payment that is not convenient for them will give notice at checkout, so the discrepancy will be rectified. Whereas when it does not favor them, they will not alert, so that undercharges would be corrected when shelf-label updates or replacement of products are made. However, a limitation of the study corresponds to having a reduced sample of supermarkets to outsource the results obtained, so an extension to the research corresponds to extending it to more supermarkets, in a larger time window.

Seeking to capture the existence of heterogeneity, models were developed that incorporated characteristics of the discrepancy. With this, better adjustments were obtained, which in turn, allowed us to better describe the situation. Thus, the existence of promotions reduces the probability of correction of discrepancies, which accounts for a low control of it. On the other hand, in the case of overcharges, if the product belongs to the drinks, cocktail or cleaning section, the discrepancies are less likely to be resolved, while for undercharges, this occurs for the cocktail and cleaning sections. That is related to the fact that the products of those sections are purchased to a lesser extent than the rest, such as groceries, so that consumers do not remember the prices and therefore do not realize that the price charged is not the one that corresponds. Finally, for both types of discrepancies, higher prices lead to greater probabilities of correction, which shows the greater concern that exists for these products by the supermarket, and that customers are able to remember higher prices than low prices, allowing them to detect wrong charges.

The last analysis arises when noticing the existence of a high rate of discrepancies identified on Mondays, which mostly corresponded to undercharges, together with the fact that there were promotions, the erroneous collections increased, an in-depth look was made of said situation. Thus, the fit of the models was studied by separating those that start on Mondays from those that do not. So, for those discrepancies that do not start on Mondays, it was obtained that for overcharges the effect of promotions is slightly increased, while for undercharges, is less accentuated when compared to the general model. As for the discrepancies started on Mondays, the effect of the promotion leads to a considerable increase in the duration, which shows that there is a close relationship in the existence of discrepancies with the execution of short-term promotions on Mondays, which causes these discrepancies to last longer.

In the literature, the time taken for discrepancies to be corrected by the supermarket had not been determined, nor did it determine the factors that affect this, so this research contributes greatly to elucidate the behavior patterns of the discrepancies, being able to compare between undercharges and overcharges, obtaining that when it is a favorable charge for the supermarket its duration is considerably shorter than when it favors the customer.

About the implications of erroneous charges for supermarkets are framed by the loss of customers and trust on their part, which would cause a decrease in sales. Additionally, when estimating the elasticities of their products, the results would not represent reality [Hardesty et al., 2014]. For consumers, widespread discontent is generated over the industry, feeling constant damage along with the feeling of vulnerability by not having policies that can reverse the situation or protect them from the existence of discrepancies. Investigators are also harmed by these errors, because their price and transaction analyzes are biased since they do not faithfully reflect the purchase intentions of customers, as a result of them not observing the price they will actually pay.

Finally, it is proposed that this type of research has to be carried out in various areas of the country, including different supermarkets and formats to determine if what is obtained is transversal to the supermarket industry. In addition, it is relevant to study discrepancies and their durations in other industries that use price scanners. This will allow for more robust public policies that protect consumers and increase the level of service they could obtain. Additionally, it is possible to identify that the use of probabilistic models as the ones used in this study can be used in other situations besides marketing applications. It is proposed that such models would be useful to describe the duration of hospitalization of patients in medical centers or the duration of products depending on their probability of becoming defective.

# Appendix

In this section is presented the mathematical formulation for the discrete time duration model. In addition, a different formulation is presented to address this problem, in which the previously findings are validated.

## Discrete time duration models

### Shifted geometric

The first model presented corresponds to a shifted geometric, which describes the probability $\theta$ of correcting the discrepancy for any of the products, due to homogeneity. Therefore, being $T$ the random variable that describes the periods of duration, it has:

- $\mathbb{P}(T = t \mid \theta) = \theta \cdot (1-\theta)^{t-1}$ is the probability that the discrepancy is corrected at time t.
- $\mathbb{P}(T > t \mid \theta) = (1-\theta)^{t}$ is the probability that the discrepancy is corrected in a time after t.

### Beta-Geometric

When the inclusion of heterogeneity in the probability of correction of the discrepancy is considered, it is assumed that $\theta$ distributes according to *Beta*, which has the following density function:

$$Beta(\theta \mid \alpha, \beta) = \frac{\theta^{\alpha-1} \cdot (1-\theta)^{\beta-1}}{B(\alpha, \beta)} \tag{3.2}$$

For the Beta-Geometric model, the probability that the discrepancy is corrected at time t as a function of the $\alpha$ and $\beta$ parameters is expressed as:

$$
\begin{aligned}
\mathbb{P}(T = t \mid \alpha, \beta) &= \int_a^b \mathbb{P}(T = t \mid \theta) Beta(\theta \mid \alpha, \beta)\ \delta\theta \\
&= \int_a^b \theta \cdot (1-\theta)^{t-1} \cdot \frac{\theta^{\alpha-1} \cdot (1-\theta)^{\beta-1}}{B(\alpha, \beta)} \delta\theta \\
&= \frac{B(\alpha+1, \beta+t-1)}{B(\alpha, \beta)}
\end{aligned} \tag{3.3}
$$

And so that it is corrected in a time after t, the following expression is had:

$$
\begin{aligned}
\mathbb{P}(T > t \mid \alpha, \beta) &= \int_a^b \mathbb{P}(T > t \mid \theta) Beta(\theta \mid \alpha, \beta)\ \delta\theta \\
&= \int_a^b (1-\theta)^{t} \cdot \frac{\theta^{\alpha-1} \cdot (1-\theta)^{\beta-1}}{B(\alpha, \beta)} \delta\theta \\
&= \frac{B(\alpha, \beta+t)}{B(\alpha, \beta)}
\end{aligned} \tag{3.4}
$$

## Geometric Regression

In the same way it is possible to consider observable heterogeneity through the characteristics of each of the products, for which another specification is proposed.

Let $x$ the vector of characteristics, where some components are variant over time and other not, and $\beta$ the vector formed by the coefficients associated with these features. So, the probability of correction $\theta$ for product i is described as follows:

$$
\theta_{\mathrm{i}} = \theta_0 \cdot \frac{\mathrm{e}^{\beta' x_{\mathrm{i}}}}{\mathrm{e}^{\beta' x_{\mathrm{i}}} + 1} \tag{3.5}
$$

## Beta-Geometric Regression

Finally, a model that considers observable and unobservable heterogeneity is proposed, for which we have the following expression, where $x$ is the vector of product features and $\gamma$ the associated coefficients:

$$
\begin{aligned}
\mathbb{P}(T_{\mathrm{i}} \;=\; t \mid \alpha, \beta, \gamma) &= \int_a^b \mathbb{P}(T = t \mid \theta, \gamma) Beta(\theta \mid \alpha, \beta)\ \delta\theta \\
&= \int_a^b \theta \cdot \frac{1}{1+\mathrm{e}^{\gamma x}} \cdot (1 - \theta \cdot \frac{1}{1+\mathrm{e}^{\gamma x}})^{t-1} \cdot \frac{\theta^{\alpha-1} \cdot (1-\theta)^{\beta-1}}{B(\alpha, \beta)} \delta\theta \\
&= \frac{\alpha \cdot Hypergeometric2F1(1-t, 1+\alpha, 1+\alpha+\beta, \frac{1}{1+\mathrm{e}^{\gamma x}})}{(1+\mathrm{e}^{\gamma x}) \cdot (\alpha+\beta)}
\end{aligned}
\tag{3.6}
$$

# Counting models

## Poisson

The durations are measured according to the number of days in which a discrepancy persists, which allows fit to be made according to counting models. That is why the first proposed model corresponds to a Poisson, with a parameter of $\lambda$, which describes the average number of periods that the price discrepancy lasts.

Let $Y$ be the random variable that counts the number of periods in which an inconsistency is maintained for any product, the probability that the duration is of y periods is given by the following expression:

$$
\mathbb{P}(Y = y \mid \lambda) = \frac{\lambda^y \cdot \mathrm{e}^{-\lambda}}{y!} \tag{3.7}
$$

Thus, when is an undercharge, the $\lambda$ parameter is equal to 4,013 (t value = 250.813) while when it is an overcharge it is 0.536 (t value = 31.529). That result shows that when the incorrect charge benefits consumers, it is expected that approximately 4 days will pass before it can be solved, while in 0.5 days it would be resolved if it is favorable for the supermarket, coinciding with what is expressed in the hypothesis.

## NBD

Heterogeneity is then proposed to the $\lambda$ parameter, which assumes that it behaves according to a distribution *Gamma*, which has the following form:

$$
g(\lambda \mid \alpha, r) = \frac{\alpha^r \cdot \lambda^{r-1} \cdot \mathrm{e}^{-\alpha \cdot \lambda}}{\Gamma(r)} \tag{3.8}
$$

This is how the model obtained is called Negative Binomial Distribution (NBD), which depends on the parameters $r$ and $\alpha$, so that the probability that the number of periods of duration of the discrepancy is y, is given by the following expression:

$$\begin{aligned} \mathbb{P}(Y \ = \ y \mid r, \alpha) &= \int_0^{\infty} \mathbb{P}(Y \ = \ y \mid \lambda) g(\lambda \mid r, \alpha) \delta\lambda \\ &= \int_0^{\infty} \frac{\lambda^y \cdot \mathrm{e}^{-\lambda}}{y!} \cdot \frac{\alpha^r \cdot \lambda^{r-1} \cdot \mathrm{e}^{-\alpha \cdot \lambda}}{\Gamma(r)} \delta\lambda \\ &= \frac{\Gamma(r+y)}{\Gamma(r) y!} \cdot \left(\frac{\alpha}{\alpha+1}\right)^r \cdot \left(\frac{1}{\alpha+1}\right)^y \end{aligned} \tag{3.9}$$

In an NBD model, the probability of correction is calculated as $\frac{\alpha}{(\alpha+1)}$, while the average of this distribution corresponds to the expected number of periods, being computed as $\frac{r}{\alpha}$. That is why, when the discrepancy is favorable for the customer, the average corresponds to 4,013, and in the case of being favorable for the supermarket the average is 0.536. So again, the number of expected periods of persistence of inconsistencies is greater when the incorrect charge favors the customer.

## Poisson Regression

Subsequently, by including heterogeneity in the Poisson model in the $\lambda$ parameter, the following specification is obtained, taking as the feature vector x, and the vector with the associated coefficients $\beta' s$.

$$\lambda_{\mathrm{i}} = \mathrm{e}^{\beta_0 + \beta' x_{\mathrm{i}}} \tag{3.10}$$

So the probability, depending on the coefficient vector $\beta$, that for the product i the duration $Y_{\mathrm{i}}$ is $y_{\mathrm{i}}$ periods is given by:

$$\begin{aligned} \mathbb{P}(Y_{\mathrm{i}} = y_{\mathrm{i}} \mid \beta) &= \frac{\lambda_{\mathrm{i}}^y \cdot \mathrm{e}^{-\lambda_{\mathrm{i}}}}{y!} \\ &= \frac{(\mathrm{e}^{\beta_0 + \beta' x_{\mathrm{i}}})^y \cdot \mathrm{e}^{-(\mathrm{e}^{\beta_0 + \beta' x_{\mathrm{i}}})}}{y!} \end{aligned} \tag{3.11}$$

## NBD Regression

Finally, observable heterogeneity is included in the Negative Binomial Distribution model, where $\beta$ corresponds to the coefficients associated with the vector of feaures $x$ of each product. This model will be called NBD Regression, so the probability that a product is corrected after $y$ periods is given by:

$$\mathbb{P}(Y_{\mathrm{i}} \;=\; y \mid r, \alpha, x_{\mathrm{i}}) = \frac{\Gamma(r+y)}{\Gamma(r)y!} \cdot \left(\frac{\alpha}{\alpha + \mathrm{e}^{\beta' x_{\mathrm{i}}}}\right)^{r} \cdot \left(\frac{\mathrm{e}^{\beta' x_{\mathrm{i}}}}{\alpha + \mathrm{e}^{\beta' x_{\mathrm{i}}}}\right)^{y} \tag{3.12}$$

## Results

In this section the results obtained by adjusting according to the different models previously postulated are presented.

Table A1: Results of counting regression models

| | Overcharges | | Undercharges | |
|---|---|---|---|---|
| | **Poisson Regression** | **NBD Regression** | **Poisson Regression** | **NBD Regression** |
| $\alpha$ | | 412.731 (6850.186) | | 1.975 (10.669) |
| $r$ | | 1048.657 (434.136)* | | 2.547 (0.044)* |
| $\beta_0$ | 0.237 (0.235) | | 1.626 (0.017)* | 1.436 (5.403) |
| **Promotion** | | | | |
| Promotion | 0.082 (0.085) | 0.082 (0.085) | 0.004 (0.013) | -0.053 (0.024)* |
| **Price segment** | | | | |
| S1 | | | | |
| S2 | -0.378 (0.185)* | -0.376 (0.185)* | -0.463 (0.013)* | -0.518 (0.021)* |
| S3 | -0.337 (0.166)* | -0.335 (0.166)* | -0.335 (0.011)* | -0.313 (0.017)* |
| **Product section** | | | | |
| Grocery | | | | |
| Drinks | -0.280 (0.452) | -0.280 (0.452) | -0.256 (0.022)* | -0.278 (0.033)* |
| Cocktail | 0.706 (0.091)* | 0.706 (0.091)* | 0.580 (0.013)* | 0.603 (0.024)* |
| Cookies | | | -0.190 (0.035)* | -0.225 (0.055)* |
| Dairy | -0.116 (0.175) | -0.115 (0.175) | -0.249 (0.011)* | -0.263 (0.017)* |
| Cleaning | 0.362 (0.102)* | 0.361 (0.102)* | 1.008 (0.013)* | 0.990 (0.025)* |
| **Day** | | | | |
| Monday | | | | |
| Tuesday | 0.206 (0.141) | 0.206 (0.141) | 0.162 (0.020)* | 0.149 (0.036)* |
| Wednesday | 0.518 (0.151)* | 0.517 (0.151)* | 0.194 (0.017)* | 0.223 (0.030)* |
| Thursday | 0.177 (0.145) | 0.176 (0.145) | 0.466 (0.014)* | 0.459 (0.028)* |
| Friday | 0.999 (0.160)* | 0.999 (0.160)* | 0.193 (0.013)* | 0.191 (0.024)* |
| Saturday | 0.563 (0.129)* | 0.563 (0.129)* | 0.224 (0.012)* | 0.196 (0.023)* |
| Sunday | 0.026 (0.129) | 0.026 (0.129) | 0.177 (0.014)* | 0.150 (0.026)* |
| **LL** | -2295 | -2296 | -45975 | -37172 |
| **AIC** | 4619 | 4623 | 91981 | 74378 |
| **BIC** | 4702 | 4711 | 92095 | 74507 |
| **MAE** | 520.29 | 362.12 | 552.09 | 638.93 |
| **MAPE** | 97.34 | 13.76 | 2.00 | 0.40 |

Table A1 shows the results obtained using Poisson and NBD regression models. For overcharges, it shows that for the Poisson Regression model, the influence of the promotion is to reduce the probability of correcting the discrepancy, increasing, in turn, the expected number of days of error persistence, given that the associated coefficient is of 0.082 (t value = 0.965).

Meanwhile, if the product is of the regular price segment, its probability increases, and to a lesser extent if it is of high prices, comparing it with items with low prices, given the coefficients of -0.378 (t value = 2.043) and -0.337 (t value = 2.030) associated. This shows that consumers are more concerned that there are no erroneous charges on expensive products.

Investigating the impact that the section has, if the product belongs to the drinks and dairy sections, the probability of correction increases, without being statistically significant, due to the coefficients of -0.280 (t value = 0.619) and -0.116 (t value = 0.663) respectively. While it decreases when it belongs to the cocktail and cleaning section, where the associated coefficients are 0.706 (t value = 7.758) and 0.362 (t value = 3.549) taking as reference the groceries section. The foregoing realizes that customers pay less attention to the price of products from sections that consume less and therefore do not have a very clear reference price.

Talking about the influence of the day the product was purchased, compared to Monday, the other days reduce the probability of correction of the discrepancy. This effect is greater on Fridays, due to the coefficient of 0.999 (t value = 6.244), which is related to the fact that consumers who attend on Friday do not care about the price of the product they buy, so they do not detect discrepancies The coefficients associated with the price and the section remain the same as in the model, while the one that measures the effect of the promotion changes sign, however, it has no statistical significance.

For the NBD Regression model, the coefficients are practically identical to those for the Poisson Regression model. Therefore the model with the best fit when considering the AIC and BIC metrics corresponds to the NBD model, while when evaluating with respect to MAE and MAPE, the Poisson model presents the best performance, being slightly higher than the model with continuous heterogeneity, having a MAE of 22.71, which indicates that it errs on average in that quantity of products and a MAPE of 0.44, alluding to the fact that the error deviation is of the order of 44.0 %. Figure A1 shows the fit of the counting models, in order to appreciate how well they behave.

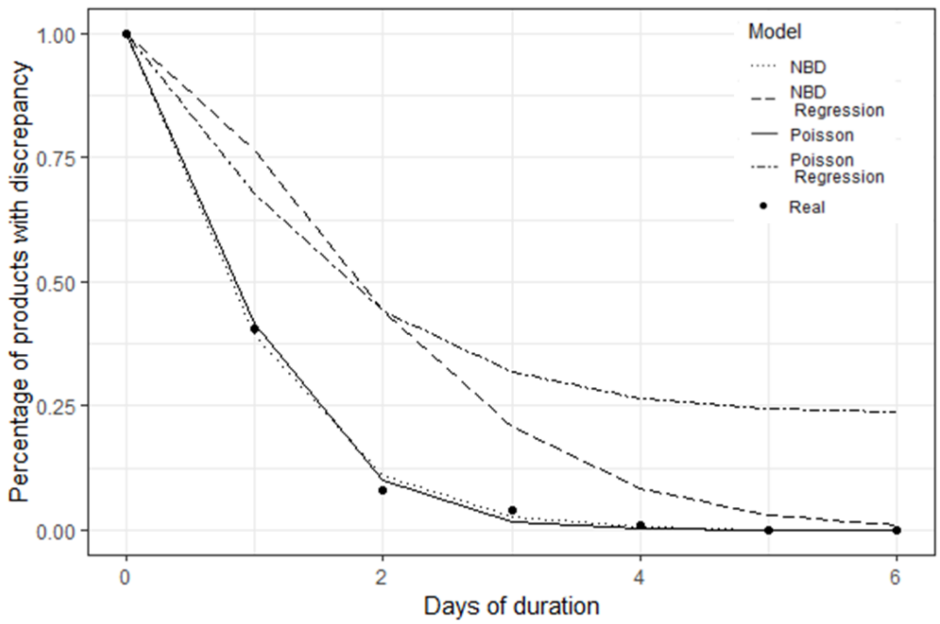


Fig. A1: Fit for counting models for overcharges

For undercharges, in the Poisson Regression model, it is not possible to indicate the effect of the promotions on the durations. However, when the product belongs to the regular or high price segment, the probability that the discrepancy is resolved increases, highlighting that belonging to the first mentioned segment increases this effect as a result of its coefficient of -0.463 (t value = 35.615). The foregoing gives the greatest concern, on the part of the supermarket administrators, in products of greater value, with which they strive in the proper handling of those for items with low prices.

In relation to the section of the product, it is obtained that when belonging to the sections of drinks, cookies and dairy products the probability of correction increases, given the value of the associated coefficients, these being -0.256 (t value = 11.636), -0.190 (t value = 5.429) and -0.249 (t value = 22.636) correspondingly, on the contrary, in the cocktail and cleaning sections, it decreases since the coefficients are positive, with values of 0.580 (t value = 44.615) and 1.008 (t value = 77.538) respectively. This is explained by which drinks, cookies, dairy and groceries products have a high turnover, so the refills have to be more followed, which means that it is more likely to detect an anomaly, while in the cocktail and cleaning sections, the rotation it is low, so there is no great handling in them.

Finally, when analyzing the effect of the day of the transaction, it has to that regard the Monday, all remaining days decrease the probability of correction, especially on Thursday with a coefficient of 0.466 (t value = 33.286). This is explained with the fact that on this day, it is not common to make price updates, being postponed for Friday with a focus on the weekend; and on Monday, in order to start the week with the products with the updated shelf-label, after the promotions made during the weekend.

The coefficients obtained for the NBD Regression model are similar to the model described above, however, this time it is possible to comment on the incidence of promotions, it is obtained that the presence of promotions increases the probability that the wrong price is corrected, with a coefficient $\beta_{promo}$ = -0.053 (t value = 2.208). That is explained by the fact that the supermarket is aware of the products that have promotion, therefore, they will have more attention in updating the shelf-label prices.

Figure A2 graphically shows that the Beta-Geometric model is the one that best fits the duration for overcharges taking into account all the metrics discussed above. Thus, it errs on average in 215.88 products, or 28.0 %. In addition, it presents the fit of the rest of the models studied.

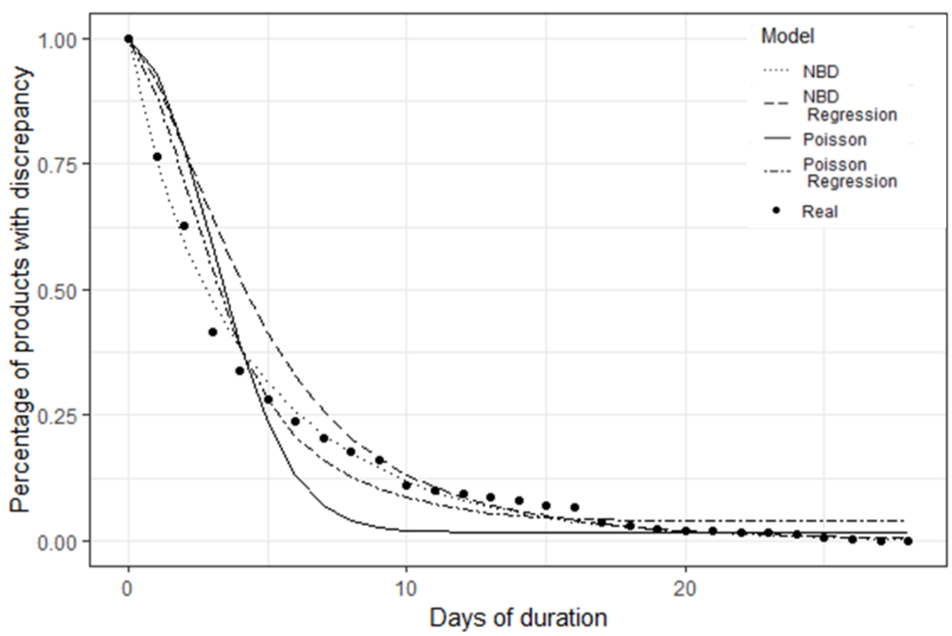


Fig. A2: Fit for counting models for undercharges

When the probabilities of correction of the Poisson Regression models developed according to the type of discrepancies are compared, in the case of being a overcharge, the average probability is 0.305 (0.075) and 0.139 (0.097) if it is an undercharge. Developing the test of means in the same way as for the models of duration in discrete time, it has to t = 70.75; therefore the null hypothesis is rejected, so that the favorable discrepancies for the supermarket are rectified more quickly than the favorable ones for the consumers.

Similar to the above, for the NBD Regression model, the probability for overcharges is 0.304 (0.075) and 0.109 (0.075) for undercharges, so doing a mean test it has a value t = 105.09. Therefore, under counting models, discrepancies that are favorable for the supermarket are rectified at a faster rate. That reaffirms what was stated in the hypothesis of this investigation. And it validates the intuitions raised about the asymmetries that consumer behaviors have when they are in the presence of erroneous charges.

# Regression

In this section the regression model is presented where the dependent variable is *"log(duration)"*, for these models the adjustment was smaller than for that with the dependent variable *"duration"*, however, the interpretation of the coefficients is consistent between them.

Table A2: Results of regression models with logarithm

| | **General** | **Overcharges** | **Undercharges** |
|---|---|---|---|
| Intercept | 0.154 (0.028)* | 0.175 (0.086)* | 1.274 (0.030)* |
| Favor customer | 1.116 (0.025)* | | |
| **Promotion** | | | |
| Promotion | -0.122 (0.021)* | 0.064 (0.033)* | -0.128 (0.024) |
| **Price segment** | | | |
| s1 | | | |
| s2 | -0.365 (0.020)* | -0.381 (0.061)* | -0.365 (0.021)* |
| s3 | -0.200 (0.016)* | -0.242 (0.054)* | -0.185 (0.018)* |
| **Product section** | | | |
| Grocery | | | |
| Drinks | -0.203 (0.029)* | -0.180 (0.142) | -0.209 (0.030)* |
| Cocktail | 0.508 (0.023)* | 0.682 (0.037)* | 0.507 (0.025)* |
| Cookies | -0.088 (0.051)* | | -0.082 (0.054)* |
| Dairy | -0.163 (0.016)* | -0.110 (0.057) | -0.177 (0.018)* |
| Cleaning | 0.852 (0.024)* | 0.274 (0.041)* | 0.885 (0.027)* |
| **Day** | | | |
| Monday | | | |
| Tuesday | 0.198 (0.039)* | 0.187 (0.054)* | 0.214 (0.036)* |
| Wednesday | 0.196 (0.027)* | 0.374 (0.058)* | 0.167 (0.030)* |
| Thursday | 0.568 (0.026)* | 0.053 (0.053) | 0.639 (0.029)* |
| Friday | 0.387 (0.023)* | 1.004 (0.072)* | 0.369 (0.025)* |
| Saturday | 0.438 (0.021)* | 0.588 (0.048)* | 0.347 (0.024)* |
| Sunday | 0.224 (0.023)* | 0.022 (0.047) | 0.294 (0.027)* |
| **Adjusted** $R_2$ | 0.283 | 0.458 | 0.219 |
| Observations | 16657 | 1835 | 14822 |

## Effect of "short-term"promotions

The plot below shows the behavior of discrepancies when those that occur on Mondays are not considered, you can see that it looks like the plot when all discrepancies are included.

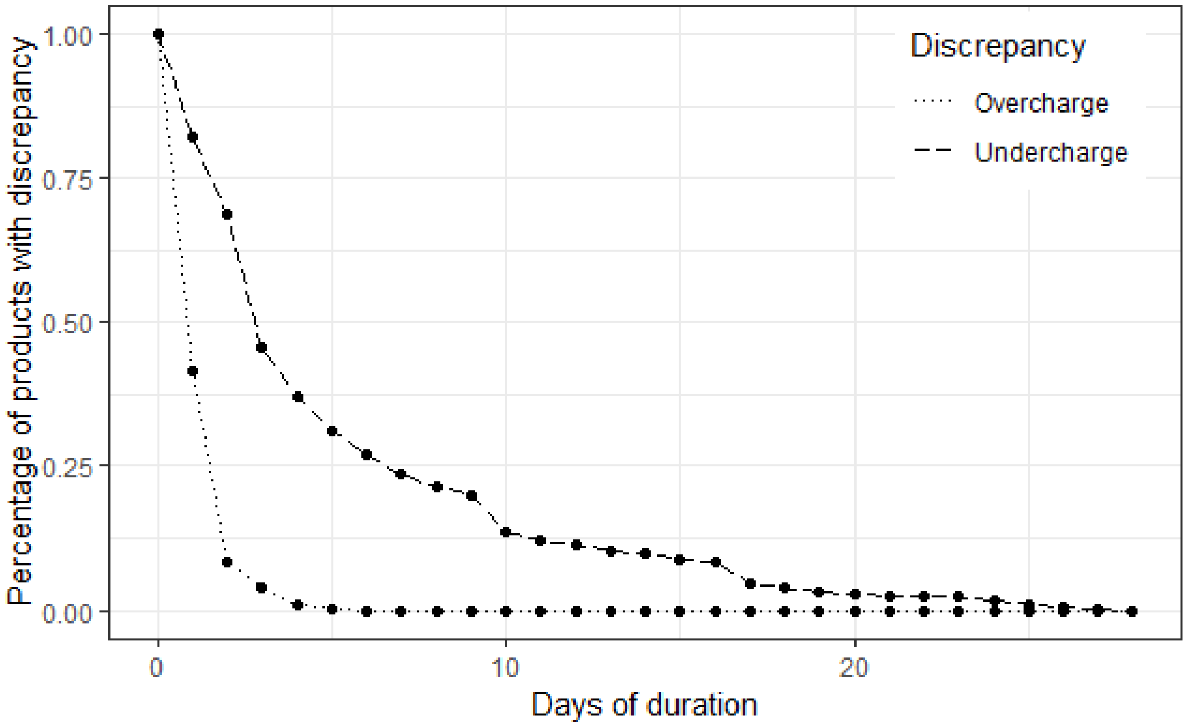


Fig. A3: Comparison of products with discrepancies according to type without Mondays

# Bibliography


[1] Doug Bartholomew. The price is wrong. *Information Week*, 14:26–36, 1992.

[2] Richard Clodfelter. Pricing accuracy at non-food retail stores using upc scanners: a preliminary study. *Retailing: End of a Century and a Look to the Future*, 8, 1997.

[3] Richard Clodfelter. Pricing accuracy at grocery stores and other retail stores using scanners. *International Journal of Retail & Distribution Management*, 26(11):412–420, 1998.

[4] Richard Clodfelter. An examination of pricing accuracy at retail stores that use scanners. *Journal of Product & Brand Management*, 13(4):269–278, 2004.

[5] Federal Trade Commission et al. A report by the staff of the federal trade commission. *Technology Services of the National Institute of Standards and Technology, the States of Florida, Michigan, Tennessee, Vermont, and Wisconsin and the Commonwealth of Massachusetts, Federal Trade Commission, Washington, DC*, 1996.

[6] Dominique Crie. Consumers' complaint behaviour. taxonomy, typology and determinants: Towards a unified ontology. *Journal of Database Marketing & Customer Strategy Management*, 11(1):60–79, 2003.

[7] Kirstie Cutler and Christopher Rowe. Scanning in the supermarket: for better or worse? a case study in introducing electronic point of sale. *Behaviour & Information Technology*, 9(2):157–169, 1990.

[8] Peter R Dickson and Alan G Sawyer. *Point-of-purchase behavior and price perceptions of supermarket shoppers.* Marketing Science Institute, 1986.

[9] Ronald C Goodstein. Upc scanner pricing systems: Are they accurate? *Journal of Marketing*, 58(2):20–30, 1994.

[10] Ronald C Goodstein and Jennifer Edson Escalas. Improving pricing accuracy at the supermarket: Electronic shelving systems and public policy. *Journal of Public Policy & Marketing*, 14(2):216–224, 1995.

[11] Elizabeth Greenfield. Omr and barcode technologies: empowering education. *THE Journal (Technological Horizons In Education)*, 19(7):10, 1992.

[12] Dhruv Grewal and Larry D Compeau. Pricing and public policy: A research agenda and an overview of the special issue. *Journal of Public Policy & Marketing*, 18(1):3–10, 1999.

[13] Dhruv Grewal, Anne L. Roggeveen, Larry D. Compeau, and Michael Levy. Retail value-based pricing strategies: New times, new technologies, new consumers. *Journal of Retailing*, 88(1):1 – 6, 2012. Pricing in a Global Marketplace.

[14] Mary Hurff Gylling. *A study of consumer attitudes toward the UPC and computerized checkout among a selected group of shoppers at Lucky's GEMCO in San Leandro, CA*. PhD thesis, thesis presented to the Office of Graduate Studies and Research, San Jose . . . , 1976.

[15] David M Hardesty, Ronald C Goodstein, Dhruv Grewal, Anthony D Miyazaki, and Praveen Kopalle. The accuracy of scanned prices. *Journal of Retailing*, 90(2):291–300, 2014.

[16] Brian F Harris and Michael K Mills. The impact of item price removal on grocery shopping behavior. *journal of Retailing*, 56(4):73–93, 1980.

[17] J Holyfield. Survey scans 9 percent error rate at checkouts. *Toledo Blade*, 23:19, 1993.

[18] Frederick W Langrehr and Virginia Blansett Langrehr. Consumer acceptance of item price removal: a survey study of milwaukee shoppers. *Journal of Consumer Affairs*, 17(1):149–171, 1983.

[19] Vanessa O'Connell. Don't get cheated by supermarket scanners. *Money*, 22(4):132–137, 1993.

[20] Department of Consumer Affairs. The scanner scam: Report on the need for a stronger item-pricing law, 1991.

[21] Virginia Office of Weights and Measures. Report on the use of uniform barcodes in the commonwealth. 1990.

[22] Paul Pickering and Sanjaya S Gaur. Price accuracy at the grocry checkout: No big deal?

[23] Michael D Pommer, Eric N Berkowitz, and John R Walton. Upc scanning-an assessment of shopper response to technological-change. *Journal of Retailing*, 56(2):25–44, 1980.

[24] Raj Sethuraman and Gerard J Tellis. An analysis of the tradeoff between advertising and price discounting. *Journal of marketing Research*, 28(2):160–174, 1991.

[25] Joel E Urbany and Peter R Dickson. Consumer normal price estimation: market versus personal standards. *Journal of consumer research*, 18(1):45–51, 1991.

[26] Joe L Welch and Tom K Massey. Consumer cost implications of reducing item omission errors in retail optical scanner environments. *Akron Business and Economic Review*, 19(2):97–105, 1988.