MASTERARBEIT | MASTER'S THESIS

Titel | Title

Do Time-Limited Offers increase the Conversion Rate in Cold Calling? - Insights from a Field Experiment

verfasst von | submitted by

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angestrebter akademischer Grad | in partial fulfilment of the requirements for the degree of

Master of Science (MSc)

Wien | Vienna, 2024

Studienkennzahl lt. Studienblatt | Degree programme code as it appears on the student record sheet:	UA 066 913
Studienrichtung lt. Studienblatt | Degree programme as it appears on the student record sheet:	Masterstudium Applied Economics
Betreut von | Supervisor:	Univ.-Prof. Dr. Wieland Müller

Abstract

The practice of contacting companies by phone, without them having previous knowledge of the products or services, with the aim of sparking their interest, is described as cold calling, one of the oldest sales strategies. A tool for measuring the success of cold calling is the conversion rate, that determines the percentage of calls that successfully lead to a desired outcome, like a meeting or sale, out of the total cold calls made. This master's thesis focuses on investigating the impact of time-limited offers on conversion rates in cold calling within a Business-to-Business (B2B) environment. Through a real-life field experiment involving nearly 2,000 calls by professional cold callers, the study examines whether the duration of time limits and the use of loss aversion framing influence the conversion rate of these offers. The findings reveal that while time-limited offers, particularly those framed as a potential loss, can slightly improve conversion rates, these differences are not statistically significant. However, the study highlights the strategic value of shorter time limits in accelerating the sales cycle and generating quicker revenue. The research concludes that while time-limited offers may not drastically increase conversion rates, they remain a useful tool for boosting short-term revenue and could be applied selectively based on the sales context and target audience.

Kurzzusammenfassung

Die Praxis, Unternehmen ohne vorherige Kenntnis von Produkten oder Dienstleistungen telefonisch zu kontaktieren, um ihr Interesse zu wecken, wird als Kaltakquise bezeichnet und gehört zu den ältesten Verkaufsstrategien. Ein gängiges Mittel zur Erfolgsmessung der Kaltakquise ist die Konversionsrate, welche den Anteil der Anrufe ermittelt, die zu einem gewünschten Ergebnis führen, etwa einem Termin oder Verkauf, im Verhältnis zur Gesamtzahl der getätigten Anrufe. Diese Masterarbeit untersucht den Einfluss zeitlich begrenzter Angebote auf die Konversionsraten im Business-to-Business-Umfeld (B2B). In einem Feldexperiment mit fast 2.000 Anrufen von professionellen Kaltakquisiteuren wird analysiert, ob die Dauer des Zeitlimits und die Verwendung von Verlustaversion in der Argumentation die Konversionsrate beeinflussen. Die Ergebnisse zeigen, dass zeitlich begrenzte Angebote, insbesondere wenn sie als potenzieller Verlust dargestellt werden, die Konversionsrate zwar leicht steigern können, diese Unterschiede jedoch statistisch nicht signifikant sind. Dennoch betont die Studie den strategischen Nutzen kürzerer Zeitlimits, da diese den Verkaufsprozess beschleunigen und schneller zu Umsätzen führen können. Insgesamt kommt die Forschung zu dem Schluss, dass zeitlich begrenzte Angebote zwar keine signifikanten Auswirkungen auf die Konversionsraten haben, jedoch ein nützliches Instrument zur kurzfristigen Umsatzsteigerung darstellen und je nach Verkaufskontext und Zielgruppe gezielt eingesetzt werden können.

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1 Introduction

A classical sales strategy for capturing the interest of new potential clients in a company's products or services, is cold calling. Cold calling refers to the practice where companies contact individuals or other businesses, known as prospects, by phone. These prospects typically have shown no previous interest in the product or service and are often unfamiliar with the company. The goal is to gain the prospect's interest through and, if successful, arrange a product demonstration, during which the company can attempt to make a sale to the prospect.

Its simplicity and cost-effectiveness - requiring nothing more than a phone and a list of numbers - make it a resilient approach for generating leads.

According to Schultz et al. (2019), 70% of sellers use cold calling to connect with their prospects. Furthermore, sellers agree that "cold calling works and [that] it's still one of the most effective ways to generate initial sales conversations". Additionally, Organizations that do not engage in cold calling, experience 42% less growth compared to those that utilize this tactic (Crunchbase, 2020). Therefore, it is crucial for companies to gain a deeper understanding of their cold calling process to enhance their success rates.

While the cold calling process may appear straightforward at first glance, it is quite challenging. Numerous sales methods have been explored to enhance the effectiveness of cold calls, yet the impact of incorporating time-limited offers in cold calling remains under-examined.

Therefore, this thesis investigates whether time-limited offers, widely studied in marketing, affect the conversion rate in cold calling. It examines whether the duration of the time limit - short or long - alters the conversion rate and assesses the influence of loss aversion framing on the conversion rate. To address these questions, four professional Cold Callers at an Austrian Tech company, who will receive training prior to the experiment, are set to conduct approximately 2,000 cold calls over a two-month period.

The findings of this study are applicable both practically and theoretically. Practically, they provide deeper understanding of customer decision-making processes, which can enhance the efficacy of cold callers and the overall sales department. Theoretically, this thesis offers a novel perspective on time-limited offers and because there is no earlier evidence, this thesis extends the existing body of research to a new domain: cold calling.

This thesis begins by stating the research questions of this master's thesis. Thereafter, the literature review examines statistics on cold calling, its significance for companies, and then delves into existing studies on time-limited offers in various fields, as well as research on loss aversion and loss aversion framing. The following section details the field experiment, covering the sales environment, the training period for cold callers, the cold calling pitch, and the data collection process. The collected data is then precisely described, followed by a thorough analysis and presentation of the results. Finally, the findings are discussed, along with the real-life implications of the experiment's results.

The results of the experiment reveal that while time-limited price discounts yield slight improvements in conversion rates, these differences are not statistically significant. Both shorter time-limited offers and loss aversion framing strategies showed marginally better performance in comparison to the longer time limit and no loss aversion framing, but again without significant impact. However, the study suggests that time-limited discounts could still be useful in accelerating the sales cycle and generating quicker revenue, particularly in specific sales contexts like Business-to-Business environments.

2 Research questions

As previously discussed, time-limited offers have been extensively researched, and most studies agree that these offers positively impact sales numbers. While most of these studies focus on Business-to-Consumer (B2C) and E-Commerce environments, where products or services are sold directly to consumers, there has been little attention paid to their use in Business-to-Business (B2B) settings, where transactions occur between companies. Notably, no study has examined the impact of time-limited offers on the success rate of cold calling, a key sales strategy.

Therefore, this study aims to analyze in a real-life field experiment, whether incorporating time-limited price discounts affects the conversion rate in cold calling. The conversion rate, a metric used to measure the success of cold calling efforts, is defined as the ratio of successful calls to the total number of calls. More details on this will be provided in the methodology section. Consequently, the first research question is:

Q1: Do time-limited price discounts increase the conversion rate in cold calling?

The key challenge when implementing time-limited price offers is determining the most effective duration for the time limit. As described by Inman and McAlister (1994, p.426), the ideal length of the time limit is highly dependent on the sales context. If the time limit is incorrectly chosen, as discussed by Sugden et al. (2019, p.22), the use of time-limited offers can deter the acceptance of the offer and cause more harm than good. This leads to the second research question:

Q2: Does a short time limit induce a higher conversion rate than a long time limit in cold calling?

By answering the first two research questions, it is determined whether time-limited offers increase the conversion rate in cold calling. However, in real-world scenarios, the mere existence of a time-limited price discount is not the only factor at play. The framing of the offer also matters. As discussed by Novemsky and Kahneman (2005, p.125), the presentation of information significantly affects buyers' decisions. This study will therefore analyze whether loss aversion - the tendency to react more strongly to losses than to equivalent gains (Kahneman & Tversky, 1984, p.342) - impacts the conversion rate in cold calling when offering a time-limited price discount:

Q3: Does framing the time-limited price discount as a loss, if turned down, lead to a higher conversion rate than framing it as a gain, if accepted?

By answering these research questions, companies can gain an additional tool to enhance their success in cold calling, and thereby increasing their revenue. With 61% of salespeople finding selling harder than five years ago, improving conversion rates in cold calling is crucial for maintaining competitiveness and gaining and competitive advantage (Wayshak, 2022, p.1). Considering that companies engaging in cold calling experience 42% more growth than those that do not (Crunchbase, 2020, p.3), this thesis can make sales teams in B2B environments perform better.

3 Literature Review

3.1 Cold Calling

Cold calling is a sales technique where a salesperson contacts potential customers who have had no prior interaction or expressed interest in the product or service being offered. This method typically involves reaching out via phone calls but can also include in-person visits or emails. Despite the rise of digital marketing channels, cold calling remains one of the oldest and most prevalent methods for attracting new customers. In this practice, companies aim to spark interest in their offerings through a sales pitch, often with the objective of arranging a product demonstration to ultimately secure a sale. This approach targets prospects who are usually unfamiliar with the company (Hayes, 2023).

Cold calling remains a crucial sales technique in today's competitive markets, demonstrating significant relevance and effectiveness. According to research provided by Rain Group (Schultz, 2023), 82% of buyers are open to meetings with sellers who proactively reach out to them, and 69% have accepted phone calls from new providers within the past year. This highlights the openness for cold calls on the buyer side, particularly among senior-level buyers, with 57% of C-Level and Vice President buyers preferring phone contact, compared to 51% of directors and 47% of managers (Schultz, 2023). The importance of cold calling is further emphasized by its impact on organizational growth. Companies that engage in cold calling experience 42% more growth than those that do not (Crunchbase, 2020). Additionally, despite advancements in digital communication, 41.2% of sales professionals still regard the phone as their most effective sales tool (Wayshak, 2022)
Increasing the conversion rate in cold calling is vital due to the rising difficulty in selling. With 61% of salespeople finding selling harder than five years ago, improving conversion rates is essential for maintaining competitiveness (Wayshak, 2022). In a huge study of Raval (2024), where 5.265 cold calling conversations have been collected, the average success rate of cold calls was 4.82%, a significant increase from the 2% success rate in 2023, demonstrating the potential for effective strategies to boost the success of cold calls.

This thesis begins by exploring whether time-limited offers can enhance the success rate of cold calling. The conversion rate, a key metric in sales and marketing, measures campaign success. Numerous definitions exist, as highlighted by Saleh & Shukairy (2010), but for the purpose of this thesis, the focus is on the two following specific measures: *Conversion Rate 1 (CVR_1)*, which is the number of product demos scheduled divided by the total number of calls made within a specified timeframe, and *Conversion Rate 2 (CVR_2)*, which is the number of product demos scheduled divided by the total number of conversations with decision-makers within the same timeframe. These metrics are crucial for assessing the effectiveness of cold calling strategies and determining if the usage of time-limited offers can improve these two conversation rates in cold calling.

3.2 Time limited offers

When considering time-limited offers, two main types typically come to mind. The first is quantity-based, such as the classic “buy 2, get 3” promotion, while the second is price-based, featuring a discount available for a limited time. Although both types of offers have been extensively researched, as indicated below, and have valid justifications for their use, this study focuses on time-limited price discounts due to the feasibility of the experiment. The following studies demonstrate that time-limited price discounts can be effective, with some working broadly and others under specific conditions, along with a brief explanation of why they are successful.

Broeder & Wentink (2022) investigated the impact of limited-time promotions on purchase intention. Their study analyzed psychological factors such as perceived scarcity and competitive arousal. The results indicate that time-limited offers create higher perceived scarcity, which in turn leads to a higher purchase intention. Tiemessen et al. (2023) explored the effects of limited-time discounts on consumer buying behavior and experience. Their findings revealed that time-limited offers with a price discount increase the customer preference for the discounted product. Additionally, these offers induce fear of missing out among consumers. However, this perceived fear can also lead to a negative reaction towards offers and websites utilizing time-limited promotions. Joo et al. (2005) examined the effects of location-based coupons sent through smartphones, which included time-limited offers for price discounts. Their results showed that purchase intention increases with time-limited discount messages. Furthermore, the effect is more pronounced when the consumer perceives a high emotional value for the product. Aggarwal & Vaidyanathan (2003) identified additional psychological reasons why time-limited offers with price discounts are effective. They found that such promotions reduce the consumer's intention to search for alternatives, foster a positive attitude towards the deal, and hasten the purchasing decision. The primary driving factor behind these effects is the fear of missing out. Guo et al. (2017) observed that higher arousal leads to increased buying pressure and urgency. When combined with the feeling of fear of missing out, time-limited offers can trigger impulsive buying behavior. Swain et al. (2006) also determined that urgency is a key reason why time-limited offers are effective. They found that these offers, when combined with price discounts, enhance consumers' intention to purchase by influencing their evaluation of the deal and their anticipation of regret. These effects are particularly strong when the perceived value of the product is high. The study by Khetarpal and Singh (2023) stands out by expanding on the current body of literature, examining the influence of time-limited appeals on purchases made without any prior shopping intentions. This is particularly relevant to cold calling scenarios, where potential customers typically have no prior intention to buy since they are often unaware of the product's existence.

But not all research on time-limited offers indicates that they are effective. Brannon & McCabe (2001) found that time-limited offers are successful only when there is a strong justification for their existence. When the reasoning behind the offer is weak, sales with time-limited offers can perform worse than those without them. Therefore, companies must carefully consider the strength of their sales appeal before designating their offers as time-limited. Conversely, Devlin et al. (2007) discovered that the presence of a time limit does not affect perceptions of value, search behavior, or purchase behavior. Their study found that the discount itself was the only factor influencing purchase behavior, suggesting that, in the context of consumer durable goods, time-limited offers may not be necessary. Further studies indicate that time-limited offers are effective only under specific conditions. Peng et al. (2019) analyzed the connection between time-limited offers and consumer involvement. Consumer involvement measures how emotionally connected buyers feel to a product—the higher the consumer involvement, the higher the perceived value of the product. The study's results demonstrate that perceived value significantly influences purchase intentions under time pressure, but only for products that require a high level of consumer involvement. These findings are supported by Kim et al. (2020). Their study examined the relationship between construal levels and the effectiveness of time-limited offers. Construal levels refer to how abstractly (high construal) or concretely (low construal) people think about a given product. The results show that participants with low construal levels responded more positively to time-limited offers, while those with only an abstract idea of the product responded more negatively.

Building on prior research, the first hypothesis emerged, stating that time-limited price discounts increase the conversion rate in cold calling. This is supported by the psychological impact these offers have in creating a sense of urgency and fear of missing out, which can effectively prompt immediate decisions to schedule a product demonstration during a cold call, even without prior buying intention:

H1: Time-limited price discounts increase the conversion rate in cold calling.

3.3 Length of time limited offers

A crucial aspect of time-limited offers is determining the appropriate length of the time limit, which can be challenging. While most studies suggest that shorter time limits are generally more effective than longer ones, setting the limit too short can have the opposite effect, deterring customers from making a purchase. The following studies highlight the importance of choosing the time limit carefully, with evidence that shorter timeframes are typically more successful.

Inman and McAlister (1994) suggest that the ideal length of time-sensitive offers is largely determined by the specific sales context and is not universally applicable, but their findings indicate that such offers have a greater impact when the expiration date is imminent. Supporting this, Krishna and Zhang (1999) also find that shorter duration offers tend to be more effective than those with extended timelines. Moreover, Aggarwal and Vaidyanathan (2003) discovered that brief promotions, like store coupons, tend to expedite purchasing decisions, while longer promotions do not have the same effect.

However, Sudgen et al. (2019) advise caution with overly restrictive time limits, noting that insufficient decision time can deter offer acceptance. One explanation for this is that the search process for alternatives is interrupted. As a result, the longer time limit received more positive responses than the shorter time limit.

Additionally, the study by Teng and Huang (2007) suggests that short time-limited offers should be used with caution. They found that longer time limits in cyber promotions lead to lower perceived time pressure by consumers and a higher likelihood of consumers choosing higher-priced items. Moreover, products that engage consumers more tend to involve higher time pressure, lower consumer satisfaction, and a lower proportion of consumers taking advantage of the promotion for that product.

The literature indicates that shorter time-limited offers are generally more effective in driving consumer decisions, though they must be balanced to avoid deterring customers by imposing excessive time pressure. Given that shorter time limits tend to create a stronger sense of urgency and prompt quicker purchasing decisions, the second hypothesis H2 posits that shorter time limits will induce a higher conversion rate than longer time limits:

H2: Shorter time limits induce a higher conversion rate than longer time limits.

3.4 Loss aversion

Khetarpal and Singh's (2024) research not only demonstrates that time-limited offers are effective for consumers with no prior shopping intentions but also uncovers a correlation between such offers and impulsive buying, mediated by the fear of missing out. Additionally, Sudgen et al. (2019) found that individuals generally want to avoid even minimal risks, such as passing up a time-limited offer and potentially regretting the decision later.

Therefore, this study also analysis whether using loss aversion in framing does have an impact on the conversion rate as well.

Loss aversion, a principle in behavioral economics established by Kahneman and Tversky (1984), reflects the tendency to experience the emotional impact of a loss more intensely than the joy of an equivalent gain. This bias towards perceiving losses more intensely than gains can lead individuals to take disproportionate risks to avert losses. Prospect theory, formulated by Kahneman and Tversky (1979), explains that decisions are made based on the perceived relative gains and losses rather than actual outcomes. The impact of framing, as discussed by Novemsky and Kahneman (2005), demonstrates that the presentation of information significantly affects individuals' decisions. Their findings implicate that consumers may not be willing to pay the market price to try a good, but they may pay the market price to avoid losing that good. Therefore, presenting an offer's rejection as a loss could be more impactful than presenting its acceptance as a gain.

Subsequent research has delved into how time pressure impacts loss aversion. Kocher et al. (2013) conducted two experiments revealing that loss aversion intensifies under time constraints, especially when potential losses are involved. Even when the scenario is positively framed, correctly applying time pressure can enhance loss aversion. Belli et al. (2023) support these findings in a meta-analysis involving over 65,000 respondents, demonstrating that risk preferences wane when outcomes are framed as losses. These studies imply that a time-limited offer depicted as a loss is more likely to be chosen than one portrayed as a gain.

The literature indicates that loss aversion, particularly when combined with time constraints, significantly influences consumer behavior, making people more likely to act to avoid losses than to achieve gains. Given the stronger psychological impact of avoiding losses compared to achieving gains, H3 hypothesizes that framing time-limited offers as a loss, if turned down, will have a higher impact on conversion rates than framing them as a gain, if accepted:

H3: *Framing time-limited offers as a loss, if turned down, induces a higher conversion rate than framing time-limited offers as a gain, if accepted.*

With the examination of the hypotheses through the literature review now complete, the following chapter will outline the methodology of the experiment designed to answer the research questions. It begins by describing the field experiment environment, followed by an in-depth exploration of the data collection process, the training period including the actual sales pitch, and concludes with the steps taken to ensure the credibility of the data.

4 Methodology

4.1 The field experiment environment

The participating company in this real-life field experiment is an Austrian business with approximately 100 employees, operating in a Business-to-Business (B2B) Software as a Service (SaaS) environment. This software provider specializes in delivering workflow automation through artificial intelligence, assisting other companies with accounting, compliance, and risk management. The company's typical clients are the finance departments in medium and large enterprises as well as accounting firms. Through privacy reasons, the company profile is anonymous. If needed, further information about the company profile can be gathered by getting in touch with the author.

The sales process for acquiring new customers is structured as follows: A team of cold callers initiates contact with other companies, aiming to reach key decision-makers such as the CEO, CTO, or CFO. They provide information about the software, and if the contact expresses interest, the cold caller schedules an appointment for a product demonstration. This product demonstration, which includes a detailed presentation of the software, is conducted by a different sales department. The primary responsibility of the cold callers is to schedule these product demonstration appointments with new potential clients. Therefore, a successful cold call results in an appointment being set, while an unsuccessful cold call occurs when the potential client declines to schedule an appointment.

4.2 Data collection process

For the experiment, the company agreed to provide four professional cold callers. These cold callers made an average of 16 calls per day over a period of 31 working days for the experiment. Before the experiment began, a statistical power test indicated that a sample size

of 1,800 calls would be sufficient (Appendix 1). In total, 1,992 calls were made for the experiment.
During each call, various data points were collected. First, it was noted whether the cold caller successfully reached the decision-maker after getting past the gatekeeper, usually a secretary or assistent. If successful, the next step was to determine whether an appointment was set.

This process allows for the calculation of two conversion rates:

$$Conversion\ Rate\ 1\ (CVR_1) = \frac{total\ number\ of\ successful\ cold\ calls}{total\ number\ of\ calls}$$

$$Conversion\ Rate\ 2\ (CVR_2) = \frac{total\ number\ of\ successful\ calls}{total\ number\ of\ conversations\ with\ a\ decison\ maker}$$

While CVR_2 provides a better measure of the effectiveness of time-limited price offers, as it focuses only on conversations with decision-makers, CVR_1 offers insights into the overall efficiency of the cold callers. Additionally, CVR_1 is a widely used metric, which can help other companies and sales teams compare and interpret the results, assessing the applicability of the findings to their own contexts.

4.3 Training

Prior to the start of the experiment, the cold callers received a training session following a methodology similar to that outlined in Shelegia and Sherman (2022). This training was designed to ensure that each cold caller possesses a similar level of knowledge regarding the product and the sales pitch. It began with an in-depth session covering every feature of the software, followed by a coaching on how to effectively present the software to prospects. To facilitate this, a script was provided which outlines how to articulate the software's features, discuss the time-limited offer, and address objections. To verify the effectiveness of the training, all cold callers were required to conduct simulated calls with the researcher, as well as real cold calls with prospects who are not part of the sample size. Only after the researcher confirmed a high quality of the cold calls of every participant, the experiment began. A documentation of the training can be found in Appendix 2. The objective of this coaching was to minimize any potential learning biases throughout the duration of the experiment. As discussed in the analysis section of this thesis, the training phase had a positive impact on the cold callers. This is evidenced by the fact that the conversion rate during the experiment was higher for every cold caller compared to their pre-experiment conversion rates. Additionally, the variance in conversion rates among the individual cold callers decreased, indicating that their knowledge and skill levels became more similar. A more detailed examination of the conversion rates is provided in the analysis section.

4.4 Randomization process

To provide a high scientific standard, the contacted companies were randomly assigned to either the control group or one of several treatment groups. Before the experiment, each cold caller was provided with a list of companies assigned to their respective groups. To mitigate biases, the demographic characteristics of the companies were kept the same across all cold callers.

The control and treatment groups followed this structure:

C_0: Control group without time-limited price discount and without framing, before the start of the experiment

C_1: Control group without time-limited price discount and without framing, during the experiment

T_1: 2-week time-limited price discount without framing

T_2: 4-week time-limited price discount without framing

T_1_gain: 2-week time-limited price discount, framed as a gain, if the offer is accepted

T_1_loss: 2-week time-limited price discount, framed as a loss, if the offer is rejected

In addition to the control group *C_1*, which collected the sample size during the experiment, a second control group, *C_0*, was used. *C_0* included aggregated data from the three months before the experiment started and served to check for potential biases in the sample size. For both control groups, no time-limited offers or particular framing was used in the sales pitch.

The treatment groups *T_1* and *T_2* were designed to examine the effects of time-limited price discounts on the conversion rate. In both groups, no framing was involved to isolate the impact of time-limited price discounts. *T_1* had a time limit of two weeks, while *T_2* had a time limit of four weeks. Prospects received the price discount if they agreed to schedule a product demonstration within the specified time frame. The two-week time limit is relatively short, while the four-week time limit provides insights into whether the mere existence of time-limited offers increases the conversion rate, as the average duration between the last call and the demo appointment was 27.3 days in the three months prior to the experiment. Thus, the four-week time limit can be seen as an additional variable, whether the pure existence of time-limited price discounts per se increases the conversion rate.

Due to resource and time constraints, it was not possible to collect a loss aversion framing sample size for both time limits. Therefore, the researcher decided to analyze the loss aversion framing only for the more effective time limit. As indicated in the results, the usage of the shorter time limit, e.g. the two-week time limited price discount, is recommended for other companies. Consequently, the loss aversion framing was only conducted for the two-week time limit price discount. Treatment *T_1_gain* incorporated the two-week time-limited offer with the price discount framed as a gain, if the offer is accepted, while treatment *T_1_loss* incorporated the two-week time-limited offer with the price discount framed as a loss, when the offer is rejected.

The data collection process was conducted in two phases. In the first phase, data for the control group *C_1* and the treatment groups *T_1* and *T_2* was gathered to observe the pure effect of time-limited price discounts on the conversion rate. In the second phase, data for the treatment groups *T_1*, *T_1_gain*, and *T_1_loss* was collected. During this phase, *T_1* acted as the new control variable because the aim of the second experiment was to determine whether incorporating loss aversion would result in a higher conversion rate for the two-week time-limited offer compared to no framing. Using *C_1* from phase 1 as the control could potentially distort the results; however, using *T_1* as the new control variable allows for more comparable results, as the only difference is in the framing and not in the usage of time-limits.

While this section outlines the randomization process and the structure of the control and treatment groups, the following section introduces the characteristics of each sales pitch and the specific differences among the individual groups.

4.5 The cold calling pitch

For simplicity, only a brief outline of the cold call structure used in this experiment is provided here. The actual pitch can be accessed via request but is handed over to the supervisor.

The cold call structure used in this experiment is the result of many years of trial and error, reflecting the most effective approach over the past few years. Therefore, this structure was adopted as-is, without attempting to reinvent the wheel and to create a new pitch. Based on private conversations with cold callers from other companies in the Business-to-Business, Software as a Service industry, it is anticipated that many other companies follow a similar cold calling structure. However, it is important to note that this script was not developed from scientific papers, so the results should only be compared with companies using a similar approach.

The cold calling pitch consists of four phases. The first phase is the introduction, which includes a conversation opener where the cold caller introduces themselves and the company they represent, followed by a brief description of the company's offering. It typically goes as follows:

"Hi Mrs. Smith, Philip Paulus here from [example company]. We provide software that does [XYZ]. Have you ever heard of [example company]?"

At this point, the introduction phase is complete. It is crucial that the prospect responds that they do not know the company, as this confirms it is a cold call. If the prospect is already familiar with the company, the call is excluded from the sample size.

The second phase is the problem statement phase. The goal of this phase is to prompt the prospect to acknowledge a problem that the cold caller's company can solve. To achieve this, calibrated questions are used. This phase is highly individualized since every conversation is unique. Therefore, cold callers are provided with a variety of questions they can choose from, depending on the situation and the prospect's responses. This list of questions serves as a toolbox. In this field experiment, and within the industry in which the participating company operates, the calibrated questions are extremely specific. Therefore, analyzing the responses to these questions is not relevant for other companies and the outcome of this study.

After the prospect acknowledges the problem, the third phase begins: the solution phase. In this phase, the cold caller presents a solution to the prospect's problem. The cold caller starts by repeating the prospect's problem statement in their own words to ensure clarity. Then, the cold caller explains how the company can address the issue by providing a clear solution. Additionally, the cold caller highlights the value proposition of the product or service, such as time savings, increased efficiency, or cost reduction, to gain the prospect's interest. This phase is standardized and consistent across all cold calls, typically structured as follows:

"So you're saying you have a problem with [XYZ]. From our experience, our software can solve this by [XYZ], resulting in [example value proposition] for you."

Typically, the prospect may have some questions that the cold caller needs to answer. Once the prospect's interest is secured, the fourth and final phase begins: the appointment phase. At this stage, the cold caller concludes the conversation by scheduling an appointment for a product demonstration. Up to this point, the cold calls are identical across the control and treatment groups, except for the problem statement phase. Differences in the groups emerge during the appointment phase, where the pitch varies.

For the control group *C_1*, the pitch includes no time-limited offer or framing, using a neutral formulation: *"If that sounds interesting to you, we can schedule a product demo. When is a good time for you?"*

For the treatment groups *T_1* and *T_2*, which involve time-limited price discounts of two and four weeks without any framing, the offer is pitched as follows: *"If that sounds interesting to you, we can schedule a product demo. If we schedule it within the next 2 (4) weeks, there is a discount of [XYZ] Euros."*

In the treatment group *T_1_gain*, the two-week time-limited offer is framed as a gain, incorporating the word "save" into the pitch: *"If that sounds interesting to you, we can schedule a product demo. If we schedule it within the next 2 weeks, you save up to [XYZ] Euros."*

In the treatment group *T_1_loss*, the two-week time-limited offer is framed as a loss if the prospect rejects setting an appointment within the next two weeks: *"If that sounds interesting to you, we can schedule a product demo. If we schedule it within the next 2 weeks, you get a discount. If we schedule it later, you lose the chance to save up to [XYZ] Euros."*

As previously mentioned, the control and treatment groups only differ at the end of the conversation when the offer for the product demonstration is made. Consequently, the results of the individual groups should be highly comparable.

4.6 Credibility of the data

This section discusses the measures taken to ensure data credibility, including reliable data collection, a detailed documentation, and randomization to set high standards. Potential biases, such as learning effects, are acknowledged and addressed in the Appendix 3 to further ensure the reliability of the findings.

To ensure the integrity of the data, several measures will be implemented. Firstly, there will be control over the identity of the cold caller via a cold caller-ID. By accessing previous performance data under standard real-life circumstances, without any experimental interventions, what is collected in the control group *C_0*, the reliability of the data for each cold caller can be assessed. Moreover, it will be ensured that each cold caller receives an equal allocation of companies with similar demographics. Like the approach used in Shelegia and Sherman (2022), this study will control for factors such as the “hot hand” phenomenon, as well as learning and fatigue effects, by examining deterministic trends, what can be found in Appendix 3.

In general, every cold caller is incentivized as they receive a base salary. However, they also earn a bonus for every software demo they schedule. This could potentially amplify the effects of the “hot hand” phenomenon, as discussed in Shelegia and Sherman (2022). Additionally, it cannot be guaranteed entirely that they do not share their experiences during the experiment, as they work from the same office. To address these challenges, the cold callers will not have access to the ongoing results of the experiment or emerging trends.

Their sole task will be to diligently record details of their calls, including whether they successfully passed the gatekeeper, without access to evolving results or trends.

5 Descriptive Statistics, Data Analysis, and Key Insights

This section provides a comprehensive analysis of the data gathered during the experiment, focusing on descriptive statistics, data analysis, and key insights. It explores the characteristics of the data, conversion rate insights, time difference analysis, and demographic influences, with a particular emphasis on the interaction between these factors and the experimental conditions. The findings from statistical tests, including the Kruskal-Wallis H test and regression analysis, offer deeper insights into the effectiveness of time-limited offers and the impact of company size on conversion rates.

5.1 Overview of Data Characteristics

In the experiment, four professional cold callers each made an average of 16 cold calls over a period of 31 working days, resulting in a total of 1,992 cold calls. Out of these, only 23.64% calls got past the gatekeeper, leading to 471 conversations with decision-makers from 471 different companies, where the aforementioned sales script was used. From these conversations, 117 product demonstration appointments were scheduled.

The conversion rate 1 (CVR_1), which measures the ratio of successful cold calls to the total number of calls, stood at 5.87%, exceeding the market average of 4.82% (Raval, 2024, p.1). The conversion rate 2 (CVR_2), which measures the ratio of successful cold calls to the total number of conversations with decision-makers, averaged 24.84% across all groups and cold callers. The detailed statistics for each individual cold caller and the aggregated data can be found in Table 1, which provides descriptive statistics for each cold caller as well as the overall data.

Table 1:

Descriptive statistics of the experiment aggregated for every individual cold caller.

	Total	Caller 1	Caller 2	Caller 3	Caller 4
Number of calls	1,992	487	518	492	496
Number of conversations with the decision maker	471	122	108	104	137
Conversation to call ratio	23.64%	25.04%	20.86%	21.16%	27.62%
Appointments scheduled	117	35	28	23	31
Overall CVR_1	5.87%	7.18%	5.41%	4.68%	6.25%
Overall CVR_2	24.84%	28.69%	25.93%	22.12%	22.63%

5.2 Conversion Rate Insights

5.2.1 Overview of conversion rate data

The exact conversion rates for each group and cold caller are detailed in Tables 2 and 3 and visualized in Graph 1 below. Interestingly, the conversion rates for *C_0* (the control group, where data was gathered before the start of the experiment) are lower than those for *C_1* across all cold callers. Additionally, *C_1* exhibits slightly lower variance in conversion rates. These two observations suggest that the training phase had a positive impact on the cold callers.

In the first phase of the experiment, the first treatment group *T_1*, which involved a two-week limited-time price discount, achieved the highest conversion rates, with CVR_1= 5.73% and CVR_2 = 23.28%, followed by *C_1* with CVR_1= 4.95% and CVR_2= 21.89%. In this phase, the second treatment group (*T_2*), involving a four-week limited-time offer, performed the worst, with CVR_1= 4.88% and CVR_2 = 19.81%. The next chapter will examine whether these differences are statistically significant.

Table 2:

Conversion rate 1 and conversion rate 2 for the first phase of the experiment.

	C_0		C_1		T_1 (Phase 1)		T_2	
	CVR_1	CVR_2	CVR_1	CVR_2	CVR_1	CVR_2	CVR_1	CVR_2
Caller 1	5.98%	24.52%	6.04%	25.00%	7.29%	27.27%	5.75%	23.81%
Caller 2	3.93%	17.67%	4.38%	26.67%	4.79%	25.00%	5.50%	20.00%
Caller 3	3.01%	14.53%	3.54%	16.67%	4.59%	20.00%	3.75%	18.75%
Caller 4	4.87%	15.83%	5.84%	19.23%	6.25%	20.83%	4.50%	16.67%
Aggregated	4.45%	18.14%	4.95%	21.89%	5.73%	23.28%	4.88%	19.81%

The second phase was generally more successful than the first, with average conversion rates of CVR_1= 6.62% and CVR_2 = 28.35%, compared to the first phase's conversion rates of CVR_1= 5.19% and CVR_2 = 21.66%. The two-week limited time offer without framing in *T_1* performed better in the second phase, with CVR_1= 6.34% and CVR_2 = 27.62%, than the same pitch in the first phase. This indicates that the companies in the second phase were somewhat more open to accepting meetings for some reason.

The best-performing group overall was treatment *T_1_loss*, where the two-week limited-time offer was framed with loss aversion, highlighting the loss if the meeting was not accepted. This group achieved CVR_1= 7.28% and CVR_2 = 31.99%. Interestingly, treatment *T_1_gain* performed worse than the control group T_1 in phase two, with CVR_1= 6.23% and CVR_2 = 25.44%. This suggests that loss aversion framing might only be effective if explicitly framed as a loss. Whether this hypothesis holds true will be examined in the next chapter when the differences are analyzed for statistical significance.

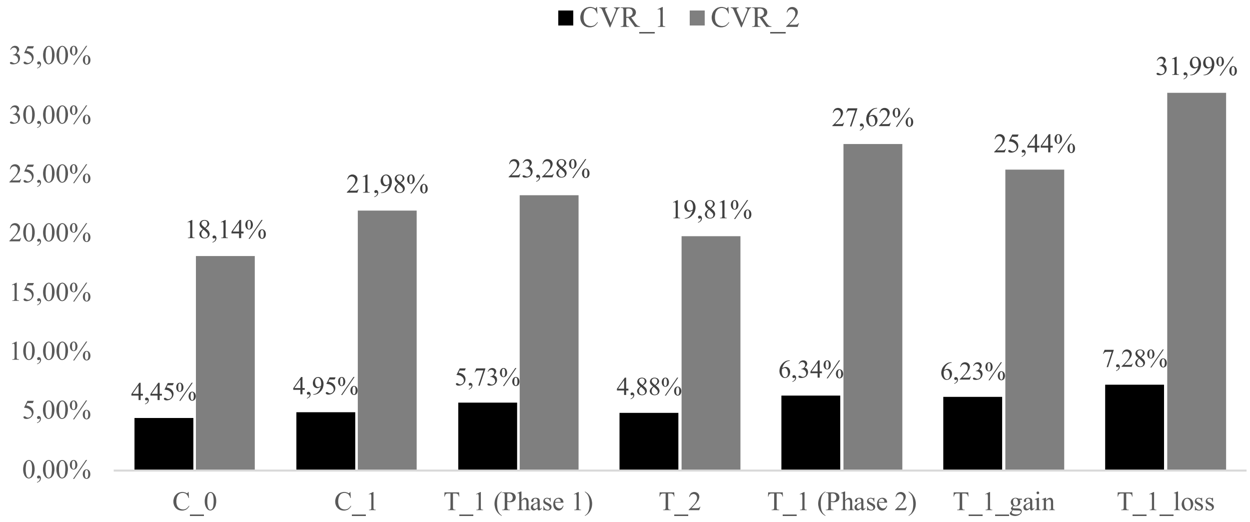
Table 3:

Conversion rate 1 and conversion rate 2 for the second phase of the experiment.

	T_1 (Phase 1)		T_1 (Phase 2)		T_1_gain		T_1_loss	
	CVR_1	CVR_2	CVR_1	CVR_2	CVR_1	CVR_2	CVR_1	CVR_2
Caller 1	7.29%	27.27%	7.78%	33.33%	7.56%	27.27%	8.89%	36.84%
Caller 2	4.79%	25.00%	6.23%	29.41%	4.89%	22.22%	6.67%	33.33%
Caller 3	4.59%	20.00%	5,11%	25.00%	5.11%	25.00%	6.01%	27.78%
Caller 4	6.25%	20.83%	6,23%	22.73%	7.34%	27.27%	7.56%	30.00%
Aggregated	5.73%	23.28%	6,34%	27.62%	6.23%	25.44%	7.28%	31.99%

Graph 1:

Aggregated conversion rates $CVR_1$and CVR_2 for every group.



5.2.2 Methodology for the analysis of conversion rates

The data analysis was conducted using the statistics software IBM SPSS and Stata with the goal of comparing the conversion rates, $CVR_1$and CVR_2, within each group. Specifically, the analysis aimed to determine whether the use of time-limited offers, and subsequently, the use of loss aversion framing in phase 2, led to significant changes in the conversion rates.

The first step involved verifying whether the sample sizes followed a normal distribution. This was assessed using the one sample Kolmogorov-Smirnov test, described in a blogpost by IBM (2023) and Razali and Wah (2011, p.23), as well as the Shapiro-Wilk test, described by Razali and Wah (2011, p.25). The results, detailed in Appendix 4 in Table 14 and Table 15, indicate that the data does not follow a normal distribution. Consequently, ANOVA was deemed inappropriate, necessitating the use of a non-parametric test.

Most non-parametric tests, like the Kruskal-Wallis H test, have the condition that the sample size needs to be independent. While different companies have been called in every call, the sample size was collected by the same four cold callers. Therefore, the intraclass correlation coefficient (ICC) was calculated in Stata to check for the independence of the sample size. The ICC is a statistic used to measure the proportion of total variance in a dependent variable that is attributable to grouping or clustering (e.g., individual-level variation in a multilevel

model). It quantifies the degree of similarity within groups compared to the overall variance across groups. An ICC close to zero indicates that most of the variance is within groups, suggesting independence, whereas an ICC closer to one implies substantial clustering (StataCorp LLC., n.d.).
The ICC of the sample size in this field experiment is estimated at 3.68e-14 (Appendix 5), so essentially zero, meaning there is virtually no clustering effect from the different callers. The variance between callers is extremely small, implying that the person collecting the data does not significantly affect the outcome. Therefore, it can be concluded that the data collected by the four callers can be treated as independent, and there is no need to account for clustering due to the individuals collecting the sample.

Therefore, the Kruskal-Wallis H test, described in Kruskal and Wallis (1952, pp.584-587) was employed to determine the significance of the results. The Kruskal-Wallis H test is a non-parametric statistical test used to determine if there are statistically significant differences between the medians of three or more independent groups. It is especially useful when the assumptions of normality and homogeneity of variances are violated, making it an alternative to the one-way ANOVA for non-normal data. To use the Kruskal-Wallis H test, the data must be ordinal, continuous, or ranked, and the groups being compared should be independent of each other. Therefore, the Kruskal-Wallis H test is a good fit for this sample size.

The procedure tests the null hypothesis, whether two sample's distributions are the same with the significance level of $p = 0.05$:

H0: The distributions of the two samples are the same.

If the p-value is smaller than the significance level of 0.05, the null hypothesis is rejected and H1 is likely:

H1: The distributions of the two samples are significantly different.

By comparing the different control and treatment groups with each other, the general hypothesis from chapter 2 can be validated or rejected. More on that can be found in the findings part. The Kruskal-Wallis H test was conducted not only for both conversion rates but also for each individual cold caller to ensure the validity of the results.

Additionally, to assess the consistency of the results across different methods, a pairwise regression analysis was performed alongside a cluster analysis, controlling for sample independence with respect to the caller ID. The regression model followed this structure:

$$CVR = \alpha + \beta * D_T + \varepsilon, \qquad with\ D_T = \begin{cases} 1, if\ sample\ is\ in\ the\ treatment\ group \\ 0, otherwise \end{cases}$$

The analysis was conducted using Stata software, incorporating the clustering function to adjust the standard errors for within-group correlation. This adjustment ensures that observations within the same cluster are not treated as independent. Such clustering is particularly relevant when data points are grouped (e.g., by individuals or regions), where intra-group correlation is likely. The cluster option in Stata was used to provide robust standard errors, correcting for potential bias arising from this dependence within clusters.

5.2.3 Key Findings on Conversion Rate

The Kruskal-Wallis H test was conducted to check whether there are significant differences in the conversion rates of the treatment groups.

Findings for phase 1 of the experiment

In phase 1 of the experiment, the sample size for the control group *C_0* and the treatment groups T_1 and T_2 has been collected. The results of the Kruskal-Wallis H test for the differences in the conversion rate CVR_1 can be found in Table 4, while the results for the conversion rate CVR_2 can be found in table 5. Overall, no significant differences in the conversion rates have been examined for any of the groups.

Table 4:

Results of Kruskal-Wallis H Test for aggregated CVR_1 in phase 1.

Sample 1 vs. Sample 2	Test Statistic	Std. Error	Std. Test Statistic	Sig.
T_2 vs. C_1	3.969	9.394	.422	.673
T_2 vs. T_1 (Phase 1)	9.156	9.394	.975	.330
C_1 vs. T_1 (Phase 1)	-5.188	9.394	-.552	.581

Each row tests the null hypothesis that the Sample 1 and Sample 2 distributions are the same with significance level of 0.05.

The Kruskal-Wallis H test results for the aggregated CVR_1 in phase 1 (Table 4) indicated no significant differences between the samples. The test statistics for the comparison of *T_2* vs. *C_1* (*H = 3.969, p = 0.673*), the comparison of *T_2* vs. *T_1 (Phase 1)* (*H = 9.156, p = 0.330*), and the comparison of *C_1 vs. T_1 (Phase 1)* (*H = -5.188, p = 0.581*) all exceeded the significance level of 0.05. This suggests that the distributions of the conversion rates in these samples are statistically similar, supporting the null hypothesis.

Table 5:

Results of Kruskal-Wallis H Test for aggregated CVR_2 and phase 1.

Sample 1 vs. Sample 2	Test Statistic	Std. Error	Std. Test Statistic	Sig.
T_2 vs. T_1 (Phase 1)	4.063	9.465	.429	.668
T_2 vs. C_1	5.250	9.465	.555	.579
T_1 (Phase 1) vs. C_1	1.188	9.465	.125	.900

Each row tests the null hypothesis that the Sample 1 and Sample 2 distributions are the same with significance level of 0.05.

The Kruskal-Wallis H test results for the aggregated conversion rate CVR_2 in phase 1 (Table 5) indicated no significant differences between the samples. The test statistics for the comparison of *T_2* vs. *T_1 (Phase 1)* (*H = 4.063, p = 0.668*), the comparison of *T_2* vs. *C_1* (*H = 5.250, p = 0.579*), and the comparison of *T_1 (Phase 1)* vs. *C_1* (*H = 1.188, p = 0.900*) all exceeded the significance level of 0.05. These findings suggest that the conversion rate distributions among these groups do not differ significantly, thereby supporting the null hypothesis.

Findings for phase 2

After collecting the sample sizes for C_1, T_1, and T_2 in Phase 1, and identifying T_1 as the best-performing group with the two-week time-limited offer, it was decided to use T_1 as the new control group for the second phase of the experiment. Overall, no significant differences in the conversion rates have been examined for any of the groups. All results are examined in Table 6 (CVR_1) and Table 7 (CVR_2).

Thus, two variables for T_1 exist: T_1 *(Phase 1)* for the first phase and T_1 *(Phase 2)* for the second phase. From Table 3 and Graph 1, the second phase showed better performance for T_1, but the Kruskal-Wallis H test results indicated no significant differences between *T_1 (Phase 1)* and *T_1 (Phase 2)* for CVR_1 (*H = 0.115, p = 0.990*) and CVR_2 (*H = -7.960, p = 0.408*).

As the second phase did not perform significantly better than the first phase, comparing the control group *C_1* and the best overall performing group, *T_1_loss*, is appropriate. The Kruskal-Wallis H test indicates no significant differences for CVR_1 (*H = -11.540, p = 0.227*) and CVR_2 (*H = -9.073, p = 0.346*). Thus, the use of time-limited price discounts with loss aversion framing shows no significant differences compared to using no time-limited offer with no framing.

Table 6:

Results of Kruskal-Wallis H Test for aggregated CVR_1 and phase 2.

Sample 1 vs. Sample 2	Test Statistic	Std. Error	Std. Test Statistic	Sig.
T_1 (Phase 2) vs. T_1 (Phase 1)	.115	9.549	.012	.990
T_1 (Phase 2) vs. T_1_gain	-1.233	9.702	-.127	.899
T_1 (Phase 2) vs. T_1_loss	-6.467	9.702	-.667	.505
T_1_gain vs. T_1_loss	5.233	9.702	.539	.590
C_1 vs. T_1_loss	-11.540	9.549	-1.208	.227

Each row tests the null hypothesis that the Sample 1 and Sample 2 distributions are the same with significance level of 0.05.

Furthermore, the Kruskal-Wallis H test results for aggregated CVR_1 and Phase 2 revealed no significant differences between the groups compared. Specifically, the test statistics for *T_1 (Phase 2)* vs. *T_1_gain* (*H = -1.233, p = 0.899*), *T_1 (Phase 2)* vs. *T_1_loss* (*H = -6.467, p = 0.505*), and *T_1_gain* vs. *T_1_loss* (*H = 5.233, p = 0.590*) all exceeded the significance level of 0.05. These results indicate that there are no statistically significant differences in conversion rates between these sample pairs.

Table 7:

Results of Kruskal-Wallis H Test for aggregated CVR_2 and phase 2.

Sample 1 vs. Sample 2	Test Statistic	Std. Error	Std. Test Statistic	Sig.
T_1 (Phase 1) vs. T_1 (Phase 2)	-7.960	9.621	-.827	.408
T_1_gain vs. T_1 (Phase 2)	3.933	9.775	.402	.687
T_1_gain vs. T_1_loss	6.233	9.775	.638	.524
T_1 (Phase 2) vs. T_1_loss	-2.300	9.775	-.235	.814
C_1 vs. T_1_loss	-9.073	9.621	-.943	.346

Each row tests the null hypothesis that the Sample 1 and Sample 2 distributions are the same with significance level of 0.05.

Additionally, the results look the same for he Kruskal-Wallis H test for the aggregated conversion rate CVR_2 in phase 2, that showed again no significant differences between the groups. The test statistics for T_1_gain vs. *T_1 (Phase 2)* (*H = 3.933, p = 0.687*), T_1_gain vs. *T_1_loss* (*H = 6.233, p = 0.524*), and *T_1 (Phase 2)* vs. *T_1_loss* (*H = -2.300, p = 0.814*) all indicated p-values above the significance threshold of 0.05. These findings suggest that the conversion rates between these sample pairs do not differ significantly.

In Appendix 6, the Kruskal-Wallis H test was conducted for every individual cold caller. These results show no significant difference in all comparisons, supporting the overall finding, that time limited offers do not induce significant conversion rate increases in cold calling.

Results of the pairwise comparison via a clustered regression

The results of these pairwise comparison via the regression with clustered errors can be found in Appendix 7. The analysis demonstrates that *T_1 (Phase 1)* is effective when compared to the control group *C_1*, indicating a significant positive impact on the outcome. However, when compared to *T_2*, *T_1 (Phase 1)* does not exhibit a statistically significant effect, suggesting that the two treatments yield similar results.

Among the different treatments, *T_1_loss* consistently outperforms the others, showing significant positive effects when compared to both *T_1 (Phase 2)* and *T_1_gain*. This indicates that *T_1_loss* is the most effective treatment across the comparisons.

In contrast, *T_1_gain* shows no significant difference when compared to *T_1 (Phase 2)*, suggesting that it has a limited effect on the outcome. Despite the significance of some treatment effects, the overall explanatory power of most models remains very low, with only small portions of the variability in the data being explained. This implies that while some treatments are impactful, the models do not capture a large proportion of the factors influencing the results.

Overall, the results remain similar and only differ in significance. The 2-week time limited offer works best overall, especially when the rejection of the offer is framed as a loss. While the Kruskal-Wallis H-test does not show significant results, the pairwise comparison via the regression shows significant increases in the conversion rate in both treatments. Nevertheless, the significance can be questioned because of very low R^2 values. Due to the low R^2 values, the subsequent sections of the thesis will focus primarily on the results of the Kruskal-Wallis H test. The pairwise comparisons conducted via clustered regression serve as a supplementary check to verify whether the findings are consistent across different methods.

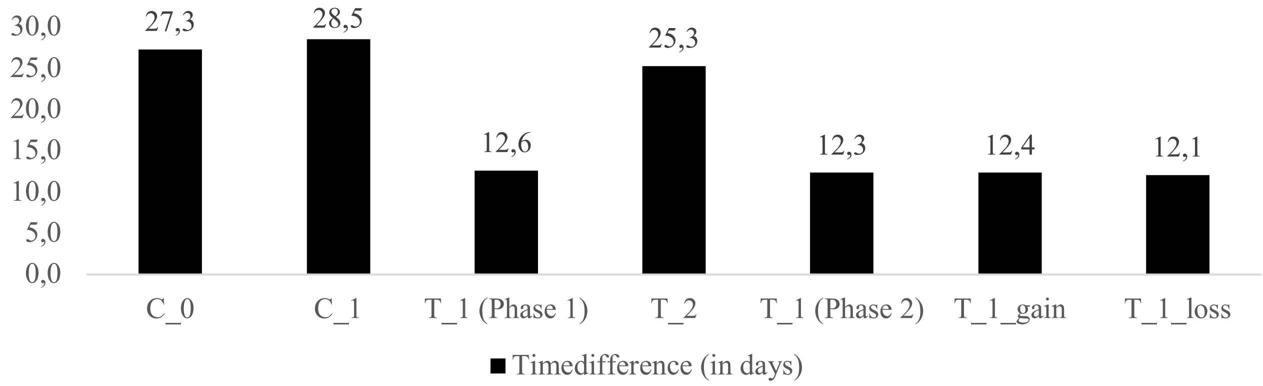
5.3 Timedifference Insights

5.3.1 Overview of Timedifference data

Cold calling is an essential metric for companies when analyzing revenue figures. In addition to enhancing cold calling efficiency, companies aim to generate quick revenue. Therefore, Graph 2 illustrates the time difference between the last cold call and the product demonstration. Notably, the time differences for the treatment groups with a two-week time limit range from 12.1 to 12.6 days, which is very low compared to the control groups and the four-week time-limited offer treatment group, which range from 25.3 to 28.5 days. The significance of these differences will be analyzed in the next chapter using a Kruskal-Wallis H test.

Graph 2:

Time difference between day of the last cold call and the day of the product demonstration.



5.3.2 Methodology for the analysis of time differences

As observed in the descriptive statistics, the time between the last call, when the demo appointment is scheduled, and the date of the product demonstration is significantly shorter in the two-week time-limited offer sample compared to the four-week time-limited offer sample and the control group. To determine if these time differences are statistically significant, a Kruskal-Wallis H test, like described in Kruskal and Wallis (1952), was conducted because of its good fit to the sample size as well.

5.3.3 Key Findings on Time Differences

Table 8 presents the results of the Kruskal-Wallis H-test, analyzing the time difference between the last cold call and the date of the product demonstration. For clarity, the analysis focuses on comparing the two-week time-limited offer treatment groups with the control group. The findings indicate significant differences in all comparisons, with p-values less than 0.001. These results suggest that time-limited offers are effective in accelerating revenue generation.

Table 8:

Results of Kruskal-Wallis H Test for time difference - pairwise comparison of C_1 to the 2-week time limited offer groups.

Sample 1 vs. Sample 2	Test Statistic	Std. Error	Std. Test Statistic	Sig.	Adj. Sig.[a]
T_1_loss vs. C_1	40.894	8.687	4.707	<.001	.000
T_1 (Phase 1) vs. C_1	38.933	8.687	4.482	<.001	.000
T_1_gain vs. C_1	38.625	9.058	4.264	<.001	.000
T_1 (Phase 2) vs. C_1	38.375	8.859	4.332	<.001	.000

_Each row tests the null hypothesis that the Sample 1 and Sample 2 distributions are the same with significance level of 0.05.

5.4 Demographic Insights

5.4.1 Overview of Demographic Data

The results indicate that while time-limited offers do not significantly increase conversion rates, they can still be valuable in accelerating revenue by prompting earlier product demonstrations. Although the previous analysis did not consider demographic factors when comparing conversion rates, this chapter introduces a new demographic dimension: *company size*, measured by the number of employees.

Company size is categorized into four groups based on the number of employees. Categories 1 and 2 represent small enterprises, with 1 to 25 and 26 to 50 employees, respectively. Category 3 includes medium-sized enterprises with 51 to 100 employees, while Category 4 comprises large enterprises with more than 100 employees for this experiment. In Category 1, 221 different companies were contacted; in Category 2, 145 companies were contacted; in Category 3, 83 companies were contacted; and in Category 4, only 22 companies were contacted. Since the target audience mainly consists of small enterprises, the CVR_2 metric is used across all categories to ensure comparability of results. Table 9 presents the conversion rates for the four different company size categories and the various experiment groups. Interestingly, in most groups, the conversion rates for small enterprises are higher than the conversion rates for medium and large enterprises. To check whether small companies are more likely to schedule product demonstrations in cold calls and to check if small companies are more sensitive to time limited offers than medium and large enterprises, a linear regression analysis is conducted in the following chapter.

Table 9:

CVR_2 for any group and different company sizes.

		Number of employees			
	Aggregated	1 – 25 (Category 1)	26 – 50 (Category 2)	51 – 100 (Category 3)	> 100 (Category 4)
Aggregated	24.8%	26.30%	27.46%	22.50%	23.10%
C_1	21.9%	24.30%	20.20%	23.30%	19.60%
T_1 (Phase 1)	23.3%	25.12%	24.90%	22.00%	21.10%
T_2	19.8%	18.30%	22.25%	17.50%	21.20%
T_1 (Phase 2)	*27.6%*	29.08%	29.80%	25.10%	26.50%
T_1_gain	*25.4%*	28.70%	27.66%	23.10%	22.30%
T_1_loss	*32.0%*	34.90%	34.22%	28.75%	30.10%

5.4.2 Methodology for analyzing the demographics

The goal of this section is to determine whether small companies are significantly more responsive to time-limited offers compared to medium and large enterprises. To assess this, the effect of company size on the conversion rate is analyzed using the following simple linear regression model:

$$CVR_2 = ß_0 + ß_1 * company\ size\ category + \varepsilon$$

In this model, the dependent variable is CVR_2 as shown in Table 4, while the company size category is a categorical variable, with 1 representing Category 1, 2 representing Category 2, and so on.

Two regression analyses are conducted for different purposes. The first analysis examines whether small companies are inherently more likely to schedule product demonstrations during cold calls compared to medium and large enterprises. To achieve this, the conversion rates from all experiment groups are included in the first regression.

The second analysis investigates whether small companies are more responsive to time-limited offers than medium and large enterprises. For this, only the conversion rates from the two-week time-limited offer groups are included in the second regression. By conducting both regressions, it can be accounted for the potential natural tendency of small companies to schedule product demonstrations more frequently during cold calls.

5.4.3 Key Findings on Demographics

Table 10 presents the results of the first regression analysis, which examines whether small companies are more likely to schedule product demonstrations during cold calls compared to medium and large enterprises. The analysis shows that the coefficient for company size is negative (-0.0132) and approaches significance (p = 0.073). While the p-value is slightly above the conventional threshold of 0.05, the trend suggests that smaller companies may have a higher conversion rate, although this effect is not strong enough to reach statistical significance. The R^2 value of 0.119 indicates that approximately 11.9% of the variance in CVR_2 can be explained by the company size category, suggesting a modest impact.

Table 10:

OLS results for the effect of the company size on CVR_2.

Variable	B	SE	t	p	95% CI [LL; UL]
Intercept	0.28285	0.0194	14.59***	<.001	[0.245; 0.321]
CVR_2	-0.0132	0.0071	-1.87	0.073	[-0.0270; 0.0006]

Note. Constant=0.28285, F(1,26)=3.50***, p<.05, R^2 = .119

Table 11 presents the results of the second regression analysis, which investigates the responsiveness of small companies to time-limited offers compared to medium and large enterprises. The coefficient for company size is again negative (-0.0178) and this time, it is statistically significant (p = 0.048). This result implies that smaller companies are more responsive to time-limited offers, with a stronger decrease in CVR_2 as the company size increases. The R^2 value of 0.251 indicates that 25.1% of the variance in CVR_2 is explained by the company size category when the two-week TLO is applied, highlighting a more substantial effect.

Table 11:

OLS results for the effect of the company size on CVR_2, when the 2-week time limited offer is used.

Variable	B	SE	t	p	95% CI [LL; UL]
Intercept	0.3152	0.0225	14.03***	<.001	[0.267; 0.3634]
CVR_2	-0.0178	0.0082	-2.16	0.048	[-0.0354; -0.0002]

Note. Constant=0.3152, F(1,14)=4.685***, p<.05, R^2=.251

The findings suggest that while company size does not significantly influence the likelihood of scheduling product demonstrations in general, there is a notable effect when a time-limited offer is introduced. Smaller companies appear to be more sensitive to these offers, as evidenced by the significant negative coefficient in the second regression analysis. This indicates that implementing time-limited offers may be particularly effective for smaller enterprises, potentially accelerating the sales process and improving overall conversion rates in this segment.

6 Discussion

6.1 Discussion of the results

The findings reveal slight, but not statistically significant, differences in conversion rates when using time-limited price discounts compared to not using them. Therefore, the first hypothesis, H1, that time-limited offers increase the conversion rate, can be rejected. This hypothesis was erased by earlier studies, which demonstrated that time-limited price discounts, among other factors, lead to higher perceived scarcity (Broeder & Wentik, 2022), increased buying pressure and urgency (Gue et al., 2017), as well as fear of missing out (Swain et al., 2006).

The marginally better conversion rates suggest that these psychological mechanisms only played a role in a few cold calls. A straightforward explanation for this could be that if a person does not perceive the pitched product or service as valuable during a cold call, the discount becomes irrelevant, and thus psychological triggers like urgency or fear of missing out are not activated. In other words, if someone doesn't see value in scheduling a product demonstration, why would a time-limited price discount make a difference? Only for individuals who are unsure about the value of the product or service might time-limited price discounts influence their decision to schedule a product demonstration, which could potentially explain the slightly higher conversion rates with time-limited discounts.

This reasoning is also supported by the findings of Peng et al. (2019) and Kim et al. (2020). Both studies show that time-limited price discounts are effective only when emotional and rational involvement with the product is high. According to their findings, time-limited offers do not work when people have only an abstract idea of the product's value (Kim et al., 2020) or when they do not feel emotionally connected to the product or service (Peng et al., 2019).

The second hypothesis, H2, proposed that shorter time-limited price discounts would result in a higher conversion rate compared to longer time-limited offers. This hypothesis was derived from current literature, with the caveat that the time limit should not be too short, as this could have adverse effects. When examining the findings, the two-week time-limited offer indeed showed a higher conversion rate than the four-week time-limited offer, although the difference is not statistically significant. Therefore, H2 can also be rejected, despite the shorter time-limited offer yielding a higher conversion rate. Consequently, the data shows that the length of the time limit does not play a crucial role, indicating that other factors might play a more critical role in influencing conversion rates.

After completing the first part of the experiment, which showed that time-limited offers do not inherently increase conversion rates and that the length of the time limit is largely irrelevant, the second phase of the experiment began by incorporating loss aversion framing into the two-week time-limited price discount. Based on current literature, the third hypothesis H3 was developed, proposing that a time-limited offer framed as a loss, if rejected, would result in a higher conversion rate than one framed as a gain, if accepted. This hypothesis was derived from previous studies, which demonstrated that loss aversion framing can lead to fear of later regret (Sudgen et al., 2024) and impulsive buying, driven by fear of missing out (Khetarpal & Singh, 2024). Additionally, studies by Kocher et al. (2013) and Belli et al. (2023) show that loss aversion increases under time pressure.
The findings indicate that the two-week time-limited offer framed as a loss had the highest conversion rate overall. The gain-framed offer performed slightly worse than the control group, which used a time-limited offer without any framing. However, there are no significant differences in the conversion rates, leading to the rejection of H3. The previous reasoning remains valid: if someone doesn't perceive value in scheduling a product demonstration, why would a time-limited price discount make a difference? The slight effectiveness of loss aversion framing compared to no framing in the control group could be explained by the fact that more individuals uncertain about the product or service's value might have scheduled a demo due to anxiety about potentially regretting their decision later.

When considering only the conversion rates, one might conclude that using time-limited price discounts in cold calling is highly questionable. However, by adding a second factor—the time gap between the cold call and the product demonstration—the use of time-limited price discounts becomes more appealing. After demonstrating that the time gap in the two-week time-limited offer was half as long as in the four-week time-limited offer and the control group, it's evident that companies can generate revenue more quickly. Ultimately, the sales cycle, which measures the time from the first interaction to closing the client, becomes shorter. A shorter sales cycle offers several benefits, including more accurate sales performance forecasting, improved cash flow, and most importantly, the ability to close

more deals within the same period, leading to higher sales volumes and increased revenue in the time after they get implemented.
The big goal of this thesis was to understand, whether time limited offers can increase the revenue for companies. While the conversion rate does not increase significantly through time limited offers, the revenue in time after the implementation increases. Therefore, companies can use offers with short time limits to get a short-term revenue boost, if needed, and short-term time limited price discounts should be in the toolbox of companies that operate in a Business-to-Business environment.

However, the effectiveness of time-limited offers is highly dependent on the sales context and the environment in which the company operates, as described by Inman & McAlister (1994). One aspect of the sales context is the target audience. While company size does not significantly influence the overall likelihood of scheduling product demonstrations, it does have a notable effect when a time-limited offer is introduced. Smaller companies tend to be more responsive to time-limited price discounts, with the conversion rate decreasing as company size increases. In hindsight, this makes perfect sense, as company size typically correlates with revenue. Logically, a €1,000 discount feels much more significant to a company with €100,000 in revenue compared to a company with €100 million in revenue.
However, the niche in which a company operates and the specific product or service it offers also play a significant role in the sales context. For example, selling subscription-based software is likely very different from selling ergonomic chairs. Therefore, it's questionable whether the results are applicable to all companies operating in a Business-to-Business environment. This study was conducted within a company that sells a software-as-a-service product, providing artificial intelligence solutions for accounting, compliance, and risk management departments. Consequently, the findings of this thesis should be particularly relevant for companies offering financial technology products and financial software to other businesses.

6.2 Strenths and weaknesses

One of the key strengths of this study is its real-life field experiment design, which enhances its practical relevance. By conducting the experiment in a real-world setting, the findings are directly applicable to actual business scenarios, making the results more valuable for practitioners who are looking to implement these strategies in their own organizations.

Another strength is the simplicity of the experimental design and the randomization process. The straightforward approach makes the study easily replicable by other researchers or companies, even in different sales contexts. This replicability is crucial for validating the results and applying the methods in various business environments.
The study also excels in eliminating potential biases. By controlling for differences in conversion rates among cold callers and ensuring there were no learning effects or the presence of the "hot hand" phenomenon, the study maintains a high level of reliability. These measures ensure that the results are not skewed by external factors, thus providing a clearer understanding of the impact of time-limited offers in cold calling.

Despite its strengths, the study has some notable weaknesses. The limited sample size and short duration of the experiment are significant limitations. Although the study involved 1,992 cold calls, only 471 resulted in conversations with decision-makers, and just 117 led to product demonstrations. This relatively small sample size limits the statistical power of the study, particularly when trying to detect small differences between treatment groups. Furthermore, the experiment was conducted over less than two months, which made the results susceptible to short-term trends. For instance, phase 1 of the experiment had a notably lower conversion rate than phase 2, despite no changes being made to the pitch. To obtain more stable and reliable results, it would be beneficial to extend the duration of the experiment.
Another impact of the small sample size could be the lack of statistically significant differences in conversion rates across the different treatment groups. This suggests that the time-limited offers and framing techniques employed may not have a strong impact on conversion rates in cold calling. If more time and resources were available, it would be advantageous to test a wider range of framing techniques to see if any would yield significant results.
The study's demographic analysis is also somewhat limited. It primarily focuses on company size, which, while important, does not provide a comprehensive understanding of how different types of companies respond to time-limited offers. Other demographic factors, such as industry sector and geographic location, were not explored due to the lack of data on companies that did not schedule a product demonstration. This omission restricts the depth of the demographic insights and limits the ability to generalize the findings across different company profiles.

In conclusion, while the study has some limitations, such as the small sample size, short duration, and limited demographic analysis, it makes a valuable contribution to the understanding of cold calling strategies in a B2B context, particularly with respect to time-limited offers. The practical relevance of the real-life field experiment, coupled with the effective elimination of biases, provides a solid foundation for future research. Expanding the sample size, exploring additional framing techniques, and conducting the experiment over a longer period could further enhance the findings and their applicability across different industries.
Future research could further enhance this research by progressing through the sales cycle and focusing on the next stage—the actual product demonstration appointment, which aims to convert the prospect into a paying customer. The research question would be similar: whether time-limited price discounts can increase the conversion rate during sales meetings. Ultimately, this research could provide readers with a valuable tool for negotiating contracts in a Business-to-Business sales environment.

7 Conclusion

This thesis set out to examine the impact of time-limited offers on conversion rates in cold calling within a Business-to-Business (B2B) environment, focusing on both the duration of these offers and the influence of loss aversion framing. The study was conducted through a real-life field experiment in which professional cold callers made nearly 2,000 calls. The experiment was divided into two distinct phases: the first phase focused on evaluating the effect of time-limited price discounts with varying durations, and the second phase introduced loss aversion framing to these time-limited offers.

The findings from the first phase indicated that while the two-week time-limited offer performed better than the four-week offer, the difference in conversion rates was not statistically significant. This suggests that the length of the time limit, within the ranges tested, does not play a crucial role in influencing conversion rates. In the second phase, loss aversion framing was applied to the two-week time-limited offer, hypothesizing that framing the offer as a loss, if rejected, would result in a higher conversion rate than framing it as a gain if accepted. While the loss aversion-framed offer did achieve the highest conversion rate overall, the results again lacked statistical significance.

Despite the lack of significant impact on conversion rates, the study did uncover an important insight: time-limited offers can substantially shorten the time between the initial cold call and the subsequent product demonstration, effectively accelerating the sales cycle. This acceleration is particularly beneficial for companies aiming to improve cash flow and close more deals within a given period, ultimately leading to increased short-term revenue.

For companies considering the use of time-limited offers in their cold calling strategies, several key recommendations emerge from this research:

First, focusing on shorter time limits, such as two weeks, can create a stronger sense of urgency and help reduce the time to revenue, prompting quicker decision-making from prospects. Additionally, while the impact of loss aversion framing was not statistically significant in this study, it did yield the highest conversion rate. Therefore, companies might benefit from framing their time-limited offers as a potential loss, especially when targeting undecided or hesitant prospects, to leverage the psychological effects of loss aversion. Furthermore, the study found that smaller companies are more responsive to time-limited offers than larger ones. As a result, companies should segment their target audience by company size, applying time-limited offers more aggressively to smaller enterprises, where the perceived value of the discount is greater. Lastly, the effectiveness of time-limited offers is highly dependent on the sales context, including the nature of the product or service and the characteristics of the target audience. Companies should carefully assess whether their sales environment aligns with scenarios where time-limited offers have been proven effective, particularly in industries such as financial technology or software-as-a-service.
In summary, while time-limited offers did not significantly boost conversion rates in cold calling, they offer strategic value by shortening the sales cycle and accelerating revenue. Companies should incorporate short-term time-limited offers into their sales strategies, particularly when targeting smaller enterprises, and consider using loss aversion framing to enhance the psychological impact of these offers. Future research could expand on these findings by exploring the effectiveness of time-limited offers at later stages of the sales process, such as during product demonstrations or contract negotiations.

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Appendix 1: Calculation of the sample size

Sample size per group

The sample size is calculated using the Cochran Formula according to Uakarn et al. (2021, p.80):

$$n = \frac{p\,(1-p)}{\frac{e^2}{z^2} + \frac{p\,(1-p)}{N}}$$

where n is the sample size needed, p is the population proportion, e is the margin of error, z is the z-score, corresponding to a confidence level of 95% and N is the population size.

The total population size is equal to the target audience of the company, where the experiment was conducted, with around 120,000 companies in Germany. Because this target audience is very homogenous, the population proportion is set to 95%. With a margin of error of 5% and a z-score of 1.98, the needed sample size should be 74.44 conversations per control and per treatment group.

Number of Calls needed

Taking into account that the decision-maker is reached only 20% of the time and considering there are five groups (including one control group and four treatment groups), the required number of calls is calculated to be 1,861. However, anticipating that some calls may not be completed and that the success rate in bypassing gatekeepers may differ across the groups, the estimated number of calls needed is approximately 2,000.

Duration of the experiment

With four professional cold callers, that do 15 calls per day for the experiment, the planned duration for the experiment is 33,3 days. To make sure, that the needed sample size can be collected, the access to these four cold callers was guaranteed for 2 months. Nevertheless, the experiment was stopped, when the needed sample size is collected.

Appendix 2: The documentation of the sales training prior to the experiment

The training phase lasted two weeks and included five meetings. The goal was to develop a strong sales pitch while also ensuring that all cold callers reached the same level of proficiency in sales skills, objection handling, and product-specific knowledge. The five meetings were structured as follows:

Meeting 1:

The first meeting focused on collaboratively developing the most effective sales script with the participation of all four cold callers. Each cold caller shared their current pitching approach, and through in-depth discussions, a solid pitch was crafted that everyone felt confident using. The structure of this pitch is detailed in chapter 4.5.

Meetings 2 & 3:

With the sales pitch finalized, the next two meetings were dedicated to product knowledge training for the software being sold. The objective was to ensure that everyone was equally knowledgeable, as a lack of product understanding should not hinder success in cold calling. Comprehensive product knowledge is crucial for effective objection handling. Therefore, an additional script was created, providing in-depth answers and questions that cold callers could use to confidently address the most frequently asked questions from prospects.

Meeting 4:

After ensuring that all cold callers possessed the same theoretical skill set, it was time to apply these skills in practice. Session 4 was dedicated to simulation calls. Each cold caller participated in simulated cold calls, where they called the researcher while the other cold callers observed. This setup provided valuable feedback in a supportive environment. After each call, the group provided feedback and discussed the call collectively. According to the cold callers, this session was particularly beneficial, as it allowed them to practice confidently without the fear of making mistakes, thereby reinforcing their knowledge and improving their cold calling skills.

Meeting 5:

The final meeting served as a dress rehearsal, where the skills were tested under real-life conditions. The cold callers made actual cold calls that were not included in the experiment's sample size. With the researcher listening in, feedback was provided after each call. Each cold caller made 10 real cold calls, and after evaluating their performance, the researcher confirmed that everyone had the necessary skill set, allowing the experiment to proceed.

Appendix 3: Controlling for learning effects, fatigue effects and the "hot hand"

As described in chapter 4.5: credibility of the data, it is controlled for learning effects, fatigue effects as well as the "hot hand" phenomenon of the cold callers, like described in Shelegia and Sherman (2022), to mitigate potential biases.

Starting with learning and fatigue effects. If there would be learning and fatigue effects in the sample, the time would correlate either significantly positive (learning effect) or significantly negative (fatigue effect) with the number of appointments made per day and per cold caller. Therefore, a linear regression analysis was conducted to measure the connection between time and number of appointments scheduled per cold caller. The results can be seen in table 12.

Table 12:

Results of OLS on learning and fatigue effects in the sample size.

	Unstandardized Coefficients		Standardized Coefficients		
Model	B	Std. Error	Beta	t	Sig.
(Constant)	.831	.135		6.131	<.001
Appointments per day	.007	.007	.086	.955	.342

*Note. Constant=0.3152, F(1,122)=.912*** P<.05, R² = .007*

The results show no strong evidence of a learning effect in this model. The small positive coefficient for Appointments per day suggests a slight upward trend in the number of deals over time, but this trend is not statistically significant. Similarly, there is no evidence of a fatigue effect. If there were a fatigue effect, you might expect a negative coefficient for Appointments per day, indicating a decrease in performance over time. However, the coefficient is positive, albeit small and insignificant.

The “hot hand” phenomenon describes the situation, where a cold caller's performance is better over a certain period than it would have been expected over the entire duration. In other words, it suggests that there are phases in the dataset where strong performance on one day leads to even better performance on the following day. To examine how previous days' results influence the subsequent day's performance, a simple linear regression was conducted. In this regression, the dependent variable is the number of appointments schedules by a cold caller on the current day, while the independent variable is the number of appointments scheduled by the same caller on the previous day. The results of this analysis are presented in Table 13.

Table 13:

Linear regression results on the hot hand phenomenon.

	Unstandardized Coefficients		Standardized Coefficients		
Model	B	Std. Error	Beta	t	Sig.
(Constant)	1.167	.107		10.869	<.001
Deals_day_before	-.221	.090	-.221	-2.461	.015

*Note. Constant=1.167, $F(1,118)=6.055$***, $p<.05$, $R^2 = .049$*

The results indicate the non-existence of the hot hand phenomenon. The intercept of 1.167 represents the expected number of appointments set on a day when no deals were made the previous day. This baseline indicates that, on average, a cold caller is likely to schedule around 1.167 appointments regardless of their prior performance. Additionally, the coefficient for Appointments_day_before is -0.221, indicating a negative relationship between the number of appointments scheduled on consecutive days. Specifically, for every additional appointment scheduled on one day, there is a decrease of approximately 0.221 appointments expected on the following day. This negative coefficient directly contradicts the hot hand theory, suggesting that a good performance one day may actually lead to a slight dip in performance the next day.

The negative coefficient found in the regression analysis strongly indicates that the hot hand phenomenon does not exist within this dataset. Rather than finding that success on one day leads to increased success on the next, the data suggests the opposite: a day of high performance may be followed by a day of slightly reduced productivity. This could be a

reflection of various factors, such as a natural regression to the mean, where an exceptionally good day is an outlier that is followed by a more typical day of performance. Alternatively, it may suggest that the effort and energy expended to achieve high results on one day could lead to fatigue or a temporary depletion of high-quality leads, resulting in fewer deals the following day.
The low R-square value further reinforces the conclusion that the previous day's performance is not a reliable predictor of the current day's success. In practical terms, this means that each day's performance should be viewed independently, with no undue expectation that a strong or weak day will necessarily set the tone for the next.

Appendix 4: Test of Normality of the sample size

The data was check for normality, using the one sample Kolmogorov-Smirnov test, described by IBM (2023) and Razali and Wah (2011), as well as the Shapiro-Wilk test, described by Razali and Wah (2011). The analysis was made with SPSS, giving the results that are indicated in Table 14 and Table 15.

The results from both the Kolmogorov-Smirnov and Shapiro-Wilk tests indicate that the data is not normally distributed, as evidenced by the significant p-values (all < 0.001) shown in Tables 14 and 15. These results suggest a significant deviation from normality, confirming that the assumption of normal distribution is violated for both CVR_1 and CVR_2.

Table 14:

Kolmogorov-Smirnov and Shapiro-Wilk test for normality of CVR_1.

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
CVR_1	.219	93	<.001	.912	93	<.001

a. Lilliefors Significance Correction

Table 15:

Kolmogorov-Smirnov and Shapiro-Wilk test for normality of CVR_2.

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
CVR_2	.125	93	.001	.930	93	<.001

a. Lilliefors Significance Correction

Appendix 5: Independence of the sample size

Like described in chapter 3.2.2, the intraclass-correlation coefficient was conducted for the four different callers using Stata. Before the ICC can be calculated, a mixed-effects model has to be estimated. The results can be seen in the tables 16-18.

Table 16:

Fixed-effects estimates for the mixed-effects model.

Variable	Coefficient	SE	z	p-value	95% CCI
Constant	0.1406	0.0105	13.45	<.001	[.1201; .1611]

Table 17:

Random-effects estimates for the mixed-effects model.

Random Effects	Estimate	SE	95% CCI
Caller ID			
Variance (_cons)	2.63e-15	1.29e-11	[0; .]
Residual	.0717	.0040	[.0643; .0799]

Table 18:

Intraclass correlation coefficients (ICC) for Caller ID.

Level	ICC	SE	95% CCI
Caller ID	3.68e-14	0.0	[3.68e-14; 3.68e-14]

Appendix 6: Results of conversion rate comparison for every individual cold caller

The following tables present the results of the Kruskal-Wallis H test, as described by Kruskal and Wallis (1952), which was used to assess significant differences between the control and treatment groups. As discussed in Chapter 5.2.3, there are no significant differences in the aggregated sample, including all cold callers, nor when comparing the worst-performing group with the best-performing group.

These findings remain consistent when analyzing each individual cold caller. As shown in the tables, there is no significant difference in any comparison, whether for CVR_1 or CVR_2. The consistency across all cold callers strongly supports the conclusion that time-limited price discounts do not inherently increase the conversion rate in cold calling.

Table 19:

Results of Kruskal-Wallis H Test for CVR_1 and Caller 1.

Sample 1 vs. Sample 2	Test Statistic	Std. Error	Std. Test Statistic	Sig.
C_1 vs. T_2	-1.656	7.809	-.212	.832
C_1 vs. T_1 (Phase 1)	-3.000	7.809	-.384	.701
T_1 (Phase 2) vs. T_1 (Phase 1)	1.540	7.938	.194	.846
T_1 (Phase 2) vs. T_1_loss	-2.433	8.065	-.302	.763
T_1 (Phase 2) vs. T_1_gain	-4.300	8.065	-.533	.594
T_1_loss vs. T_1_gain	-1.867	8.065	-.231	.817

Each row tests the null hypothesis that the Sample 1 and Sample 2 distributions are the same with significance level of 0.05.

Table 20:

Results of Kruskal-Wallis H Test for CVR_1 and Caller 2.

Sample 1-Sample 2	Test Statistic	Std. Error	Std. Test Statistic	Sig.
T_1_gain vs. T_1_loss	3.633	7.777	.467	.640
T_1_gain vs. T_1 (Phase 2)	6.200	7.777	.797	.425
C_1 vs. T_2	-3.844	7.531	-.510	.610
C_1 vs. T_1 (Phase 1)	-5.031	7.531	-.668	.504
T_1_loss vs. T_1 (Phase 2)	2.567	7.777	.330	.741
T_2 vs. T_1 (Phase 1)	1.188	7.531	.158	.875
T_1 (Phase 2) vs. T_1 (Phase 1)	.227	7.655	.030	.976

Each row tests the null hypothesis that the Sample 1 and Sample 2 distributions are the same with significance level of 0.05.

Table 21:

Results of Kruskal-Wallis H Test for CVR_1 and Caller 3.

Sample 1 vs. Sample 2	Test Statistic	Std. Error	Std. Test Statistic	Sig.
C_1 vs. T_2	-.719	7.197	-.100	.920
C_1 vs. T_1 (Phase 1)	-2.438	7.197	-.339	.735
T_2 vs. T_1 (Phase 1)	1.719	7.197	.239	.811
T_1 (Phase 1) vs. T_1 (Phase 2)	-1.513	7.316	-.207	.836
T_1 (Phase 2) vs. T_1_loss	-1.833	7.433	-.247	.805
T_1_gain vs. T_1_loss	1.833	7.433	.247	.805
T_1 (Phase 2) vs. T_1_gain	.000	7.433	.000	1.000

Each row tests the null hypothesis that the Sample 1 and Sample 2 distributions are the same with significance level of 0.05.

Table 22:

Results of Kruskal-Wallis H Test for CVR_1 and Caller 4.

Sample 1 vs. Sample 2	Test Statistic	Std. Error	Std. Test Statistic	Sig.
T_2 vs. C_1	.469	7.533	.062	.950
T_2 vs. T_1 (Phase 1)	1.781	7.533	.236	.813
C_1 vs. T_1 (Phase 1)	-1.313	7.533	-.174	.862
T_1 (Phase 2) vs. T_1 (Phase 1)	.544	7.657	.071	.943
T_1 (Phase 2) vs. T_1_gain	-2.600	7.780	-.334	.738
T_1 (Phase 2) vs. T_1_loss	-3.300	7.780	-.424	.671
T_1_gain vs. T_1_loss	.700	7.780	.090	.928

Each row tests the null hypothesis that the Sample 1 and Sample 2 distributions are the same with significance level of 0.05.

Table 23:

Results of Kruskal-Wallis H Test for CVR_2 and Caller 1.

Sample 1 vs. Sample 2	Test Statistic	Std. Error	Std. Test Statistic	Sig.
T_2 vs. C_1	1.119	7.129	.157	.875
T_2 vs. T_1 (Phase 1)	3.536	7.301	.484	.628
C_1 vs. T_1 (Phase 1)	-2.417	7.564	-.319	.749
T_1_gain vs. T_1 (Phase 2)	1.729	7.503	.230	.818
T_1_gain vs. T_1_loss	4.029	7.503	.537	.591
T_1 (Phase 1) vs. T_1 (Phase 2)	-1.300	7.918	-.164	.870
T_1 (Phase 2) vs. T_1_loss	-2.300	8.104	-.284	.777

Each row tests the null hypothesis that the Sample 1 and Sample 2 distributions are the same with significance level of 0.05.

Table 24:

Results of Kruskal-Wallis H Test for CVR_2 and Caller 2.

Sample 1 vs. Sample 2	Test Statistic	Std. Error	Std. Test Statistic	Sig.
T_1_gain vs. T_1 (Phase 2)	4.247	7.414	.573	.567
T_1_gain vs. T_1_loss	5.608	7.930	.707	.479
T_2 vs. C_1	.667	6.763	.099	.921
T_2 vs. T_1 (Phase 1)	1.350	7.173	.188	.851
C_1 vs. T_1 (Phase 1)	-.683	7.173	-.095	.924
T_1 (Phase 1) vs. T_1 (Phase 2)	-2.122	7.414	-.286	.775
T_1 (Phase 2) vs. T_1_loss	-1.362	7.790	-.175	.861

Each row tests the null hypothesis that the Sample 1 and Sample 2 distributions are the same with significance level of 0.05.

Table 25:

Results of Kruskal-Wallis H Test for CVR_2 and Caller 3.

Sample 1 vs. Sample 2	Test Statistic	Std. Error	Std. Test Statistic	Sig.
C_1 vs. T_1 (Phase 1)	-1.058	6.334	-.167	.867
C_1 vs. T_2	-2.896	7.465	-.388	.698
T_1 (Phase 1) vs. T_2	-1.838	7.160	-.257	.797
T_1 (Phase 1) vs. T_1 (Phase 2)	-3.700	6.677	-.554	.579
T_1 (Phase 2) vs. T_1_gain	.000	7.314	.000	1.000
T_1 (Phase 2) vs. T_1_loss	-.575	7.003	-.082	.935
T_1_gain vs. T_1_loss	.575	7.003	.082	.935

Each row tests the null hypothesis that the Sample 1 and Sample 2 distributions are the same with significance level of 0.05.

Table 26:

Results of Kruskal-Wallis H Test for CVR_2 and Caller 4.

Sample 1 vs. Sample 2	Test Statistic	Std. Error	Std. Test Statistic	Sig.
T_2 vs. C_1	.179	6.894	.026	.979
T_2 vs. T_1 (Phase 1)	1.083	7.031	.154	.878
C_1 vs. T_1 (Phase 1)	-.904	6.894	-.131	.896
T_1 (Phase 1) vs. T_1 (Phase 2)	-1.068	7.189	-.149	.882
T_1 (Phase 2) vs. T_1_gain	-2.909	7.343	-.396	.692
T_1 (Phase 2) vs. T_1_loss	-4.482	7.525	-.596	.551
T_1_gain vs. T_1_loss	1.573	7.525	.209	.834

Each row tests the null hypothesis that the Sample 1 and Sample 2 distributions are the same with significance level of 0.05.

Appendix 7: Results of clustered regression for pairwise comparison of the experiment groups

A regression was conducted as described in section 3.2.3. The results are shown into the following Tables 24 – 29.

Table 27:

Pairwise regression with cluster analysis for caller ID for the comparison *T_1 (Phase 1)* and *C_1*.

Variable	B	SE	t	p	95% CI [LL; UL]
T_1 (Phase 1)	.00779	.00168	4.64	.010	[.00312; .01245]
C_1 (Intercept)	.05516	.00732	7.53	.002	[.03482; .07550]

Note. N=160, F(1,4)=21.50***, p<.05, R^2 = .0014, SE adjusted for 4 clusters in caller ID.

The treatment *T_1 (Phase 1)* has a significant positive effect on the conversion rate in comparison to the control group. The model is statistically significant overall, as evidenced by the low p-value of the F-statistic. However, the model's explanatory power is extremely low (R-squared = 0.0014), meaning that while the treatment *T_1 (Phase 1)* is significant, the model accounts for only a very small portion of the variability in value.

Table 28:

Pairwise regression with cluster analysis for caller ID for the comparison of *T_1 (Phase 1)* and *T_2*.

Variable	B	SE	t	p	95% CI [LL; UL]
T_1 (Phase 1)	.00459	.00546	0.84	.448	[-.01056; .01974]
T_2 (Intercept)	.05836	.00964	6.05	.004	[.03159; .08513]

Note. N=160, F(1,4)=.71***, p<.05, R^2 = .0005, SE adjusted for 4 clusters in caller ID.

The treatment *T_1 (Phase 1)* does not have a significant positive effect on the conversion rate compared to *T_2*. The coefficient of 0.00459 is small, and the high p-value of 0.448 suggests that this effect is statistically not significant.

The model is not statistically significant overall, as evidenced by the high p-value of the F-statistic (0.71). The model's explanatory power is extremely low (R-squared = 0.0005), meaning that the treatment T_1 (Phase 1) explains virtually none of the variability in the conversion rate.

Table 29:

Pairwise regression with cluster analysis for Caller ID for the comparison of *T_2* and *C_1*.

Variable	B	SE	t	p	95% CI [LL; UL]
T_2	.00320	.00514	0.62	.568	[-.01108; .01748]
C_1 (Intercept)	.05516	.00732	7.53	.002	[.03483; .07549]

Note. N=160, F(1,4)=.39***, $p<.05$, $R^2 = .0003$, SE adjusted for 4 clusters in caller ID.

The treatment *T_2* shows no significant effect compared to the control group *C_1*. The coefficient is 0.00320, and the effect is not statistically significant ($p = 0.568$). The model has extremely low explanatory power (R-squared = 0.0003).

Table 30:

Pairwise regression with cluster analysis for Caller ID for the comparison of *T_1_loss* and *T_1 (Phase 2)*.

Variable	B	SE	t	p	95% CI [LL; UL]
T_1_gain	.00945	.00148	6.37	.003	[.00534; .01357]
T_1 (Phase 2) (Intercept)	.06334	.00426	14.88	.000	[.05156; .07521]

Note. N=150, F(1,4)=40.64, $p<.05$, $R^2 = .002$, SE adjusted for 4 clusters in caller ID.

The treatment *T_1_loss* has a significant positive effect compared to *T_1 (Phase 2)*. The coefficient is 0.00945, and the effect is highly significant ($p = 0.003$). The model explains a small portion of the variance (R-squared = 0.002).

Table 31:

Pairwise regression with cluster analysis for Caller ID for the comparison of *T_1_loss* and *T_1_gain*.

Variable	B	SE	t	p	95% CI [LL; UL]
T_1_gain	.01055	.00257	4.10	.015	[.00340; .01770]
T_1_loss (Intercept)	.06229	.00551	11.30	.000	[.04699; .07760]

Note. N=150, F(1,4)=16.78, $p<.05$, $R^2 = .0027$, SE adjusted for 4 clusters in caller ID.

The treatment *T_1_loss* has a significant positive effect compared to *T_1_gain*. The coefficient is 0.01055, and the effect is significant (p = 0.015). The model explains a small portion of the variance (R-squared = 0.0027).

Table 32:

Pairwise regression with cluster analysis for Caller ID for the comparison of *T_1_gain* and *T_1 (Phase 2)*.

Variable	B	SE	t	p	95% CI [LL; UL]
T_1_loss	-.00109	.00390	-.28	.793	[-.01191; .00973]
T_1 (Phase 2) (Intercept)	.06339	.00426	14.88	.000	[.05156; .07521]

Note. N=150, F(1,4)=0.08, $p<.05$, $R^2 = .0000$, SE adjusted for 4 clusters in caller ID.

The treatment *T_1_gain* has no significant effect compared to *T_1 (Phase 2)*. The coefficient is -0.00109, and the effect is not statistically significant (p = 0.793). The model has no explanatory power (R-squared = 0.0000).