”Den 25:e smäller det!”
Payday Arbitrage in Swedish Consumer Market Behavior

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Abstract:

This thesis investigates the impact of the Swedish salary disbursement schedule on consumer behavior, particularly on the 25th of each month, a notable payday for most employees in Sweden. The study examines whether the anticipation of a monthly salary influences consumer decisions and spending patterns, potentially leading to payday-related arbitrage opportunities in Swedish marketplaces. By scrutinizing transaction data from Tradera, this research seeks to reveal if there is a discernible fluctuation in prices that corresponds with the inflow of regular salaries. Our analysis uncovers a modest but statistically significant increase in bidding activity post-payday, with a 2% rise in prices and a notable increase in bid volumes. However, this effect does not translate into substantial arbitrage opportunities due to the platform's fee structure and shipping costs. Intriguingly, day-of-the-week patterns emerged as more influential in shaping bidding behavior than payday effects. These findings contribute to the understanding of consumer market dynamics in response to synchronized salary disbursements, enriching the discourse on behavioral finance and auction theory.

Keywords:

Payday effect, Household liquidity, Behavioral Household Finance

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1 Introduction

"Den 25:e Smäller det!" - Magnus Uggla [1]

In Sweden, the synchronization of payday across the workforce engenders a unique societal rhythm, notably encapsulated by the term "Lönehelg"[2] which is well known cultural phenomena when Swedes consume more once they recieve their salary and is well depicted in Magnus Ugglas song *Kung för en dag*.

Conventional economic models, as postulated by Friedman [1957], typically advocate for a paradigm of consistent consumption patterns, positing these as instrumental in optimizing utility. Yet, empirical observations, particularly around the timing of paydays, present a challenge to this classical perspective. Such patterns, underscored by the work of Gabaix and Laibson [2022], reveal that consumer spending behaviors are often inconsistent with time preferences and exhibit a notable bias. This is evident in the spending spikes immediately following payday, deviating from the steady consumption spread anticipated by traditional economic theory. Our study endeavors to decode this divergence from classical models, drawing on the behavioral economics framework articulated by Huffman and Barenstein [2005] and Thaler [1999]. These seminal works suggest that the observed anomalies in spending behavior may be rooted in behavioral biases, particularly in contexts characterized by periodic liquidity boosts. The concept of 'mental accounting,' as introduced by Thaler, provides a theoretical underpinning for understanding how consumers mentally categorize and subsequently spend their income, potentially leading to disparate spending patterns post-payday. Huffman's insights into the monthly pay cycle further underscore the role of temporal factors in shaping consumer financial decision-making, especially in the presence of self-control challenges. By integrating these behavioral economics perspectives, our analysis aims to offer a nuanced understanding of the deviations from classical consumption models observed in real-world consumer behavior.

In this paper, we'll investigate if this payday-effect can be observed, when looking at transactional data from Tradera, a prominent Swedish online auction platform. The implication we'll investigate if due to this predicitble change in consumption and demand for second-hand will imply a form of arbitrage, where the same goods will be sold for more during payday, and thus it would be possible to create an algorithm that utilize this. Building up from a similar approach from Huffman and Barenstein [2004] [3].

Our preliminary empirical investigation reveals intricate patterns in consumer bidding behavior on Tradera, particularly in relation to the Swedish payday cycle. Consistent with the liquidity hypothesis posited by Deaton [1991], we

[1] Eng: The 25:th is banging! In Magnus Uggla's song *Kung För en Dag* (Eng: King For A Day) he sings about the enjoyment of getting his paycheck on the 25:th and spending all his money the same day.

[2] "Lönehelg" translates to "Salary Weekend" in English, referring to the weekend when most Swedes receive their salary.

[3] By implementing a weekly expenditure profile

observe a notable augmentation in both the volume of bids and overall transactional activity following payday. This pattern aligns with the findings of Stephens Jr [2003], who documented similar post-payday [4] increases in spending in the context of social security payments. However, when scrutinizing the data for evidence of payday arbitrage, as conceptualized by Mian and Sufi [2014], the results are less pronounced. The data indicates marginal price increases for comparable items around payday, yet the extent of these increases does not substantiate a robust arbitrage opportunity, especially when accounting for transactional costs such as fees and shipping, as highlighted by Dobbie and Skiba [2013]. This suggests that while payday influences consumer behavior on Tradera, its impact on pricing dynamics is constrained, warranting a more nuanced examination of the interplay between liquidity constraints and consumer decision-making in auction-based marketplaces.

Previous research has set the stage for examining the influence of scheduled income on consumer behavior, notably in the context of social security payments as seen in the study "3rd of Tha Month" by Stephens Jr [2003] using daily expenditure data from CES (Current Employment Statistics), Stephen's showed that people's spending increased significantly more right after the 3th of the month. This effect was however looked for a subpopulation i.e US Citizens receiving social security while this paper will see if we can observe the same effects on the aggregated bidding market at Tradera.

Extending the analysis beyond mere consumption to encompass the demand dynamics for similar products. The concept of "payday arbitrage"[5] inspired by the observed "Payday Anomaly" in financial markets detailed by Ma and Pratt [2018], will be examined to understand if similar market dynamics occur around paydays in the consumer sphere. Specifically, we investigate whether the influx of funds during payday induces a behavior akin to arbitrage, where consumers optimize their purchasing power by timing the market for certain goods and services. This behavior, hitherto unexplored, could offer new insights into the economic activities that follow payday synchronizations.

In extending the frontiers of finance and economics literature, our research introduces the concept of "payday arbitrage" within consumer markets, a phenomenon unexplored in existing scholarly discourse. This investigation builds upon the foundational understanding of consumer behavior influenced by regular income schedules, a topic that has been central to the works of Bos et al. [2017] and Baugh and Correia [2022]. These studies have significantly illuminated the realms of financial scarcity and the cyclic nature of paychecks, laying the groundwork for our exploration.

Our research goes beyond the traditional analysis of consumption patterns to examine how synchronized salary disbursements impact the demand dynamics for comparable products within the auction-based marketplace of Tradera. By analyzing how consumers strategically respond to periodic financial influxes,

[4] Once individuals get a liquidity individuals may assign a part of their new salary for short-term consumption

[5] That a significance change in prices of similar products changes such that it exist an arbitrage opportunity

particularly in terms of their bidding behavior and pricing strategies, we offer a nuanced comprehension of market dynamics during pay cycles. This approach is not only novel in its exploration of the "payday arbitrage" phenomenon but also in its application to a real-world auction platform, thereby providing empirical evidence to a concept that has hitherto been largely theoretical. The contribution of our study to the literature is twofold. First, it enriches the discourse on economic behavior under regular income schedules by providing empirical insights into how these schedules affect consumer behavior in online marketplaces. Second, by introducing and exploring the concept of payday arbitrage, our research sheds light on a previously unexamined aspect of consumer market movements in response to synchronized salary disbursements. Such an exploration is critical, as it reveals the intricate interplay between financial predictability and consumer decision-making, thereby enhancing our understanding of calendar anomalies in financial markets. Ultimately, this line of inquiry promises to broaden the scope of behavioral finance and economics, offering new perspectives on how regular income cycles influence market dynamics and consumer strategies.

The structure of this paper is organized into several key sections to thoroughly investigate the payday arbitrage phenomenon in the Swedish consumer market. Following this introduction, Section 2, 'Data Description,' delves into the specifics of the Tradera dataset, detailing the auction system and criteria for identifying successful sales. Section 3, 'Methodology,' outlines our analytical approach, including the panel models and the rationale behind the selection of fixed and random effects models. Section 4, 'Empirical Results and Analysis,' presents our findings, analyzing the effects of paydays on different dimensions of consumer behavior on Tradera. This section contextualizes our results within existing literature and discusses their implications. Section 5, 'Robustness Check,' evaluates the reliability of our findings, including placebo tests and other robustness checks. Finally, the paper concludes with a comprehensive discussion of the study's contributions, limitations, and potential avenues for future research in this area. The Appendix provides supplementary data and detailed descriptions of our methodological approach, ensuring transparency and reproducibility of our analysis.

2 Data Description

Our research utilizes a comprehensive dataset from Tradera, a key player in Sweden's online auction market for second-hand goods. Since its inception in 1999, Tradera has been at the forefront of the Swedish e-commerce scene, offering an eclectic mix of products in categories ranging from collectibles to electronics and fashion. Our focus is particularly on the auction-based segment of Tradera's offerings, which operates alongside its fixed-price sales model.

Tradera's auctions are marked by a fixed-end-time approach, ensuring that the highest bidder at the close of the auction wins the item. This format includes a 'Bid Ladder' system, setting minimum increments for subsequent bids, and allows sellers to set hidden reserve prices, ensuring their items are not sold below a desired value. These elements, akin to those observed in Hossain and Morgan [2009]'s eBay auction study, play a significant role in shaping both seller strategies and buyer bidding behaviors.

Our analysis centers on auctions resulting in a sale, a common focus in auction-based research such as in Bajari and Hortaçsu [2003]. An auction is deemed successful if it receives more than one bid by its conclusion. While generally reliable, this criterion assumes full compliance with transaction terms by both sellers and buyers. Our dataset encompasses 23 months of transaction data[6], with a total of x million rows[7], capturing all bids up to the auction end dates.

The ideal dataset for our study would encompass a wider time frame and a more granular breakdown of bidder demographics and behaviors[8]. However, the dataset at hand provides a substantial basis for our current research.

It is also essential to note the occasional exceptional cases deviating from typical auction behaviors on Tradera. A prominent instance was the high-profile auction of a Swedish rapper's platinum award plaque, with bids exceeding a billion SEK, which was subsequently removed from the platform. Such anomalies, while notable, are outliers and hence excluded from our analysis to ensure data integrity and representativeness[9].

The dataset in our analysis is derived exclusively from active members on Tradera, ensuring a high relevance and accuracy of the consumer behavior insights we aim to derive. It's important to note that the scope of our dataset is limited to active user interactions; data from inactive members are not included, which may influence the completeness of historical transaction patterns. Moreover, the dataset is rich in categorical granularity, featuring four category levels in a category tree where leaf categories, which is the last category in a branch of the category tree, can appear at any level between two and four. In total, the data contains 5747 different leaf categories.

[6] 1 January 2022 to 27 November 2023

[7] Redacted due to confidentiality

[8] An expanded dataset would provide deeper insights into long-term trends and nuanced bidder profiles, enhancing the robustness of our analysis.

[9] For details on this specific auction prior to its removal, see: https://www.tradera.com/item/341175/615831028/dree-low-pippi-multiplatina-plaque

Table 1: Data Description for Tradera Listings Dataset

Field	Description
externalAuctionId	Unique identifier for the listing
externalSellerMemberId	Unique seller identifier
StartDate	The date the listing was scheduled to go live
EndDate	The date the listing was scheduled to stop
StartPrice	The starting price (SEK) for the listing
Title	The title of the listing
leaf_category_id	The leaf category that the auction was posted in. To figure out the full category path, join leaf_category_id with the external_DimCategory table.
total_bids	Total number of bids on an item.
Max_bids	Largest bid on an item. Assumed to be the price sold for when number of bids is greater than one
Vertical_id	Vertical that the item was listed in, join to external_DimAuctionVertical to get the vertical name

3 Methodology

We will be studying the payday effect in two dimensions. The payday effect on (1) listing ending prices (2) listing ending number total of bids. Since Tradera sells a wide range of items propose that a Panel model that adjusts for constant differences can be utilized. Moreover, we will also study the total volumes of sold items and total number of bids where an ordinary OLS regression is used.

3.1 General Considerations

In our analysis, the determination of payday is crucial, as it is hypothesized to influence consumer behavior significantly. In Sweden, the standard payday is typically set for the 25th of each month. However, to reflect real-world practices accurately, adjustments are made if this date falls on a weekend. Specifically, if the 25th is a Saturday or Sunday, the payday is shifted to the preceding Friday. This adjustment is essential in our study, as it ensures that the analysis corresponds with the actual days when consumers receive their salaries. By aligning our investigation with these adjusted paydays, we aim to capture the true impact of salary disbursement on consumer spending and bidding behavior, particularly in the context of the Swedish market and its unique payday rhythms.

A set of indicators have been calculated to comprehensively analyze the auction data from Tradera. These indicators are derived to capture the temporal dynamics associated with payday schedules and weekly patterns. The aim is to understand how these factors might influence bidding behavior. The indicators are also conceptually divided in two group, payday indicators that are related to the payday. Secondly, weekday indicators that are added to account for intra-week variability across the days. The following table summarizes these indicators:

Table 2: Description of Indicators Used in the Analysis

Indicator	**Description**
	Payday Indicators
payday_indicator_week_1	Indicator for auction ending 0-6 days after payday
payday_indicator_week_2	Indicator for auction ending 7-13 days after payday
payday_indicator_week_-1	Indicator for auction ending 0-6 days before payday
payday_indicator_week_-2	Indicator for auction ending 7-13 days before payday
	Weekday Indicators
monday_indicator	Indicator for auctions ending on Monday
tuesday_indicator	Indicator for auctions ending on Tuesday
wednesday_indicator	Indicator for auctions ending on Wednesday
thursday_indicator	Indicator for auctions ending on Thursday
friday_indicator	Indicator for auctions ending on Friday
saturday_indicator	Indicator for auctions ending on Saturday
sunday_indicator	Indicator for auctions ending on Sunday

The indicators act as the independent, exogenous variables, in our model. The two dependent variables that are studied are max_bid and total_bids.

In our comprehensive analysis, we examine four distinct regression combinations, each representing a unique combination of variables and indicators. These models incorporate either the independent variable max_bid or total_bids, coupled with two different sets of explanatory variables. The first set includes all payday indicators along with weekday indicators, while the second set comprises only the payday indicators in conjunction with a constant term. This approach allows us to capture the intricacies of auction dynamics in relation to payday cycles and weekday patterns.

Crucially, the baseline comparison for our parameters hinges on periods as distant from the payday as feasible[10]. This choice of baseline ensures that the influence of paydays on auction behavior is distinctly contrasted against non-payday periods.

The following table provides a clear overview of these models, labeled from A to D for easy reference:

[10]Given that the payday indicators extend two weeks before and after the payday, the length of this reference period slightly varies each month.

Table 3: Overview of Regression Models. const stands for a constant in the models.

Model	Regression Equation
A	max_bid $\sim$ payday_indicators + weekday_indicators
B	total_bids $\sim$ payday_indicators + weekday_indicators
C	max_bid $\sim$ const + payday_indicators
D	total_bids $\sim$ const + payday_indicators

This structured approach to model selection and analysis facilitates a nuanced understanding of the varying impacts of payday and weekday factors on both the maximum bid and the total number of bids in online auctions.

3.2 Data Preprocessing

In order to ensure that only data according to the assumptions stated in section 2 two steps of data preprocessing are conducted

1. All listings that have ended with zero bids are filtered out.
2. Outliers in the max_bid and total_bids are removed by calculating the means and removing all values outside of three standard deviations.

The raw data includes about several millions of rows which where we end up with about 16 million rows after the data preprocessing, details of the sample sizes and exlusion criteria can be found in figure 1.

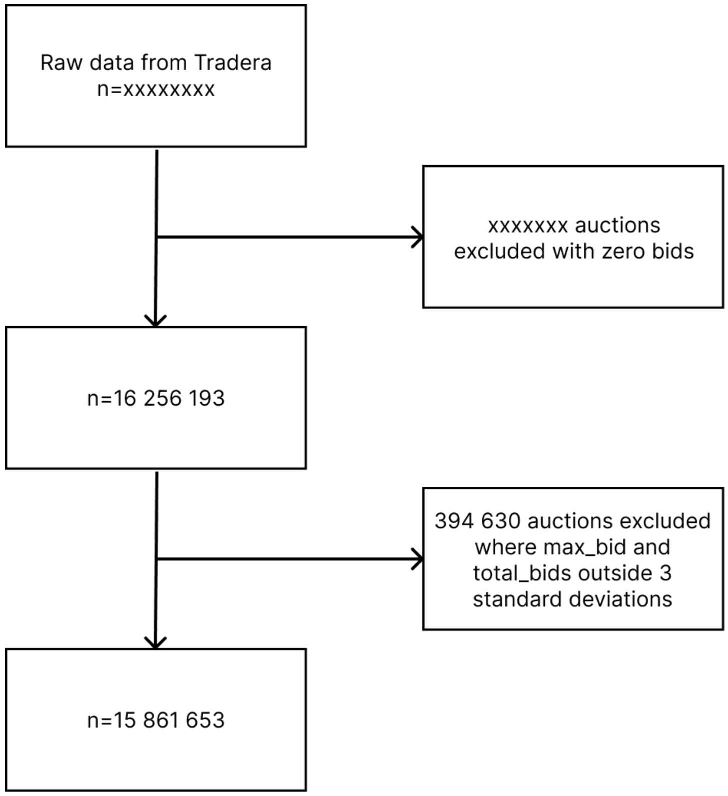

Figure 1: Data filtration process for Tradera auction dataset. The flowchart illustrates the sequential steps taken to clean the dataset, detailing the exclusion criteria at each stage and the resulting number of observations retained for analysis. Size of raw data set and number of rows excluded are redacted due to confidentiality.

3.3 Panel Models

Our analysis employs panel models to account for variations across different categories of data. We assume that a fixed effects model is suitable for capturing these variations. Both fixed effects and random effects models are utilized in this study. The choice between these models is informed by the results of Hausman tests, which provide guidance on the appropriateness of either model based on their assumptions and the nature of our data.

3.3.1 Fixed Effects

The fixed effects model is designed to analyze the impact of variables that vary over time. It is particularly useful in panel data analysis where the interest lies in investigating how predictors affect the outcome variable within an entity.

The fixed effects model includes entity-specific constants (intercepts), which capture all time-invariant characteristics of the entities. This allows the model to control for unobserved heterogeneity when this heterogeneity is constant over time and correlated with the independent variables. The model focuses on within-entity variation over time. It essentially compares an entity to itself over different time periods, controlling for all time-invariant characteristics of the entity. By using entity-specific constants and focusing on within-entity variations, the fixed effects model effectively removes the influence of time-invariant confounders, thereby reducing omitted variable bias ScienceDirect Topics [a].

The major limitation of the fixed effects model is that it cannot estimate the effects of time-invariant variables, as these are absorbed by the entity-specific constants.

In our case, the leaf_category is used as a proxy for different entities, and time variations are modeled on a month-by-month basis with time fixed effects. To implement this approach, we utilize a PanelOLS model[11].

A general fixed effects model is specified as follows:

$$y_{it} = \alpha_i + \gamma_t + \sum_k \beta_k x_{k,it} + \epsilon_{it} \tag{1}$$

where i indexes the entity, t indexes time, y is the dependent variable, and x_k are the exogenous independent variables. In this model, γ_t represents time-fixed effects and α_i entity-fixed effects.

For regression combination A and B it will be implemented as following

$$y_{it} = \alpha_i + \gamma_t + \sum_{\text{weekday}=1}^{7} \beta_{\text{weekday}} \mathbb{1}_{\text{weekday},it} + \sum_{\text{payday indicator}=1}^{4} \beta_{\text{payday indicator}} \mathbb{1}_{\text{payday indicator},it} + \epsilon_{it} \tag{2}$$

where α_i and γ_t correspond to the entity and time effects and the rest of the exogenous variables are indicator defined as in section 3.1.

For regression combination C and D the weekday indicator are left out and instead a constant is added denoted by β_0 according to the following formula

$$y_{it} = \alpha_i + \gamma_t + \beta_0 + \sum_{\text{payday indicator}=1}^{4} \beta_{\text{payday indicator}} \mathbb{1}_{\text{payday indicator},it} + \epsilon_{it} \tag{3}$$

3.3.2 Random Effects

For comparison, a random effects model is also considered. The random effects model is another approach to panel data analysis. It assumes that the entity-specific effect is a random variable that is uncorrelated with the independent variables. This model is useful when the focus is on both within-entity and between-entity variations.

[11] Using linearmodels version 5.3 implemented in Python. https://github.com/bashtage/linearmodels/

Unlike fixed effects, the random effects model includes random entity-specific effects. These effects are assumed to be uncorrelated with the regressors, allowing for time-invariant variables to play a role in the model. The random effects model is generally more efficient than the fixed effects model, as it uses both within-entity and between-entity variations. This can lead to more precise estimates under the correct model assumptions. The random effects model can estimate the effects of time-invariant variables, making it more versatile in certain contexts. The crucial assumption of the random effects model is that the entity-specific effects are not correlated with the regressors. Violation of this assumption can lead to biased and inconsistent estimators, making the fixed effects model a more appropriate choice in such cases ScienceDirect Topics [c].

To implement this approach, we utilize a RandomEffects model[12]. The general random effects model is given by:

$$y_{it} = u_i + \sum_k \beta_k x_{k,it} + \epsilon_{it} \tag{4}$$

Here, u_i represents the random effect, unique to each entity but uncorrelated with the independent variables x_k.

For regression combination A and B it will be implemented as following

$$y_{it} = u_i + \sum_{\text{weekday}=1}^{7} \beta_{\text{weekday}} \mathbb{1}_{\text{weekday},it} + \sum_{\text{payday indicator}=1}^{4} \beta_{\text{payday indicator}} \mathbb{1}_{\text{payday indicator},it} + \epsilon_{it} \tag{5}$$

For regression combination C and D the weekday indicator are left out and instead a constant is added denoted by β_0 according to the following formula

$$y_{it} = u_i + \beta_0 + \sum_{\text{payday indicator}=1}^{4} \beta_{\text{payday indicator}} \mathbb{1}_{\text{payday indicator},it} + \epsilon_{it} \tag{6}$$

3.3.3 Hausman Test

The Hausman test is a statistical test used to determine whether a fixed effects or random effects model is more appropriate for a given dataset. It tests the null hypothesis that the preferred model is random effects against the alternative of fixed effects. The test is based on the difference in coefficients estimated by the fixed and random effects models. If the difference is systematic and significant, it suggests that the random effects model produces biased estimators, and hence the fixed effects model is preferredScienceDirect Topics [b].

The Hausman test statistic is calculated as follows:

$$H = (\beta_{FE} - \beta_{RE})' \left[Var(\beta_{FE}) - Var(\beta_{RE})\right]^{-1} (\beta_{FE} - \beta_{RE}) \tag{7}$$

where β_{FE} and β_{RE} are the coefficient vectors obtained from the fixed effects and random effects models, respectively. $Var(\beta_{FE})$ and $Var(\beta_{RE})$ are the variance matrices of these estimators. A significant Hausman test statistic implies

[12] Using linearmodels version 5.3 implemented in Python. https://github.com/bashtage/linearmodels/

that the fixed effects model is more appropriate for the analysis.

The distribution of the Hausman test statistic under the null hypothesis is a key factor in determining the p-value. Under the null hypothesis that the random effects model is appropriate, the Hausman test statistic follows a chi-square (χ^2) distribution. The degrees of freedom for this distribution are equal to the number of regressors being tested – essentially, the number of coefficients in the model.

- A high Hausman test statistic relative to the chi-square distribution indicates a low p-value, leading to rejection of the null hypothesis in favor of the fixed effects model.
- A lower test statistic suggests a higher p-value, meaning the evidence is insufficient to reject the null hypothesis, and the random effects model may be more appropriate.

3.4 Ordinary OLS

One part of our methodology includes looking at the total volume of items sold and total number of bids across the time period not taking account any entity effects. Here a simple ordinary OLS model is used with the same combinations A to D of dependent and independent variables.

For regression combination A and B an ordinary OLS is implemented as following

$$\hat{y} = \sum_{\text{weekday}=1}^{7} \beta_{\text{weekday}} \mathbb{1}_{\text{weekday},it} + \sum_{\text{payday indicator}=1}^{4} \beta_{\text{payday indicator}} \mathbb{1}_{\text{payday indicator},it} + \epsilon_{it} \tag{8}$$

For regression combination C and D the weekday indicator are left out and instead a constant is added denoted by β_0 according to the following formula

$$\hat{y} = \beta_0 + \sum_{\text{payday indicator}=1}^{4} \beta_{\text{payday indicator}} \mathbb{1}_{\text{payday indicator},it} + \epsilon_{it} \tag{9}$$

The sum $\hat{y}$ is calculated over both time and entities

$$\hat{y} = \sum_{i} \sum_{t} y_{it} \tag{10}$$

4 Empirical Results and Analysis

Our analysis explores the dynamics of consumer bidding behavior, with a particular focus on how payday timing and day-of-the-week patterns influence auction activity. This investigation entailed conducting twelve distinct regression analyses across three different models, and four different combinations of dependent and independent variables.

By adopting this multifaceted analytical approach, we were able to delve deeply into the nuances of how consumers interact with online auctions, considering both the magnitude of their bids and the frequency of bidding. The varied combinations of variables within each model were strategically selected to isolate and evaluate the individual and combined effects of paydays and weekdays, thus providing a comprehensive view of their impact on consumer behavior. The extensive and detailed results of these regressions are methodically presented in Appendix A.

We employed the Hausman test the most appropriate panel model for each regression[13]. This test is crucial in determining whether a fixed effects or random effects model better suits the data structure and inherent characteristics of the variables. The outcomes, detailed in 4 and further elaborated in Appendix C, revealed a preference for the fixed effects model in most regressions. However, an intriguing exception was noted in regression B, which studies the total number of bids with both payday and weekday indicators as dependent variables. Here, the Hausman test indicated that a random effects model might be more appropriate.

This suggestion that a random effects model is suitable for understanding the total number of bids is significant. It implies that there might be unobserved, time-invariant individual characteristics influencing the number of bids that are not captured by the fixed effects model. In essence, this finding suggests that while payday and weekday effects have a consistent impact across the dataset, there are underlying, unchanging factors unique to each bidder that also play a pivotal role in determining their bidding behavior. These factors could range from individual financial stability to personal bidding strategies, hinting at a more complex interplay of influences in online auction settings than initially presumed.

Table 4: Model Selection Based on Hausman Test

Model	**Selection Conclusion**
max_bid (weekday included)	Fixed effects model is preferred
total_bids (weekday included)	Random effects model may be appropriate
max_bid (weekday excluded)	Fixed effects model is preferred
total_bids (weekday excluded)	Fixed effects model is preferred

The empirical findings from our study present a clear and consistent pattern that aligns with the theoretical underpinnings of the payday effect in consumer behavior. Specifically, our analysis demonstrates a discernible trend in both the maximum bid and the total number of bids in relation to the timing of paydays.

We observed that in the first week following payday, there is a notable increase in both the max_bid and total_bids. This uptick suggests that consumers are more willing and able to engage in higher bidding and more frequent participation in auctions immediately after receiving their salaries. The magnitude of

[13] Not including the ordinary OLS

this effect, although still significant, tends to diminish in the second week after payday. This gradual decrease can be attributed to the dwindling disposable income as the month progresses.

Conversely, the two weeks preceding payday exhibit a contrasting trend. During this period, both max_bid and total_bids are generally lower than the baseline. The baseline, in this context, represents the days that are as far removed from payday as possible. This decline in auction activity before payday can be explained by the natural decrease in consumers' financial liquidity as they approach the end of their monthly budget cycle.

The analysis of our data yields distinct insights into the significance of bidding behavior in relation to the timing of paydays, particularly when examining total bids and maximum bids. The findings indicate a marked difference in the impact of financial liquidity (or the lack thereof) on consumer behavior in online auctions.

For total bids, the significance is exceptionally high, with p-values close to zero across all instances. This strong statistical significance suggests a robust and consistent effect of payday timing on the total number of bids placed in the auctions. Such a trend underscores the influence of paydays on consumers' participation levels in auction activities, reflecting a heightened willingness or ability to engage in bidding post-payday.

In contrast, for maximum bids, the data reveals a more pronounced significance for the payday indicators in the weeks leading up to payday. This suggests that the constraint of being cash-strapped before payday is a more influential factor than the increased financial capacity following payday. The urgency or necessity to secure goods before the impending low-liquidity period might drive consumers to place higher maximum bids in the pre-payday phase.

Interestingly, the least significant impact is observed in the period of the second week after payday, particularly in regression C of the Fixed Effects model, where the p-value hovers around 0.5. This indicates that while the immediate post-payday period sees a surge in bidding activity, this diminishes significantly as consumers move further away from the payday. It reflects a normalization of bidding behavior as the immediate effects of increased liquidity begin to decrease.

The examination of the magnitudes of the effects on bidding behavior in relation to payday cycles provides crucial insights into the feasibility of arbitrage opportunities on Tradera. Our findings indicate a price variation of approximately 2-4% and a variation in total bids of about 5-10% across different regression models. While these variations are statistically significant, they are relatively modest in scale.

This moderate level of fluctuation in both prices and bid volumes around paydays suggests that, although consumer behavior is indeed influenced by payday cycles, the extent of this influence is not substantial enough to create straightforward arbitrage opportunities. In the context of Tradera, this is particularly relevant due to the platform's fee structure and the inherent costs associated with transactions, commonly referred to as transaction friction.

The fees and other costs associated with buying and selling on Tradera would likely offset the potential gains from exploiting the small variations in prices and bidding volume tied to payday timings. For an arbitrage strategy to be successful, the price differential needs to be sufficient to cover these additional costs and still yield a profit. Given the observed price and bid volume variations, it appears that the potential for such profitable arbitrage on Tradera is limited.

The cumulative trends observed in the total volume of items sold and the total number of bids present an interesting fact about consumer behavior in relation to payday cycles. A key observation is the disparity in significance between the weeks following payday compared to other weeks.

In the week immediately following payday, there is a notable increase in both the volume of items sold and the total number of bids. This trend is statistically significant, suggesting a direct correlation between the influx of funds into consumers' hands and their increased activity in online auctions. The post-payday period, marked by enhanced financial liquidity, seems to encourage consumers to participate more actively in auctions, both in terms of bidding frequency and in the purchase of a higher volume of items.

Conversely, for the weeks leading up to payday and those further from the payday, the significance drops markedly. This implies a reduced inclination or ability of consumers to engage in auction activities during these periods. The decrease in bidding and purchasing behavior could be attributed to a more cautious financial approach as consumers anticipate or experience a reduction in disposable income before the next payday.

These empirical results not only corroborate the existence of a payday effect in the context of online auctions but also offer a nuanced understanding of its temporal dynamics. The pattern of increased bidding activity following paydays and subdued participation before them is in harmony with the anticipated behavior of consumers responding to their cyclical financial liquidity. This insight into consumer spending patterns around paydays adds a valuable dimension to the understanding of bidding behavior in online auction platforms, highlighting the significant role of personal financial cycles in economic decision-making.

5 Robustness Check

To ensure the robustness of our main regression results and to ascertain that they are not merely artifacts of statistical noise, we have implemented a placebo test. This test involves the random assignment of payday dates within the calendar for each data point, followed by a reevaluation of the regression models. Specifically, we employ a permutation test, about 600 times [14], to rigorously examine the stability of our findings[15].

[14] The exact number of simulations is 623

[15] Optimally we would have liked to execute the simulation thousands or tens of thousands times; however, due to the large size of the data set, containing about 16 million rows after data pre-processing, the computing power and time needed was not enough within the time constraint of this thesis.

During this permutation test, we compare the distribution of parameter estimates from each iteration to the baseline coefficients obtained from our primary regression analysis. A key aspect of this comparison is the focus on the positioning of the baseline coefficients within the distribution range of the permutation test results. Should these coefficients consistently reside in the extremities or tails of this distribution, it would significantly diminish the likelihood that our original findings are mere consequences of random noise.

It is crucial to note that throughout this process, the original dates of the auction listings are preserved. Altering these dates would risk losing vital time-series information, leading to non-converging regression models. This preservation is fundamental to maintain the temporal integrity of the data, ensuring that the robustness checks accurately reflect the dynamics captured in the initial analysis.

To calculate the p-values in this context, we utilize the permutation test's distribution of parameter estimates. By assessing where the original regression coefficients fall within this distribution, we can estimate the probability of observing such coefficients under the null hypothesis. This method allows us to derive p-values that are not only robust but also grounded in the empirical distribution of the data, rather than relying on theoretical assumptions. Such an approach is deeply rooted in the statistical literature, with early references found in the works of Eden and Yates and Dwass, who pioneered these non-parametric methods of hypothesis testing Dwass [1957], Eden and Yates [1933].

The regression that we have selected to do a robustness check of is the panel model with entity effects and time effects that only includes the payday windows and not the weekday indicators as described in section 3.3.1. This model, as detailed earlier in our study [Reference to previous discussion in the paper], encompasses five key parameters, including the constant. Upon completion of the simulations, we plotted the estimated parameter values in a histogram alongside the corresponding Gaussian curve. This approach assumes that the parameter distributions approach normal distribution as the number of simulations increases Dwass [1957].

For each parameter, we have already determined baseline p-values. To contrast these with our simulation results, we computed the estimated p-values using the following formula:

$$\hat{p} = \frac{\text{count of test-statistics that are as or more extreme than our baseline}}{\text{total count of test-statistics calculated}} \tag{11}$$

Additionally, we determined one-sided confidence intervals for these estimated p-values, adhering to a confidence level of $\alpha = 0.01$. This calculation follows the binomial proportion confidence interval formula:

$$\text{Confidence interval of estimated p-value} = \left[0, \hat{p} + z_\alpha \sqrt{\frac{\hat{p}(1-\hat{p})}{N}}\right] \tag{12}$$

where, N denotes the total count of test-statistics computed.

Table 5 presents a side-by-side comparison of the baseline p-values, the p-values estimated from the simulation, and their respective confidence intervals. For a comprehensive examination of the test-statistic distributions arising from this robustness check, please refer to Appendix B.

Table 5: Comparison of Baseline and Estimated P-Values with Confidence Intervals

Variable	**P-values**		**Confidence intervals**
	Baseline	**Estimated from simulation**	
const	0.0000	0.0706	[0,0.0945]
payday_indicator_week_1	0.2781	0.0000	[0,0.0000]
payday_indicator_week_2	0.5099	0.08989	[0,0.1165]
payday_indicator_week_-1	0.0066	0.0000	[0,0.0000]
payday_indicator_week_-2	0.0087	0.0000	[0,0.0000]

Our estimated p-values, in comparison to the baseline, skew significantly towards the lower end of the spectrum. This observation indicates a substantial deviation from what might be expected under the null hypothesis, thereby strengthening the credibility of our original findings. Each estimated p-value, notably smaller than its corresponding baseline, suggests a reduced likelihood that the observed effects in our regression analysis are merely artifacts of statistical randomness.

However, it is imperative to approach these results with a degree of caution. The limitations imposed by the number of simulations introduce a margin of uncertainty. A higher volume of simulations would invariably lead to more robust and confident results. Despite this limitation, the trend observed in the simulation outcomes provides a compelling indication that the effects captured in our regression model are indeed reflective of underlying economic phenomena rather than spurious correlations.

These findings lend confidence to the hypothesis that the dynamics we have identified and modeled are not merely statistical anomalies but are grounded in actual market behavior. Which underscores the robustness of our analytical approach and the validity of the insights derived from our study.

6 Conclusion

This paper presents a comprehensive exploration of the payday effect in the Swedish consumer market, focusing on the online auction platform Tradera. Our study rigorously examines the interplay of payday effects and day-of-the-week patterns on bidding behavior. By analyzing extensive transaction data, we have uncovered subtle but significant influences of payday timing on consumer bidding behavior. The analysis reveals a modest but statistically significant increase in both bid volume and prices around paydays, with a 2% increase in prices post-payday. This finding aligns with behavioral economics theory, suggesting that consumers may experience a change in their financial disposition following a payday, as discussed in Shefrin [2009]. However, the magnitude of this effect does not create a viable arbitrage opportunity, primarily due to Tradera's commission structure and associated shipping costs.

More pronounced than the payday effect, our study identifies a significant day-of-the-week pattern in bidding behavior. The number of bids increases notably on specific days, particularly weekends, indicating a strong temporal pattern in bidding behavior, resonating with the findings of Agarwal et al. [2013]. This observation underscores the dominance of day-of-the-week effects over payday impacts in shaping bidding behavior, offering new insights into temporal patterns in consumer decision-making.

From a practical standpoint, while the payday effect is noticeable, its exploitation for arbitrage is limited within Tradera's platform. However, these insights offer strategic implications for Tradera's auction scheduling. Aligning auction end dates with periods of increased bidding activity, such as post-payday or weekends, could potentially enhance revenue. This recommendation is in line with the revenue optimization strategies discussed in Ostrovsky and Schwarz [2009] and contributes to a more nuanced understanding of bidder behavior, offering practical avenues for revenue optimization in online marketplaces.

The implications of these findings are twofold. Firstly, they provide valuable insights for online marketplaces like Tradera to optimize auction scheduling. Secondly, they contribute to the broader discourse in behavioral finance and economics, enriching our understanding of how regular income schedules influence consumer behavior in digital market spaces.

Despite the robustness of our findings, this study is not without limitations. The specific context of Tradera and the Swedish market may restrict the generalizability of the results. Future research could extend this analysis to other online marketplaces and cultural contexts, exploring whether similar patterns emerge. Additionally, examining the interplay between consumer behavior and other cyclic economic factors, such as holiday seasons or tax return periods, could offer further insights into the dynamics of online auction markets, additional resarch could also be done relating to the specific time-stamps people make these bids and specifically related to weekend shopping and if alcohol consumption has an increase in bidding behavior.

In conclusion, this thesis illuminates the subtle yet significant influence of payday timing on consumer bidding behavior in online auctions. It contributes to the literature on behavioral finance by revealing the intricate relationship between regular income cycles and consumer market dynamics, offering practical insights for online auction platforms and paving the way for future research in this evolving field.

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A Appendix: Detailed regressions results

A.1 Fixed Effect Variable Combination A: max_bid ~ payday_indicators + weekday_indicators

Dep. Variable:	max_bid	**R-squared:**	5.59e-05
Estimator:	PanelOLS	**R-squared (Between):**	-0.0079
No. Observations:	15861563	**R-squared (Within):**	5.735e-05
		R-squared (Overall):	0.0001
		Log-likelihood	-1.321e+08
Cov. Estimator:	Unadjusted		
		F-statistic:	88.642
Entities:	5747	**P-value**	0.0000
Avg Obs:	2760.0	**Distribution:**	F(10,15855784)
Min Obs:	1.0000		
Max Obs:	2.233e+05	**F-statistic (robust):**	9.361e+04
		P-value	0.0000
Time periods:	23	**Distribution:**	F(10,15855784)
Avg Obs:	6.896e+05		
Min Obs:	2.168e+05		
Max Obs:	8.819e+05		

F-test for Poolability: 640.86
P-value: 0.0000
Distribution: F(5768,15855784)

Included effects: Entity, Time

	Parameter	Std. Err.	T-stat	P-value	Lower CI	Upper CI
monday_indicator	265.48	1.1637	228.12	0.0000	263.20	267.76
tuesday_indicator	263.54	1.1764	224.03	0.0000	261.24	265.85
wednesday_indicator	264.41	1.1724	225.52	0.0000	262.12	266.71
thursday_indicator	261.56	1.1743	222.73	0.0000	259.26	263.86
friday_indicator	261.88	1.2000	218.24	0.0000	259.53	264.24
saturday_indicator	250.98	1.1232	223.44	0.0000	248.77	253.18
sunday_indicator	248.15	0.9988	248.46	0.0000	246.20	250.11
payday_indicator_week_1	1.7419	1.0591	1.6447	0.1000	-0.3339	3.8176
payday_indicator_week_2	1.2068	1.0773	1.1203	0.2626	-0.9046	3.3183
payday_indicator_week_-1	-2.3404	1.0681	-2.1913	0.0284	-4.4338	-0.2471
payday_indicator_week_-2	-2.2012	1.0661	-2.0646	0.0390	-4.2908	-0.1116

A.2 Fixed Effect Variable Combination B: total_bids ∼ payday_indicators + weekday_indicators

Dep. Variable:	total_bids	**R-squared:**	0.0095
Estimator:	PanelOLS	**R-squared (Between):**	0.0095
No. Observations:	15861563	**R-squared (Within):**	0.0097
		R-squared (Overall):	0.0114
		Log-likelihood	-5.351e+07
Cov. Estimator:	Unadjusted		
		F-statistic:	1.524e+04
Entities:	5747	**P-value**	0.0000
Avg Obs:	2760.0	**Distribution:**	F(10,15855784)
Min Obs:	1.0000		
Max Obs:	2.233e+05	**F-statistic (robust):**	7.423e+05
		P-value	0.0000
Time periods:	23	**Distribution:**	F(10,15855784)
Avg Obs:	6.896e+05		
Min Obs:	2.168e+05		
Max Obs:	8.819e+05		

F-test for Poolability: 190.79
P-value: 0.0000
Distribution: F(5768,15855784)

Included effects: Entity, Time

	Parameter	Std. Err.	T-stat	P-value	Lower CI	Upper CI
monday_indicator	4.3730	0.0082	531.95	0.0000	4.3569	4.3891
tuesday_indicator	4.2303	0.0083	509.05	0.0000	4.2140	4.2466
wednesday_indicator	4.2694	0.0083	515.49	0.0000	4.2532	4.2857
thursday_indicator	4.4175	0.0083	532.53	0.0000	4.4012	4.4337
friday_indicator	4.2840	0.0085	505.37	0.0000	4.2674	4.3006
saturday_indicator	4.4707	0.0079	563.44	0.0000	4.4552	4.4863
sunday_indicator	5.8160	0.0071	824.34	0.0000	5.8022	5.8298
payday_indicator_week_1	0.2881	0.0075	38.503	0.0000	0.2734	0.3027
payday_indicator_week_2	0.1568	0.0076	20.603	0.0000	0.1419	0.1717
payday_indicator_week_-1	0.1134	0.0075	15.027	0.0000	0.0986	0.1282
payday_indicator_week_-2	0.0592	0.0075	7.8607	0.0000	0.0444	0.0740

A.3 Fixed effect Variable Combination C: max_bid ∼ const + payday_indicators

Dep. Variable:	max_bid	**R-squared:**	3.377e-06
Estimator:	PanelOLS	**R-squared (Between):**	-0.0080
No. Observations:	15861563	**R-squared (Within):**	3.935e-06
		R-squared (Overall):	4.613e-06
		Log-likelihood	-1.321e+08
Cov. Estimator:	Unadjusted		
		F-statistic:	13.384
Entities:	5747	**P-value**	0.0000
Avg Obs:	2760.0	**Distribution:**	F(4,15855790)
Min Obs:	1.0000		
Max Obs:	2.233e+05	**F-statistic (robust):**	13.384
		P-value	0.0000
Time periods:	23	**Distribution:**	F(4,15855790)
Avg Obs:	6.896e+05		
Min Obs:	2.168e+05		
Max Obs:	8.819e+05		

F-test for Poolability: 641.18
P-value: 0.0000
Distribution: F(5768,15855790)

Included effects: Entity, Time

	Parameter	**Std. Err.**	**T-stat**	**P-value**	**Lower CI**	**Upper CI**
const	257.14	0.9259	277.71	0.0000	255.32	258.95
payday_indicator_week_1	1.1484	1.0588	1.0846	0.2781	-0.9269	3.2236
payday_indicator_week_2	0.7098	1.0771	0.6590	0.5099	-1.4013	2.8209
payday_indicator_week_-1	-2.9026	1.0678	-2.7182	0.0066	-4.9956	-0.8097
payday_indicator_week_-2	-2.7980	1.0659	-2.6250	0.0087	-4.8871	-0.7089

A.4 Fixed Effect Variable Combination D: total_bids ∼ const + payday_indicators

Dep. Variable:	total_bids	**R-squared:**	0.0002
Estimator:	PanelOLS	**R-squared (Between):**	-9.872e-05
No. Observations:	15861563	**R-squared (Within):**	0.0002
		R-squared (Overall):	0.0002
		Log-likelihood	-5.358e+07
Cov. Estimator:	Unadjusted		
		F-statistic:	773.57
Entities:	5747	**P-value**	0.0000
Avg Obs:	2760.0	**Distribution:**	F(4,15855790)
Min Obs:	1.0000		
Max Obs:	2.233e+05	**F-statistic (robust):**	773.57
		P-value	0.0000
Time periods:	23	**Distribution:**	F(4,15855790)
Avg Obs:	6.896e+05		
Min Obs:	2.168e+05		
Max Obs:	8.819e+05		

F-test for Poolability: 196.70
P-value: 0.0000
Distribution: F(5768,15855790)

Included effects: Entity, Time

	Parameter	**Std. Err.**	**T-stat**	**P-value**	**Lower CI**	**Upper CI**
const	4.7973	0.0066	730.03	0.0000	4.7844	4.8102
payday_indicator_week_1	0.3339	0.0075	44.435	0.0000	0.3192	0.3486
payday_indicator_week_2	0.1961	0.0076	25.648	0.0000	0.1811	0.2110
payday_indicator_week_-1	0.1545	0.0076	20.383	0.0000	0.1396	0.1693
payday_indicator_week_-2	0.0995	0.0076	13.147	0.0000	0.0846	0.1143

A.5 Random Effect Variable Combination A: max_bid ∼ payday_indicators + weekday_indicators

Dep. Variable:	max_bid	**R-squared:**	7.343e-05
Estimator:	RandomEffects	**R-squared (Between):**	1.398e-07
No. Observations:	15861563	**R-squared (Within):**	5.741e-05
		R-squared (Overall):	-0.0138
		Log-likelihood	-1.321e+08
Cov. Estimator:	Unadjusted		
		F-statistic:	116.47
Entities:	5747	**P-value**	0.0000
Avg Obs:	2760.0	**Distribution:**	F(10,15861552)
Min Obs:	1.0000		
Max Obs:	2.233e+05	**F-statistic (robust):**	119.61
		P-value	0.0000
Time periods:	23	**Distribution:**	F(10,15861552)
Avg Obs:	6.896e+05		
Min Obs:	2.168e+05		
Max Obs:	8.819e+05		

	Parameter	Std. Err.	T-stat	P-value	Lower CI	Upper CI
monday_indicator	397.16	21.301	18.645	0.0000	355.41	438.91
tuesday_indicator	394.92	21.302	18.539	0.0000	353.17	436.68
wednesday_indicator	395.63	21.302	18.573	0.0000	353.88	437.38
thursday_indicator	392.80	21.302	18.440	0.0000	351.05	434.55
friday_indicator	393.18	21.303	18.456	0.0000	351.42	434.93
saturday_indicator	382.22	21.299	17.946	0.0000	340.48	423.97
sunday_indicator	379.45	21.293	17.821	0.0000	337.72	421.18
payday_indicator_week_1	1.4025	1.0403	1.3482	0.1776	-0.6364	3.4414
payday_indicator_week_2	0.6913	1.0545	0.6555	0.5121	-1.3755	2.7581
payday_indicator_week_-1	-3.0261	1.0539	-2.8712	0.0041	-5.0917	-0.9604
payday_indicator_week_-2	-2.8682	1.0507	-2.7297	0.0063	-4.9275	-0.8088

A.6 Random Effect Variable Combination B: total_bids ~ payday_indicators + weekday_indicators

Dep. Variable:	total_bids	**R-squared:**	0.0101
Estimator:	RandomEffects	**R-squared (Between):**	0.0087
No. Observations:	15861563	**R-squared (Within):**	0.0097
		R-squared (Overall):	0.0108
		Log-likelihood	-5.352e+07
Cov. Estimator:	Unadjusted		
		F-statistic:	1.617e+04
Entities:	5747	**P-value**	0.0000
Avg Obs:	2760.0	**Distribution:**	F(10,15861552)
Min Obs:	1.0000		
Max Obs:	2.233e+05	**F-statistic (robust):**	1.583e+04
		P-value	0.0000
Time periods:	23	**Distribution:**	F(10,15861552)
Avg Obs:	6.896e+05		
Min Obs:	2.168e+05		
Max Obs:	8.819e+05		

	Parameter	Std. Err.	T-stat	P-value	Lower CI	Upper CI
monday_indicator	4.1872	0.0422	99.242	0.0000	4.1045	4.2699
tuesday_indicator	4.0454	0.0422	95.833	0.0000	3.9627	4.1281
wednesday_indicator	4.0881	0.0422	96.851	0.0000	4.0054	4.1708
thursday_indicator	4.2330	0.0422	100.28	0.0000	4.1503	4.3158
friday_indicator	4.1002	0.0422	97.056	0.0000	4.0174	4.1830
saturday_indicator	4.2988	0.0421	102.01	0.0000	4.2162	4.3814
sunday_indicator	5.6447	0.0420	134.45	0.0000	5.5624	5.7270
payday_indicator_week_1	0.2921	0.0074	39.726	0.0000	0.2777	0.3065
payday_indicator_week_2	0.1562	0.0075	20.952	0.0000	0.1416	0.1708
payday_indicator_week_-1	0.1196	0.0074	16.054	0.0000	0.1050	0.1342
payday_indicator_week_-2	0.0635	0.0074	8.5544	0.0000	0.0490	0.0781

A.7 Random effect Variable Combination C: max_bid ∼ const + payday_indicators

Dep. Variable:	max_bid	**R-squared:**	1.98e-05
Estimator:	RandomEffects	**R-squared (Between):**	-0.0002
No. Observations:	15861563	**R-squared (Within):**	3.966e-06
		R-squared (Overall):	-0.0139
		Log-likelihood	-1.321e+08
Cov. Estimator:	Unadjusted		
		F-statistic:	78.514
Entities:	5747	**P-value**	0.0000
Avg Obs:	2760.0	**Distribution:**	F(4,15861558)
Min Obs:	1.0000		
Max Obs:	2.233e+05	**F-statistic (robust):**	15.650
		P-value	0.0000
Time periods:	23	**Distribution:**	F(4,15861558)
Avg Obs:	6.896e+05		
Min Obs:	2.168e+05		
Max Obs:	8.819e+05		

	Parameter	**Std. Err.**	**T-stat**	**P-value**	**Lower CI**	**Upper CI**
const	388.61	21.401	18.158	0.0000	346.66	430.55
payday_indicator_week_1	0.9587	1.0401	0.9217	0.3567	-1.0799	2.9974
payday_indicator_week_2	0.3417	1.0544	0.3241	0.7459	-1.7249	2.4084
payday_indicator_week_-1	-3.4452	1.0538	-3.2693	0.0011	-5.5106	-1.3798
payday_indicator_week_-2	-3.3187	1.0506	-3.1589	0.0016	-5.3778	-1.2596

A.8 Random Effect Variable Combination D: total_bids ∼ const + payday_indicators

Dep. Variable:	total_bids	**R-squared:**	0.0006
Estimator:	RandomEffects	**R-squared (Between):**	-0.0009
No. Observations:	15861563	**R-squared (Within):**	0.0002
		R-squared (Overall):	-0.0004
		Log-likelihood	-5.359e+07
Cov. Estimator:	Unadjusted		
		F-statistic:	2433.3
Entities:	5747	**P-value**	0.0000
Avg Obs:	2760.0	**Distribution:**	F(4,15861558)
Min Obs:	1.0000		
Max Obs:	2.233e+05	**F-statistic (robust):**	782.49
		P-value	0.0000
Time periods:	23	**Distribution:**	F(4,15861558)
Avg Obs:	6.896e+05		
Min Obs:	2.168e+05		
Max Obs:	8.819e+05		

	Parameter	Std. Err.	T-stat	P-value	Lower CI	Upper CI
const	4.6186	0.0422	109.37	0.0000	4.5358	4.7014
payday_indicator_week_1	0.3305	0.0074	44.749	0.0000	0.3161	0.3450
payday_indicator_week_2	0.1856	0.0075	24.783	0.0000	0.1709	0.2003
payday_indicator_week_-1	0.1516	0.0075	20.261	0.0000	0.1370	0.1663
payday_indicator_week_-2	0.0945	0.0075	12.672	0.0000	0.0799	0.1092

A.9 Ordinary OLS Variable Combination A: sum of max_bid $\sim$ payday_indicators + weekday_indicators

Dep. Variable:	max_bid	**R-squared:**	0.762
Model:	OLS	**Adj. R-squared:**	0.758
Method:	Least Squares	**F-statistic:**	216.2
		Prob (F-statistic):	3.47e-203
		Log-Likelihood:	-10795.
No. Observations:	688	**AIC:**	2.161e+04
Df Residuals:	677	**BIC:**	2.166e+04
Df Model:	10		
Covariance Type:	nonrobust		

Omnibus:	447.877	**Durbin-Watson:**	0.644
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	11006.397
Skew:	-2.491	**Prob(JB):**	0.00
Kurtosis:	21.950	**Cond. No.**	7.07

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
monday_indicator	4.631e+06	2.6e+05	17.842	0.000	4.12e+06	5.14e+06
tuesday_indicator	4.281e+06	2.6e+05	16.496	0.000	3.77e+06	4.79e+06
wednesday_indicator	4.382e+06	2.6e+05	16.886	0.000	3.87e+06	4.89e+06
thursday_indicator	4.267e+06	2.6e+05	16.441	0.000	3.76e+06	4.78e+06
friday_indicator	4.036e+06	2.6e+05	15.531	0.000	3.53e+06	4.55e+06
saturday_indicator	5.268e+06	2.59e+05	20.328	0.000	4.76e+06	5.78e+06
sunday_indicator	1.235e+07	2.59e+05	47.734	0.000	1.18e+07	1.29e+07
payday_indicator_week_1	9.022e+05	2.48e+05	3.636	0.000	4.15e+05	1.39e+06
payday_indicator_week_2	1.233e+05	2.47e+05	0.499	0.618	-3.62e+05	6.08e+05
payday_indicator_week_-1	8.835e+04	2.48e+05	0.356	0.722	-3.98e+05	5.75e+05
payday_indicator_week_-2	1.382e+05	2.47e+05	0.560	0.576	-3.47e+05	6.23e+05

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

A.10 Ordinary OLS Variable Combination B: sum of total_bids ~ payday_indicators + weekday_indicators

Dep. Variable:	total_bids	**R-squared:**	0.826
Model:	OLS	**Adj. R-squared:**	0.823
Method:	Least Squares	**F-statistic:**	321.1
		Prob (F-statistic):	2.95e-249
		Log-Likelihood:	-8256.4
No. Observations:	688	**AIC:**	1.653e+04
Df Residuals:	677	**BIC:**	1.658e+04
Df Model:	10		
Covariance Type:	nonrobust		

Omnibus:	462.907	**Durbin-Watson:**	0.848
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	14110.176
Skew:	-2.536	**Prob(JB):**	0.00
Kurtosis:	24.598	**Cond. No.**	7.07

	coef	std err	t	P> |t|	[0.025	0.975]
monday_indicator	6.987e+04	6478.539	10.784	0.000	5.71e+04	8.26e+04
tuesday_indicator	6.136e+04	6478.539	9.471	0.000	4.86e+04	7.41e+04
wednesday_indicator	6.456e+04	6478.539	9.965	0.000	5.18e+04	7.73e+04
thursday_indicator	6.647e+04	6478.539	10.261	0.000	5.38e+04	7.92e+04
friday_indicator	5.994e+04	6487.711	9.239	0.000	4.72e+04	7.27e+04
saturday_indicator	9.319e+04	6469.593	14.404	0.000	8.05e+04	1.06e+05
sunday_indicator	3.096e+05	6460.801	47.917	0.000	2.97e+05	3.22e+05
payday_indicator_week_1	2.635e+04	6193.346	4.255	0.000	1.42e+04	3.85e+04
payday_indicator_week_2	6144.6032	6167.608	0.996	0.319	-5965.336	1.83e+04
payday_indicator_week_-1	7426.1537	6188.105	1.200	0.231	-4724.032	1.96e+04
payday_indicator_week_-2	6750.7516	6162.596	1.095	0.274	-5349.347	1.89e+04

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

A.11 Ordinary OLS Variable Combination C: sum of max_bid ~ const + payday_indicators

Dep. Variable:	max_bid	**R-squared:**	0.012
Model:	OLS	**Adj. R-squared:**	0.006
Method:	Least Squares	**F-statistic:**	1.991
		Prob (F-statistic):	0.0942
		Log-Likelihood:	-11285.
No. Observations:	688	**AIC:**	2.258e+04
Df Residuals:	683	**BIC:**	2.260e+04
Df Model:	4		
Covariance Type:	nonrobust		

Omnibus:	263.968	**Durbin-Watson:**	1.787
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	761.772
Skew:	1.954	**Prob(JB):**	3.83e-166
Kurtosis:	6.363	**Cond. No.**	8.88

	coef	**std err**	**t**	**P> |t|**	**[0.025**	**0.975]**
const	5.603e+06	4.31e+05	12.999	0.000	4.76e+06	6.45e+06
payday_indicator_week_1	9.457e+05	5.03e+05	1.881	0.060	-4.17e+04	1.93e+06
payday_indicator_week_2	1.331e+05	5.01e+05	0.266	0.790	-8.5e+05	1.12e+06
payday_indicator_week_-1	1.295e+05	5.02e+05	0.258	0.797	-8.57e+05	1.12e+06
payday_indicator_week_-2	1.382e+05	5e+05	0.276	0.783	-8.44e+05	1.12e+06

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

A.12 Ordinary OLS Variable Combination D: sum of total_bids ~ const + payday_indicators

Dep. Variable:	total_bids	**R-squared:**	0.009
Model:	OLS	**Adj. R-squared:**	0.003
Method:	Least Squares	**F-statistic:**	1.600
		Prob (F-statistic):	0.172
		Log-Likelihood:	-8854.4
No. Observations:	688	**AIC:**	1.772e+04
Df Residuals:	683	**BIC:**	1.774e+04
Df Model:	4		
Covariance Type:	nonrobust		

Omnibus:	292.546	**Durbin-Watson:**	1.936
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	907.164
Skew:	2.162	**Prob(JB):**	1.03e-197
Kurtosis:	6.599	**Cond. No.**	8.88

	coef	std err	t	P> |t|	[0.025	0.975]
const	1.036e+05	1.26e+04	8.216	0.000	7.88e+04	1.28e+05
payday_indicator_week_1	2.768e+04	1.47e+04	1.882	0.060	-1196.561	5.66e+04
payday_indicator_week_2	6417.2607	1.46e+04	0.438	0.661	-2.23e+04	3.52e+04
payday_indicator_week_-1	8680.2344	1.47e+04	0.591	0.555	-2.02e+04	3.75e+04
payday_indicator_week_-2	6750.7516	1.46e+04	0.461	0.645	-2.2e+04	3.55e+04

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

B Appendix: Robustness Check

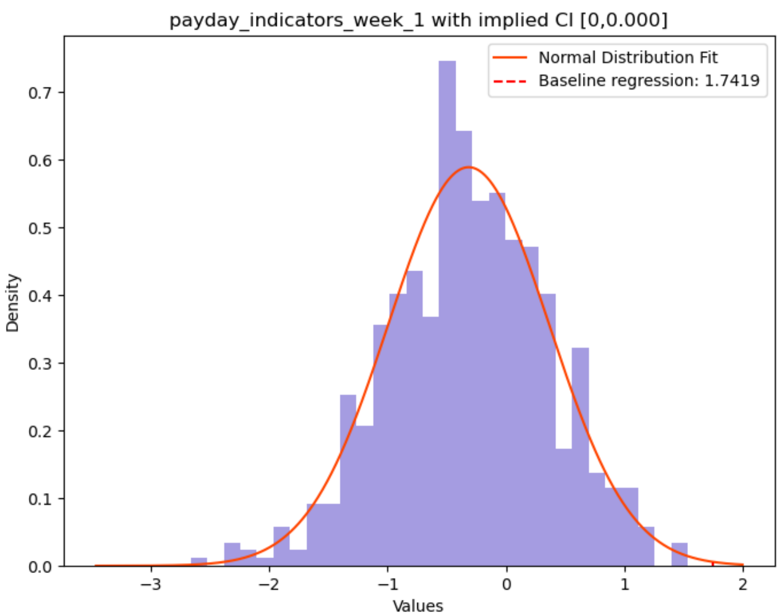

Figure 2: Permutation Test Histogram with Gaussian Fit for payday_indicator_week_1

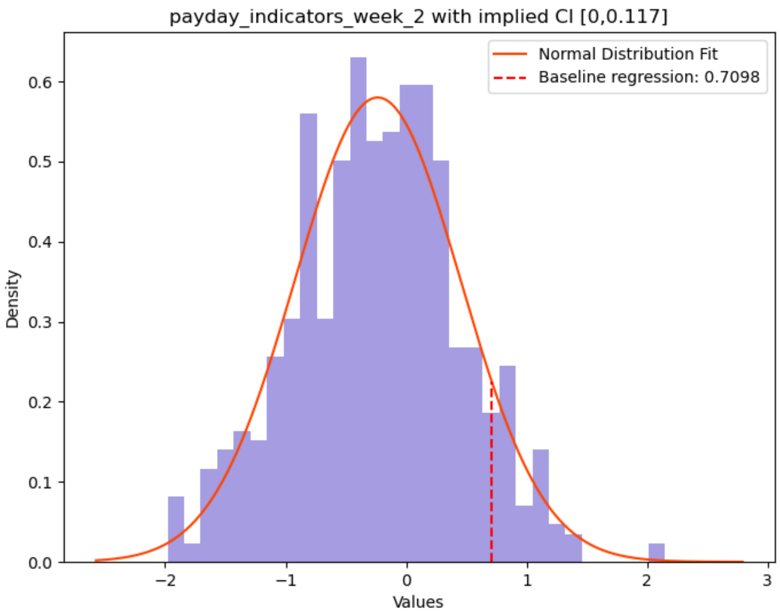

Figure 3: Permutation Test Histogram with Gaussian Fit for payday_indicator_week_2

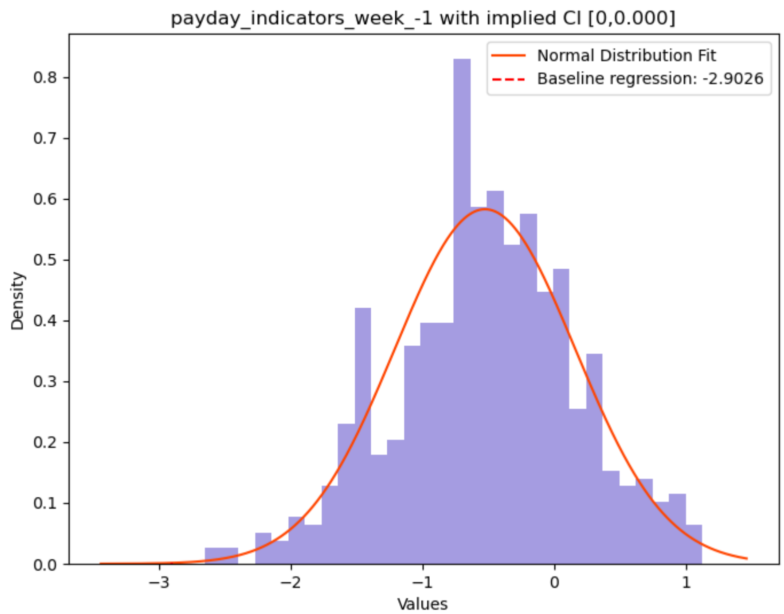

Figure 4: Permutation Test Histogram with Gaussian Fit for payday_indicator_week_-1

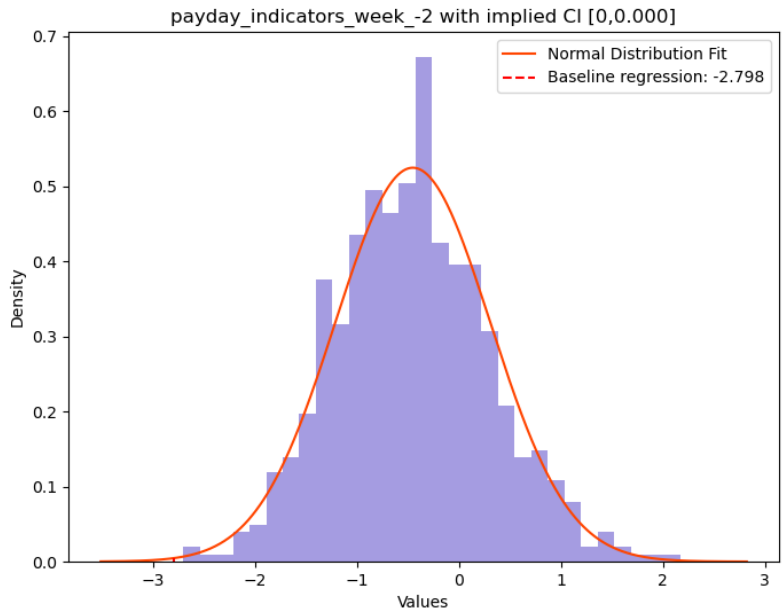

Figure 5: Permutation Test Histogram with Gaussian Fit for payday_indicator_week_-2

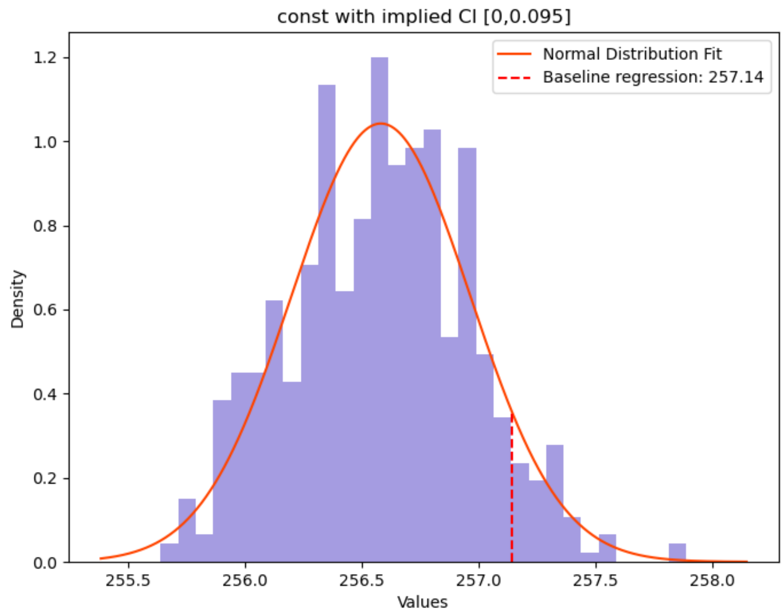

Figure 6: Permutation Test Histogram with Gaussian Fit for const

C Appendix: Results from Hausman Test

Table 6: Hausman Test Results for Model Selection

Model	**Variables**	**Hausman Test Statistic**	**P-value**
max_bid	payday_indicators + weekday_indicators	346.9101	1.80e-68
total_bids	payday_indicators + weekday_indicators	-2297.0580	1.0
max_bid	const + payday_indicators	61.9191	1.15e-12
total_bids	const + payday_indicators	58.9288	4.87e-12

Table 7: Model Selection Based on Hausman Test

Model	**Selection Conclusion**
max_bid (weekday included)	Fixed effects model is preferred
total_bids (weekday included)	Random effects model may be appropriate
max_bid (weekday excluded)	Fixed effects model is preferred
total_bids (weekday excluded)	Fixed effects model is preferred

D Appendix: Data Summary

	StartPrice	BuyItNowPrice	ReservePrice
mean	268.782	743.657	275.427
std	15083.546	218119.708	15218.258
min	1.000	1.000	1.000
25%	39.000	70.000	39.000
50%	78.000	150.000	79.000
75%	199.000	351.000	199.000
max	99999999.000	555555555.000	99999999.000

	total_bids	max_bid
mean	1.444	299.862
std	5.868	34865.457
min	0.000	1.000
25%	0.000	45.000
50%	0.000	89.000
75%	0.000	200.000
max	419.000	242551100.000