Structure Cost Efficiency and Financial Accessibility in Ireland's Retail Payment System Report

BUSINESS ANALYTICS

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INTRODUCTION

In a context of euro area payment integration, financial digitalisation, and a worldwide increase of instant payments, payment systems are becoming a necessary infrastructure for household consumption, corporate settlement, cross-border capital flows, and financial inclusion, with particular importance for Ireland (e.g. here the Card, Credit Transfer, E-money, and online channels are having ever more importance). Though, there are also structural issues. Those issues are segmentation, asymmetries in cross-border costs, and unevenness of financial services accessibility.

In this paper, the Irish payment system is studied within the "structure–efficiency–adoption" framework. First, structural characteristics are analysed, across payment instruments, channels, transaction value, and digitalisation. Then, IE–IT SEPA cross-border payments are analysed to understand the impact of payment schemes, transaction size, transaction purpose, and directionality on processing time, costs, and fee rates. Finally, it is examined what is the role of financial accessibility in the adoption of instant payments.

The contributions of this paper are threefold. First, there are functional stratifications in payment instruments and channels. Second, payment schemes impact efficiency and costs, with a corresponding speed–cost trade-off and scale effects. Third, payment adoption is affected not only by payment mechanisms but also by regional differences and financial services accessibility. The conclusions of this paper are that the Irish payment system will need to be improved not only by speedier payments, but also by faster and more cost-effective solutions and more equitable and accessible ones.

The rest of this paper is organised as follows: first, structural characteristics are examined in Section 1; second, cross-border payment efficiency and costs are analysed in Section 2; third, financial accessibility and instant payment adoption are discussed in Section 3; and lastly, policy implications are presented.



1. Structural Analysis of the Irish Retail Payment System

1.1 Characteristics of Payment Instrument Structure

1.1.1 Data Sources and Analytical Dimensions

In a context of euro area payment integration, financial digitalisation, and a worldwide increase of instant payments, payment systems are becoming a necessary infrastructure for household consumption, corporate settlement, cross-border capital flows, and financial inclusion, with particular importance for Ireland (e.g. here the Card, Credit Transfer, E-money, and online channels are having ever more importance). Though, there are also structural issues. Those issues are segmentation, asymmetries in cross-border costs, and unevenness of financial services accessibility.

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The rest of this paper is organised as follows: first, structural characteristics are examined in Section 2; second, cross-border payment efficiency and costs are analysed in Section 3; third, financial accessibility and instant payment adoption are discussed in Section 4; and lastly, policy implications are presented.

1.1.2 Descriptive Analysis of Payment Instruments

Structuring choice: data and techniques used for structural analysis of payment system. We analyse the structure of the Irish retail payment system using transaction-level data and a new structural framework based on four dimensions – payment instruments, transaction structure, digitalisation and payment channels and a tripartite approach to the structural framework. The use of transaction-level data, as opposed to the usual macro-level data, allows us to analyse the structure of

the payment system at a more detailed level. Based on the transaction data, we create indicators that measure the structure of the payment system and we use a structural analysis to assess the evolution of the system. The dimensions of the structural framework capture the internal logic of the payment system. We focus on four dimensions: the instruments used in payments, the structure of the payments, digitalisation and, when payments occur. These are analytically independent but interact with one another in practice. Payment instruments are classified in Card, Credit Transfer, Direct Debit, E-money and split between high frequency, low value transactions and low frequency, high value transactions. Digitalisation is a continuum that represents the degree of electronicisation and automation of payment, including the degree of instant-ness of the payments. Payment channels include POS terminals, mobile applications, web portals, bank branches, and contactless transactions. The dimensions are mapped to the transaction data. Transaction data are aggregated to macro-level indicators: transaction and value shares. The dimensions and the indicators are used for a subsequent (descriptive and structural) analysis.

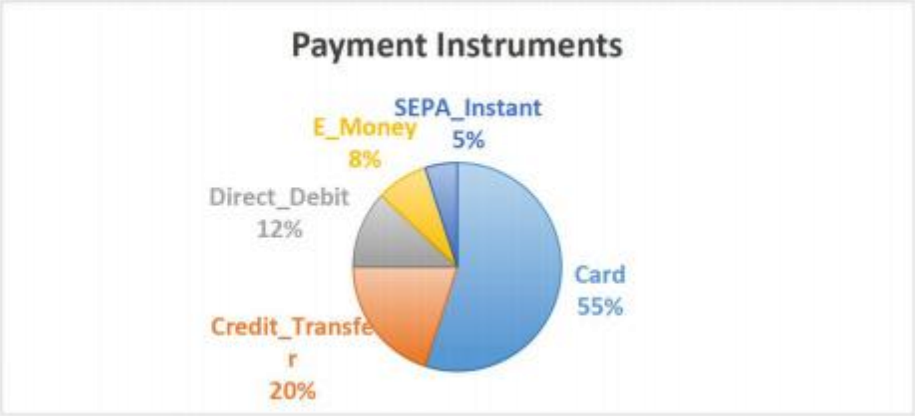


Figure 1. 1 Payment Instruments

As illustrated in Figure 1. 1, card payments constitute 55% of the total use of payment tools and is much higher than other payment tools. This indicates that under the scenario of retail payments, consumers tend to choose a more convenient payment tool with a short response time (Humphrey et al., 2001). The result shows that card payments, as a widely accepted and low cost payment tool, have become a core payment tool, especially in the scenarios of POS terminals and contactless payments, where its advantage is even more pronounced.

Credit transfers make up 20%. Although the transaction frequency is relatively small compared with that of card payments, it is of great advantage in single transaction amount when total payment amount is taken into consideration. This shows that credit transfers are mainly used for paying large amounts in the form of large-value payments and fund settlements, its role in the payment system is partly reflected in high-value "transfers" rather than innumerable transactions.

Moreover, direct debits account for 12% and are more stable with an intermediate structure. This payment tool is mainly used in a recurring payment scenario, such as utility bills and subscription fees. Its stable role indicates that there is a "recurring payment" mechanism in the payment system, and it promotes the stability and predictability of the system to some extent.

Looking further, E-money, SEPA Instant account for 8% and 5% respectively. While their total size is relatively small, their growth trends are striking. This result shows that the digital payment tools are increasingly permeating into the retail payment system (BIS, 2021; World Bank, 2021). Especially for mobile and instant payments, the extent of their development potential is large, which suggests that the payment system is gradually tending towards digital and real-time.

It is worth pointing out that the above structural characteristics are all on the basis of statistical results of transaction data of the past few years (especially the past decade) can accurately reflect the current existence of the payment system. Compared with the pre-data, the data in the past decade is more representative, can better reflect the structural changes in the payment system of the digital transformation.

In short, the results from the descriptive statistics show the hierarchical structural characteristics of the payment system in the dual dimensions of "frequency, amount", which means that Card payments are the main tool for high-frequency transactions, Credit Transfer is the main tool for high-value transactions, while Direct Debit and new digital payment tools play a supplementary role in the middle layer, thus revealing the "high frequency, low amount - low frequency, high amount" structural differentiation of the payment system. This not only reflects the functional division of the different payment tools, but also provides a solid basis for subsequent structural decomposition analysis.

1.1.3 Payment Structure Decomposition Analysis

Follow up the decomposition of payment instruments, this paper decomposes the payment system from the perspective of transaction structure, so as to more clearly identify the functional positioning of various payment instruments in the economic system and the interrelationships between them. This paper, compared with single-dimensional analysis, comprehensively describes the payment structure from the two dimensions of "transaction frequency" and "transaction amount", thus more fully revealing its inherent hierarchical features.

Firstly, from the perspective of transaction frequency, bank card payment is the "high-frequency core layer" of the payment system. Because it is widely used in daily consumption scenarios, it dominates the payment system in terms of transaction volume. This feature points out that receiving payment itself is dominated by small-amount, high-frequency transactions.

Secondly, from the perspective of transaction amount, credit transfer is also the "high-value core layer" of the payment system. Even though it has a low transaction frequency, the overall transaction amount contributed by each transaction is large and it is therefore dominant in the payment system on the basis of transaction amount. This feature indicates that credit transfer mainly guarantees the functions of cross-enterprise settlement and large-scale flow of funds, thus playing a core role in "value transfer" in the payment system.

Meanwhile, Direct Debit is a relatively stable intermediate structure, which is at the same level of transaction frequency and transaction amount. It is mainly used

for recurring payment scenarios, such as the payment of bills and subscript fees, so Direct Debit plays a role as the "stabilizer" in the payment system.

According to the analysis above, the Irish retail payment system can be classified into three typical structures from the perspective of two dimensional "frequency-amount" structure:1, high-frequency and low-amount payment structure mainly composed of Cards and E-money for daily consumption; 2, low-frequency and high-amount payment structure mainly composed of Credit Transfer for large-scale fund flow and settlement; 3, middle-frequency and middle-amount payment structure mainly composed of Direct Debit for recurring payment mechanisms. The two dimensional structure shows that payment instruments are not just substitutes but also complement each other in different dimensions: high-frequency payment instruments focus on the efficiency of transaction and high-amount payment instruments focus on the function of fund transfer and clearing. This two dimensional structure further demonstrates the balance mechanism of value and efficiency in the payment system.2, Analyzing the transaction relationship (such as P2P, B2B), different payment instruments show differentiated distribution in different transaction scenarios. This eliminates the role of payment instruments. This phenomenon further demonstrates the multi-layer structure of the payment system.

Thus, the Irish retail payment system is not a monopoly of a payment instrument but is instead a hierarchy of different payment instruments, with each instrument complementary to the others. This multi-level structure contributes to operational efficiency of the payment system which is an essential support for the stability and flexibility of the system.

However, structure alone does not measure the degree of concentration in the system. In this article we adopt the approach of Schmiedel et al. (2012) and develop the Herfindahl Index (HHI) to measure the concentration in the spread of the payment instruments. The HHI is the sum of the squares of the shares of each payment instrument. The calculation formula is:

$$HHI=\sum S_i^2$$

Here, Si denotes the market share of each payment instrument.

According to sample data, the HHI value of the Irish retail payment system is around 0.3658, which is much higher than the high concentration threshold of 0.25. The above result shows that the payment system is highly structured concentrated (Schmiedel et al., 2012).

The above conclusion also shows that despite the variety of payment instruments, the payment system still depends on card payments in practice. A disruption to the card payment network could seriously affect the whole payment system, thus creating systemic risks.

Meanwhile, although the market share of credit transfers and direct debits is lower than that of card payments, they are still substantial in terms of the volume and certain scenarios of payment, showing that the payment system has centralized structure, but still exhibits a degree of functional stratification and instrument variety.

In addition, although emerging payment instruments (e-money and SEPA Instant) have small market shares, the existence of these payment instruments shows the continued trend towards a digital and real-time payment system. The above structure is "high concentration + incremental innovation", which allows the payment system to strike a balance between efficiency and stability.

In sum, the core structure of the Irish retail payment system is "core centralization + multi-layered supplementation", which shows card payments are the core pillar, other payment instruments perform supplementation roles under various scenarios. This structure promotes system efficiency, but also introduces a certain degree of structural risks, which provides an important basis for subsequent analyses of the resilience and efficiency of the payment system.

1.1.4 Digital Dimensional Analysis

This paper goes further by introducing a digital dimension to the analysis of payment instrument and transaction structure, and therefore, characterizes the level and structure of digital development in the payment system, through an analysis of the technological characteristics of the payment system. From a digital perspective, the retail payment system in Ireland shows a clear trend towards electronic development (BIS, 2019). The trend is reflected in both payment instruments and payment channels.

Firstly, at the payment instrument level, Card, E-money and Credit Transfer are all conventional electronic payment methods. The broad application of these in transactions demonstrates that the payment system in Ireland has essentially completed its digital transformation from cash-to-cash payments to digital payments. Specifically, the widespread application of contactless Card payments has greatly improved payment efficiency, and further enhanced the dominance of digital payments.

Secondly, at the payment channel level, the proportion of online channels Mobile Apps and Web Portals gradually increasing shows that payment behavior is migrating from the traditional offline scenario towards an online scenario (ECB, 2020; OECD, 2021). This indicates not only the influence of technological innovation, but also a change in consumer behavior.

Furthermore, there is also an aspect of digitalization in the degree of automation of payment processing mechanisms, such as the use of instant payment.



Figure1.2 Instant payments

As depicted in Figure 1.2, instant payments comprise around 13% of total payments, whereas non-instant payments account for about 87%. This suggests that despite the fact that the Irish payment system has achieved a high level of digitization in terms of payment instruments and channels, the "real-time" level of payment processing mechanisms still remains relatively weak. This phenomenon illustrates that the payment system's digitization does not evolve in a single dimension (BIS, 2021), but exhibits the characteristics of "electronic" and "real-time" phased development. That is, the various payment instruments' widespread use of electronic payment does not imply that the payment processing mechanisms have achieved "real-time" level, which suggests that the technological structure of the payment system is not uniform development.

From the perspective of the payment processing mechanisms, this low proportion of instant payments can be affected by many factors, such as inadequate coverage of the system infrastructure, limitations of interbank clearing mechanisms and the lack of instant payment demand from users. Thus, the current payment system can be viewed as a development stage of "highly electronic but moderately real-time".

Meanwhile, it is worth mentioning that despite the existence of digital payments, branch channels still exist. This suggests that the payment system undergoing digitization still introduces the needs of different groups. This reflects the characteristics of a certain degree of financial inclusion.

In general, the Irish retail payment system is typified by a structure of "highly electronic but not fully real-time processing". Such a structure is, while making payment more efficient and convenient, still allows for a certain degree of system stability and risk control flexibility. This characterizes the aforementioned payment system's phased development.

1.1.5 Payment Channel Structure Analysis

Afterconsidering the payment conditions from the aspects of payment instruments, transaction amount, and digitalization from the preceding section, we learn that payment behaviors not only exist in "payment method choice", "value distribution", but also depend on specific implementation routes and technological backgrounds. Thus, it is to be further introduced the dimension of payment channels to systematically outline the specific scenarios of payment behavior and the implementation routes.

From a structural point-of-view, the Irish retail payment system has a relatively prominent characteristic of "multi-channel coexistence" (ECB, 2023), as different channels have significant differences in transaction volume and usage contexts. To further illustrate the distribution of each channel in overall transactions, this paper conducts a statistical analysis on different payment channels, and the results are displayed below.

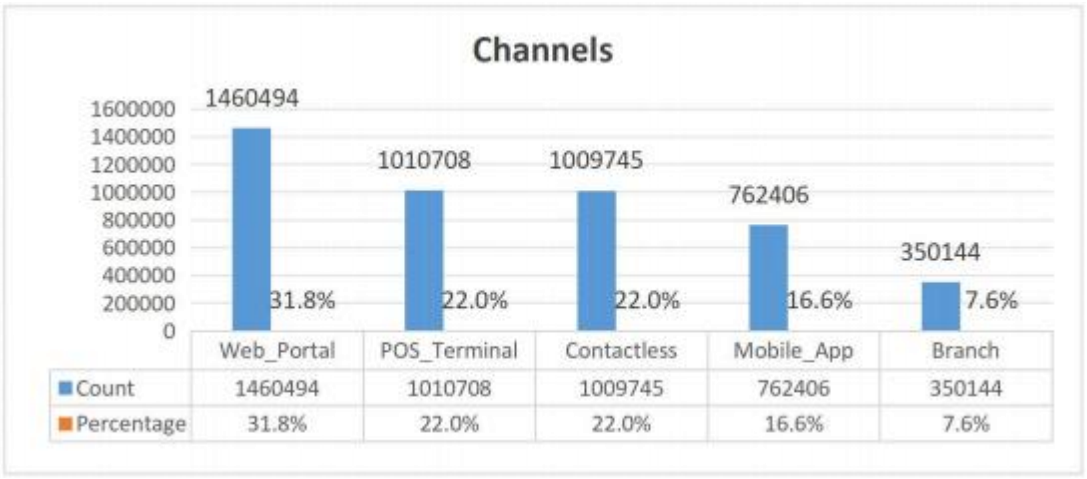


Figure 1.3 Channels

As shown in Figure 1.3, the proportion of Web portal channel is the largest, which is 31.8%, which indicates that online payment is one of the main implementation forms in the current payment system. This can show that in the era of e-commerce and digital services, consumer's pay channel has been changing towards online channels, and thus promote the digitalization and platformization of the whole payment system (OECD, 2021).

Secondly, POS Terminal and Contactless payment account for 22.0% each, which shows that offline payment still has a crucial position, especially for the real economy, such as retail, catering, and services. Since the POS Terminal is the main channel form of traditional offline payment, it still carries a large amount of transaction functions, and thus, offline consumption scenario has become the core foundation of the payment system, and so far, is difficult to be replaced in the short term, which is also the case of digitalization.

Meanwhile, contactless payment is the channel of technology. It has a lot advantages in small-amount and high-frequency transaction, through shortening the transaction time and the operation steps, it improves the payment efficiency well. It is well designed for the high-frequency consumption scenario, such as public transportation and convenient services. This reflects that the introduction of technology has altered the payment habit of the consumers, and paid more attention to the direction of more "seamless" payment.

Furthermore, the Mobile App channel only accounts for 16.6%, lower than that of Web Portal and offline payment channels, the development trend of Mobile App channel is very significant, indicating that mobile payment has been moving into more payment scenarios. Pay with mobile devices has been the trend of consumers, and this change not only reduces transaction cost, but also improves the convenience and timeliness to a great extent. From the point of view of behavioral economics, the change of channel is a dynamic tradeoff between convenience, security and cost of users (Rochet and Tirole,2003).

Moreover, the Branch (bank counter) channel accounts for only 7.6%, indicating that the importance of offline counter payments in the overall payment system has been greatly weakened. But this channel still exists to some extent, and the existence of the channel itself is significant. On the one hand, this channel pays the necessary support of payment for the group with relatively weak digital payment ability; on the other hand, the Branch channel still plays a supplementary role in the complex transaction and large value payment scenario. Therefore, from the perspective of the system, Branch channel cannot be abstracted as "interaction"

and the existence of Branch channel is a compromise of the efficiency and financial inclusion of the payment system.

In summary, the channel structure of Ireland's retail payment system is not the simple "old with the new," but the evolutionary trajectory of "multi-channel synergy and coexistence," digital channels such as Web Portal and Mobile Payment are gradually becoming the dominant in the overall payment and offline channels such as POS and contactless payment still play a role, and Branch channels are a supplement for traditional backup. This "online dominance + offline supplementation + traditional backup" structure not only improves the flexibility of the payment system, but also has a certain impact on the resilience and sustainable development ability of the payment system.

2. Analysis of Cost Efficiency in Cross-Border Payments

Expanding the structural analysis of payment instruments, channels, and characteristics-channels based on those characteristics, this paper reports that the Irish retail payment system is increasingly digitalised, as electronic payments increase relative to cash and ATM channels. Structural analysis does not, however, indicate whether and to what extent efficiency and cost differences come from heterogeneity in payment methods and transaction characteristics. This is particularly true for cross-border payments, where payment schemes, transaction size, and purpose could affect processing time and cost. Relying on micro-level cross-border data, this paper performs descriptive and regression analysis of cross-border payment efficiency and cost, thus moving beyond structural description to mechanism identification.

2.1 Statistical Analysis

2.1.1 Variable Description and Explanation of Indicators

This section primarily utilizes the transaction amount (Amount), processing time (Initiation-to-Credit Hours), and total charges (Total Charges) as continuous variables to indicate transaction size, payment efficiency, and absolute cost, respectively. At the same time, the payment scheme (Payment Scheme), the taking of charge (Charge Bearer), the purpose code (Purpose Code), and the direction (Direction) have been employed as categorical variables to identify efficiency and cost differences amongst payment mechanisms, charge bearer arrangements, payment contexts, and bilateral movements.

Previously, studies have highlighted the payment preferences, differences in payment instruments, and transaction heterogeneity with micro-level payment-transaction data. All these three factors have been 'central' to payment research at this stage of fulfilment. Transaction size is also a relevant covariate affecting payment behaviour (Meyer and Teppa 2024; Lippi and Moracci 2024).

The categorical variables are: payment scheme, which has 3 categories SEPA_CT, SEPA_DD, and SEPA_Inst, that allows to distinguish between differences in speed of settlement and cost structure between payment mechanisms; charge bearer, which has SHA, OUR, and BEN, and allows to investigate whether different cost sharing mechanisms lead to different cost performance; and direction, that is built from origin_country and destination_country in order to differentiate IE→IT and IT→IE. Cross-border payment systems and differences in bilateral payment flows themselves have clear empirical research relevance (Mariani et al., 2024).

In the descriptive statistics, this study reports variables distributional characteristics using mainly Mean, Median, Std. Dev., Min, Q1, Q3, and Max

values. In particular, since payment transaction data have is usually accompanied with a great deal of heterogeneity and long tail distribution, it is deemed more robust to report simultaneously the mean, the median, as well as the quantiles (Lippi and Moracci, 2024; Meyer and Teppa, 2024).

2.1.2 Construction of Key Variables

To measure the relative cost burden of cross-border payments, this study constructs a new variable,

charge_rate, defined as:

$$charge_{rate} = \frac{total_{charges}}{amount}$$

Unlike total_charges, which represents the magnitude of the fees, charge_rate is introduced to represent the cost burden paid per unit of transaction amount. The rationale behind this is that if we consider only total charges, we will lose the opportunity to discover instances where a small absolute amount of fees is extracted as a heavy cost burden for a small transaction. Therefore, total_charges

and charge_rate are indicated as costs for the following analysis (Lippi and Moracci, 2024).

2.1.3 Descriptive Statistics

The D08 dataset contains a total of 749,706 cross-border SEPA transactions.

In terms of transaction direction, IE → IT accounts for 374,763 transactions, representing 49.99%, while IT→IE accounts for 374,943 transactions, representing 50.01%, indicating that bilateral flows are essentially balanced.

In terms of payment scheme, SEPA_CT accounts for 75.07% and is the dominant payment method, while SEPA_Inst and SEPA_DD account for 13.01% and 11.92%, respectively.

In terms of charge bearer, SHA accounts for 85.01%, which is significantly higher than OUR and BEN.

In terms of transaction purpose, the four categories GDDS, SCVE, OTHR, and UTIL together account for approximately three-quarters of the total sample, suggesting that the distribution of payment purposes is highly concentrated.

2.1.4 Analysis of Descriptive Statistics

The descriptive statistics for amount, initiation_to_credit_hours, total_charges, and charge_rate are reported in Table 2.1 at the end of this paper.

The analysis results give a mean of amount of €164.3043, a median of €41.3300 and a maximum of €100,000. This indicates that transaction amounts are heavily to the right, with a few high-value transactions pulling the mean price up substantially.

The mean of initiation_to_credit_hours is 21.7451 hours while the median is 23.0900 hours so the overall distribution is pretty tight with most transaction processing times clustered between 15.84 hours and 29.16 hours.

The average value for total_charges is €0.2547 and the median is €0.2100 so that the fees are clustered in a small interval, although some outliers with very high fees are present.

The mean of charge_rate is 0.0147, the medians is 0.0054, and the max is 3.3333, indicating that the charge rate is also evidently right-skewed as some of the low-priced transactions have disproportionately high percentage cost.

In general, the D08 data set shows that transaction amount and charge rate are strongly right-skewed, whereas processing time and total charges are more concentrated. This suggests that further analysis should not only consider absolute fees but also should consider the relative cost burden.

2.1.5 Analysis of Descriptive Statistics

(1) Grouped by Payment Scheme

Table 2.2 presents the descriptive statistics for each scheme. It is obvious that processing time and cost differs by scheme.

As for them, the SEPA_Inst has an average processing time of only 0.0207 hours, which is nearly 23.9998 hours and 31.2514 hours for the SEPA_CT and SEPA_DD, on the other hand, the average total charges and average charge rate of 0.5157 and 0.0306, respectively, is much larger than those of the other two schemes.

By contrast, the median transaction amount from the three schemes is almost the same. This means that the efficiency and cost disparity between the payment schemes is largely driven by the payment mechanism, again with an apparent trade -off between speed and cost for SEPA_Inst, which conforms with the prevailing results in the instant payment literature (Khiaonarong and Humphrey, 2022; Iglesias-Rodríguez, 2025).

(2) Grouped by Charge Bearer

Descriptive statistics by charge_bearer are in Table 2.3. The differences in time to process, total charges, and charge rate among the different charge-bearing arrangements are very small.

The three charge bearer categories all have mean processing times of approximately 21.7 hours, mean total charges of approximately 0.255, and median

charge rates of approximately 0.0147-0.0148. This suggests that fee sharing is not a significant factor in explaining differences in cross-border payment efficiency and cost.

(3) Grouped by Purpose Code

The descriptive statistics by purpose_code are displayed in Table 2.4. There are major differences in transaction amount and cost structure for different purpose codes and minor differences in processing time.

The COMM, SERV, SUPP and TRAD have the highest avg transaction amount(top 1/4, which is all above 900), thus have the highest total charge, but their rate is only about 0.003; while BONU, CHAR, GIFT and SALA have only avg transaction about 50, which have lower total charge but much higher rate around 0.023-0.024.

This implies that high-value transactions have high absolute but low relative fees, and the other way round for low-value transactions. Average processing times for different purposes are indistinguishable in the range 21.6−21.8 hours. This is in line with research on payment behaviour that underlines heterogeneity of transaction contexts (Meyer and Teppa,2024; Rysman et al., 2025).

(4) Grouped by Direction

The descriptive statistics by direction are presented in Table 2.5. Almost no asymmetry is seen in processing time, in contrast to there being asymmetry in cost.

The average processing time IE → IT, 21.7340, is rather closer to the average processing time IT→IE, 21.7561, than could be expected because the difference is very small. But both the average total charges IT → IE, 0.2556, and the average charge rate IT → IE, 0.0163, are higher than the average total charges IE → IT, 0.2539, and the average charge rate IE→IT, 0.0131.

This indicates that the transaction direction has a small effect on processing time, but has an impact on relative cost burden. Cross-border payment systems and bilateral variation in transaction flows per se are interesting subjects to provide empirical analysis (Mariani et al., 2024).

2.2Difference Testing

2.2.1 Methodology and Test Results

Initially, this paper conducts difference testing between groups to conduct a preliminary comparison of mean differences. After testing differences, this paper conducts regression analysis. Meyer and Teppa (2024) and Rysman et al. (2025) argue that difference testing is useful because it indicates whether differences across groups are due to random drift or involve underlying structural differences.

In line with the research objectives, this paper primarily examines:

- the impact of payment scheme on processing time, total charges, and charge rate;
- the impact of charge bearer on total charges and charge rate;
- the impact of purpose code on transaction amount, processing time, total charges, and charge rate;
- and the impact of transaction direction (IE→IT vs IT→IE) on processing time, total charges, and charge rate (Khiaonarong and Humphrey, 2022; Drakopoulos et al., 2024).

Methodologically, independent sample ttest is used for variables with two groups; One way ANOVA is used for categorical variables with three or more groups and assumes equal means (null hypothesis is that all means are equal, rejection of the null hypothesis indicates that at least one mean differs significantly from the others). Pairwise ttests follow the overall significance test to specify the source of differences.

Regarding statistical inference, the F-statistic is a measure of the magnitude of between-group variation relative to within-group measures, and the p-values are the probability of the observed test statistic (or more extreme) under the null hypothesis. In this article we use $p < 0.05$ as the major indicator of statistical significance. In addition, when $F > F$ crit, group differences are also significant. Results are shown in Appendix Table A1.

2.2.2 Interpretation of Results

The difference test shows that payment scheme is the main determinant of the difference in cross-border payment efficiency, and it is transaction size, purpose and direction that primarily influence the cost. The detailed results are shown in the Table 2.6.

First, the processing time model shows that the coefficient of scheme_DD is significantly positive and that of scheme_Inst is significantly negative. Compared with the baseline category (SEPA_CT), SEPA_DD is associated with an increased settlement time whereas SEPA_Inst significantly reduces it. This is consistent with the fact that payment scheme is the major reason for the efficiency of cross-border payments. By contrast, the coefficients of ln(amount) and direction are not statistically significant, suggesting that settlement time is not systematically affected by the magnitude or direction of the transaction. This confirms that it is mainly the payment scheme that determines settlement time efficiency (Khiaonarong and Humphrey, 2022; Ragazzo and Caminha, 2025).

Second, in the total charges model ln(amount) is coefficient is significantly positive, suggesting that total fees are higher for bigger transactions. Concerning payment schemes scheme_Inst is significant positive, whereas scheme_DD is non-significant, implying that instant payments increase the total charges significantly, whereas no stable cost difference is remaining between a SEPA_DD and a SEPA_DT. At the same time direction is significantly positive, implying that the direction of the payments IT→IE has a higher cost than the opposite direction IE→IT. In addition, all categories of purpose_group are significant positive, implying that income-related, commercial and transfer/charity payments, besides "bill/other", have higher fee levels, where income-related payments show the biggest effect (Iglesias-Rodríguez, 2025; Ragazzo and Caminha, 2025).

Third, in the charge rate model, the coefficient for ln(amount) is significantly negative, suggesting that larger amounts have lower unit cost rates, implying a strong scale effect. As in the total charges model, scheme_Inst is significantly positive and scheme_DD not, suggesting that instant payments are still more

expensive, in absolute and relative terms. Direction remains significantly positive, implying higher charge rates in IT→IE transactions. Similarly, all purpose_group variables remain significantly positive, implying that purpose explains relative cost, with highest rates associated with income-related payments, followed by commercial transactions and then transfer/charity payments (Iglesias-Rodríguez, 2025; Ragazzo and Caminha, 2025).

Taken together, the results from the three models imply that payment scheme is associated with processing efficiency and has a larger effect on cost, while transaction size, purpose and direction mainly affect cost dimensions. In particular, SEPA_Inst decreases processing time while increasing the total charges and charge rates, suggesting that there is a clear speed–cost trade-off in cross-border payments. Additionally, the negative coefficient of transaction size in the charge rate model, meaning that, although larger transactions have higher total charges, they also have lower charge rates, which confirms there are economies of scale (Khiaonarong and Humphrey, 2022; Iglesias-Rodríguez, 2025).

2.2.3 Summary and Research Hypotheses

According to the above difference test results, we can see that the variables of the different effects on cross-border payment efficiency and cost, respectively (Meyer and Teppa, 2024; Rysman et al., 2025).

Specifically, payment scheme is the key source of variations in processing time, total charge and charge rate since it significantly impacts these variables. In contrast, charge bearer does not significantly impact cost indicators, and thus, it is not considered a core explanatory variable for the following regression models. Furthermore, purpose code impacts only transaction size and cost, but not processing time; direction does not impact processing time, but significantly impacts cost measures.

Time and cost efficiency for cross-border payments. Our results imply that payment scheme dominates time efficiency for cross-border payments, whereas cost efficiency depends on transaction size, payment purpose and transaction direction.

Based on these results, the study formulates two research hypotheses for subsequent regression analysis:

H1: Different payment schemes significantly affect processing time and cost performance in cross-border payments.

H2: Transaction size, payment purpose, and transaction direction significantly affect cost performance in cross-border payments.

Therefore, the difference testing not only verifies the preliminary relationships between variables and indicators of efficiency, but also determines the basis for the choice of variables in regression analysis. The processing time model uses payment scheme, and direction is added as a control variable; the total charges and charge rate models use scheme, ln(amount), purpose_group, and direction to determine the net effects (Lippi and Moracci, 2024; Meyer and Teppa, 2024; Rysman et al., 2025).

2.3 Regression Analysis

2.3.1 Model Specification and Variable Definition

The objectives of this study comprise to analyze how payment scheme, transaction size, payment purpose and transaction direction affect the efficiency and cost performance of cross-border payments. Accordingly, multiple linear regression models are developed to reinvestigate the systematic influence of these four factors on processing time, total charges and unit cost (Meyer and Teppa, 2024; Rysman et al., 2025).

Given that processing time, total charges, and charge rate exhibit clear skewed distributions, and that cost-related variables may include very small or zero values, the baseline models adopt logarithmic transformations of the dependent variables, specifically:

- ln(initiation_to_credit_hours)
- ln(total_charges + 1)
- ln(charge_rate + 0.0001)

These transformations help mitigate the influence of extreme values and improve the stability of estimation results. Detailed variable definitions are provided in Table 2.7.

The use of log transformation serves to reduce skewness and outlier effects, while also allowing regression coefficients to be interpreted as relative changes (Meyer and Teppa, 2024; Rysman et al., 2025).

2.3.2 Model Specification

The three baseline models are accordingly defined by the variables above. The empirical approach, and our use of micro-level payment data to evaluate the impact of payment methods, transaction size, and transaction type is aligned with recent research in payments (Meyer and Teppa, 2024; Rysman et al., 2025).

Moreover, existing research identifies transaction size as a key covariate in explaining payment behaviour and outcomes, which justifies its inclusion in the model (Lippi and Moracci, 2024).

Model 1: Processing Time Model

$$\ln\left(\text{initiation}_{\text{to}_{\text{credit}_{\text{hours}}}}\right) = \alpha + \beta_1 * \text{scheme}_{\text{DD}} + \beta_2 * \text{scheme}_{\text{Inst}} + \beta_3 * \ln(\text{amount}) + \beta_4 * \text{direction} + \varepsilon$$

The model is to estimate the impact of payment scheme on cross-border payment efficiency. The inclusion of scheme as the main explanatory variable is based on the fact that different payment schemes offer different settlement mechanisms and processing speeds, especially given that instant payments generally have higher speeds (Khiaonarong and Humphrey, 2022).

The variable direction is also included, as cross-border payment systems and bilateral flow asymmetries have clear empirical relevance (Mariani et al., 2024).

Model 2: Total Charges Model

$$\ln(\text{total}_{\text{charges}} + 1) = \alpha + \beta_1 * \text{scheme}_{\text{DD}} + \beta_2 * \text{scheme}_{\text{Inst}} + \beta_3 * \ln(\text{amount}) + \beta_4 * \text{purpose}_{\text{group}} + \beta_5 * \text{direction} + \varepsilon$$

This model examines how payment scheme, transaction size, payment purpose, and direction affect total transaction fees.

The inclusion of ln(amount) is justified by the strong relationship between transaction size and both payment costs and payment choices (Lippi and Moracci, 2024; Rysman et al., 2025).

We propose to allow the variable purpose_group to have values because typically the payment contexts are usually associated with different transaction sizes and cost structures and payment heterogeneity is one of the main concerns in micro-level payment research (Meyer and Teppa, 2024).

Model 3: Charge Rate Model

$$\ln(\text{charge_rate} + 0.0001) = \alpha + \beta_1 * \text{scheme}_{\text{DD}} + \beta_2 * \text{scheme}_{\text{Inst}} + \beta_3 * \ln(\text{amount}) + \beta_4 * \text{purpose}_{\text{group}} + \beta_5 * \text{direction} + \varepsilon$$

This model also unearthed predictors of unit cost efficiency. By contrast to the total charges model, the charge rate model directly reflects the relative cost burden per unit of the transaction amount, which is consistent with the literature emphasis on transaction size in accounting for payment outcomes (Lippi and Moracci, 2024).

Furthermore, the cost and efficiency in cross-border payment are considered as two important dimensions that need to be analysed at the same time, which are why it is appropriate to incorporate scheme, purpose_group, and direction into the model (Mariani et al., 2024).

2.3.3 Overview of Regression Results

The main regression results for the three models are presented in Table 2.8. Overall, the models demonstrate strong explanatory power:

- Processing time model: $R^2 = 0.9805$
- Charge rate model: $R^2 = 0.9879$
- Total charges model: $R^2 = 0.8200$

The Significance F values for all models are close to zero, indicating that the models are statistically significant overall.

(1) Model 1: Processing Time

Coefficient for SEPA_DD is significantly positive, SEPA_Inst is significantly negative. In the processing time model, coefficients for SEPA_DD are significantly positive, SEPA_Inst is significantly negative. This means SEPA_DD compared with baseline group (SEPA_CT) longer processing times and SEPA_Inst significantly reduces settlement time.

In contrast, ln(amount) and direction are not statistically significant, showing that processing efficiency is dominated by payment scheme rather than transaction size or direction.

(2) Model 2: Total Charges

In the total charges model, ln(amount) is significantly positive, indicating that larger transactions incur higher total fees.

In parallel, SEPA_DD is not significant, and SEPA_Inst is significantly positive, implying that instant payments significantly raise total charges, but there is no stable difference between SEPA_DD and SEPA_CT.

Direction and all categories of purpose_group are significantly positive, implying that IT→IE transactions, but also payments for income, commercial, and transfer/charity purposes cause higher total charges.

(3) Model 3: Charge Rate

In the charge rate model, ln(amount) is negative and significant, indicating that larger transactions a related to lower unit cost, constituting evidence that there is a clear economies of scale effect (Meyer and Teppa, 2024; Rysman et al., 2025).

On the other hand, SEPA_Inst is significantly positive, while SEPA_DD is not, indicating that instant payments are not only more expensive in absolute terms but also in relative terms, while the difference between SEPA_DE and SEPA_DD is negligible.

Also, direction and purpose_group are significantly positive, indicating that transaction direction and payment purpose systematically influence unit cost.

2.4 Robustness Checks

2.4.1 Re-estimation Using Original Dependent Variables

To determine whether the main findings are a result of variable transformations or due to a few extreme observations, we perform two robustness checks. First, we re-estimate the regressions using the original scale of the dependent variables rather than the log-transformed values. Second, we re-estimate the regressions after dropping the top 1% and bottom 1% on the main dependent variables.

For the first regression, we estimate the same models using initiation_to_credit_hours, total_charges and charge_rate instead of ln(initiation_to_credit_hours), ln(total_charges + 1) and ln(charge_rate + 0.0001), respectively. We hold the same explanatory variables in place. Results are presented in Table 2.9.

Overall, the levels of some coefficients change marginally - for example, SEPA_DD is weakly significant in the total charges model - but the coefficients themselves remain economically small. The findings are therefore not greatly changed from the baseline models. In particular, the two most important findings - that SEPA Instant is both faster and more expensive and that larger transaction sizes are associated with lower charge rates - are robust.

2.4.2 Robustness Check with Outlier Exclusion

In the second robustness check, we drop extreme observations in key variables (such as processing time/charge rate) and re-estimate the models with the trimmed sample. The results are shown in the robustness tables at the end of the paper.

The results suggest that, after dropping outliers, both the direction of core coefficients and its statistical significance remain largely unchanged.

Compared with the regressions conducted on the original scale, the results based on the trimmed sample are even more consistent with the baseline models. In the processing time model, payment scheme remains the key determinant of the settlement speed. In the total charges model, SEPA_Inst remains significantly more expensive, while the difference between SEPA_DD and SEPA_CT remains insignificant. In the charge rate model, the negative coefficient on transaction size, the positive coefficient on SEPA_Inst, and the positive coefficient on IT→IE direction all remain stable.

These results suggest that the main finding is not driven by a small number of extremely large observations.

2.4.3 Summary of Robustness Checks

The analysis of the previous robustness checks allows us to derive several conclusions.

Firstly, the significant influence of the payment scheme on processing time applies regardless of the variable scaling and sample adjustments.

Secondly, the high-cost character of SEPA Instant in total charges and charge rates is very robust.

Thirdly, the negative correlation of the transaction size with the charge rate, therefore showing economies of scale, is corroborated by all the models.

Fourthly, the finding that the direction significantly influences the cost but not the processing time also applies regardless of the variable transformations.

In summary, neither the transformations applied to the variables or the exclusion of the outliers change the core findings of this study.

3. Analysis of asymmetric accessibility of financial services and mechanisms on instant payment adoption

3.1 Distribution analysis of financial service channels

3.1.1 Structural characteristics of financial service channels and analysis framework

Assessing the financial services channel access and usage characteristics to local payment system performance

To analyse how different characteristics of financial services channels affect payment system development, this study outlines an analytical framework that includes channel type and specific auxiliary variables according to data availability and research questions, to describe the supply structure, usage characteristics, and possible constraints of the financial services channels (Demirgüç-Kunt et al., 2018; ECB, 2022).

Financial services channel is divided into three types: (i) Traditional channels (bank branches and ATMs) represent the physical financial infrastructure and the level of access to in-person payers. These channels are commonly used for cash treatment and are an indication of the level of access to the traditional banking service (Allen et al., 2016; ECB, 2020); (ii) POS terminals are an intermediary between traditional and digital channels. Although POS terminals are mainly used by consumers and are an indicator of potential penetration of the electronic payments, they still use physical infrastructure and therefore have a relatively low level of digitalization (Bolt et al., 2010); and (iii) Digital channels (mobile apps and web applications) represent the basic infrastructure of digital payment systems and constitute a key foundation for the development of pagoda payments (CPMI, 2020; ECB,2022).

Digitalisation at provider level is available only at the national level and thus lacks regional variability. We therefore exclude digitalisation from the regressions. However, the unequal spatial distribution of digital financial services is an important question (Ozili, 2018; World Bank, 2021).

Three auxiliary variables are included to capture the regional characteristics and usage of the channels: (i) location type (urban, suburban, rural, remote) as a measure of financial services accessibility, (ii) the population served as a measure of channel capacity and pressure on its services, and (iii) the monthly transaction volume per capita as a measure of channel usage intensity and efficiency (Shirono et al., 2024; Auer et al., 2020).

In summary, this framework captures the characteristics of financial services channels in terms of availability, capacity, and usage efficiency, and their relationship to payment adoption.

3.1.2 Descriptive statistical analysis of financial service channel usage

This section performs a descriptive statistical analysis of the usage of financial service Channel in Ireland based on the data after excluding inactive channels and indicates the distribution patterns in various Channel types and regions, which offers a basic support for identification of the underserved areas.

(1) Distribution characteristics at the overall level

The overall mean transaction volume is 6,070.50, while the median is 871.00, and the standard deviation and skewness as high as 30,296.51 and 17.76, indicating a strong right-skewness. This means that transaction activities are highly concentrated on a small number of Channel or areas, while the vast majority of observations display relatively low transaction activity, which illustrates a significant imbalance in the usage of financial services. Payment concentration, even with continuing growth of digital payment, is also observed in most recent international payment statistics (Di Iorio, Kosse and Szemere, 2024).

(2) Analysis at the Channel level From the perspective of channel structure, the POS terminal for example accounts for 78.20% of all Channel, which therefore dominates the construction quantity, while their average transaction volume is only 841.97, which is far lower than ATMs (16,401.57) and bank branches (8,708.84). In contrast, the Digital Channel (Mobile App and Online Portal) are not many, but the average transaction volumes are relatively high - 104,816.18 and 48,745.67 respectively, which indicates the importance of Digital Channel.

In terms of the ratio of the total transaction volume, the Mobile App at 33.89% and the ATM at 29.62% dominate the contribution to the total transaction volume. The POS terminal accounts for only 10.84%. The mismatch between the Channel quantity and the contribution to transaction volume and the importance of digital Channel in the entire payment system are both displayed, which is consistent with the outstanding scale effects of mobile finance and digital payment (Aron, 2018).

It is worth mentioning that digital Channel is recorded only at the national level without regional information, which limits the analysis of digital financial accessibility in regions to some extent.

(3) Analysis at the regional-type level In terms of spatial type, transaction activities show a spatial gradient: the urban areas account for 76.43%, suburban areas for 16.45%, rural areas for 6.67% and remote areas for only 0.45%.

This decreasing trend from urban to remote areas indicates financial service usage is highly spatially concentrated, and relatively low-level transaction in rural areas and remote areas is perhaps because of the gap in access to financial services, or even “service gaps”.

(4) County-level analysis

At the county-level, transaction level follows the same trend of concentration. The National category, i.e., Digital, covers49.65% of all transaction volume, and its coverage of transaction in Dublin is15.89%, a lot higher than other regions. In contrast, the Border (2.69%) and Midlands (1.71%) account for a small share, and therefore calculate to have relatively weak financial activity. It should be pointed out that National is not a region, and therefore not comparable with other regions. It also represents the spatial limitation of digital financial data.

(5) Population coverage and service pressure

After removing the observation with population_served = 0, the mean covered population is74,929.48, its distribution is also very dispersed, suggesting that service pressure may vary significantly from access point to access point.

At the channel level, the digital channel covers more people. However, as there is no regional information, we cannot assess its spatial accessibility.

(6) Summary In short, the descriptive statistical results reveal four important implications. First, there is clear concentration and imbalance in financial service usage. Second, the mismatch of channel structure shows that digital channels dominate the transaction scale. Third, financial activity is highly concentrated spatially around urban areas. Fourth, some access points suffer relatively strong population service pressure. In short, the French financial service system has significant structural imbalance in the channel mix and spatial composition, which may have implications for the usage of digital payments and instant payments in a region-wise perspective.

3.1.3 Structural Differences of Financial Service Accessibility

(1) Location differences

From the perspective of location type, the utilization of financial services has a clear spatial gradient, following the trend of low to high, from rural areas to urban areas, indicating a high concentration of financial transaction activity in urban areas. This not only reflects the high intensity of urban economic activities, but also that non-urban areas may have a certain degree of financial service access discrimination. This is in line with the findings of financial accessibility literature, which shows that the supply and utilization of financial services are subject to systematic spatial unevenness (Maravalle and Gonzalez Pandiella, 2022).

It should be noted that the two digital channels, Mobile App and Online Portal, are all considered urban. This is more likely to be a manifestation of the centrality of the statistical reporting framework. It is not necessarily that the actual use is limited to urban areas. Hence, the feature should be treated as unobservable rather than real.

(2) Differences in population scale

The results on population coverage show a significant difference in the number of people covered by different types of financial service access points. This indicates a significant unevenness in the distribution of financial infrastructure.

At the same time, at an access point that covers a relatively large population, a single channel is needed to serve a large number of users, which increases the service pressure and thus affects service efficiency. The "service pressure" is suspected to be more significant in areas where financial infrastructure is relatively scarce.

Meanwhile, the average population coverage of the digital channels is lower than that of the non-digital channels, showing an advantage in scale expansion. However, it is not possible to judge whether the coverage is spatially balanced due

to the lack of information on regional distribution. In general, "service pressure" - "channel supply" mismatch is probably one of the main reasons for inadequate financial service supply.

(3) Differences in channel structure

From the perspective of channel structure, the financial service system of Ireland shows a significant structural imbalance. The number of POS terminals is more significant, while the number of transactions is lowest.

On the other hand, digital channels are much sparser yet dominate the transaction scale. This means the quantity and intensity in the system are separated, reflecting a stratification structure in the financial service system. Namely, there is a widely spread low-intensity physical channel network (POS terminals and ATMs), and a concentrated high-intensity digital channel system.

This structure indicates that high-efficiency financial services are in a way unevenly located across space such that instant payments relying heavily on digital channels suffer structural disadvantages, which might be translated in regional disparities in digital payment capacity. This spatial limitation seems likely to be noticeable in those areas which are relatively more dependent on conventional channels.

(4) Identification of areas that are unlikely to be served By the above analysis, generally, areas that are less likely to be served are characterized by relatively low transaction activity, relatively higher reliance on conventional channels, relatively weaker availability of digital channels (or immobility), higher pressures on net population by each access point.

These characteristics are relatively more pronounced in rural and remote areas, as well as in some areas that have a relatively lower share of the transaction activity. This demonstrates the relative disadvantage of these areas in the sense that the access degree to financial services and the digital payment capacity are relatively lower. Thus, these areas are more likely to suffer with structural limitations in the development and utilization of instant payments.

3.1.4 Summary and research hypothesis

Based on the preceding descriptive analysis and structural analysis of the distributional characteristics and regional differences of financial service channels, it is found that there is a large imbalance in channel coverage, service capacity, and usage performance in different regions. There is a lack of financial service outlets and a fragmentary layout of channels in rural and remote areas; and in some regions, the population load per channel is relatively large, which leads to a higher pressure on each channel, and a lower service capability and actual usage performance.

Therefore, this study, integrating the above two points from the perspective of structural constraints, gives a mechanism-based explanation for the results above. Not only the regional geographical location, but also the capacity constraints of the population served, jointly determine the channel operation. The geographical disadvantage reduces channel accessibility, while the population pressure is too large, which leads to a decline in the service capacity of the channels. A literature

review on the relationship between financial inclusion and financial stability has noted that there are significant interactions between financial accessibility, usage conditions, and institutional arrangements, and that structural differences can

amplify inequalities in access to financial services (Čihák, Mare and Melecky, 2021).

In addition, the differences in the usage efficiency caused by structural constraints in channel provision also influence the diffusion of digital payment instruments, not only in terms of traditional financial services, but also indirectly, because of the higher frequency of users accessing and using services. Existing research has found that financial accessibility is significantly related to the digital finance, and that the lack of infrastructure constraints is an important barrier to the use of digital finance (Frost et al., 2024).

Therefore, based on the analysis above, the following research hypothesis was proposed:

H: Structural constraints of financial service channels, such as geographical location and population service pressure, aggravate regional inequality in financial service provision by reducing channel usage efficiency, and thereby continuing to restrict the diffusion of instant payments.

3.2 Analysis of the Impact of Financial Service Channels on Payment Behaviour

3.2.1 Empirical Model Specification and Variable Description

Our goal is to investigate the impact of financial service channels and regional characteristics on the intensity of payment usage, and thus we build a multivariate regression model for this purpose, in which we assume that the channel structure and regional characteristics systematically affect the payment usage intensity

(1) Dependent variable

The key dependent variable that we employ in this study is channel usage efficiency. In particular, we adopt the logarithm of transaction volume per 1,000 people as the key indicator of the service performance level of specific financial service channels. As we have theoretically argued, this indicator reflects the actual intensity of channel usage per unit population served, and thus plays an important role in measuring the channel service performance level. In addition, the measurement of the intensity of financial service usage based on population-normalized indicators is also commonly used in studies about financial access and usage. For instance, the IMF also extensively adopts various indicators to represent the financial service usage level and accessibility status expressed per 1,000 people or per 100,000 people in Financial Access Survey.

$$. \ln(1+tx_per_1000i)$$

Where tx_per_1000i denotes the transaction intensity of channel unit i.

(2) Independent variables

Regarding to independent variables, we mainly consider the following two types of structural constraints. First, to depict the accessibility of financial service channels in different areas, we use location-type variables to represent the geographical locations of channels, i.e., Urban, Suburban, Rural, and Remote. Second, although we do not directly consider population service pressure as a continuous variable in the baseline model, such effect is already endogenously incorporated into the construction of the dependent variable, since the transaction intensity per capita

implicitly reflects the service performance level a channel can achieve under the population served scale that it adopts.

The core explanatory variable in this paper is a channel-type dummy variable: Branchi: a dummy variable for bank branches (Branch = 1, ATM = 0).

It is used to measure the impact difference among different physical channels on payment usage intensity.

Secondly, we introduce location-type dummy variables to describe the regional characteristics, namely Suburbani, Rurali, and Remotei (Urban is the reference group) to capture any structural differences of payment usage intensity among different regions.

(3) Control variables To control for other factors influencing the usage of payment methods, the following control variables are included:

Inactivei: dummy variable that identifies whether the channel is inactive.

γc: county fixed effects, which control for unobservable institutional or economic differences between the counties.

(4) Baseline model

(5) According to the above definitions of the variables, the baseline regression model can be expressed as follows:

$$ln(1+tx_per_1000_i)=\beta_0+\beta_1 Branch_i+\beta_2 Suburban_i+\beta_3 Rural_i+\beta_4 Remote_i+\beta_5 Inactive_i+\gamma_c+\varepsilon_i$$

where ε_i is the random error term.

In summary, the model is used to test whether these constraint structures of financial service channels have systematic differences in channel usage efficiency, which provides a basis for the subsequent research on the inequality of financial services and instant payment adoption.

3.2.2 Baseline Regression Method and Estimation Strategy

In order to analyze the influence of structural constraints on the usage efficiency of financial service channels, a multivariate linear regression model, namely the OLS method, is employed for estimation in this study. The OLS method is widely used as a baseline estimation method in empirical research, because via OLS it becomes possible to recognize the marginal effects of different structural factors on channel usage efficiency while controlling for other variables.

To increase the reliability of parameters' estimates and avoid a biased inference of the statistical significance caused by heteroskedasticity, this study adopts heteroskedasticity-robust standard errors for the error term in the estimation process. This error treatment has its origins in the heteroskedasticity-consistent covariance matrix estimator suggested by White (1980).

(1) Coefficient interpretation

In the current model, the dependent variable is expressed in logarithmic form. Thus each coefficient reflects the relative effect on channel usage efficiency, which is here denoted as generation intensity per unit of the served population. The dummy variables, such as Branchi, Suburbani, Rurali and Remotei, denote the difference relative to the reference group. In a semi-logarithmic model, the effect of a dummy variable cannot generally be viewed as a percentage change; rather,

eβ−1 provides the correct interpretation, which is commonly discussed in the literature (Halvorsen and Palmquist, 1980; Giles, 1982).

In this study, these coefficients are used to capture not simply the mere difference in usage, but more fundamentally the systematic differences in channel operating efficiency under various forms of structural constraint.

(2) Statistical significance

This paper uses the t-statistic and its associated p-values to test the statistical significance of the estimated coefficients, using the following significance levels:

•$p<0.01$: significance at the 1% level
•$p<0.05$: significance at the 5% level
•$p<0.10$: significance at the 10% level

If a coefficient is statistically significant, this means that the structural factor has a stable effect on channel usage efficiency. Otherwise, it will not be statistically significantly different from 0.

(3) Main research focus

The following coefficients are the main focus points of this study:

Branchi: indicates the difference in channel use efficiency across channel types and reflects the role of channel supply structure.

Location variables(Suburbani, Rurali, Remotei): represent the constraints of geographical location in terms of accessibility; it is one dimension of structural constraints.

Inactivei: reflects the impact of channel activity status on channel use efficiency and indicates the difference of operation quality across channels.

The study contributes to identify systematic variations in channel usage efficiency under various structural constraints by analyzing the direction and significance of the coefficients of these variables; it provides an empirical base for the following analysis on financial inequality and instant payment.

3.2.3 Discussing Baseline

Table X summarises the regression results of the baseline model. As a whole, the model has reasonably good explanatory power, R2 = 0.299, and the F-statistic is significant at the 1% level, indicating that the overall model is statistically significant.

In the analytical framework of this study, the core purpose of the model is to find out the differences in the usage efficiency of financial service channels under various structural constraints, which to give foundation for subsequent discussion of the inequality of financial services and adoption of instant payments.

(1) The channel type factor (Branch)

The regression results of the coefficient of Branchi are -2.278 and are significant at the 1% level ($p<0.01$), indicating that if regional factors and other factors are controlled, the transaction intensity per unit population that bank branches can serve is significantly lower than ATMs, and the channel usage efficiency is significantly lower.

From the perspective of the structural constraint, the above results reflect the differences in service function and usage situation between the channel types. The ATM is more inclined to service high-frequency and standardised transaction

scenarios, the bank branch is less inclined to service low-frequency and service process items. Channel supply structure thus has a significant impact on overall service efficiency and is a source of structural heterogeneity in the financial service structure (Humphrey, 1994; Nigatu et al., 2023).

(2) The location difference factor (Location Effects)

Compared with Urban, all the location variable factors are significantly negative:

Suburban: -0.429 ($p<0.01$)
Rural: -1.281 ($p<0.01$)
Remote: -2. 184 ($p<0.01$)

Furthermore, the negative impact becomes increasingly severe with increasing remoteness, showing a clear gradient: Urban > Suburban > Rural > Remote.

In the analytical framework of this study, the above results have important mechanisms for discussion. The impact of location variables is no simple spatial difference. The variables contain the structural constraints faced by financial service channels in terms of service accessibility. The remote areas seriously limit the availability of financial services. The above results show that the bank branches and ATMs are scattered, and the distance is relatively far, which in turn negatively affects channel usage efficiency (OECD, 2020).

Thus, this finding indicates that geographical location, as a spatial constraint, systematically reduces channel usage efficiency and yields considerable differences across regions.

(3) The effect of channel operating status (Inactive)

The coefficient on Inactivei is 0.074 but not statistically significant ($p>0. 1$). That is, after taking into account the other variables, the item that a channel is inactive has no significant effect on channel usage efficiency.

This finding may suggest that, as to the sample investigated in this study, the marginal effect of channel operating status to the efficiency is limited, or its effect has already been reflected by other more structural variables such as channel type and regional characteristics. In the light of this study, this finding further points to the prevailing influence of structural constraints such as geographical location and channel configuration to performance differentials.

(4) Overall interpretation In sum, the baseline regression results give rise to the following main findings.

First, channel supply configuration significantly contributes to channel usage efficiency. Compared to bank branches, ATMs have greater transaction volume, implying that different channels perform very different functions within the financial service system.

Second, geographical location, as a spatial constraint, significantly contributes to channel usage efficiency. Compared to urban areas, usage efficiency in rural and more remote areas is significantly lower, and the variations show a clear gradient pattern.

Third, the contribution of structural constraints is a systematic phenomenon. The observed efficiency variation among regions is a manifestation of channel access variations, rather than random fluctuations, and thus reflects the uneven spatial distribution of financial provision.

As such, the baseline regression results provide empirical evidence that structural constraints in the financial service channels, particularly geographical location,

materially reduce channel usage efficiency, and so lend themselves to the subsequent analysis of instant payment adoption and financial service inequality.

3.2.4 Robustness Checks

In order to further verify the validity of the baseline regression results, the study adopts the dependent variable specification, sample scope and model form from multiple aspects to conduct robustness checks. Overall, the estimation results under different model specifications are consistent with those in the baseline regression, which demonstrates that the conclusion on the impact of structural constraints on channel usage efficiency is generally reliable.

Verifying the results via other dependent variables, expanding the sample scope, and assuming parameter nonlinearities are a common empirical robustness analysis approach as well (Cameron and Trivedi 2013).

First, this study performs tests on the baseline model by changing the dependent variable and adding the population variable for control. In this specification, the dependent variable is changed to the log of total transaction volume, and the log of population is added as a control variable:

$$\ln(1+\text{transaction_volume_monthly}_i)=\beta_0+\beta_1\ln(1+\text{population_served}_i)+\beta_2\text{Branch}_i+\beta_3\text{Suburban}_i+\beta_4\text{Rural}_i+\beta_5\text{Remote}_i+\beta_6\text{Inactive}_i+\gamma_c+\varepsilon_i$$

The regression results indicate that the location variables remain significant negative gradient. The efficiency of channel use declines successively in the suburbs, rural, and remote areas, compared with urban areas. This is fully consistent with the baseline regression. In addition, the coefficient of the population variable remains significantly negative, implying that the unit service efficiency decreases when a single channel serves more people. This indirectly reflects the suppressing effect of channel capacity pressure, a structural constraint. It should be noted that under this specification the coefficient of Branch changes from negative to positive and is significant. When the population served is controlled, bank branches may still be better than other channels in terms of absolute transaction volume. However, this result does not change the conclusion on the efficiency per unit of the population served in the baseline model.

Second, this study adds POS channels to the sample to test whether the original conclusions would change when the channel types varied:

$$\ln(1+\text{transaction_volume_monthly}_i)=\beta_0+\beta_1\text{Branch}_i+\beta_2\text{POS}_i+\beta_3\text{Suburban}_i+\beta_4\text{Rural}_i+\beta_5\text{Remote}_i+\beta_6\text{Inactive}_i+\gamma_c+\varepsilon_i$$

The regression results indicate that the location variables remain significant negative, and thus the regional differences of the sample are not caused by the selections of channel types in the original samples. At the same time the coefficient on POS is significantly negative which shows that its transaction intensity is significantly lower than that of ATMs, further indicating the functional differences with service efficiency of different channels. Secondly, the coefficient on Branch continues to be significantly negative, which is the same as that in the baseline model, showing that ATMs still carry out high-frequency transaction functions even in a broader channel sample. Furthermore, existing research has also found that the ATM network is highly related to cash usage, and that the structure of the payment network itself influences transaction behaviour, justifying

the use of different channel types jointly in a robustness test (Snellman and Virén, 2006).

Thirdly, to rule out potential interference from inactive channels, this paper limits the sample to active channels only and re-estimate the regression:

$$ln(1+tx_per_1000_i)=\beta_0+\beta_1 Branch_i+\beta_2 Suburban_i+\beta_3 Rural_i+\beta_4 Remote_i+\gamma_c+\varepsilon_i$$

The regression shows that after excluding channels that are inactive, the coefficient on Branch remains significantly negative, and the gradient trend of the location variables does not change, showing that the conclusions of the baseline model are not simply driven by a few inactive channels, but are widely existent in the overall channel system and thus further increase the credibility of the results.

Last, this paper alters the form of the dependent variable and makes it a binary variable that indicates low usage, and the model is then estimated as a Logit model:

$$Pr(low_usage_i=1)=\Lambda(\beta_0+\beta_1 Branch_i+\beta_2 Suburban_i+\beta_3 Rural_i+\beta_4 Remote_i+\beta_5 Inactive_i+\gamma_c)$$

In the regression results, the coefficients on suburban, rural and remote areas are all significantly positive, indicating that they are more likely to be in a low-usage state, with the effect in remote areas being strongest. Besides, the marginal effects show that compared with urban areas, the probability of being in a low-usage state in remote areas significantly increases, and areas that are slightly more general rural areas show a similar but weaker trend. At the same time, the channel variable is no longer significant, indicating that when explaining whether a channel is in a low-usage state, geographical structural constraints play a greater role. The Logit model is one of the standard estimation methods for this type of binary outcome variable (Hosmer, Lemeshow and Sturdivant, 2013).

Taken together, we find that across robustness checks, the stability and significance of regional differences hold regardless of alternative dependent variables specification, sample composition, and model form, and continue to point at persistent disadvantages in terms of channel usage efficiency in rural and remote areas. The stability of the effect of channel structure also holds across different models. Taken together, our results consistently demonstrate that the main inference of robustness derived from baseline regression is not model-specification external robustness.

3.2.5 Heterogeneity Analysis

To provide a deeper understanding of the mechanisms by which structural constraints on financial services channels influence channel usage efficiency, this study analyzes channel usage heterogeneity from three aspects: location type, population service pressure, and their interaction. Following the baseline model, this study employs both subgroup regressions and specifying interaction terms to test the heterogeneity of channel effects and regional differences. First, from a regional perspective, this study estimates four separate regressions for the four location-type subsamples: Urban, Suburban, Rural, and Remote.

$$ln(1+tx_per_1000i)=\beta_0^g+\beta_1^g Branch_i+\beta_2^g Inactive_i+\gamma_c^g+\varepsilon_i^g$$

$$(g \in \{Urban, Suburban, Rural, Remote\})$$

The result shows that bank branches have significantly lower channel usage efficiency than ATMs in any location category and this negative relationship

consistently exists in any location-based regional group. That is, the coefficient on Branch term is significantly negative in any location group, which means that differences in the channel structure are not just caused by any one type of area, but exist across different locations. This result proves ATMs always perform transaction functions with higher frequencies in any type of location, while financial service banks are more likely to be used to carry out low-frequency or service-oriented activities and thus magnify the differences compared with the baseline regression result: the channel structure will influence the efficiency of the channel. This is consistent with the understanding in the literature on payment systems that ATMs is more suitable for standardised high-frequency cash access functions (CPMI and World Bank, 2016).

Second, from a population service pressure perspective, this study divides the pool of institutions into three groups, namely LowPop, MediumPop, and HighPop, based on the distribution of population_served, and estimates three separate regressions for these three groups:

$$ln(1+tx_per_1000i)=\beta_0^g+\beta_1^g Branch_i+\beta_2^g Suburban_i+\beta_3^g Rural_i+\beta_4^g Remote_i+\beta_5^g Inactive_i+\gamma_c^g+\varepsilon_i^g$$

The heterogeneity analysis suggests that Coefficient on Branch remain significantly negative in both low- and medium-pressure groups, although the absolute value gradually decreases, which means that the channel difference becomes somewhat weakened under population pressure. But the coefficient turns positive and becomes significantly positive in the high-pressure group, which suggests that when the population density served by each channel is relatively high, bank branches may show higher transaction intensity than ATMs, which means that the role of bank branches in the payment system could be transformed from low-frequency service provision to high-frequency transaction processing as the population served by bank or ATM increases, which means that their differences weaken and even reverse. Existing studies have highlighted that the viability of channels and transaction choice is jointly constrained by population density, channel infrastructure and transaction type, and thus changing the population service pressure itself could have an effect on the differences of channels (Soursourian et al., 2021).

Based on the above emotional, this paper further adds an interaction term of Rural/Remote and population pressure to test the hypothesis that population pressure strengthens the effect of structural constraints:

$$ln(1+tx_per_1000_i)=\beta_0+\beta_1 RuralRemote_i+\beta_2 HighPop_i+\beta_3(RuralRemote_i\times HighPop_i)+\beta_4 Branch_i+\beta_5 Inactive_i+\gamma_c+\varepsilon_i$$

The regression results show that the coefficient of Rural/Remote dummy variable itself is significantly negative, which suggests that the Rural/Remote areas well show a clear difference in channel channel usage efficiency compared to that in the urban areas. And the coefficient on HighPop is also significantly negative, which means that the overall channel usage efficiency will deteriorate under high pressure. More importantly, the interaction term is significantly negative, which suggests that when population pressure is high and the Rural/remote areas themselves are not strong where financial services are usually set up, the efficiency difference becomes more significant. In other words, population pressure does not affect all areas equally, but it will have a more disadvantage cumulative effect. This is in line with related research that points out that low-density areas are usually at a disadvantage in channel investment because of the

lack of channel distribution points, and there will also be higher service costs when adding new digital channels or physical investment (Bianchi et al., 2023).

In summary, the heterogeneity analysis shows that the effect of structural constraints in financial service channels on efficiency is different under different situations. On the one hand, the differences of charge structure in different regions are very common, which means that the effect of Structural constraints on service efficiency is very robust. On the other hand, population pressure serves to change the form under which the effect of channels manifests itself, and significantly increases the degree of regional inequality. In particular, in the Rural and remote areas, the efficiency gaps between the weak and strong financial service areas become more significant under high pressure. These results provide mechanism-level evidence for the hypothesis that spatial constraints and related challenges such as the distance d from the service area to the channel act to reduce channel usage efficiency, leading to greater inequality in financial services.

3.2.6 Hypothesis testing and discussion

Drawing on the empirical findings presented above, this paper then undertakes a comprehensive evaluation of the main hypothesis outlined in the first part. Overall, the estimation outcomes are consistently high across the model specifications and support the mechanism in multiple dimensions of structural constraints worsening the financial service inequality by undermining the channel usage efficiency.

Firstly, as shown in the baseline regression, the gradient relationship on the location variables is significantly negative. Relative to the urban location, the channel usage efficiency declines in suburban, rural, and remote areas, suggesting that the access restrictions imposed by geographical location weaken the channel usage efficiency, and are also an important cause of regional differences.

Secondly, as shown in the robustness test, after controlling for the size of the population served, population pressure has a significantly negative relationship with channel usage efficiency. The larger the population served by a single channel, the smaller its unit service efficiency, suggesting that the population service pressure, as another important structural constraint, suppresses the operating efficiency.

Thirdly, as shown in the heterogeneity analysis, the influence of the structural constraints also has certain heterogeneity.

On one hand, the differences in the channel structure in different regions are stable. \on the other hand, the efficiency of the rural and remote areas is relatively weak under dual population pressure, further intensifying the population pressure and making the differences in the spatial distribution more apparent.

In view of the above, the empirical findings of this paper show that structural constraints such as geographical location and population service pressure in the financial service channel affect regional differences to a certain extent, that is to say, it is an important source of regional differences in channel service quality. The mechanism in detail is that the imposition of structural constraints further suppresses the channel usage efficiency, exacerbating the service inequality. Thus, this paper does a unified mechanism-based explanation of the structural problem in the payment system and provides a theoretical foundation for the subsequent exploration of the instant payment.

4. Recommendations of the Irish Retail Payment System

Extending the analysis: I argue that payment system optimisation should strike a balance between efficiency, cost and inclusion rather than one and its digitalisation or speed. While Ireland has a highly digitalised and structured payment system, cross-border cost asymmetries and inconsistent access to financial channels are the main impediments to instant payments.

Firstly, the push for instant payments should be matched with cost-control motives. Despite that SEPA Instant cuts processing time considerably, it also raises the total cost and the fee rates, suggesting a clear trade-off between speed and cost. Policymakers should therefore increase the fee transparency and cut the marginal cost, especially for low-value transactions.

Secondly, pricing cross-border payments should better distinguish between transaction purpose and direction. In our study, we find that pricing can be explained mainly by such factors, where the cost is higher for income-related, commercial and IT → IE transactions. Accordingly, pricing transparency and standardisation should be improved, contributing to lower hidden fees and a fairer price system.

Third, economies of scale should be harnessed to lower cross-border payment costs. Regression analyses indicate that larger transaction sizes result in lower unit costs, confirming the existence of scale effects. Policies should foster platform-based clearing, batch processing and standardised procedures to lower the unit costs, especially for SMEs and frequent cross-border transactions.

Fourth, access to services matters for instant-payment adoption. Substantial regional disparities exist, particularly lower efficiency at the suburban, rural and especially remote levels. Reducing access gaps needs to focus on access conditions and target neglected regions, rather than expanding digital infrastructure.

Fifth, the construction of online services should be further promoted with the support of offline services. As presented in the overview, the structure of the payment system in Ireland is "online-dominant, offline-assisted, and the traditional channels are only the safety net". Digital channels like Web Portals and Mobile Apps are developing very fast, but the traditional channels like branches still play a supplementary role for specific groups of people and complex transaction scenarios. Thus, the policy should not interpret reform of the payment system predictably as "completely digital replacement". Therefore, while continuing to promote digital channels, necessary offline service channels should be preserved for people with weak digital literacy, remote-area residents, and complicated business scenarios to balance the improvement of efficiency and financial inclusiveness.

Sixth, strengthen monitoring of the financial infrastructure at the regional level and construction of related data. As pointed out in Part Three, the existing data of digital channels are mainly at the national level and lack the specific regional dimension. This will result in the lack of identification of regional digital financial accessibility. If the policymakers want to accurately promote the adoption of instant payments, they also need to construct a more specific regional-level data system to continuously track the coverage of channels, the pressure of the service

population, the volume of transactions, and the volume of instant payment transactions in different regions to identify the underserved areas and carry out more targeted improvement measures.

In general, the policy implications of this paper can be summarized as follows: payment system reform should move from "speed first" to "efficiency-cost-inclusiveness balance". On the one hand, the development of instant and digital payments should continue to be promoted; on the other hand, it is also necessary to control the cost spillovers, reduce the pricing asymmetry in usage and direction, and pay attention to the financial service accessibility of rural areas, remote areas, and high-service-pressure areas. Only and truly by combining the optimization of cross-border payment efficiency and the inclusiveness of financial services can the payment system digital transformation bring about a broader, more balanced, and sustainable expansion.

5. Conclusion

In conclusion, this paper establishes an analytical framework from "structural description, mechanism identification, policy implications," based on the structural characteristics of the payment system in Ireland, the differences in the efficiency and cost of cross-border payments, and the impact mechanism of uneven accessibility of financial services on the popularization of instant payments. The findings reveal that the entire payment system in Ireland has typical characteristics of high degree of digitalization, relatively obvious structural stratification, and multi-channel collaborative evolution. At the cross-border payment level, the payment scheme is an important factor affecting processing efficiency and cost performance. Although instant payments can be completed faster, they are still accompanied by higher fees and rates, and there is a clear speed-cost tradeoff. At the same time, transaction volume, payment purpose and transaction direction are mainly reflected in the cost dimension, showing significant scale effects and structural differences. Moreover, at a more profound level, the regional distribution of financial service channels, pressure on the service population, and differences in channel types also affect the channel utilization efficiency and may further restrict the popularization of instant payments. Hence, payment system reform cannot stand only on technological and speed aspects, but should simultaneously take into consideration the issues of cost efficiency, regional balance and financial inclusion. Only by integrating the digital development of the payment system and improving the accessibility of financial services can the payment system undergo a truly more efficient, fair and sustainable transformation.

APPENDIX

Variable	Mean	Median	Std. Dev.	Min	Q1	Q3	Max
Amount	164.3043	41.33	852.8708	0.07	16.16	109.35	100000
Initiation_to_Credit_hours	21.74507	23.09	11.25373	0.0022	15.84	29.16	50
Total_charges	0.254744	0.21	0.132242	0.2	0.2	0.22	10.5
Charge_rate	0.014706	0.005432	0.035828	0.000102	0.002107	0.014194	3.333333

Table 2.1 Descriptive Statistics of Key Variables in D08

Payment Scheme	*Count*	*Avg. Processing Time (Hours)*	*Avg. Total Charges*	*Avg. Charge Rate*	*Median Amount*
SEPA_CT	562,779	23.9998	0.2158	0.0123	41.31
SEPA_DD	89,397	31.2514	0.2152	0.0123	41.45
SEPA_Inst	97,530	0.0207	0.5157	0.0306	41.36
Total	**749,706**	**21.7451**	**0.2547**	**0.0147**	—

Table 2.2 Grouped Descriptive Statistics by Payment Scheme

Charge Bearer	*Count*	*Avg. Processing Time (Hours)*	*Avg. Total Charges*	*Avg. Charge Rate*
BEN	37,574	21.7087	0.2543	0.0148
OUR	74,785	21.7608	0.2551	0.0147
SHA	637,347	21.7454	0.2547	0.0147
Total	**749,706**	**21.7451**	**0.2547**	**0.0147**

Table 2.3 Grouped Descriptive Statistics by Charge Bearer

Purpose Code	*Count*	*Avg. Processing Time (Hours)*	*Avg. Total Charges*	*Avg. Charge Rate*	*Avg. Amount*
BONU	28,018	21.7309	0.2437	0.0233	52.1842
CHAR	28,236	21.807	0.2426	0.0237	51.5661
COMM	18,925	21.8287	0.3323	0.003	940.932

GDDS	140,918	21.7396	0.2467	0.0145	85.7986
GIFT	28,095	21.7082	0.2441	0.0241	51.5149
OTHR	140,522	21.7438	0.2468	0.0144	84.7566
SALA	28,032	21.6295	0.2444	0.0239	50.6785
SCVE	140,883	21.74	0.2468	0.0146	84.2118
SERV	18,714	21.6937	0.3301	0.0029	913.0423
SUPP	18,549	21.7077	0.3312	0.003	924.2271
TRAD	18,839	21.6567	0.3328	0.0031	932.7544
UTIL	139,975	21.7903	0.2465	0.0144	85.1555
Total	**749,706**	**21.7451**	**0.2547**	**0.0147**	**164.304**

Table 2.4 Grouped Descriptive Statistics by Purpose Code

Direction Processing	***Count***	***Avg. Time (Hours)***	***Avg. Total Charges***	***Avg. Charge Rate***
IE→IT	374,763	21.734	0.2539	0.0131
IT→IE	374,943	21.7561	0.2556	0.0163
Total	**749,706**	**21.7451**	**0.2547**	**0.0147**

Table 2.5 Grouped Descriptive Statistics by Direction

Test Variable	***Metric***	***Method***	***Result***
scheme	initiation_to_credit_hours	ANOVA + pairwise t-test	Significant; all pairwise differences among the three schemes are significant
scheme	total_charges	ANOVA + pairwise t-test	Significant; all pairwise differences among the three schemes are significant
scheme	charge_rate	ANOVA + pairwise t-test	Significant; all pairwise differences among the three schemes are significant
charge_bearer	total_charges / charge_rate	ANOVA	Not significant
purpose_code	amount / total_charges / charge_rate	ANOVA	Significant
purpose_code		ANOVA	Not significant
direction	initiation_to_credit_hours	t-test	Not significant
direction	initiation_to_credit_hours total_charges / charge_rate	t-test	Significant

Table 2.6 Summary of ANOVA and t-test Results

Variable Type Definition	Variable Name	Description/ Reference Group

Variable Type	*Variable Name*	*Definition*	*Description/ Reference Group*
Dependent variable	ln(initiation_to_credit_hours)	Natural logarithm of the time from payment initiation to credit	Measures processing efficiency
Dependent variable	ln(total_charges + 1)	Natural logarithm of total charges per transaction plus 1	Measures total cost
Dependent variable	ln(charge_rate + 0.0001)	Natural logarithm of charge rate plus a small constant, where charge_rate = total_charges / amount	Measures unit cost
Key independent variable	scheme_DD	Equals 1 if the transaction is SEPA_DD, and 0 otherwise	Reference group: SEPA_CT
Key independent variable	scheme_Inst	Equals 1 if the transaction is SEPA_Inst, and 0 otherwise	Reference group: SEPA_CT
Transaction characteristic variable	ln(amount)	Natural logarithm of transaction amount	Measures transaction size
Transaction characteristic variable	purpose_income	Equals 1 if the payment purpose belongs to the income category, and 0 otherwise	Reference group: Bills/Other
Transaction characteristic variable	purpose_business	Equals 1 if the payment purpose belongs to the business/trade category, and 0 otherwise	Reference group: Bills/Other
Transaction characteristic variable	purpose_transfer	Equals 1 if the payment purpose belongs to the transfer/charity category, and 0 otherwise	Reference group: Bills/Other
Direction variable	direction_IT_IE	Equals 1 if the transaction direction is IT→IE, and 0 otherwise	Reference group: IE→IT

Table 2.7 Variable Definitions and Reference Groups for the Regression Models

Key Variable	Processing Time Model	Total Cost Model	Charge Rate Model	Summary Conclusion
ln(amount)	Not significant (p = 0.874)	Significantly positive (p < 0.001)	Significantly negative (p < 0.001)	Transaction size does not affect processing time; larger transactions are associated with

Key Variable	Processing Time Model	Total Cost Model	Charge Rate Model	Summary Conclusion
				higher total charges but lower unit charge rates
SEPA_DD	Significantly positive ($p < 0.001$)	Not significant ($p = 0.062$)	Not significant ($p = 0.316$)	DD is significantly slower than CT, but its cost difference from CT is not stable
SEPA_Inst	Significantly negative ($p < 0.001$)	Significantly positive ($p < 0.001$)	Significantly positive ($p < 0.001$)	Inst is significantly faster but also more expensive, indicating a clear speed–cost trade-off
IT→IE	Not significant ($p = 0.668$)	Significantly positive ($p < 0.001$)	Significantly positive ($p < 0.001$)	Direction mainly affects cost, but not processing time
Income category	—	Significantly positive ($p < 0.001$)	Significantly positive ($p < 0.001$)	Relative to the Bills/Other category, income-related payments have the highest cost
Business/Trade category	—	Significantly positive ($p < 0.001$)	Significantly positive ($p < 0.001$)	Relative to the Bills/Other category, business/trade payments are associated with higher costs
Transfer/Charity category	—	Significantly positive ($p < 0.001$)	Significantly positive ($p < 0.001$)	Relative to the Bills/Other category, transfer/charity payments are also associated with higher costs

Table 2.8 Summary of Main Regression Results

Model	Core Results	Comparison with the Main Model	Robustness Conclusion
Processing Time Model	SEPA_DD remains significantly positive; SEPA_Inst remains significantly negative; ln(amount) and direction remain insignificant	Consistent with the main model; R^2 decreases from 0.9805 to 0.6000, but the signs and significance of the core coefficients remain unchanged	Scheme remains the key determinant of processing time
Total Cost Model	ln(amount) remains significantly positive; SEPA_Inst remains significantly positive; direction and purpose remain significant	Broadly consistent with the main model; SEPA_DD becomes weakly significantly negative in the raw-value model, but the coefficient is very small and economically insignificant	The conclusions that Inst is more expensive and that direction and purpose affect cost remain unchanged

Model	Core Results	Comparison with the Main Model	Robustness Conclusion
Charge Rate Model	ln(amount) remains significantly negative; SEPA_Inst remains significantly positive; SEPA_DD remains insignificant; direction and purpose remain significant	Consistent with the main model; R^2 decreases to 0.3166, but the core mechanism remains unchanged	The scale effect and the higher charge rate of Inst are robust

Table 2.9 Robustness Check Results Using the Original Dependent Variables

Model	Change in Sample Size	Core Results	Comparison with the Main Model	Robustness Assessment
Processing Time Model	749,706 → 735,019	DD: significantly positive; Inst: significantly negative; ln(amount) and direction: insignificant	Highly consistent	Not sensitive to outliers
Total Cost Model	749,706 → 747,147	ln(amount): significantly positive; Inst: significantly positive; direction and purpose: significant; DD: insignificant	Results become clearer	The main model conclusions are further strengthened
Charge Rate Model	749,706 → 734,775	ln(amount): significantly negative; Inst: significantly positive; DD: insignificant	Highly consistent	The scale effect and the speed–cost trade-off are robust

Table 2.10 Robustness Check Results After Removing Extreme Values

Hypothesis	Main Evidence	Conclusion
H1: Different payment schemes significantly affect the processing time and cost performance of cross-border payments.	In the processing time model, SEPA_DD is significantly positive and SEPA_Inst is significantly negative; in the total cost and charge rate models, SEPA_Inst is significantly positive, while the difference between SEPA_DD and SEPA_CT is insignificant or unstable.	Supported
H2: Transaction size, payment purpose, and transaction direction significantly affect the cost performance of cross-border payments.	In the charge rate model, ln(amount) is significantly negative; purpose_group is significant in both the total cost and charge rate models; direction is significant in the total cost and charge rate models, but insignificant in the processing time model.	Supported

Table 2.11 Summary of Hypothesis Testing Results

Appendix Table A1 Summary of Difference Test Results

Test Module	Test Object	Method	Test Statistic	p-value	Conclusion	Additional Notes
Scheme	initiation_to_credit_hours	ANOVA	F = 562292.233	0.000		All pairwise comparisons among the three schemes are significant
Scheme	total_charges	ANOVA	F = 522829.725	0.000	Significant	All pairwise comparisons among the three schemes are significant
Scheme	charge_rate	ANOVA	F = 11322.216	0.000	Significant	SEPA_CT and SEPA_DD are not significantly different (p = 0.6444), while both differ significantly from SEPA_Inst
Charge bearer	total_charges	ANOVA	F = 0.505	0.604	Not significant	Different charge-bearing arrangements do not significantly affect total charges
Charge bearer	charge_rate	ANOVA	F = 0.179	0.836	Not significant	Different charge-bearing arrangements do not significantly affect charge rates
Purpose code	amount	ANOVA	F = 6684.949	0.000	Significant	All pairwise comparisons are significant
Purpose code	initiation_to_credit_hours	ANOVA	F = 0.844	0.596	Not significant	Different payment purposes do not significantly affect processing time
Purpose code	total_charges	ANOVA	F = 2666.635	0.000	Significant	All pairwise comparisons are

Test Module	Test Object Method	Test Statistic	p-value	Conclusion	Additional Notes
					significant
Purpose code	charge_rate ANOVA	F = 1409.730	0.000	Significant	All pairwise comparisons are significant
Direction	initiation_to_credit_hours t-test	—	> 0.05	Not significant	No significant difference in processing time between IE→IT and IT→IE
Direction	total_charges t-test	—	< 0.05	Significant	There is a significant difference in total charges between the two directions
Direction	charge_rate t-test	—	< 0.05	Significant	There is a significant difference in charge rates between the two directions

Note: The significance threshold is set at $p < 0.05$. Pairwise comparisons for ANOVA are conducted only when the overall test is significant.

Appendix Table A2 Mean Values by Key Payment Scheme Groups

Payment Scheme	Sample Size	Average Processing Time (Hours)	Average Total Charges	Average Charge Rate
SEPA_CT	562,779	23.9998	0.2158	0.01234
SEPA_DD	89,397	31.2514	0.2152	0.01229
SEPA_Inst	97,530	0.0207	0.5157	0.03057

Appendix Table A3 Classification Scheme for Payment Purpose Categories

Merged Purpose Category	Included Original Purpose Codes

Merged Purpose Category	*Included Original Purpose Codes*
Income category	SALA, BONU, COMM
Business/Trade category	GDDS, SERV, SUPP, TRAD, SCVE
Transfer/Charity category	GIFT, CHAR
Bills/Other category	UTIL, OTHR

Appendix Table B1. Summary of Main Regression Results

Variable	Processing Time Model	Total Charges Model	Charge Rate Model
Intercept	3.1329***	0.1329***	-1.9096***
ln(amount)	0.0000	0.0151***	-0.8991***
SEPA_DD	0.2538***	-0.0002	-0.0005
SEPA_Inst	-7.1300***	0.2209***	0.8607***
IT→IE	-0.0003	0.0015***	0.0103***
Income-related	—	0.0105***	0.0566***
Commercial	—	0.0076***	0.0427***
Transfer / Charity	—	0.0048***	0.0241***
R^2	0.9805	0.8200	0.9879
Adjusted R^2	0.9805	0.8200	0.9879
N	749,706	749,706	749,706

Notes:

1. The dependent variables are ln(initiation_to_credit_hours), ln(total_charges + 1), and ln(charge_rate + 0.0001), respectively.
2. The reference groups are SEPA_CT, IE→IT, and Bills / Other, respectively.
3. *** indicates $p < 0.01$; coefficients without stars are not statistically significant at the 5% level.

Appendix Table B2. Summary of Significance and Direction of Core Variables

Variable	Processing Time	Total Charges	Charge Rate	Interpretation
Payment scheme: its cost	Positive and significantly lengthens	Not significant	Not significant	DD processing time, but

Variable	Processing Time	Total Charges	Charge Rate	Interpretation
SEPA_DD				difference relative to CT is not stable
Payment scheme: SEPA_Inst	Negative and significant	Positive and significant	Positive and significant	Inst is faster but more expensive
Transaction amount	Not significant	Positive and significant	Negative and significant	Larger transaction amounts are associated with higher total charges but lower unit charge rates
Direction (IT→IE)	Not significant	Positive and significant	Positive and significant	Direction mainly affects cost rather than time
Purpose group	—	Positive and significant	Positive and significant	Purpose mainly affects the cost structure

Appendix Table C1. Robustness Check Results Using the Original Dependent Variables

Model	Sample Size	Core Results	Comparison with Main Model	Conclusion
Processing time model	749,706	SEPA_DD remains significantly positive; SEPA_Inst remains significantly negative; ln(amount) and direction remain insignificant	Consistent	Scheme remains the key determinant of processing time
Total charges model	749,706	ln(amount) is significantly positive; SEPA_Inst is significantly positive; direction and purpose_group are significant; SEPA_DD is weakly significant and negative	Broadly consistent	The conclusions that Inst is more expensive and that direction and purpose affect cost remain unchanged
Charge rate model	749,706	ln(amount) is significantly negative; SEPA_Inst is significantly positive; SEPA_DD is not significant; direction and purpose_group are significant	Consistent	The scale effect and the conclusion of a higher charge rate for Inst are robust

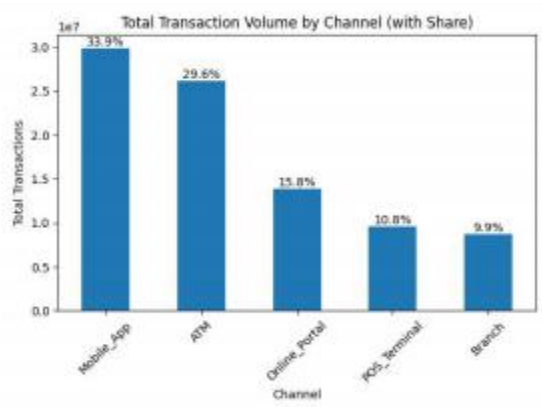
Note: The original dependent variables are initiation_to_credit_hours, total_charges, and charge_rate, respectively. Compared with the main models, the direction and significance of the core variables remain generally stable. Only SEPA_DD in the total

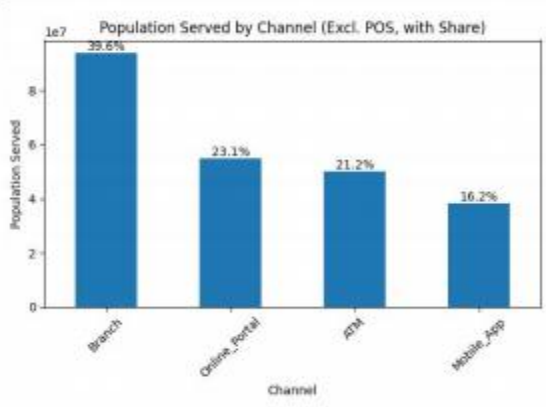
charges model becomes weakly significant, but its coefficient is small and of limited economic significance.

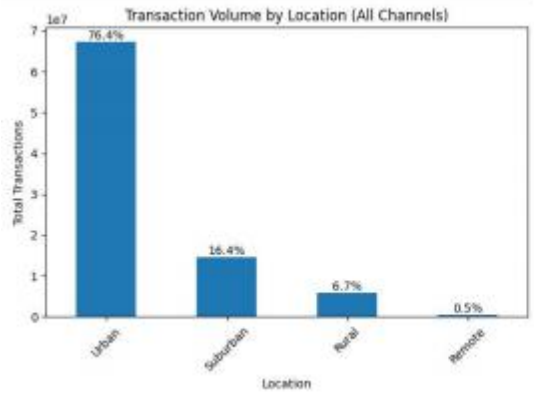
Appendix Table C2. Robustness Check Results After Removing Extreme Values

Model	Change in Sample Size	Core Results	Comparison with Main Model	Conclusion
Processing time model	749,706 → 735,019	SEPA_DD remains significantly positive; SEPA_Inst remains significantly negative; ln(amount) and direction remain insignificant	Highly consistent	Not sensitive to outlier treatment
Total charges model	749,706 → 747,147	ln(amount), SEPA_Inst, direction, and purpose_group remain significant; SEPA_DD remains insignificant	Results become clearer	The conclusions of the main model are further strengthened
Charge rate model	749,706 → 734,775	ln(amount) remains significantly negative; SEPA_Inst remains significantly positive; SEPA_DD remains insignificant; direction and purpose_group remain significant	Highly consistent	The scale effect and the speed–cost trade-off are highly robust

Note: Extreme values are treated by excluding the top and bottom 1% of observations in the distributions of the key dependent variables. The results show that the main conclusions of this study are not driven by a small number of outliers.







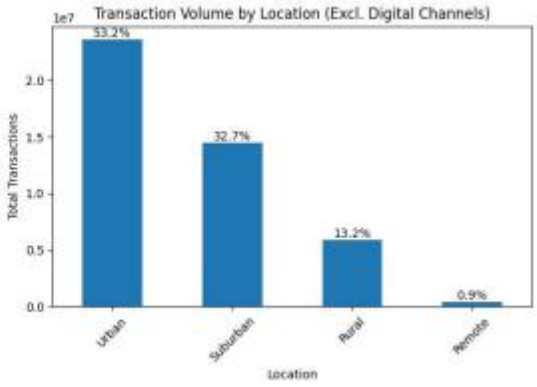
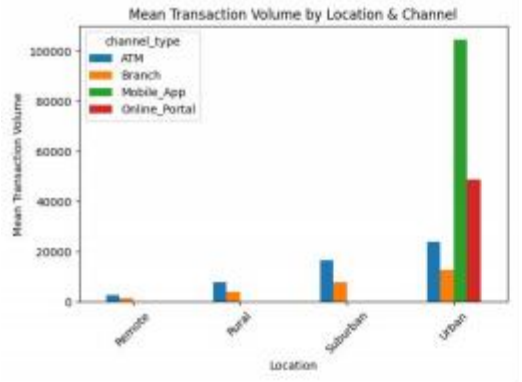
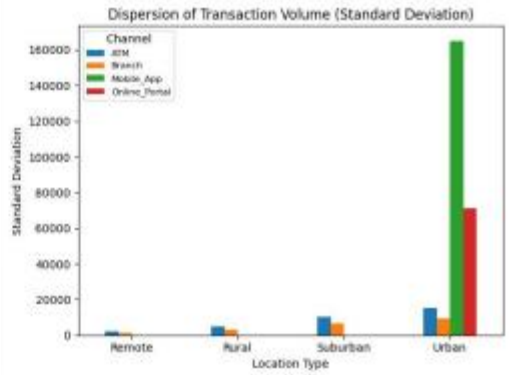


Table 3.1





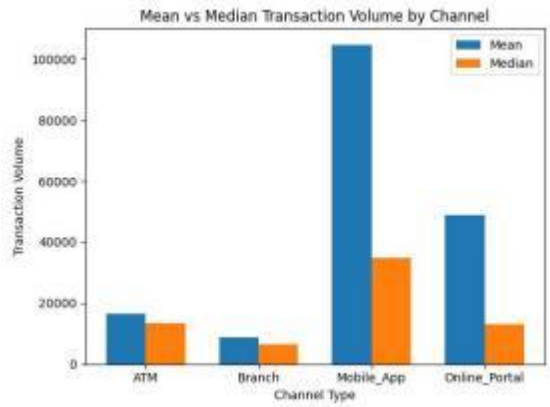


Table 3.2

```
Main model sample size: 2799

Channel type distribution:
ATM       1738
Branch    1061
Name: channel_type, dtype: int64

Location type distribution:
Urban       1071
Suburban     914
Rural        697
Remote       117
Name: location_type, dtype: int64

Inactive status distribution:
0    2593
1     206
Name: Inactive, dtype: int64
```

OLS Regression Results

Dep. Variable:	ln_tx_per_1000	R-squared:	0.299
Model:	OLS	Adj. R-squared:	0.296
Method:	Least Squares	F-statistic:	97.05
Date:	Wed, 01 Apr 2026	Prob (F-statistic):	1.24e-214
Time:	12:12:11	Log-Likelihood:	-5715.6
No. Observations:	2799	AIC:	1.146e+04
Df Residuals:	2785	BIC:	1.154e+04
Df Model:	13		
Covariance Type:	HC1		

	coef	std err	z	P>|z|	[0.025	0.975]
Intercept	8.0521	0.158	50.956	0.000	7.742	8.362
C(location_type, Treatment(reference='Urban'))[T.Suburban]	-0.4294	0.090	-4.785	0.000	-0.605	-0.254
C(location_type, Treatment(reference='Urban'))[T.Rural]	-1.2807	0.122	-10.531	0.000	-1.519	-1.042
C(location_type, Treatment(reference='Urban'))[T.Remote]	-2.1843	0.201	-10.855	0.000	-2.579	-1.790
C(county)[T.Dublin]	-1.1602	0.161	-7.228	0.000	-1.475	-0.846
C(county)[T.Mid_East]	-0.3568	0.168	-2.121	0.034	-0.687	-0.027
C(county)[T.Mid_West]	0.1432	0.188	0.760	0.447	-0.226	0.513
C(county)[T.Midlands]	0.6604	0.186	3.553	0.000	0.296	1.025
C(county)[T.Northern_and_Western]	0.3652	0.156	2.349	0.019	0.060	0.670
C(county)[T.South_East]	-0.1585	0.172	-0.923	0.356	-0.495	0.178
C(county)[T.South_West]	-0.2764	0.159	-1.733	0.083	-0.589	0.036
C(county)[T.West]	0.0895	0.178	0.502	0.615	-0.260	0.439
Branch	-2.2784	0.073	-31.125	0.000	-2.422	-2.135
Inactive	0.0741	0.139	0.532	0.595	-0.199	0.347

Omnibus:	558.075	Durbin-Watson:	0.276
Prob(Omnibus):	0.000	Jarque-Bera (JB):	953.771
Skew:	-1.311	Prob(JB):	7.78e-208
Kurtosis:	4.142	Cond. No.	14.5

```
Notes:
[1] Standard Errors are heteroscedasticity robust (HC1)

Key variable coefficients:
Branch                                                    -2.278371
C(location_type, Treatment(reference='Urban'))[T.Suburban]   -0.429365
C(location_type, Treatment(reference='Urban'))[T.Rural]     -1.280736
C(location_type, Treatment(reference='Urban'))[T.Remote]    -2.184256
Inactive                                                   0.074059
dtype: float64

Key variable significance (p-values):
Branch                                                    1.116795e-212
C(location_type, Treatment(reference='Urban'))[T.Suburban]   1.707886e-06
C(location_type, Treatment(reference='Urban'))[T.Rural]      6.237631e-26
C(location_type, Treatment(reference='Urban'))[T.Remote]     1.880202e-27
Inactive                                                    5.949171e-01
dtype: float64
```

Table 3.3

```
Robustness Check 1 sample size: 2799

Channel type distribution:
ATM       1738
Branch    1061
Name: channel_type, dtype: int64

Location type distribution:
Urban       1071
Suburban     914
Rural        697
Remote       117
Name: location_type, dtype: int64

Inactive status distribution:
0    2593
1     206
Name: Inactive, dtype: int64
```

OLS Regression Results

Dep. Variable:	ln_tx	R-squared:	0.669
Model:	OLS	Adj. R-squared:	0.667
Method:	Least Squares	F-statistic:	338.6
Date:	Wed, 01 Apr 2026	Prob (F-statistic):	0.00
Time:	12:14:02	Log-Likelihood:	-2798.1
No. Observations:	2799	AIC:	5626.
Df Residuals:	2784	BIC:	5715.
Df Model:	14		
Covariance Type:	HC1		

	coef	std err	z	P>|z|	[0.025	0.975]
Intercept	14.8283	0.123	120.501	0.000	14.587	15.069
C(location_type, Treatment(reference='Urban'))[T.Suburban]	-0.4388	0.032	-13.887	0.000	-0.501	-0.377
C(location_type, Treatment(reference='Urban'))[T.Rural]	-1.1109	0.044	-24.969	0.000	-1.198	-1.024
C(location_type, Treatment(reference='Urban'))[T.Remote]	-2.2156	0.077	-28.912	0.000	-2.366	-2.065
C(county)[T.Dublin]	0.5094	0.061	8.373	0.000	0.390	0.629
C(county)[T.Mid_East]	0.0933	0.064	1.468	0.142	-0.031	0.218
C(county)[T.Mid_West]	-0.2625	0.070	-3.773	0.000	-0.399	-0.126
C(county)[T.Midlands]	-0.2508	0.072	-3.482	0.000	-0.392	-0.110
C(county)[T.Northern_and_Western]	-0.0982	0.057	-1.711	0.087	-0.211	0.014
C(county)[T.South_East]	-0.0019	0.061	-0.032	0.975	-0.121	0.118
C(county)[T.South_West]	0.0914	0.059	1.544	0.122	-0.025	0.207
C(county)[T.West]	-0.1149	0.062	-1.847	0.065	-0.237	0.007
ln_population	-0.5621	0.013	-44.151	0.000	-0.587	-0.537
Branch	0.0895	0.030	2.960	0.003	0.030	0.149
Inactive	-0.0254	0.045	-0.559	0.576	-0.114	0.064

Omnibus:	46.826	Durbin-Watson:	1.285
Prob(Omnibus):	0.000	Jarque-Bera (JB):	64.752
Skew:	-0.202	Prob(JB):	8.69e-15
Kurtosis:	3.627	Cond. No.	120.

```
Notes:
[1] Standard Errors are heteroscedasticity robust (HC1)

Key variable coefficients:
ln_population                                                -0.562084
Branch                                                        0.089535
C(location_type, Treatment(reference='Urban'))[T.Suburban]   -0.438791
C(location_type, Treatment(reference='Urban'))[T.Rural]      -1.110882
C(location_type, Treatment(reference='Urban'))[T.Remote]     -2.215584
Inactive                                                     -0.025366
dtype: float64

Key variable significance (p-values):
ln_population                                                 0.000000e+00
Branch                                                        3.075852e-03
C(location_type, Treatment(reference='Urban'))[T.Suburban]    7.564032e-44
C(location_type, Treatment(reference='Urban'))[T.Rural]      1.321169e-137
C(location_type, Treatment(reference='Urban'))[T.Remote]     8.407785e-184
Inactive                                                      5.759191e-01
dtype: float64
```

Table 3.4

```
Robustness Check 2 sample size: 14391

Channel type distribution:
POS_Terminal    11592
ATM              1738
Branch           1061
Name: channel_type, dtype: int64

Location type distribution:
Rural       4518
Suburban    4481
Urban       4480
Remote       912
Name: location_type, dtype: int64

Inactive status distribution:
0    13937
1      454
Name: Inactive, dtype: int64
```

OLS Regression Results

Dep. Variable:	ln_tx	R-squared:	0.561
Model:	OLS	Adj. R-squared:	0.561
Method:	Least Squares	F-statistic:	1766.
Date:	Wed, 01 Apr 2026	Prob (F-statistic):	0.00
Time:	12:30:16	Log-Likelihood:	-22061.
No. Observations:	14391	AIC:	4.415e+04
Df Residuals:	14376	BIC:	4.427e+04
Df Model:	14		
Covariance Type:	HC1		

	coef	std err	z	P>|z|	[0.025	0.975]
Intercept	9.8684	0.044	223.582	0.000	9.782	9.955
C(location_type, Treatment(reference='Urban'))[T.Suburban]	-0.4186	0.026	-16.298	0.000	-0.469	-0.368
C(location_type, Treatment(reference='Urban'))[T.Rural]	-1.1290	0.031	-36.082	0.000	-1.190	-1.068
C(location_type, Treatment(reference='Urban'))[T.Remote]	-2.0495	0.047	-43.655	0.000	-2.142	-1.957
C(county)[T.Dublin]	-0.0732	0.044	-1.662	0.096	-0.160	0.013
C(county)[T.Mid_East]	-0.0590	0.046	-1.289	0.197	-0.149	0.031
C(county)[T.Mid_West]	-0.0675	0.043	-1.566	0.117	-0.152	0.017
C(county)[T.Midlands]	-0.0044	0.040	-0.109	0.913	-0.083	0.074
C(county)[T.Northern_and_Western]	0.0311	0.039	0.804	0.421	-0.045	0.107
C(county)[T.South_East]	-0.0333	0.042	-0.793	0.428	-0.116	0.049
C(county)[T.South_West]	-0.0427	0.042	-1.027	0.304	-0.124	0.039
C(county)[T.West]	-0.0458	0.043	-1.077	0.281	-0.129	0.038
Branch	-0.7829	0.038	-20.457	0.000	-0.858	-0.708
POS	-3.0038	0.024	-125.622	0.000	-3.051	-2.957
Inactive	0.0419	0.050	0.842	0.400	-0.056	0.139

Omnibus:	4198.258	Durbin-Watson:	0.434
Prob(Omnibus):	0.000	Jarque-Bera (JB):	10422.206
Skew:	-1.621	Prob(JB):	0.00
Kurtosis:	5.622	Cond. No.	16.1

```
Notes:
[1] Standard Errors are heteroscedasticity robust (HC1)

Key variable coefficients:
Branch                                                    -0.782878
POS                                                       -3.003806
C(location_type, Treatment(reference='Urban'))[T.Suburban]  -0.418568
C(location_type, Treatment(reference='Urban'))[T.Rural]     -1.128967
C(location_type, Treatment(reference='Urban'))[T.Remote]    -2.049508
Inactive                                                   0.041859
dtype: float64

Key variable significance (p-values):
Branch                                                     5.159948e-93
POS                                                        0.000000e+00
C(location_type, Treatment(reference='Urban'))[T.Suburban]  1.013570e-59
C(location_type, Treatment(reference='Urban'))[T.Rural]    4.406963e-285
C(location_type, Treatment(reference='Urban'))[T.Remote]    0.000000e+00
Inactive                                                   3.999113e-01
dtype: float64
```

Table 3.5

```
Robustness Check 3 sample size: 2593

Channel type distribution:
ATM       1592
Branch    1001
Name: channel_type, dtype: int64

Location type distribution:
Urban       986
Suburban    856
Rural       640
Remote      111
Name: location_type, dtype: int64
                            OLS Regression Results
==============================================================================
Dep. Variable:         ln_tx_per_1000   R-squared:                       0.299
Model:                            OLS   Adj. R-squared:                  0.296
Method:                 Least Squares   F-statistic:                     96.69
Date:                Wed, 01 Apr 2026   Prob (F-statistic):          7.60e-198
Time:                        12:35:59   Log-Likelihood:                -5289.4
No. Observations:                2593   AIC:                         1.060e+04
Df Residuals:                    2580   BIC:                         1.068e+04
Df Model:                          12
Covariance Type:                  HC1
=================================================================================================================================
                                                                    coef    std err          z      P>|z|      [0.025      0.975]
---------------------------------------------------------------------------------------------------------------------------------
Intercept                                                          8.0442      0.164     49.061      0.000       7.723       8.366
C(location_type, Treatment(reference='Urban'))[T.Suburban]        -0.4578      0.093     -4.921      0.000      -0.640      -0.275
C(location_type, Treatment(reference='Urban'))[T.Rural]           -1.2934      0.125    -10.328      0.000      -1.539      -1.048
C(location_type, Treatment(reference='Urban'))[T.Remote]          -2.1860      0.208    -10.520      0.000      -2.593      -1.779
C(county)[T.Dublin]                                               -1.1325      0.167     -6.775      0.000      -1.460      -0.805
C(county)[T.Mid_East]                                             -0.3146      0.175     -1.803      0.071      -0.657       0.027
C(county)[T.Mid_West]                                              0.1392      0.197      0.706      0.480      -0.247       0.525
C(county)[T.Midlands]                                              0.6466      0.195      3.323      0.001       0.265       1.028
C(county)[T.Northern_and_Western]                                  0.3452      0.165      2.094      0.036       0.022       0.668
C(county)[T.South_East]                                           -0.1838      0.181     -1.018      0.309      -0.538       0.170
C(county)[T.South_West]                                           -0.2171      0.164     -1.323      0.186      -0.539       0.105
C(county)[T.West]                                                  0.1292      0.182      0.711      0.477      -0.227       0.486
Branch                                                            -2.2737      0.075    -30.138      0.000      -2.422      -2.126
==============================================================================
Omnibus:                      509.384   Durbin-Watson:                   0.282
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              861.437
Skew:                          -1.300   Prob(JB):                    8.74e-188
Kurtosis:                       4.100   Cond. No.                         14.5
==============================================================================

Notes:
[1] Standard Errors are heteroscedasticity robust (HC1)

Key variable coefficients:
Branch                                                   -2.273678
C(location_type, Treatment(reference='Urban'))[T.Suburban]   -0.457838
C(location_type, Treatment(reference='Urban'))[T.Rural]      -1.293420
C(location_type, Treatment(reference='Urban'))[T.Remote]     -2.185966
dtype: float64

Key variable significance (p-values):
Branch                                                    1.548462e-199
C(location_type, Treatment(reference='Urban'))[T.Suburban]   8.614989e-07
C(location_type, Treatment(reference='Urban'))[T.Rural]      5.265989e-25
C(location_type, Treatment(reference='Urban'))[T.Remote]     6.986339e-26
dtype: float64
```

Table 3.6

```
Robustness Check 4 sample size: 2799

Channel type distribution:
ATM       1738
Branch    1061
Name: channel_type, dtype: int64

Location type distribution:
Urban       1071
Suburban     914
Rural        697
Remote       117
Name: location_type, dtype: int64

Inactive status distribution:
0    2593
1     206
Name: Inactive, dtype: int64

low_usage distribution:
0    2098
1     701
Name: low_usage, dtype: int64

low_usage share by channel type:
channel_type
ATM       0.250288
Branch    0.250707
Name: low_usage, dtype: float64

low_usage share by location type:
location_type
Urban       0.223156
Suburban    0.236324
Rural       0.278336
Remote      0.444444
Name: low_usage, dtype: float64
```

Logit Regression Results

Dep. Variable:	low_usage	No. Observations:	2799
Model:	Logit	Df Residuals:	2785
Method:	MLE	Df Model:	13
Date:	Wed, 01 Apr 2026	Pseudo R-squ.:	0.02711
Time:	12:39:56	Log-Likelihood:	-1532.6
converged:	True	LL-Null:	-1575.3
Covariance Type:	nonrobust	LLR p-value:	1.042e-12

	coef	std err	z	P>|z|	[0.025	0.975]
Intercept	-1.6144	0.203	-7.945	0.000	-2.013	-1.216
C(location_type, Treatment(reference='Urban'))[T.Suburban]	0.2874	0.116	2.474	0.013	0.060	0.515
C(location_type, Treatment(reference='Urban'))[T.Rural]	0.7670	0.162	4.747	0.000	0.450	1.084
C(location_type, Treatment(reference='Urban'))[T.Remote]	1.6017	0.257	6.230	0.000	1.098	2.106
C(county)[T.Dublin]	0.7060	0.201	3.512	0.000	0.312	1.100
C(county)[T.Mid_East]	-0.0992	0.228	-0.435	0.663	-0.546	0.348
C(county)[T.Mid_West]	-0.2065	0.255	-0.811	0.417	-0.706	0.293
C(county)[T.Midlands]	-0.5393	0.253	-2.132	0.033	-1.035	-0.044
C(county)[T.Northern_and_Western]	-0.2343	0.196	-1.197	0.231	-0.618	0.149
C(county)[T.South_East]	-0.0294	0.213	-0.138	0.891	-0.448	0.389
C(county)[T.South_West]	0.1378	0.197	0.699	0.485	-0.249	0.524
C(county)[T.West]	-0.1682	0.224	-0.752	0.452	-0.607	0.270
Branch	0.0177	0.092	0.193	0.847	-0.162	0.197
Inactive	-0.0039	0.171	-0.023	0.982	-0.338	0.330

Table 3.7(1)

Odds ratio results:

	coef	odds_ratio	\
Branch	0.017683	1.017840	
C(location_type, Treatment(reference='Urban'))[...	0.287403	1.332962	
C(location_type, Treatment(reference='Urban'))[...	0.766969	2.153230	
C(location_type, Treatment(reference='Urban'))[...	1.601690	4.961408	
Inactive	-0.003909	0.996099	

	ci_lower_or	ci_upper_or	\
Branch	0.850653	1.217887	
C(location_type, Treatment(reference='Urban'))[...	1.061512	1.673826	
C(location_type, Treatment(reference='Urban'))[...	1.568745	2.955482	
C(location_type, Treatment(reference='Urban'))[...	2.997537	8.211932	
Inactive	0.713078	1.391451	

	p_value
Branch	8.468397e-01
C(location_type, Treatment(reference='Urban'))[...	1.336945e-02
C(location_type, Treatment(reference='Urban'))[...	2.068110e-06
C(location_type, Treatment(reference='Urban'))[...	4.666401e-10
Inactive	9.817143e-01

Average marginal effects:

Logit Marginal Effects

Dep. Variable:	low_usage
Method:	dydx
At:	overall

	dy/dx	std err	z	P>|z|	[0.025	0.975]
C(location_type, Treatment(reference='Urban'))[T.Suburban]	0.0523	0.021	2.481	0.013	0.011	0.094
C(location_type, Treatment(reference='Urban'))[T.Rural]	0.1395	0.029	4.797	0.000	0.083	0.197
C(location_type, Treatment(reference='Urban'))[T.Remote]	0.2914	0.046	6.368	0.000	0.202	0.381
C(county)[T.Dublin]	0.1285	0.036	3.532	0.000	0.057	0.200
C(county)[T.Mid_East]	-0.0181	0.041	-0.435	0.663	-0.099	0.063
C(county)[T.Mid_West]	-0.0376	0.046	-0.811	0.417	-0.128	0.053
C(county)[T.Midlands]	-0.0981	0.046	-2.138	0.033	-0.188	-0.008
C(county)[T.Northern_and_Western]	-0.0426	0.036	-1.198	0.231	-0.112	0.027
C(county)[T.South_East]	-0.0053	0.039	-0.138	0.891	-0.081	0.071
C(county)[T.South_West]	0.0251	0.036	0.699	0.485	-0.045	0.095
C(county)[T.West]	-0.0306	0.041	-0.752	0.452	-0.110	0.049
Branch	0.0032	0.017	0.193	0.847	-0.029	0.036
Inactive	-0.0007	0.031	-0.023	0.982	-0.062	0.060

Table 3.7(2)

```
============================================================
Heterogeneity Analysis 1: Urban subsample
============================================================
Sample size: 1071
Channel type distribution:
ATM       648
Branch    423
Name: channel_type, dtype: int64
                            OLS Regression Results
==============================================================================
Dep. Variable:         ln_tx_per_1000   R-squared:                       0.267
Model:                            OLS   Adj. R-squared:                  0.262
Method:                 Least Squares   F-statistic:                     60.49
Date:                Wed, 01 Apr 2026   Prob (F-statistic):           3.53e-73
Time:                        12:42:54   Log-Likelihood:                -2210.9
No. Observations:                1071   AIC:                             4438.
Df Residuals:                    1063   BIC:                             4478.
Df Model:                           7
Covariance Type:                  HC1
================================================================================================
                                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------------------------
Intercept                     6.8604      0.102     67.512      0.000       6.661       7.060
C(county)[T.Mid_East]         0.7663      0.144      5.328      0.000       0.484       1.048
C(county)[T.Mid_West]         1.2025      0.257      4.683      0.000       0.699       1.706
C(county)[T.South_East]       1.0139      0.236      4.300      0.000       0.552       1.476
C(county)[T.South_West]       1.0504      0.206      5.110      0.000       0.648       1.453
C(county)[T.West]             1.4661      0.232      6.311      0.000       1.011       1.921
Branch                       -2.1829      0.119    -18.345      0.000      -2.416      -1.950
Inactive                     -0.1968      0.244     -0.806      0.420      -0.675       0.282
==============================================================================
Omnibus:                      227.203   Durbin-Watson:                   0.381
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              391.831
Skew:                          -1.348   Prob(JB):                     8.22e-86
Kurtosis:                       4.228   Cond. No.                         6.04
==============================================================================

Notes:
[1] Standard Errors are heteroscedasticity robust (HC1)

Key variable coefficients:
Branch     -2.182887
Inactive   -0.196774
dtype: float64

Key variable significance (p-values):
Branch      3.640460e-75
Inactive    4.203168e-01
dtype: float64
```

Table 3.8(1)

```
============================================================
Heterogeneity Analysis 1: Suburban subsample
============================================================
Sample size: 914
Channel type distribution:
ATM       569
Branch    345
Name: channel_type, dtype: int64
                            OLS Regression Results
==============================================================================
Dep. Variable:         ln_tx_per_1000   R-squared:                       0.330
Model:                            OLS   Adj. R-squared:                  0.323
Method:                 Least Squares   F-statistic:                     51.60
Date:                Wed, 01 Apr 2026   Prob (F-statistic):           7.45e-82
Time:                        12:42:54   Log-Likelihood:                -1859.4
No. Observations:                 914   AIC:                             3741.
Df Residuals:                     903   BIC:                             3794.
Df Model:                          10
Covariance Type:                  HC1
==============================================================================================================
                                    coef    std err          z      P>|z|      [0.025      0.975]
--------------------------------------------------------------------------------------------------------------
Intercept                        7.7451      0.244     31.683      0.000       7.266       8.224
C(county)[T.Dublin]             -1.2064      0.270     -4.473      0.000      -1.735      -0.678
C(county)[T.Mid_East]           -0.3400      0.278     -1.222      0.222      -0.885       0.205
C(county)[T.Mid_West]            0.0617      0.315      0.196      0.845      -0.555       0.678
C(county)[T.Midlands]            0.7782      0.393      1.980      0.048       0.008       1.549
C(county)[T.Northern_and_Western]    0.3213      0.319      1.006      0.314      -0.305       0.947
C(county)[T.South_East]         -0.2349      0.304     -0.773      0.440      -0.831       0.361
C(county)[T.South_West]         -0.5228      0.292     -1.788      0.074      -1.096       0.050
C(county)[T.West]               -0.1964      0.321     -0.612      0.541      -0.825       0.432
Branch                          -2.4015      0.130    -18.475      0.000      -2.656      -2.147
Inactive                         0.2767      0.223      1.243      0.214      -0.160       0.713
==============================================================================
Omnibus:                      181.240   Durbin-Watson:                   0.420
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              300.375
Skew:                          -1.280   Prob(JB):                     5.95e-66
Kurtosis:                       4.156   Cond. No.                         15.3
==============================================================================

Notes:
[1] Standard Errors are heteroscedasticity robust (HC1)

Key variable coefficients:
Branch     -2.401501
Inactive    0.276660
dtype: float64

Key variable significance (p-values):
Branch      3.268856e-76
Inactive    2.138972e-01
dtype: float64
```

Table 3.8(2)

```
============================================================
Heterogeneity Analysis 1: Rural subsample
============================================================
Sample size: 697
Channel type distribution:
ATM       449
Branch    248
Name: channel_type, dtype: int64
                            OLS Regression Results
==============================================================================
Dep. Variable:         ln_tx_per_1000   R-squared:                       0.272
Model:                            OLS   Adj. R-squared:                  0.264
Method:                 Least Squares   F-statistic:                     32.71
Date:                Wed, 01 Apr 2026   Prob (F-statistic):           1.04e-43
Time:                        12:42:54   Log-Likelihood:                -1411.7
No. Observations:                 697   AIC:                             2841.
Df Residuals:                     688   BIC:                             2882.
Df Model:                           8
Covariance Type:                  HC1
=================================================================================================================
                                    coef    std err          z      P>|z|      [0.025      0.975]
-----------------------------------------------------------------------------------------------------------------
Intercept                         6.6491      0.153     43.447      0.000       6.349       6.949
C(county)[T.Mid_West]             0.4082      0.324      1.260      0.208      -0.227       1.043
C(county)[T.Midlands]             0.6759      0.247      2.739      0.006       0.192       1.160
C(county)[T.Northern_and_Western] 0.5345      0.204      2.619      0.009       0.134       0.934
C(county)[T.South_East]          -0.0932      0.257     -0.362      0.717      -0.598       0.411
C(county)[T.South_West]          -0.1044      0.225     -0.464      0.643      -0.545       0.337
C(county)[T.West]                 0.2464      0.267      0.922      0.357      -0.278       0.770
Branch                           -2.2553      0.148    -15.215      0.000      -2.546      -1.965
Inactive                          0.2507      0.255      0.982      0.326      -0.250       0.751
==============================================================================
Omnibus:                      132.440   Durbin-Watson:                   0.446
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              209.898
Skew:                          -1.260   Prob(JB):                     2.64e-46
Kurtosis:                       3.936   Cond. No.                         6.85
==============================================================================

Notes:
[1] Standard Errors are heteroscedasticity robust (HC1)

Key variable coefficients:
Branch     -2.255349
Inactive    0.250746
dtype: float64

Key variable significance (p-values):
Branch      2.820199e-52
Inactive    3.260825e-01
dtype: float64
```

Table 3.8(3)

```
============================================================
Heterogeneity Analysis 1: Remote subsample
============================================================
Sample size: 117
Channel type distribution:
ATM       72
Branch    45
Name: channel_type, dtype: int64
                            OLS Regression Results
==============================================================================
Dep. Variable:         ln_tx_per_1000   R-squared:                       0.338
Model:                            OLS   Adj. R-squared:                  0.315
Method:                 Least Squares   F-statistic:                     13.33
Date:                Wed, 01 Apr 2026   Prob (F-statistic):           6.46e-09
Time:                        12:42:54   Log-Likelihood:                -223.99
No. Observations:                 117   AIC:                             458.0
Df Residuals:                     112   BIC:                             471.8
Df Model:                           4
Covariance Type:                  HC1
=================================================================================================================
                                    coef    std err          z      P>|z|      [0.025      0.975]
-----------------------------------------------------------------------------------------------------------------
Intercept                         6.1976      0.272     22.755      0.000       5.664       6.731
C(county)[T.Midlands]             0.3718      0.402      0.926      0.354      -0.415       1.159
C(county)[T.Northern_and_Western]    -0.3267      0.360     -0.907      0.364      -1.033       0.379
Branch                           -2.3351      0.331     -7.055      0.000      -2.984      -1.686
Inactive                          0.4237      0.701      0.604      0.546      -0.951       1.798
==============================================================================
Omnibus:                       24.575   Durbin-Watson:                   0.797
Prob(Omnibus):                  0.000   Jarque-Bera (JB):               32.254
Skew:                          -1.249   Prob(JB):                     9.91e-08
Kurtosis:                       3.609   Cond. No.                         5.41
==============================================================================

Notes:
[1] Standard Errors are heteroscedasticity robust (HC1)

Key variable coefficients:
Branch     -2.335099
Inactive    0.423680
dtype: float64

Key variable significance (p-values):
Branch      1.732008e-12
Inactive    5.457467e-01
dtype: float64
```

Table 3.8(4)

```
Population group sample size:
LowPop       1036
HighPop       939
MediumPop     824
Name: pop_group, dtype: int64

============================================================
Heterogeneity Analysis 2: LowPop subsample
============================================================
Sample size: 1036
Location type distribution:
Suburban    355
Urban       340
Rural       282
Remote       59
Name: location_type, dtype: int64
                            OLS Regression Results
==============================================================================
Dep. Variable:         ln_tx_per_1000   R-squared:                       0.505
Model:                            OLS   Adj. R-squared:                  0.499
Method:                 Least Squares   F-statistic:                     87.48
Date:                Wed, 01 Apr 2026   Prob (F-statistic):          8.34e-156
Time:                        12:59:18   Log-Likelihood:                -843.62
No. Observations:                1036   AIC:                             1715.
Df Residuals:                    1022   BIC:                             1784.
Df Model:                          13
Covariance Type:                  HC1
================================================================================================================================
                                                                   coef    std err          z      P>|z|      [0.025      0.975]
--------------------------------------------------------------------------------------------------------------------------------
Intercept                                                        8.8759      0.076    117.520      0.000       8.728       9.024
C(location_type, Treatment(reference='Urban'))[T.Suburban]      -0.4061      0.044     -9.319      0.000      -0.491      -0.321
C(location_type, Treatment(reference='Urban'))[T.Rural]         -1.1376      0.062    -18.239      0.000      -1.260      -1.015
C(location_type, Treatment(reference='Urban'))[T.Remote]        -2.1910      0.097    -22.508      0.000      -2.382      -2.000
C(county)[T.Dublin]                                             -0.7071      0.078     -9.012      0.000      -0.861      -0.553
C(county)[T.Mid_East]                                           -0.2424      0.081     -2.990      0.003      -0.401      -0.084
C(county)[T.Mid_West]                                            0.1784      0.094      1.896      0.058      -0.006       0.363
C(county)[T.Midlands]                                            0.4138      0.103      4.016      0.000       0.212       0.616
C(county)[T.Northern_and_Western]                                0.3028      0.072      4.235      0.000       0.163       0.443
C(county)[T.South_East]                                          0.1781      0.083      2.153      0.031       0.016       0.340
C(county)[T.South_West]                                         -0.0418      0.078     -0.538      0.591      -0.194       0.111
C(county)[T.West]                                                0.2243      0.087      2.590      0.010       0.055       0.394
Branch                                                          -1.4552      0.154     -9.429      0.000      -1.758      -1.153
Inactive                                                         0.0556      0.058      0.960      0.337      -0.058       0.169
==============================================================================
Omnibus:                        4.418   Durbin-Watson:                   1.702
Prob(Omnibus):                  0.110   Jarque-Bera (JB):                4.255
Skew:                          -0.120   Prob(JB):                        0.119
Kurtosis:                       2.796   Cond. No.                         13.3
==============================================================================

Notes:
[1] Standard Errors are heteroscedasticity robust (HC1)

Key variable coefficients:
Branch                                                  -1.455160
C(location_type, Treatment(reference='Urban'))[T.Suburban]  -0.406084
C(location_type, Treatment(reference='Urban'))[T.Rural]     -1.137591
C(location_type, Treatment(reference='Urban'))[T.Remote]    -2.190966
Inactive                                                 0.055566
dtype: float64

Key variable significance (p-values):
Branch                                                   4.150581e-21
C(location_type, Treatment(reference='Urban'))[T.Suburban]   1.169739e-20
C(location_type, Treatment(reference='Urban'))[T.Rural]      2.518048e-74
C(location_type, Treatment(reference='Urban'))[T.Remote]    3.503045e-112
Inactive                                                 3.371330e-01
dtype: float64
```

Table 3.9(1)

```
============================================================
Heterogeneity Analysis 2: MediumPop subsample
============================================================
Sample size: 824
Location type distribution:
Urban       296
Suburban    254
Rural       241
Remote       33
Name: location_type, dtype: int64
                            OLS Regression Results
==============================================================================
Dep. Variable:         ln_tx_per_1000   R-squared:                       0.446
Model:                            OLS   Adj. R-squared:                  0.438
Method:                 Least Squares   F-statistic:                     55.30
Date:                Wed, 01 Apr 2026   Prob (F-statistic):          2.31e-102
Time:                        12:59:18   Log-Likelihood:                -825.42
No. Observations:                 824   AIC:                             1679.
Df Residuals:                     810   BIC:                             1745.
Df Model:                          13
Covariance Type:                  HC1
================================================================================================================================
                                                                   coef    std err          z      P>|z|      [0.025      0.975]
--------------------------------------------------------------------------------------------------------------------------------
Intercept                                                        7.4937      0.109     68.876      0.000       7.280       7.707
C(location_type, Treatment(reference='Urban'))[T.Suburban]      -0.4099      0.059     -6.982      0.000      -0.525      -0.295
C(location_type, Treatment(reference='Urban'))[T.Rural]         -1.1052      0.082    -13.431      0.000      -1.266      -0.944
C(location_type, Treatment(reference='Urban'))[T.Remote]        -2.2180      0.147    -15.098      0.000      -2.506      -1.930
C(county)[T.Dublin]                                             -0.1334      0.117     -1.144      0.253      -0.362       0.095
C(county)[T.Mid_East]                                           -0.1201      0.104     -1.152      0.249      -0.324       0.084
C(county)[T.Mid_West]                                            0.0694      0.123      0.566      0.572      -0.171       0.310
C(county)[T.Midlands]                                           -0.2973      0.164     -1.808      0.071      -0.620       0.025
C(county)[T.Northern_and_Western]                                0.2789      0.105      2.660      0.008       0.073       0.484
C(county)[T.South_East]                                         -0.0442      0.103     -0.431      0.667      -0.246       0.157
C(county)[T.South_West]                                          0.0328      0.099      0.332      0.740      -0.161       0.227
C(county)[T.West]                                                0.1334      0.106      1.257      0.209      -0.075       0.341
Branch                                                          -0.4748      0.054     -8.720      0.000      -0.582      -0.368
Inactive                                                         0.1219      0.088      1.391      0.164      -0.050       0.294
==============================================================================
Omnibus:                       19.098   Durbin-Watson:                   1.619
Prob(Omnibus):                  0.000   Jarque-Bera (JB):               19.789
Skew:                          -0.368   Prob(JB):                     5.05e-05
Kurtosis:                       3.185   Cond. No.                         14.1
==============================================================================

Notes:
[1] Standard Errors are heteroscedasticity robust (HC1)

Key variable coefficients:
Branch                                                  -0.474832
C(location_type, Treatment(reference='Urban'))[T.Suburban]  -0.409918
C(location_type, Treatment(reference='Urban'))[T.Rural]     -1.105208
C(location_type, Treatment(reference='Urban'))[T.Remote]    -2.218027
Inactive                                                 0.121887
dtype: float64

Key variable significance (p-values):
Branch                                                  2.784944e-18
C(location_type, Treatment(reference='Urban'))[T.Suburban]  2.919017e-12
C(location_type, Treatment(reference='Urban'))[T.Rural]     3.990871e-41
C(location_type, Treatment(reference='Urban'))[T.Remote]    1.677796e-51
Inactive                                                 1.643319e-01
dtype: float64
```

Table 3.9(2)

```
============================================================
Heterogeneity Analysis 2: HighPop subsample
============================================================
Sample size: 939
Location type distribution:
Urban       435
Suburban    305
Rural       174
Remote       25
Name: location_type, dtype: int64
                            OLS Regression Results
==============================================================================
Dep. Variable:         ln_tx_per_1000   R-squared:                       0.128
Model:                            OLS   Adj. R-squared:                  0.116
Method:                 Least Squares   F-statistic:                     13.10
Date:                Wed, 01 Apr 2026   Prob (F-statistic):           7.21e-27
Time:                        12:59:18   Log-Likelihood:                -1807.5
No. Observations:                 939   AIC:                             3643.
Df Residuals:                     925   BIC:                             3711.
Df Model:                          13
Covariance Type:                  HC1
================================================================================================================================
                                                                   coef    std err          z      P>|z|      [0.025      0.975]
--------------------------------------------------------------------------------------------------------------------------------
Intercept                                                        4.1205      0.263     15.668      0.000       3.605       4.636
C(location_type, Treatment(reference='Urban'))[T.Suburban]      -0.4538      0.135     -3.365      0.001      -0.718      -0.190
C(location_type, Treatment(reference='Urban'))[T.Rural]         -1.1810      0.207     -5.718      0.000      -1.586      -0.776
C(location_type, Treatment(reference='Urban'))[T.Remote]        -2.1968      0.345     -6.369      0.000      -2.873      -1.521
C(county)[T.Dublin]                                              0.1634      0.262      0.623      0.533      -0.351       0.677
C(county)[T.Mid_East]                                           -0.1847      0.281     -0.656      0.512      -0.736       0.367
C(county)[T.Mid_West]                                           -0.5320      0.306     -1.740      0.082      -1.131       0.067
C(county)[T.Midlands]                                           -0.2438      0.351     -0.695      0.487      -0.931       0.443
C(county)[T.Northern_and_Western]                               -0.0837      0.260     -0.322      0.748      -0.594       0.426
C(county)[T.South_East]                                         -0.1910      0.266     -0.718      0.473      -0.713       0.331
C(county)[T.South_West]                                         -0.3538      0.257     -1.376      0.169      -0.858       0.150
C(county)[T.West]                                               -0.1887      0.285     -0.663      0.507      -0.747       0.369
Branch                                                           0.3033      0.118      2.561      0.010       0.071       0.535
Inactive                                                        -0.2894      0.240     -1.207      0.227      -0.759       0.180
==============================================================================
Omnibus:                       68.801   Durbin-Watson:                   0.640
Prob(Omnibus):                  0.000   Jarque-Bera (JB):               43.846
Skew:                          -0.402   Prob(JB):                     3.01e-10
Kurtosis:                       2.311   Cond. No.                         18.9
==============================================================================

Notes:
[1] Standard Errors are heteroscedasticity robust (HC1)

Key variable coefficients:
Branch                                                    0.303327
C(location_type, Treatment(reference='Urban'))[T.Suburban]   -0.453810
C(location_type, Treatment(reference='Urban'))[T.Rural]      -1.180967
C(location_type, Treatment(reference='Urban'))[T.Remote]     -2.196782
Inactive                                                  -0.289444
dtype: float64

Key variable significance (p-values):
Branch                                                    1.043706e-02
C(location_type, Treatment(reference='Urban'))[T.Suburban]   7.640603e-04
C(location_type, Treatment(reference='Urban'))[T.Rural]      1.077714e-08
C(location_type, Treatment(reference='Urban'))[T.Remote]     1.902320e-10
Inactive                                                  2.273429e-01
dtype: float64
```

Table 3.9(3)

```
Heterogeneity Analysis 3 sample size: 2799

Channel type distribution:
ATM       1738
Branch    1061
Name: channel_type, dtype: int64

RuralRemote distribution:
0    1985
1     814
Name: RuralRemote, dtype: int64

HighPop distribution:
0    1860
1     939
Name: HighPop, dtype: int64

Interaction distribution:
0    2600
1     199
Name: Interaction, dtype: int64

Inactive status distribution:
0    2593
1     206
Name: Inactive, dtype: int64
```

OLS Regression Results

Dep. Variable:	ln_tx_per_1000	R-squared:	0.685
Model:	OLS	Adj. R-squared:	0.683
Method:	Least Squares	F-statistic:	377.9
Date:	Wed, 01 Apr 2026	Prob (F-statistic):	0.00
Time:	13:05:48	Log-Likelihood:	-4598.1
No. Observations:	2799	AIC:	9224.
Df Residuals:	2785	BIC:	9307.
Df Model:	13		
Covariance Type:	HC1		

	coef	std err	z	P>|z|	[0.025	0.975]
Intercept	7.8696	0.084	93.449	0.000	7.705	8.035
C(county)[T.Dublin]	0.1248	0.100	1.253	0.210	-0.070	0.320
C(county)[T.Mid_East]	0.0434	0.099	0.439	0.660	-0.150	0.237
C(county)[T.Mid_West]	0.2014	0.112	1.801	0.072	-0.018	0.421
C(county)[T.Midlands]	0.3397	0.123	2.771	0.006	0.099	0.580
C(county)[T.Northern_and_Western]	0.2548	0.094	2.706	0.007	0.070	0.439
C(county)[T.South_East]	0.1740	0.104	1.679	0.093	-0.029	0.377
C(county)[T.South_West]	0.0332	0.094	0.353	0.724	-0.151	0.218
C(county)[T.West]	0.2509	0.104	2.409	0.016	0.047	0.455
RuralRemote	-0.8700	0.063	-13.770	0.000	-0.994	-0.746
HighPop	-3.3739	0.077	-43.773	0.000	-3.525	-3.223
Interaction	-0.4417	0.133	-3.325	0.001	-0.702	-0.181
Branch	-0.7345	0.058	-12.633	0.000	-0.848	-0.621
Inactive	0.0626	0.090	0.692	0.489	-0.115	0.240

Omnibus:	54.764	Durbin-Watson:	1.198
Prob(Omnibus):	0.000	Jarque-Bera (JB):	61.900
Skew:	-0.298	Prob(JB):	3.62e-14
Kurtosis:	3.418	Cond. No.	14.0

```
Notes:
[1] Standard Errors are heteroscedasticity robust (HC1)

Key variable coefficients:
RuralRemote   -0.869969
HighPop       -3.373851
Interaction   -0.441728
Branch        -0.734453
Inactive       0.062551
dtype: float64

Key variable significance (p-values):
RuralRemote    3.867049e-43
HighPop        0.000000e+00
Interaction    8.854119e-04
Branch         1.382381e-36
Inactive       4.888243e-01
dtype: float64
```

Table 3.10

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