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Patricio Saavedra-Espinosa[1,2], Nelson León-Silva[1], María Teresa Espinosa-Jaramillo[3], and Jairo Dote-Pardo[1,2*]

Abstract

This study examines the factors associated with bank credit card usage from a banking ecosystem perspective. The analysis uses nationally representative microdata from the 2024 Household Financial Survey conducted by the Central Bank of Chile. Survey-adjusted Probit models are estimated under a complex, stratified, and clustered sampling design incorporating expansion weights and bootstrap replicate weights. Average marginal effects and predicted probabilities are computed to assess economic significance and segmentation patterns. Income and education are positively and significantly associated with the probability of credit card usage, consistent with a structural capacity channel. Digital financial engagement is strongly and positively associated with credit card usage across specifications; traditional banking integration is also positively associated with it, although the magnitude of this association depends on how its two indicators are weighted. Homeownership, our proxy for asset ownership, is negatively associated with usage, contrary to the hypothesized direction. The structural block alone shows a higher goodness of fit than the ecosystem block alone, though combining both fits better than either. We do not find robust statistical evidence that the two ecosystem dimensions reinforce each other: their interaction is not significant in our primary specification, although a sensitivity check using a linear probability model suggests one. Because the design is cross-sectional, the results describe associations and should not be interpreted as causal effects.

Keywords: Bank credit cards; Banking ecosystems; Digital banking; Household finance; Relationship marketing; Emerging markets.

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Abstract

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1. Introduction

Understanding how customers integrate into banking ecosystems has become a central concern for both scholars and practitioners in financial services (Ofori-Okyere & Edghiem, 2026). In increasingly digitalized financial environments, banks no longer compete solely through individual products but through interconnected portfolios of services that shape long-term customer relationships (Felipe et al., 2025). Credit cards, as hybrid instruments combining

payment functionality, revolving credit, and digital integration, occupy a strategic position within this ecosystem (del Valle et al., 2024).

Credit card usage is not merely a function of income or credit eligibility; it reflects the depth of customer integration into formal banking systems (Trinh et al., 2020). From the perspective of both household finance and bank strategy, adoption and sustained usage of bank-issued credit cards signal product engagement, cross-selling potential, and the consolidation of multi-product financial relationships (Kim et al., 2025). Understanding the drivers of credit card usage therefore provides insight into broader mechanisms of customer engagement and financial ecosystem integration (Juusola et al., 2023).

Prior research has predominantly examined financial inclusion through measures of account ownership and access (Beck et al., 2007), while behavioral approaches have focused on technology adoption and financial literacy (Ajzen, 1991); (Davis, 1989); (Lusardi & Mitchell, 2014). However, much of this work focuses on access or ownership rather than actual usage, and frequently overlooks the role of digital–traditional complementarities within banking portfolios. Moreover, empirical analyses often ignore the complex sampling structures underlying nationally representative financial surveys, potentially biasing inference and limiting external validity.

Specific strands of the literature illustrate this gap. Studies of credit card use have examined perceived risk and intention to use (Trinh et al., 2020), financial knowledge and responsible use (Chen et al., 2024), and trust and literacy in survey-based structural models (Pérez-Campdesuñer et al., 2025), typically one behavioral or attitudinal channel at a time. Work on digital channels has shown that they can both substitute for and add to traditional service use: online banking adoption at a large U.S. bank was associated with lower use of ATM and telephone channels but higher use of branch and call-center services and a higher total transaction volume (Campbell & Frei, 2010), and mobile payment adoption at a large Asian bank was linked to higher credit card activity, although mobile payments substituted for physical cards in offline payments (Xu et al., 2024). These two studies rely on customer records from a single institution, and none of the studies above observes digital and traditional engagement jointly, for a nationally representative population of households, in relation to credit card usage. Whether the two forms of engagement

are complementary in accounting for credit card usage at the household level therefore remains empirically open, particularly in emerging markets.

This study addresses these gaps by examining the factors associated with bank credit card usage using nationally representative microdata from the 2024 Household Financial Survey (Central Bank of Chile, 2024), estimated under a complex, stratified, and clustered sampling design. By explicitly incorporating survey weights and bootstrap replicate weights, the analysis provides population-representative evidence on how structural capacity and financial ecosystem integration are jointly associated with credit card participation.

We conceptualize credit card usage as the outcome of two interacting dimensions: structural capacity and ecosystem integration. Structural capacity captures income, education, and asset ownership, which determine eligibility and financial sophistication. Ecosystem integration reflects engagement with digital financial services and traditional banking channels, which may reinforce cross-product adoption and deepen customer relationships.

For household finance and bank strategy alike, the key question is whether digital financial engagement complements or substitutes traditional banking relationships in relation to credit card usage. If digital usage reinforces formal credit participation, banks may leverage digital ecosystems as gateways to cross-product expansion. Conversely, if digital services operate independently of traditional credit instruments, different segmentation strategies may be required.

Formally, the study addresses the following research question: to what extent are digital financial engagement and traditional banking integration associated with the probability of using a bank-issued credit card, over and above structural capacity, and are the two forms of engagement complementary or substitutable? The theoretical arguments developed in Section 2 translate into eight testable hypotheses: H1–H3 concern structural capacity, H4 and H5 concern the digital and traditional dimensions of ecosystem integration, H6 and H7 concern life-cycle and household context, and H8 concerns the complementarity between the digital and traditional dimensions.

Our findings indicate that digital financial usage and traditional banking engagement are both positively associated with credit card usage, even after controlling for income and asset

ownership. Models that include the ecosystem variables show a higher goodness of fit (McFadden's pseudo-R^2) than structural-only specifications, although this comparison is descriptive. These results are consistent with the view that customer integration into broader banking ecosystems is associated with credit card participation beyond structural economic capacity, although they do not identify causal effects.

The contribution of this study is threefold, and we distinguish its theoretical, empirical, and methodological components. Theoretically, we define banking ecosystem integration as a usage-based, household-level construct with a digital and a traditional dimension, we separate it from digital banking (a channel) and relationship marketing (a firm-side strategy) (Section 2.1 and Table 1), and we state explicitly when complementarity between the two dimensions is, and is not, implied by the evidence. Empirically, we provide nationally representative evidence for Chile, an emerging market with high account ownership and a strong retail credit presence, on how digital and traditional engagement are associated with bank credit card usage beyond structural capacity; the analysis complements evidence on non-bank credit cards from the same survey (Dote Pardo, 2026). Methodologically, we use design-based inference with expansion and bootstrap replicate weights, latent-variable scoring appropriate for binary usage indicators (polychoric correlations), and average marginal effects with design-consistent standard errors. Managerial and policy implications are discussed in Section 5.

The remainder of the paper is structured as follows. Section 2 develops the theoretical framework linking structural capacity and ecosystem integration to credit card usage. Section 3 describes the data, sampling design, and empirical strategy. Section 4 presents survey-adjusted Probit results and marginal effects. Section 5 discusses the findings, their managerial and policy implications, and the limitations of the study, and Section 6 concludes.

2. Theoretical Framework

2.1. Credit Card Usage within Banking Ecosystems

Retail banking has evolved from product-based competition toward ecosystem-based integration, where customers interact with interconnected portfolios of financial services (Felipe et al., 2025). In this environment, credit cards represent more than liquidity instruments; they function as relational nodes within broader banking ecosystems, linking payment services, credit

provision, digital platforms, and customer relationship management strategies (Karim & Lucey, 2024).

From a banking perspective, credit card usage signals customer integration into multi-product financial relationships (Trinh et al., 2020). Relationship marketing theory suggests that deeper product portfolios increase switching costs, reinforce institutional trust, and enhance customer lifetime value (Hidayat & Idrus, 2023). Accordingly, the decision to use a bank-issued credit card reflects both structural economic conditions and the degree of integration into formal financial infrastructures (Pérez-Campdesuñer et al., 2025).

This ecosystem approach implies that credit card participation should be analyzed not only through traditional credit constraint models but also through engagement mechanisms that reflect digital and traditional banking interactions (Gaviyau & Godi, 2025).

We therefore conceptualize credit card usage as the outcome of two interacting dimensions: i) Structural capacity, capturing economic resources and financial human capital, and; ii) Ecosystem integration, reflecting digital engagement and traditional banking relationships.

We define banking ecosystem integration as the extent to which a household's financial activity is embedded, through both digital and traditional channels, in the interconnected set of payment, deposit, and credit services of the formal banking system, as observed in the household's actual use of those services. The definition differs from two neighboring constructs. Digital banking refers to a single interaction channel and to the technology through which services are accessed (Bhuiyan et al., 2025); it captures only one of the two dimensions of integration considered here. Relationship marketing refers to the firm-side strategies and relational outcomes, such as trust, commitment, and switching barriers, that banks build with customers (Lewin & Johnston, 1997; Hidayat & Idrus, 2023); it describes the supplier's perspective, is not observed directly in household survey data, and is used here as a theoretical mechanism rather than as a measured construct. Ecosystem integration, by contrast, is a household-level and usage-based construct that combines the breadth of instruments used and the mix of channels through which they are used. Table 1 summarizes the constructs, their operationalization, and the associated hypotheses.

2.2. Structural Capacity and Credit Eligibility

Structural capacity provides the foundational conditions enabling access to formal credit markets. Income relaxes liquidity constraints and increases eligibility for revolving credit. Higher-income customers are more likely to satisfy risk assessment criteria, experience greater transaction demand, and perceive stronger benefits from credit card usage (Chen et al., 2024); (Trinh et al., 2020); (Gan et al., 2016); (Peterson, 1977). From the issuer's standpoint, these customers represent segments with higher cross-selling potential and creditworthiness.

H1. Income is positively associated with bank credit card usage.

Education represents accumulated human capital and financial capability (Xiao et al., 2022); (Lanzi, 2007). Engaging with credit cards requires understanding interest rates, repayment schedules, and risk management (Chen et al., 2024). More educated customers face lower informational barriers and are better equipped to integrate revolving credit products into their financial portfolios (Morris et al., 2023).

H2. Education is positively associated with bank credit card usage.

Asset ownership, proxied by tenure status, signals economic stability and institutional embeddedness. Customers with asset-backed profiles may be perceived as lower-risk clients and are more likely to be integrated into formal financial systems. Asset ownership may therefore facilitate multi-product adoption within banking portfolios (Iqbal et al., 2026); (Ahmed et al., 2024).

H3. Asset ownership is positively associated with bank credit card usage.

Together, income, education, and asset ownership define the structural conditions under which customers can participate in formal credit ecosystems.

2.3. Digital Financial Engagement and Cross-Product Complementarity

Digital banking has fundamentally reshaped customer–bank interactions. Online transfers, mobile payments, and electronic transactions increase interaction frequency and reduce transaction costs (Bhuiyan et al., 2025). Technology adoption theory (Davis, 1986) suggests that

familiarity with digital financial interfaces lowers psychological and operational barriers to adopting additional financial products (Junior Ladeira et al., 2026).

Digital engagement may therefore operate as a gateway to credit card usage. Customers accustomed to digital financial channels may be more willing to integrate electronic credit instruments into their payment routines (Blanchard et al., 2026). Rather than substituting traditional banking products, digital usage may reinforce cross-product adoption through ecosystem complementarities.

In ecosystem terms, digital financial engagement reflects active participation in the bank's technological infrastructure, increasing exposure to credit card offerings and strengthening perceived convenience (Ghosh & Golder, 2026).

H4. Digital financial usage is positively associated with bank credit card usage.

2.4 Traditional Banking Integration and Relationship Depth

Traditional banking engagement—such as holding deposit accounts or regularly interacting with bank services—reflects established institutional relationships (Zhengmeng et al., 2024). Relationship marketing theory emphasizes that repeated interactions foster trust, reduce perceived risk, and enhance openness to additional product adoption (Lewin & Johnston, 1997).

Customers already integrated into traditional banking channels may face lower search costs and benefit from bundled product offerings. Established banking relationships may also facilitate credit screening and targeted marketing efforts, reinforcing portfolio expansion (Barjaktarovic Rakocevic et al., 2025).

Within this framework, credit card usage can be interpreted as a natural extension of relationship depth within formal banking systems.

H5. Traditional banking usage is positively associated with bank credit card usage.

2.5. Life-Cycle and Household Context

Although ecosystem integration and structural capacity constitute the core mechanisms, demographic factors may influence financial engagement patterns. Age captures life-cycle

dynamics affecting financial experience and cognitive capacity. Financial decision-making ability may increase with accumulated experience but decline at later stages due to cognitive constraints, suggesting a potential non-linear relationship (Gamble et al., 2015).

H6. Age exhibits a non-linear relationship with bank credit card usage.

Household size may affect liquidity needs and consumption variability. Larger households face greater expenditure uncertainty, which may increase demand for revolving credit or alternatively constrain borrowing capacity (Laborda & Suárez, 2024). The net effect remains theoretically ambiguous.

H7. Household size is associated with bank credit card usage.

2.6. Integrated Conceptual Model

The theoretical framework proposes that credit card usage emerges from the interaction between structural economic conditions and customer integration into banking ecosystems. Structural capacity determines eligibility and financial sophistication, while ecosystem integration reflects relational engagement and potential cross-product complementarities.

The model predicts that ecosystem engagement variables may retain explanatory power even after controlling for income and asset ownership, indicating that financial integration mechanisms extend beyond purely economic determinants.

The preceding arguments treat the two dimensions separately, but the central question is whether they reinforce each other. If digital engagement lowers search and transaction costs and traditional relationships lower perceived risk and screening frictions, the association of one dimension with credit card usage should be stronger when the other dimension is also present, that is, the two indices should interact positively. If digital channels instead displaced traditional relationships, no such reinforcement, or a negative interaction, would be expected. Two positive main effects are compatible with either pattern and therefore do not, by themselves, identify complementarity.

H8. The association between digital financial usage and bank credit card usage is stronger at higher levels of traditional banking usage (positive interaction between the two indices).

By distinguishing structural capacity from ecosystem-based engagement, this study contributes to the household finance and banking literatures on customer portfolio expansion, digital–traditional complementarity, and financial ecosystem integration in emerging markets.

The operationalization is deliberately partial. A complete banking ecosystem would also include institution-specific product bundling, relationship duration, perceived trust, and supply-side offers, none of which is captured by the two usage indices. The indices therefore measure two observable, usage-based dimensions of household-level integration into the formal payment and banking system, and we interpret the results as evidence about these dimensions rather than about the ecosystem of any particular bank.

Table 1. Constructs, operationalization, and hypotheses.

Construct	Conceptual definition	Operationalization in this study	Hypotheses
Structural capacity	Economic resources and financial human capital that determine eligibility for, and sophistication in the use of, credit products.	Log household income; log years of schooling of the household head; homeownership (asset ownership); household size; age and age^2 as life-cycle controls.	H1–H3, H6–H7
Banking ecosystem integration (overarching construct)	Extent to which a household's financial activity is embedded, through digital and traditional channels, in the interconnected payment, deposit, and credit services of the formal banking system, as observed in actual use.	Two latent usage scores (digital and traditional), estimated from binary usage indicators through polychoric exploratory factor analysis and standardized (Section 3.3.3; Appendix Table A2).	H4, H5, H8

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Construct	Conceptual definition	Operationalization in this study	Hypotheses
Digital financial engagement (dimension 1)	Use of electronic payment instruments, such as debit and prepaid cards and bank transfers.	Digital usage index (standardized factor score).	H4, H8
Traditional banking engagement (dimension 2)	Use of conventional, relationship-based banking instruments and routines.	Traditional usage index (standardized factor score).	H5, H8
Digital banking (neighboring construct)	A single interaction channel and the technology through which services are accessed.	Not used as a separate construct; it corresponds to one of the two dimensions above.	—
Relationship marketing (neighboring construct)	Firm-side strategies that build trust, commitment, and switching barriers with customers.	Not observed in the survey; used as a theoretical mechanism underlying H5.	—

Source: Authors' own elaboration.

3. Materials and Methods

3.1. Data Source and Sampling Design

This study uses microdata from the 2024 Household Financial Survey (Encuesta Financiera de Hogares, EFH) conducted by the Central Bank of Chile (Central Bank of Chile, 2024). The EFH is a nationally representative survey designed to collect detailed information on

household financial behavior, asset ownership, debt participation, and financial service usage (Central Bank of Chile, 2025).

The 2024 wave, the sixth national edition of the survey, completed 4,649 in-person interviews between July 22, 2024 and January 13, 2025 (Central Bank of Chile, 2025a, 2025b). The target population is urban households in private dwellings, and the sample is representative at the national urban level, by macrozone, and by wealth stratum, defined from the fiscal valuation of the dwelling; it represents approximately 6.7 million households (Central Bank of Chile, 2025b). The design is probabilistic, stratified, and three-stage (municipalities, blocks, and dwellings), with oversampling of the highest wealth stratum, and combines a refreshment sample of households interviewed for the first time (2,848 interviews) with a panel sample of households from the 2021 refreshment sample (1,801 interviews). The overall response rate was 71.5% (64.1% in the refreshment sample and 87.2% in the panel sample) and the refusal rate was 11.3% (Central Bank of Chile, 2025a).

Fieldwork was contracted to an external survey company, while the sampling design, questionnaire, weights, and imputations were developed by the Central Bank. Design weights were adjusted for non-response and coverage in each sample, combined into a single cross-sectional weight, and calibrated by generalized regression to the national statistics institute's urban population projections by age, gender, and macrozone. Item non-response in amount variables, such as income, is imputed by the Central Bank through multiple imputation by chained equations (30 imputed datasets, stacked in the public file) or hot deck. Because the public files do not identify strata or clusters, variance estimation relies on 1,000 sets of bootstrap replicate weights in which the whole weighting process, including the non-response and calibration adjustments, is replicated for each replicate (Central Bank of Chile, 2025a). The estimation sample comprises 4,631 households: 18 households with missing values in at least one variable of the models were excluded.

The survey follows a complex, stratified, multi-stage sampling design. Households are selected through geographic stratification and clustering procedures to ensure representativeness across wealth strata and macrozones. The dataset includes expansion weights that allow inference at the population level, as well as bootstrap replicate weights to account for sampling variability and clustering.

Given the objective of understanding customer integration into banking ecosystems at the national level, incorporating the survey design is essential to ensure external validity. All estimations therefore incorporate sampling weights and replicate-weight adjustments to produce design-consistent standard errors.

Chile is an informative setting for this question for three reasons:

i) It combines a high level of formal financial inclusion with a large share of digital payments: account ownership and the use of accounts and cards are on par with or above upper-middle-income averages, largely because of the simplified demand account Cuenta RUT and, more recently, prepaid cards (World Bank Group, 2022), so that variation in credit card usage is unlikely to be driven mainly by the lack of a transaction account.

ii) Second, bank credit cards coexist with a sizable retail credit sector: in the EFH 2024, 16.6% of households report debt on bank credit cards and 19.0% on retail-store credit cards (Central Bank of Chile, 2025b), which makes the distinction between bank-issued and non-bank cards analytically relevant; evidence on non-bank cards from the same survey is provided by Dote Pardo (2026), and the present study focuses on bank-issued cards, where relationship banking is the most direct mechanism.

iii) Third, the regulatory environment is changing: the Fintech Law (Law No. 21.521) created an Open Finance System in which customers can share financial information across institutions with their consent (Comisión para el Mercado Financiero [CMF], 2024), which places the interaction between digital engagement and traditional banking relationships at the center of the current policy debate.

The findings should nevertheless be read as evidence from one emerging market and are not assumed to generalize to economies with different banking structures.

3.2. Dependent Variable

The dependent variable is bank credit card usage, measured as a binary indicator equal to 1 if the household reports using a bank-issued credit card and 0 otherwise. Unlike studies that focus on access or ownership, this measure captures actual usage behavior. From a banking perspective, usage reflects product engagement and integration into formal financial ecosystems rather than mere eligibility.

3.3. Independent Variables

Following the theoretical framework, explanatory variables are grouped into two conceptual dimensions: structural capacity and ecosystem integration.

3.3.1. Structural Capacity

Structural capacity captures economic resources and financial human capital: i) Income: Total household income, transformed using the natural logarithm to reduce skewness and reflect diminishing marginal effects; ii) Education: Years of schooling of the household head, also log-transformed; iii) Homeownership: A binary indicator equal to 1 if the household owns its main residence, outright or with an outstanding mortgage, and 0 if it rents or holds the dwelling under another arrangement, used as a proxy for asset ownership; iv) Household size: Number of household members, and; v) Age and Age^2: Included to capture potential life-cycle non-linearities. These variables reflect eligibility, financial sophistication, and structural integration into formal credit markets.

3.3.2. Ecosystem Integration

Ecosystem integration reflects customer engagement within formal financial infrastructures: i) Digital usage index: Composite measure capturing use of electronic payment instruments (e.g., debit and prepaid cards, transfers), and; ii) Traditional usage index: Composite measure reflecting participation in conventional banking channels. These indices capture usage-based indicators of cross-product engagement within the banking ecosystem.

The digital usage index therefore measures the extent to which a household relies on electronic payment instruments, such as debit and prepaid cards and transfers, whereas the traditional usage index measures reliance on conventional, relationship-based banking instruments and routines. Both are usage-based, standardized latent scores: they do not measure attitudes, trust, or the identity of the issuing institution, and they should be read as partial indicators of the two dimensions of ecosystem integration defined in Section 2.1 (Table 1).

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3.3.3 Construction of Composite Indices

Homeownership is measured directly (Section 3.3.1); the ecosystem usage indices were constructed using latent-variable techniques appropriate for dichotomous survey items. All variables were originally coded as binary responses ("Yes"/"No") in the EFH dataset and were recoded as 1 ("Yes") and 0 ("No") prior to estimation.

Homeownership (Structural Embeddedness): To capture asset ownership, we use a direct binary indicator, rather than a composite index, equal to 1 if the household reports owning its main residence, whether outright or with an outstanding mortgage, and 0 if it rents or holds the dwelling under another arrangement. We initially explored a composite tenure index built from banking indicators (current account holding and non-bank credit card holding), but a reviewer's concern about the theoretical distinction between banking indicators and asset ownership led us to replace it with this direct housing-based measure, which more closely matches the construct named in H3.

Because homeownership is observed directly, no latent-variable extraction is required for this construct, and the diagnostics reported for the earlier banking-based tenure index (sampling adequacy, factor loadings, and eigenvalues) no longer apply; we retain a brief record of that earlier specification in Appendix Table A1 for transparency, alongside the item-selection procedure used for the usage indices below.

Following psychometric criteria for item screening in exploratory factor analysis (Child, 2006), payment instruments with communalities below 0.2 (specifically, cash use and use of prepaid instruments, which is distinct from the prepaid card indicator retained in the digital index) were excluded from the final indices. Communalities below this cutoff indicate that over 80% of the variance reflects uniqueness and error rather than shared latent structure, meaning that their inclusion would introduce noise into the composite factor scores (Child, 2006).

A further indicator, automatic payment charged to a credit card, was excluded after we established that the 2024 EFH questionnaire asks this item only of households that already report holding a bank credit card (module D, question D6_8, conditional on D4 = 1), the same eligibility condition as the dependent variable; retaining it would have made the traditional usage

index partly circular with the outcome it is meant to predict. The final usage indices are built from the six remaining binary indicators described below.

Ecosystem Usage Indices (Traditional vs Digital): To measure ecosystem integration, we constructed two latent dimensions from the six binary usage indicators that remained after the exclusions described above: use of debit cards, use of non-bank credit cards, use of checks, use of bank transfers, use of prepaid cards, and use of automatic bill payment from a checking account. A polychoric correlation matrix was estimated due to the dichotomous nature of the variables. Sampling adequacy was satisfactory (overall KMO = 0.75; item-level MSA values ranged from 0.67 to 0.90), and Bartlett's test confirmed factorability ($\chi^2(15) = 9{,}321.2$, $p < 0.001$).

An exploratory factor analysis was conducted using maximum likelihood extraction with oblimin rotation to allow correlated dimensions. A two-factor solution was retained to align with the theoretical distinction between traditional banking integration and digital ecosystem engagement (RMSEA = 0.063, TLI = 0.971); it is also consistent with the Kaiser criterion, since only the first two eigenvalues of the polychoric correlation matrix exceed unity (2.98 and 1.05, together 67.1% of total variance; Appendix Table A2). The two factors jointly explain 56.7% of total common variance (21.5% traditional, 35.2% digital), and are moderately correlated (φ = 0.39), noticeably less so than in the specification that included the excluded item.

The first factor (Traditional Usage) loads on checks and automatic bill payment, with checks now carrying most of the weight (loading 0.98) once automatic card payment is excluded; with only two strong indicators, we treat this factor as a narrower measure of conventional, account-based routines than originally intended, and note this explicitly as a limitation (Section 5.7). The second factor (Digital Usage) loads on debit card use, bank transfers, prepaid cards, and, more weakly, non-bank credit card use. Factor scores were computed using Thurstone's method and standardized prior to inclusion in the regression models. Detailed loadings and diagnostics are reported in Appendix Tables A1–A2. Because a factor defined by only two indicators is weakly identified, Appendix Table A4 re-estimates the main model with rotation-free indices built from a fixed item assignment.

3.4. Empirical Strategy

To estimate the factors associated with credit card usage, we employ survey-adjusted Probit models. The binary nature of the dependent variable makes Probit estimation appropriate, while incorporation of survey design ensures design-consistent population-level inference. Formally, the probability of credit card usage is modeled as:

$$P(Y_i = 1) = \Phi(X_i\beta) \quad (1)$$

where Φ denotes the cumulative standard normal distribution, X_i is the vector of explanatory variables, and β is the parameter vector.

All models are estimated using survey-adjusted generalized linear models with a Probit link function, incorporating expansion weights and bootstrap replicate weights to account for stratification and clustering.

To assess the relative contribution of structural capacity and ecosystem integration, we estimate four model specifications: i) Baseline model: Includes all structural and ecosystem variables; ii) No tenure model: Excludes homeownership; iii) Structural-reduced model: Excludes income and homeownership, and; iv) Alternative demographic specification: Tests robustness to age functional form.

Model fit is evaluated using McFadden's pseudo-R^2 computed relative to the survey-adjusted intercept-only model. McFadden's pseudo-R^2 is a likelihood-based goodness-of-fit index; it is not a measure of explained variance, and its values are not comparable to the R^2 of linear models (Hemmert et al., 2018). We therefore use it only to compare specifications estimated on the same sample and do not interpret it as the share of variation in credit card usage accounted for by the covariates. As complementary measures, we report the weighted area under the ROC curve (AUC) and the weighted percentage of observations correctly classified with a 0.5 cutoff, averaged across the imputed datasets.

All estimates are interpreted as conditional associations. The data are cross-sectional, and digital and traditional engagement are measured at the same time as the outcome, so the estimates may reflect reverse causality (for example, households that already hold a credit card may adopt more electronic payment routines), self-selection, and unobserved heterogeneity,

such as preferences, credit history, or issuer marketing, that is not observed in the survey. We therefore avoid causal language and discuss the implications of these limitations in Section 5.7.

Because household income is built from components that the Central Bank imputes, each model is estimated separately on each of the 30 imputed datasets and the results are combined with Rubin's rules (Central Bank of Chile, 2025a): the point estimate is the average across imputations, and the total variance adds the between-imputation variance, weighted by $1 + 1/30$, to the within-imputation variance obtained from the bootstrap replicate weights. In our models household income is the only imputed variable, so the imputation affects mainly the coefficient of income; models that exclude income (Models 3–4) do not vary across imputations.

3.5. Marginal Effects and Predicted Probabilities

To enhance interpretability and managerial relevance, we compute average marginal effects (AME), expressed in percentage points. Average marginal effects are computed as the average, across observations, of the individual-level marginal effects evaluated at each observation's observed covariate values, weighted by the expansion weights. For continuous covariates, the marginal effect is the derivative of the predicted probability with respect to the covariate; age and age^2 are treated jointly, so that a single AME for age that accounts for the quadratic term is reported. Because income and education enter in logarithms, their effects are expressed for a 10% increase in the variable, and the two ecosystem indices, which are standardized, are expressed per one standard deviation. Standard errors are obtained by re-estimating the model and recomputing each AME with every set of bootstrap replicate weights, so that inference on the AMEs reflects the complex survey design.

Additionally, predicted probabilities are generated across the distributions of income and education while holding other variables at their median values. Confidence intervals are derived using the delta method based on the estimated variance–covariance matrix. This approach allows visual assessment of segmentation effects and cross-product integration mechanisms, consistent with the study's focus on segmentation in retail banking.

3.6. Multicollinearity and Robustness Checks

Variance inflation factors (VIF) are computed to assess multicollinearity. High VIF values for age and age squared reflect mechanical polynomial collinearity rather than substantive overlap. All other regressors exhibit VIF values well below conventional thresholds.

The four specifications in Section 3.4 provide a first assessment of the stability of the ecosystem coefficients when income and homeownership are excluded. Table 6 reports a further set of checks: a logit specification, a linear probability model (LPM), the subsample of households that already hold a bank credit card, income-tercile and age-group subsamples, and an Oster (2019)-type sensitivity bound for selection on unobserved confounders. Across all of these, the digital usage index remains positive and significant; the traditional usage index is materially less stable and is discussed in Section 5.7. Appendix Table A4 shows that both associations remain positive and significant, with Oster bounds above unity, when the indices are rebuilt without factor rotation, whereas their relative magnitude depends on how the indicators are weighted.

4. Results

4.1 Survey-adjusted Probit Estimates

Table 2 reports weighted descriptive statistics for the estimation sample of 4,631 households. Bank credit card usage is reported by 28.6% of households. The household head is on average 49.8 years old and has 13.4 years of schooling, households have 2.7 members on average, and mean monthly household income is approximately CLP 2.2 million (standard deviation, CLP 3.7 million).

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Table 2. Weighted descriptive statistics (N = 4,631 households).

Variable	Mean / proportion	SD	SE
Panel A. Continuous variables			
Age (household head)	49.83	16.17	0.272
Household income (CLP)	2,203,940	3,654,795	69,680
log(Income + 1)	14.120	1.514	0.043
Years of schooling (head)	13.39	3.87	0.072
log(Education + 1)	2.613	0.378	0.008
Household size	2.660	1.450	0.033
Digital usage index	-0.022	0.968	0.020
Traditional usage index	-0.041	0.960	0.021
Panel B. Binary variables (proportion)			
Bank credit card usage (= 1)	0.2861	—	0.0099
Homeowner (= 1)	0.5219	—	0.0125
Current account holding	0.4875	—	0.0106

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Variable	Mean / proportion	SD	SE
Non-bank credit card holding	0.3937	—	0.0102
Uses cash	0.9031	—	0.0075
Uses debit card	0.8972	—	0.0066
Uses bank transfers	0.6785	—	0.0099
Uses prepaid instruments	0.0888	—	0.0067
Uses prepaid card	0.1491	—	0.0071
Uses non-bank credit card	0.2614	—	0.0094
Uses checks	0.0592	—	0.0053
Automatic card payment (excluded from indices; see Section 3.3.3)	0.1104	—	0.0061
Automatic bill payment	0.2250	—	0.0085

Source: Authors' calculations based on the 2024 Household Financial Survey (Central Bank of Chile, 2024). Means and standard errors are combined across the 30 imputed datasets with Rubin's rules; SE = standard error.

Table 3 presents the survey-adjusted Probit estimates for bank credit card usage. All models incorporate expansion weights and bootstrap replicate weights to ensure design-consistent inference under the complex sampling framework.

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The baseline specification (Model 1) shows a McFadden's pseudo-R^2 of 0.327 and a weighted AUC of 0.866, and it classifies 81.7% of households correctly at a 0.5 cutoff; the pseudo-R^2 is a measure of relative fit and not of explained variance (Section 3.4). Income, education, and homeownership are the strongest correlates in absolute terms, the digital usage index also shows a large association, and the traditional usage index shows a weaker association in this specification, whose magnitude depends on how the index is weighted (Appendix Table A4).

4.1.1. Structural Capacity

Income and education are strongly and statistically significantly associated with credit card usage in every specification in which they are included. In the baseline model, the coefficient on log income is positive and highly significant, supporting H1 and consistent with a structural capacity channel. Similarly, education displays a robust positive association (H2), consistent with the human capital mechanism reducing informational frictions and facilitating engagement with revolving credit products.

Homeownership, our proxy for asset ownership (H3), is negatively and significantly associated with bank credit card usage (Table 3), contrary to the hypothesized direction. Owning rather than renting is associated with a probability of usage 5.65 percentage points lower (Table 4). A plausible explanation is that our binary measure pools mortgaged and outright owners: households still paying off a mortgage carry a recurring debt obligation that may compete with, rather than support, revolving credit use, while renters in this sample include higher-income, credit-active households for whom homeownership is not yet a priority. We return to this in Sections 5.7 and the limitations.

4.1.2. Ecosystem Integration

Digital financial usage (H4) and traditional banking usage (H5) are both positively associated with credit card usage. The digital index is statistically significant in every specification; the traditional index is significant in Models 3 and 4 but only marginally significant in the baseline model, once income and homeownership are controlled for.

Both indices are positively associated with credit card usage after controlling for each other, which is not consistent with a substitution pattern in which digital engagement displaces traditional banking relationships: customers engaged in digital financial channels are more likely, not less likely, to use bank credit cards. The association is strong for the digital index; for the traditional index it is positive but only marginally significant ($p = 0.067$), a result that partly reflects the exploratory weighting of this two-item factor, in which checks carry almost all of the weight; when checks and automatic bill payment are weighted equally, the traditional index is significant at the 1% level (Appendix Table A4). The two indices are nonetheless jointly significant ($F(2, 998.1) = 48.01$, $p < 0.001$). Positive main effects alone do not establish complementarity, which requires a positive interaction between the two dimensions (H8). Adding the digital × traditional interaction to Model 1 yields a small, statistically non-significant coefficient (0.022, SE = 0.047, $p = 0.642$; Wald $F(1, 993.3) = 0.22$, $p = 0.642$).

The conditional marginal effects in Table A3 point the same way: the association of digital usage with the probability of card usage barely changes with the level of the traditional index (12.7 to 14.1 percentage points; difference not significant, $p = 0.429$), and the association of the traditional index stays small and mostly non-significant across levels of digital usage (0.6 to 2.5 points; difference not significant, $p = 0.221$). A linear probability model with the same interaction term gives a different picture: there the interaction is 3.35 percentage points and statistically significant (SE = 1.26, $p = 0.008$). We report this discrepancy rather than choosing the specification that favors significance: in our primary, pre-specified Probit model, H8 is not supported, and we treat the linear-probability result as a sensitivity finding that depends on functional form rather than as confirmatory evidence (Section 5.7).

A key insight emerges when comparing Models 1 and 2. Excluding homeownership (Model 2) slightly reduces model fit (pseudo-R^2 declines from 0.327 to 0.322) but increases the magnitude of the digital usage coefficient. This suggests partial overlap between wealth-based structural integration and ecosystem engagement mechanisms, indicating that digital participation may capture dimensions of financial embeddedness not fully explained by asset ownership.

4.1.3. Demographic Controls

Contrary to H6, age and age squared are not individually significant in the baseline model or in any specification that includes both terms. While the life-cycle hypothesis predicts a non-linear relationship, the absence of individual significance indicates that, conditional on the structural and ecosystem variables, no independent association of age with credit card usage is detected; whether age operates through digital engagement is a question that would require a mediation design. We also test the joint significance of the linear and quadratic terms and report a single average marginal effect of age that accounts for both (Table 4). The joint Wald test does not reject the null that both terms are zero at the 5% level ($F(2, 998.5) = 2.32$, $p = 0.099$), and the average marginal effect of age is close to zero (0.07 percentage points per year, SE = 0.06). Age is associated with usage only when income and homeownership are excluded: in Models 3 and 4 its average marginal effect is small but significant (0.13 and 0.12 percentage points per year, $p < 0.05$), which suggests that the age gradient observed without these controls reflects life-cycle differences in income and asset ownership rather than an independent association with age.

Household size exhibits a small but statistically significant negative association in the baseline model. Larger households appear slightly less likely to use credit cards, possibly reflecting tighter liquidity management or alternative consumption smoothing strategies.

Table 3. Factors associated with bank credit card usage (survey-adjusted Probit, pooled across the 30 imputed datasets).

Variables	**Model 1** (Baseline)	**Model 2 (No Homeowner)**	**Model 3 (No Income & No Homeowner)**	**Model 4 (Linear Age; No Income & No Homeowner)**
Age	-0.0118 (0.0140)	-0.0152 (0.0140)	0.0123 (0.0124)	0.0046** (0.0023)
Age²	0.0002 (0.0001)	0.0002 (0.0001)	-0.0001 (0.0001)	—

Variables	Model 1 (Baseline)	Model 2 (No Homeowner)	Model 3 (No Income & No Homeowner)	Model 4 (Linear Age; No Income & No Homeowner)
log(Income + 1)	0.7288*** (0.0644)	0.6928*** (0.0594)	—	—
log(Education + 1)	0.9590*** (0.1712)	0.9907*** (0.1697)	1.7150*** (0.1906)	1.7212*** (0.1903)
Household size	-0.0737*** (0.0236)	-0.0780*** (0.0236)	0.0122 (0.0218)	0.0146 (0.0215)
Homeowner	-0.2496** (0.1020)	—	—	—
Digital usage index	0.5328*** (0.0724)	0.5381*** (0.0718)	0.5851*** (0.0656)	0.5860*** (0.0653)
Traditional usage index	0.0807* (0.0440)	0.0767* (0.0449)	0.1626*** (0.0423)	0.1627*** (0.0422)
Intercept	-13.2516*** (0.8781)	-12.7965*** (0.8277)	-5.7451*** (0.6111)	-5.5901*** (0.5665)
McFadden pseudo R^2	**0.327**	**0.322**	**0.252**	**0.252**
Weighted AUC	0.866	0.864	0.833	0.833

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Variables	Model 1 (Baseline)	Model 2 (No Homeowner)	Model 3 (No Income & No Homeowner)	Model 4 (Linear Age; No Income & No Homeowner)
Correctly classified (%, 0.5 cutoff)	81.7	81.8	78.8	78.7
Observations (households)	4,631	4,631	4,631	4,631

- Standard errors in parentheses combine the bootstrap replicate-weight variance and the between-imputation variance (Rubin's rules, 30 imputed datasets).
- Dependent variable: bank credit card usage (1 = Yes, 0 = No).
- Estimator: svyglm with quasibinomial(link="probit") and replicate-weight survey design.
- Significance: *** p<0.01, ** p<0.05, * p<0.10.
- The pseudo-R^2 is computed relative to the survey-adjusted intercept-only model using model deviances. It is a measure of relative fit, not of explained variance.
- Design degrees of freedom: 999. AUC is the weighted area under the ROC curve. Age and Age^2 are not individually significant in Model 1, and their joint test is significant only at the 10% level, not at 5% ($F(2, 998.5) = 2.32$, $p = 0.099$).
- The homeownership measure and the construction of the ecosystem usage indices are described in Section 3.3.3, with detailed factor loadings and diagnostics provided in Appendix Tables A1–A2.

4.2. Average Marginal Effects

To enhance interpretability, Table 4 reports average marginal effects (AME) in percentage points, combined across the 30 imputed datasets. In the baseline model: i) a 10% higher household income is associated with a probability of credit card usage 1.60 percentage points higher; ii) 10% more years of schooling of the household head, 2.11 points higher; iii) one

additional household member, 1.67 points lower; iv) owning rather than renting the home, 5.65 points lower; v) a one-standard-deviation higher digital usage index, 13.02 points higher; and vi) a one-standard-deviation higher traditional usage index, 1.86 points higher (only marginally significant, $p = 0.067$). The average marginal effect of age is not statistically different from zero in Models 1 and 2; in Models 3 and 4, which exclude income and homeownership, it is small but significant (0.13 and 0.12 percentage points per year).

The magnitude of ecosystem variables remains economically meaningful for the digital index, and more modest for the traditional index, after controlling for structural capacity. The larger coefficients in models that exclude income and homeownership (Models 3–4, where the traditional index becomes strongly significant, $p < 0.001$) are what one would expect if the ecosystem indices partly proxy for economic capacity; the baseline model, which controls for income and homeownership, is therefore the relevant benchmark for the association beyond economic eligibility.

This pattern provides strong support for H4; support for H5 is weaker, since the traditional index is only marginally significant once income and homeownership are included (Table 3, Model 1), although it becomes significant (5.6 to 6.1 percentage points per SD) when its two indicators are weighted equally (Appendix Table A4). Neither pattern, by itself, identifies an independent causal pathway to credit card participation.

Table 4. Average Marginal Effects (Survey-adjusted Probit).

Variable	**Model 1** (Baseline)	**Model 2 (No Homeowner)**	**Model 3 (No Income & Homeowner)**	**Model 4 (Linear Age; No Income & Homeowner)**
Age (per year)	0.07 (0.06)	0.01 (0.06)	0.13** (0.06)	0.12** (0.06)
Income (+10%)	1.60*** (0.14)	1.53*** (0.13)	—	—

Variable	Model 1 (Baseline)	Model 2 (No Homeowner)	Model 3 (No Income & Homeowner)	Model 4 (Linear Age; No Income & Homeowner)
Education (+10%)	2.11*** (0.37)	2.19*** (0.37)	4.28*** (0.46)	4.30*** (0.46)
Household size (per member)	-1.67*** (0.53)	-1.78*** (0.54)	0.31 (0.54)	0.37 (0.54)
Homeowner (0 to 1)	-5.65** (2.32)	—	—	—
Digital usage index (+1 SD)	13.02*** (1.70)	13.24*** (1.68)	16.10*** (1.61)	16.13*** (1.60)
Traditional usage index (+1 SD)	1.86* (1.01)	1.77* (1.03)	4.26*** (1.12)	4.26*** (1.12)

- Dependent variable: Bank credit card usage (1=Yes).
- AME in percentage points. Age and household size: change per additional year or member (numerical derivative; for age, the linear and quadratic terms are treated jointly); income and education: change for a 10% increase; the homeowner indicator: change from renting (0) to owning (1); the two usage indices: change for a one-standard-deviation increase.
- *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.
- Estimates derived from survey-adjusted Probit models with bootstrap replicate weights. Standard errors combine the replicate-weight variance and the between-imputation variance (Rubin's rules, 30 imputed datasets).
- Model 1 includes full specification.
- Model 2 excludes homeownership.

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- Model 3 excludes income and homeownership.
- Model 4 excludes income, homeownership, and the quadratic age term.

4.3. Structural Capacity versus Ecosystem Integration

To further assess the relative importance of the two conceptual dimensions, we compare goodness of fit across model blocks. The structural-only specification (income, education, age, household size) achieves a pseudo-R^2 of 0.262 (AUC = 0.835). In contrast, the ecosystem-only model (digital usage and traditional usage, without homeownership) achieves a lower pseudo-R^2 of 0.198 (AUC = 0.798). The full model combining both blocks reaches 0.327 (AUC = 0.866).

This comparison should be read with caution. In this specification, the structural-only block shows a higher pseudo-R^2 than the ecosystem-only block, and combining both blocks yields a further increase in fit over either block alone. However, pseudo-R^2 is not a variance decomposition, the two blocks contain a different number of variables, and their components are constructed differently. The comparison therefore describes relative fit, not a causal or variance-based ranking, and it does not show that either dimension dominates the other; it shows that both contribute to the fit of the full model.

From a banking perspective, these results indicate that customer integration into financial ecosystems, and in particular digital engagement, is associated with credit card adoption over and above economic capacity, even though the ecosystem block alone does not outperform the structural block alone in this specification.

4.4. Robustness and Multicollinearity

High VIF values for age and age squared (about 42 in Model 1) reflect mechanical polynomial collinearity rather than substantive multicollinearity concerns. All other regressors display VIF values well below conventional thresholds, confirming model stability. The digital usage index remains positive and significant across the alternative specifications, subsamples, and index constructions in Table 6 and Appendix Table A4, whereas the traditional index does so only in some of them (Section 5.7).

Table 5. Multicollinearity (VIF), Model 1.

Variable	Model 1 (average across imputations)
Age	42.20
Age²	42.40
log(Income + 1)	1.74
log(Education + 1)	1.37
Household size	1.11
Homeowner	1.76
Digital usage index	1.99
Traditional usage index	1.60

Note: The age polynomial inflates VIF mechanically. As a direct check, re-estimating Model 1 with age entered in mean-centered form reduces the VIF for age and age squared to 1.46 and 1.18m respectively, while leaving all coefficients, standard errors, and significance levels unchanged. The remaining covariates show no evidence of problematic multicollinearity, including the two usage indices, whose VIF fell once the shared item was removed from the traditional index. Values are averages across the 30 imputed datasets; only Model 1 is reported.

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Table 6. Robustness and subsample checks (Model 1).

Specification	N	Digital index (coef.)	Traditional index (coef.)	Digital AME (pp)	Traditional AME (pp)
Base (Probit, Model 1)	4,631	0.533*** (0.072)	0.081* (0.044)	13.02*** (1.70)	1.86* (1.01)
Logit	4,631	0.955*** (0.133)	0.120 (0.079)	13.38*** (1.78)	1.58 (1.03)
Linear probability model (pp)	4,631	10.57*** (1.26)	8.33*** (1.27)	—	—
Only households already holding a bank card	1,750	0.383*** (0.091)	0.127** (0.053)	8.26*** (1.52)	3.04** (1.22)
Income tercile 1 (low)	1,464	0.590*** (0.202)	0.375* (0.209)	8.36*** (3.17)	4.83 (3.07)
Income tercile 2	1,429	0.559*** (0.136)	0.053 (0.094)	15.69*** (3.67)	1.32 (2.31)
Income tercile 3 (high)	1,738	0.465*** (0.081)	0.082 (0.054)	14.07*** (2.15)	2.60 (1.69)
Age < 35	735	0.515*** (0.174)	-0.014 (0.151)	13.18*** (3.73)	-0.34 (3.43)

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Specification	N	Digital index (coef.)	Traditional index (coef.)	Digital AME (pp)	Traditional AME (pp)
Age 35-49	1,465	0.458*** (0.103)	0.140 (0.087)	11.75*** (2.55)	3.48 (2.11)
Age 50-64	1,361	0.509*** (0.117)	0.043 (0.068)	12.48*** (2.84)	0.98 (1.53)
Age >= 65	1,070	0.737*** (0.136)	0.113 (0.078)	13.31*** (2.15)	1.79 (1.24)

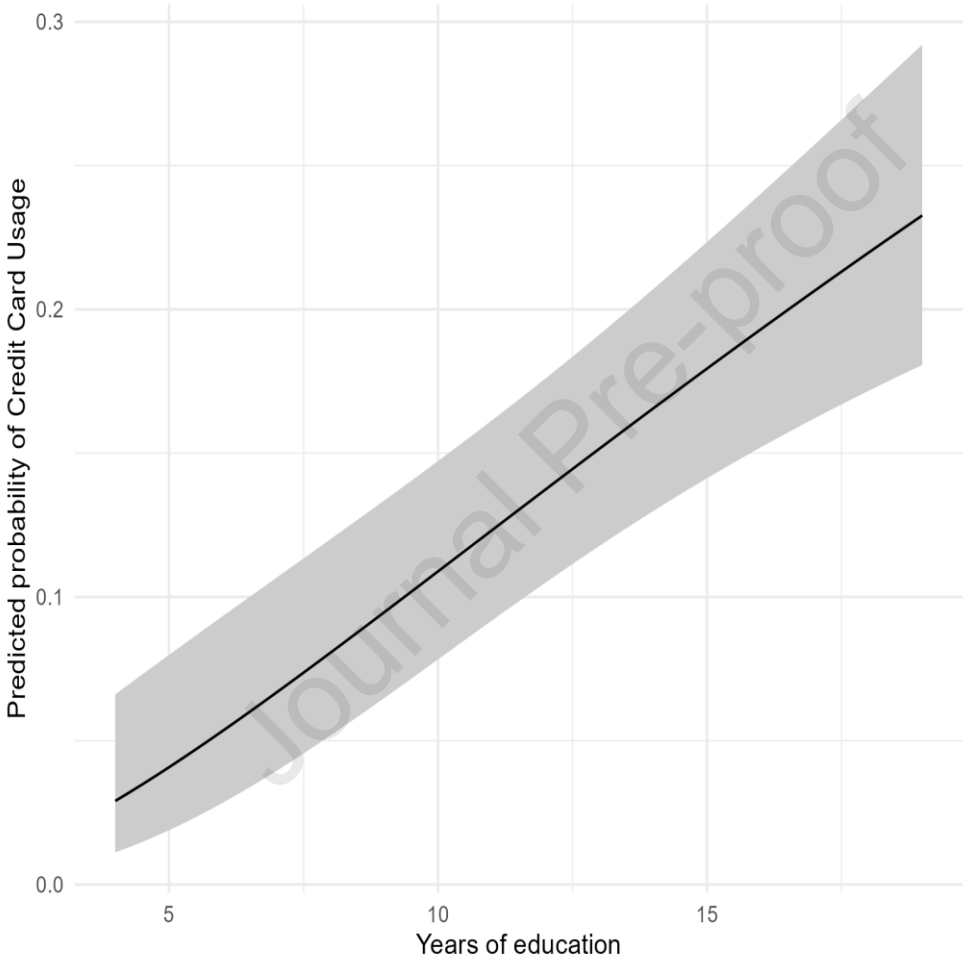
Note: Coefficients and average marginal effects (AME, in percentage points) for the digital and traditional usage indices, combined across the 30 imputed datasets (Rubin's rules). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. The macrozone subsample check could not be run because the macrozone variable was not identified in the public file. Oster (2019)-type sensitivity bound (Model 1, first imputed dataset, $R^2max = 1.3 \times R^2$ with controls): the bias-adjusted coefficient keeps its sign and the delta needed to drive it to zero exceeds 1 for both indices (digital: $\delta = 1.19$; traditional: $\delta = 1.16$), indicating that unobserved confounders would need to be somewhat stronger than the observed controls to explain away either association. This bound is sensitive to index construction: dropping the weakest indicator (non-bank credit card use) from the exploratory solution lowers it to $\delta = 0.25$ for the digital index, whereas rotation-free indices yield $\delta = 1.69$–2.90 for the digital index and 2.80–3.00 for the traditional index (Appendix Table A4). The digital index is positive and significant in every specification and subsample; the traditional index is significant only in the base specification, among households that already hold a bank card, and in the lowest income tercile, and is not significant in the remaining subsamples.

4.5. Education, Financial Sophistication and Product Integration

Figure 1 illustrates the predicted probability of bank credit card usage across the distribution of education, computed from the pooled Model 1 coefficients with the other

covariates held at their weighted median values. The predicted probability rises from about 3% at 4 years of schooling to about 28% at 19 years. The confidence bands widen toward the upper end of the distribution, where fewer households are observed. This pattern is consistent with the positive association of education documented in Table 3 (H2).

Figure 1. Predicted Probability of Bank Credit Card Usage Across Education Levels (95% CI).



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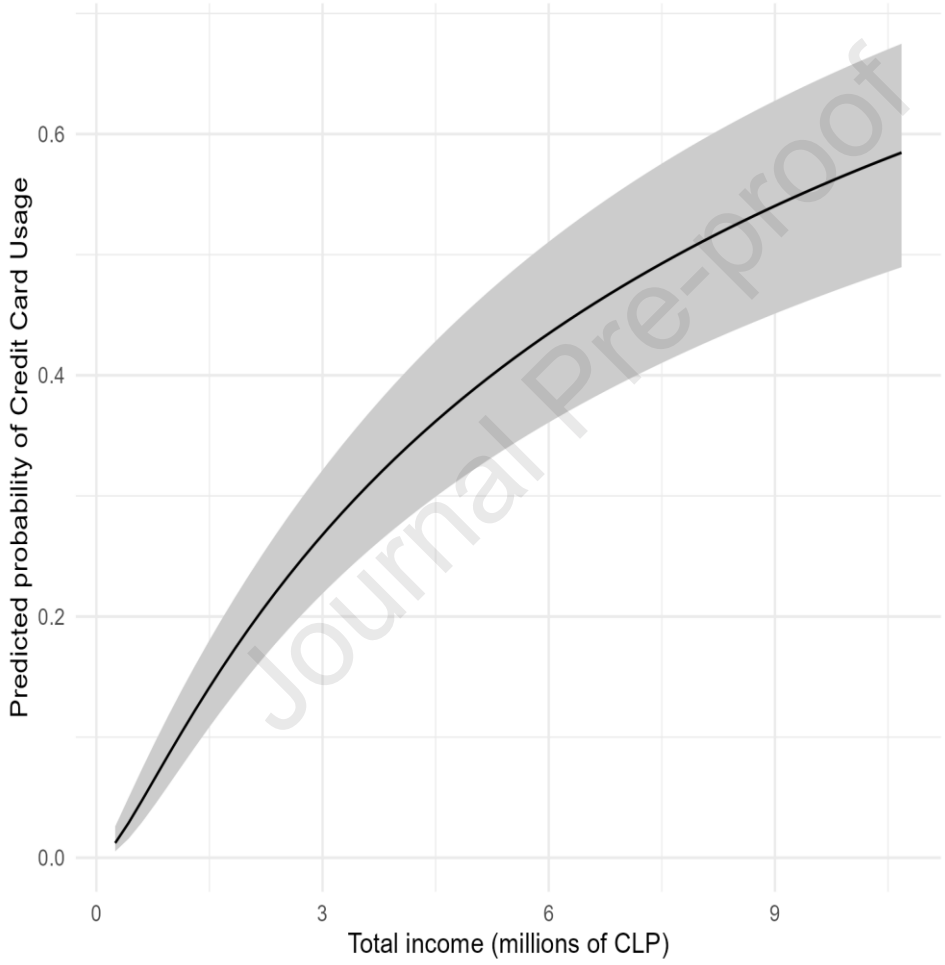
Source: Authors' calculations based on the 2024 Household Financial Survey (Central Bank of Chile, 2024).

4.6. Income-Based Market Segmentation and Credit Card Adoption

Figure 2 presents predicted probabilities of bank credit card usage across the observed income distribution (2nd to 98th percentile), computed from the pooled Model 1 coefficients

with the other covariates held at their weighted median values. The relationship is increasing and concave: predicted probability rises from about 1% at the lowest incomes shown (CLP 250,000) to about 67% at the highest (CLP 10.7 million), with the confidence band widening toward the upper end of the distribution. This pattern is consistent with the positive association of income documented in Table 3 (H1).

Figure 2. Income-Based Segmentation and Predicted Credit Card Usage Probability (95% CI).



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Source: Authors' calculations based on the 2024 Household Financial Survey (Central Bank of Chile, 2024).

4.7. Summary of Hypothesis Testing Results

Table 7 summarizes the hypothesis testing results. Income and education (H1–H2) receive strong empirical support; homeownership (H3) is significant but in the direction opposite to the one hypothesized. Digital usage (H4) receives strong support; traditional usage (H5) receives only weak support in the main specification and stronger support under rotation-free index construction (Appendix Table A4). In contrast, the life-cycle hypothesis (H6) is not supported: the age terms are not significant at the 5% level once income and homeownership are controlled for, and the small positive age gradient in Models 3 and 4 disappears when these variables are included. Household size (H7) shows limited and specification-sensitive effects. H8 (complementarity) is not supported by the interaction analysis in the primary Probit specification, although a linear probability model suggests a significant interaction (Section 4.1.2, Table A3).

Table 7. Summary of Hypotheses Testing.

Hypothesis	Statement	Supported?	Evidence
H1	Income is positively associated with bank credit card usage.	Supported	Positive and significant in all models (Tables 3 & 4)
H2	Education is positively associated with bank credit card usage.	Supported	Strong positive effect; large AME
H3	Asset ownership is positively associated with bank credit card usage.	Not supported (opposite sign)	Homeownership negatively associated with usage ($b = -0.25$, $p = 0.015$); see Section 5.7

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Hypothesis	Statement	Supported?	Evidence
H4	Digital financial usage is positively associated with bank credit card usage.	Supported	Positive and robust across all specifications
H5	Traditional banking usage is positively associated with bank credit card usage.	Weakly supported	Positive but only marginally significant in Model 1 ($p = 0.067$); significant once income and homeownership are excluded (Models 3–4) and under rotation-free index construction (Table A4)
H6	Age exhibits a non-linear relationship with bank credit card usage.	Not supported	Age and Age^2 jointly not significant at 5% ($F(2, 998.5) = 2.32$, $p = 0.099$); age AME significant only in Models 3–4, which exclude income and homeownership
H7	Household size is associated with bank credit card usage.	Partially supported	Significant in baseline, unstable across specifications
H8	The association between digital financial usage and bank credit card usage is stronger at higher levels	Not supported	Interaction not significant in the primary Probit specification (coefficient 0.022, $p = 0.642$; Wald

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Hypothesis	Statement	Supported?	Evidence
	of traditional banking usage.		F(1, 993.3) = 0.22, p = 0.642); conditional marginal effects do not differ significantly across levels of the other index (Table A3). A linear probability model with the same terms shows a significant interaction (3.35 pp, p = 0.008), so the result is sensitive to functional form (Section 5.7)

Source: Authors' own elaboration.

5. Discussion

This study advances the household finance and banking literatures by showing that credit card usage is associated not only with structural economic capacity but also with households' integration into broader banking ecosystems. Using nationally representative data estimated under a complex survey design, we find that digital engagement, in particular, is positively associated with credit card usage beyond income, education, and homeownership; the association for traditional engagement is weaker and more sensitive to how the index is constructed, and homeownership itself is negatively associated with usage, contrary to our initial hypothesis.

Our findings contribute to three interconnected debates:

i) Financial capability and product usage
ii) Digital–traditional complementarity
iii) Relationship marketing and portfolio depth.

5.1. Structural Capacity and Financial Capability

Consistent with prior research, income and education are strongly associated with credit card usage. This aligns with evidence that financial knowledge and capability facilitate responsible engagement with revolving credit products (Chen et al., 2024); (Xiao et al., 2022). The association is particularly large for education, in line with the human capital mechanism proposed in the financial literacy literature (Lusardi & Mitchell, 2014).

Our results are more nuanced than this literature in one respect: a model with structural variables alone (including homeownership) shows a higher relative fit than one with the two ecosystem indices alone, although combining both blocks fits better than either alone. While financial literacy and income relax eligibility constraints (Peterson, 1977); (Gan et al., 2016), they do not fully capture the relational dimension of product integration. In other words, possessing economic resources is necessary but insufficient for active credit card usage within formal banking systems.

These findings complement Pérez-Campdesuñer et al. (2025), who show that trust and literacy jointly shape responsible credit card behavior. Our results suggest that engagement mechanisms embedded in banking ecosystems may also be relevant to this relationship.

5.2. Digital–Traditional Complementarity in Banking Ecosystems

A central contribution of this study lies in documenting that digital financial usage and traditional banking engagement are both positively associated with credit card usage at the same time, the former strongly and the latter with a magnitude that depends on index construction, a pattern that is not consistent with a substitution story in which one displaces the other, even though the formal interaction test does not support statistical complementarity (H8) in the primary specification.

These findings challenge substitution narratives suggesting that digital channels displace traditional banking relationships. Instead, consistent with digital transformation literature (Felipe et al., 2025); (Gaviyau & Godi, 2025), digital participation appears to be associated with, rather than to displace, cross-product integration.

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Technology adoption theory (Davis, 1989) and recent meta-analytic evidence in financial services (Junior Ladeira et al., 2026) indicate that familiarity with digital interfaces reduces psychological and operational barriers to product adoption. Our results are consistent with this view: customers engaged in digital payments and online transfers are more likely to use bank-issued credit cards.

Moreover, the magnitude of the digital and traditional coefficients increases when structural variables are excluded (Models 3–4), which is consistent with both ecosystem indices partly proxying for income, education, and homeownership. This resonates with the open banking and digital finance literature emphasizing ecosystem-based competition (Blanchard et al., 2026); (Karim & Lucey, 2024).

5.3. Relationship Depth and Portfolio Integration

Traditional banking engagement is also positively associated with credit card usage, although the size of this association depends on how its two indicators are weighted (Appendix Table A4). This supports relationship marketing theory, which posits that repeated interactions build trust, reduce perceived risk, and enhance openness to additional product adoption (Lewin & Johnston, 1997); (Hidayat & Idrus, 2023).

Credit card usage may therefore reflect relationship depth rather than isolated credit demand. Customers integrated into traditional banking systems face lower search costs and are more likely to encounter bundled offerings and targeted marketing initiatives (Barjaktarovic Rakocevic et al., 2025).

In our data the structural-only block in fact shows a higher relative fit than the ecosystem-only block (Section 4.3), which qualifies this line of argument; what the evidence does support is that relational engagement, and digital engagement specifically, adds to economic capacity rather than substituting for it. Such evidence aligns with loyalty and credit card engagement research (Juusola et al., 2023), which highlights motivational and relational drivers of sustained usage.

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5.4. Life-Cycle Effects Revisited

Contrary to prior research suggesting non-linear life-cycle patterns in financial decision-making (Gamble et al., 2015), age effects are not statistically significant once income is included (Models 1 and 2); a small positive age gradient appears only when income and homeownership are both excluded (Models 3 and 4). This pattern does not allow us to conclude that demographic influences operate through financial engagement.

One possible interpretation, which these data cannot test, is that the age gradient observed without these controls reflects life-cycle differences in income and asset accumulation; generational differences in digital adoption and banking integration may also contribute, and testing either explanation would require a mediation design or longitudinal data. The second interpretation aligns with evolving digital banking adoption research (Kim et al., 2025).

5.5. Theoretical Implications for Banking and Household Finance

This study introduces a structural–ecosystem framework for understanding credit card usage. Rather than viewing adoption as a binary outcome driven by eligibility constraints, we conceptualize it as the product of: i) Structural capacity (income, education, asset ownership), and; ii) Ecosystem integration (digital engagement and traditional relationship depth).

The evidence is consistent with digital engagement remaining associated with credit card usage beyond economic determinants, and with traditional engagement doing so less robustly, which suggests, subject to the limitations discussed in Section 5.7, that banks may compete not only by expanding access but also by strengthening digital engagement in particular.

Our findings therefore contribute to the ecosystem-based competition paradigm emerging in financial services research (Ofori-Okyere & Edghiem, 2026). Credit cards function as relational nodes within interconnected service portfolios rather than standalone credit instruments.

5.6. Managerial and Policy Implications in the Chilean Context

For banks, the associations reported above suggest that digital engagement and traditional relationships are not competing routes to credit card usage and that cross-product strategies

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need not choose between them. Segmentation and cross-selling initiatives could combine both signals, for example by treating regular use of electronic transfers and of established banking routines as joint indicators of readiness for credit card offers, while assessing affordability and suitability given the risks of revolving credit.

For policy, the findings are relevant to two Chilean initiatives. First, the Fintech Law (Law No. 21.521) has among its objectives the promotion of competition and financial inclusion and mandates an Open Finance System (CMF, 2024); the Financial Market Commission amended the implementing regulation in June 2026 and postponed the start of the phased rollout to July 2027 (CMF, 2026). If digital engagement is associated with, rather than a substitute for, traditional banking relationships, information sharing across institutions could support product offers and credit assessment, but it also increases the importance of consent, data protection, and responsible-lending safeguards, particularly for households with limited financial literacy. Second, financial inclusion in Chile has advanced largely through simplified accounts and, more recently, prepaid cards (World Bank Group, 2022); our results suggest that households with active digital payment routines are also more likely to use bank credit cards, so that inclusion policies may need to pair digital onboarding with financial-education and consumer-protection measures that address over-indebtedness. These implications are conditional on associations and should be evaluated with causal designs before they are used to justify targeted interventions.

5.7. Limitations and Directions for Future Research

Six limitations qualify the findings:

i) Endogeneity and reverse causality: the design is cross-sectional, and digital engagement, traditional engagement, and credit card usage are observed at the same point in time. Households that hold and use credit cards may adopt electronic payment routines because of the card, and unobserved factors such as preferences, credit history, risk attitudes, and issuer marketing may drive both engagement and usage. The estimates are therefore conditional associations, not causal effects.

ii) We removed one usage indicator, automatic payment charged to a credit card, from the traditional index: the 2024 EFH questionnaire asks this item only of households that already report holding a bank credit card, the same eligibility condition as the dependent variable, so including it would have made the index partly circular with the outcome.

Removing it leaves the traditional index resting on two indicators, checks and automatic bill payment from a checking account (Appendix Table A2); with only two items, ordinal alpha can be computed but omega cannot, and the earlier, more favorable results for the traditional index and for the digital–traditional interaction depended substantially on the excluded item.

iii) The ecosystem indices remain partial and usage-based more broadly: they do not capture institution-specific product bundling, relationship duration, perceived trust, or supply-side offers, and the 2024 questionnaire removed the earlier questions on digital financial services from the payment-instruments module (Central Bank of Chile, 2025a), so the digital index reflects the use of electronic payment instruments rather than the use of digital banking channels such as mobile or online banking.

iv) Our proxy for asset ownership, homeownership, is measured as a single binary indicator that pools mortgaged and outright owners; it came out negatively associated with card usage, contrary to our hypothesis, and we cannot rule out that this reflects the debt burden of an active mortgage rather than the absence of asset-backed stability.

v) Evidence on complementarity between digital and traditional engagement (H8) is mixed: it is not supported in our primary Probit specification, but a linear probability model with the same variables shows a significant interaction, so the conclusion is sensitive to functional form and should not be treated as settled. Relatedly, the robustness checks in Table 6 show that the association of the traditional index with usage is not stable: it loses significance in most income and age subsamples and is significant only in the base specification, among households that already hold a bank card, and in the lowest income tercile; the digital index, by contrast, is positive and significant throughout. An Oster (2019)-type bound suggests both associations are robust to omitted confounders of similar strength to the observed controls ($\delta > 1$), but the bound is sensitive to how the indices are weighted: it falls to $\delta = 0.25$ for the digital index when the weakest indicator is dropped from the exploratory solution, and ranges from 1.69 to 2.90 under rotation-free construction (Appendix Table A4); it also does not address the instability across subsamples.

vi) Goodness of fit: McFadden's pseudo-R^2 is a relative measure; the value for Model 1 (0.327) lies above the sample-sensitive range for good fit reported by Hemmert et al. (2018) for binary models with more than 200 observations and an asymmetric outcome

(0.11–0.20), but it is not a share of explained variance, and unobserved factors may still account for much of the heterogeneity in card usage; the results also refer to urban households in one emerging market at one point in time, and the outcome is a binary indicator of usage that does not distinguish transactors from revolvers or usage intensity.

Future research can address these limitations in specific and feasible ways:

i) The EFH is repeated every three years and includes a rotating panel component (Central Bank of Chile, 2025a); linking waves for re-interviewed households would allow fixed-effects or lagged specifications that examine whether changes in digital engagement precede changes in credit card usage.
ii) Quasi-experimental designs could exploit staggered product or regulatory rollouts, such as the phased implementation of the Open Finance System scheduled from July 2027 (CMF, 2026), with difference-in-differences comparisons in the spirit of bank-level evidence on mobile payment adoption (Xu et al., 2024).
iii) Issuer or transaction-level data combined with survey data could measure usage intensity, revolving balances, and delinquency, and distinguish transactors from revolvers.
iv) Sensitivity analyses for unobserved confounding, such as coefficient-stability or bounding approaches, can be applied to the present data to gauge how strong an omitted factor would have to be to overturn the main associations.
v) Comparative designs using household surveys from other Latin American countries would test whether the digital–traditional pattern is specific to Chile.

6. Conclusions

This study examines the factors associated with bank credit card usage using nationally representative microdata from the 2024 Household Financial Survey conducted by the Central Bank of Chile. Employing survey-adjusted Probit models under a complex sampling design, we provide population-representative evidence on how structural capacity and ecosystem integration are jointly associated with credit card participation.

Three principal conclusions emerge:

i) Structural capacity matters: income and education are positively associated with usage, while homeownership is negatively associated with it.
ii) Digital engagement is positively associated with credit card usage beyond structural capacity; traditional engagement is also positively associated with it, with a magnitude that depends on index construction, and the structural block alone shows a higher relative fit than the ecosystem block alone.
iii) Digital and traditional engagement are jointly and positively associated with credit card usage, which is not consistent with substitution, but we do not find robust statistical evidence of complementarity between them (H8): the interaction is not significant in our primary Probit specification.

For bank strategy, these findings imply that credit card growth should not rely solely on income-based segmentation. Instead, banks may leverage digital ecosystem engagement as a pathway for portfolio expansion and relationship deepening.

From a policy standpoint in emerging economies, digital financial participation is associated with higher formal credit card usage, but because the evidence is cross-sectional, any promotion of digital participation should be accompanied by monitoring of responsible usage. Given the risks associated with revolving credit and the weaker, less settled evidence for traditional engagement and for complementarity between the two dimensions, future research should examine these associations with designs that can speak to causality.

Future studies could extend this framework cross-nationally, explore causal pathways using panel data, or integrate behavioral variables such as trust and perceived risk (Trinh et al., 2020). Additionally, examining how fintech ecosystems reshape traditional banking complementarities represents a promising avenue for further investigation. Section 5.7 sets out specific research designs to address the limitations of the present cross-sectional evidence.

Finally, this study shows that credit card usage is associated with economic eligibility and, to varying degrees across its digital and traditional dimensions, with customer integration into banking ecosystems. In an era of digital transformation, these associations suggest that banks' position in the credit card market may depend not only on product access but also on how they

engage customers across digital and traditional channels, a proposition that future causal research should test.

Data availability

The microdata of the 2024 Household Financial Survey (Encuesta Financiera de Hogares, EFH) are publicly available from the Central Bank of Chile (https://www.bcentral.cl). The R script that reproduces all tables and figures reported in this article, including the appendix sensitivity analyses, is openly available on Zenodo at https://doi.org/10.5281/zenodo.22967786.

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Appendix

Table A1. Diagnostics of the earlier banking-based tenure index, superseded by the direct homeownership measure used in the reported models (Section 3.3.3).

Specification	Diagnostics
Three-item version (current account, savings account, non-bank credit card)	KMO = 0.45; savings account MSA = 0.30, loading = 0.170; Bartlett $\chi^2(3) = 40{,}172.8$, $p < 0.001$
Two-item version retained (current account, non-bank credit card)	Loadings 0.853 (both items); eigenvalue 1.71; 72.7% of variance explained

Note: This index is not used in the reported models; homeownership (Table 3, Model 1) is used instead as the measure of asset ownership (H3).

Table A2. Ecosystem Usage Index – Exploratory Factor Analysis (Polychoric, ML, Oblimin Rotation).

Item	Traditional (F1)	Digital (F2)	Communality	Uniqueness	MSA
Use of Checks	0.978	-0.033	0.932	0.068	0.671
Use of Automatic Bill Payment	0.485	0.406	0.553	0.447	0.722
Use of Debit Card	-0.043	0.760	0.554	0.446	0.759
Use of Bank Transfers	0.005	0.920	0.851	0.149	0.728

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Item	Traditional (F1)	Digital (F2)	Communality	Uniqueness	MSA
Use of Prepaid Cards	-0.043	0.569	0.307	0.693	0.860
Use of Non-Bank Credit Cards	0.172	0.360	0.207	0.793	0.900

- **Extraction method:** Maximum Likelihood
- **Rotation:** Oblimin (correlated factors)
- **KMO (overall):** 0.75
- **Bartlett's test:** $\chi^2(15)=9{,}321.2$, $p<0.001$
- **SS Loadings:** 1.292 (F1); 2.112 (F2)
- **Eigenvalues (polychoric matrix):** 2.975; 1.048; 0.747; 0.603; 0.365; 0.263 (two above 1)
- **Proportion of Variance:** 21.5% (F1); 35.2% (F2)
- **Cumulative Variance:** 56.7%
- **Note:** All six retained indicators are shown, without suppressing small loadings. Cash use, prepaid instruments, and automatic payment charged to a credit card (PAT) were excluded before estimation (Section 3.3.3): the first two for weak communality (below 0.20) in preliminary diagnostics, and PAT because the EFH 2024 questionnaire asks it only of households that already hold a bank credit card, the same eligibility condition as the dependent variable. Fit of the two-factor solution: RMSEA = 0.063, TLI = 0.971. Ordinal reliability from the polychoric matrix: traditional index (2 items: checks, automatic bill payment) $\alpha = 0.76$, ω not computed (undefined for two items); digital index (4 items) $\alpha = 0.75$, $\omega = 0.77$. The KMO and Bartlett statistics use the 4,649 households. Polychoric correlations were used due to the dichotomous nature of the items. Sampling adequacy was satisfactory for the usage index (KMO = 0.75), and Bartlett's test rejected the null of an identity matrix. The two-factor solution was retained to align with the theoretical distinction between traditional banking integration and digital ecosystem engagement. Factor scores were computed using Thurstone's regression method and standardized prior to estimation.

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Table A3. Conditional average marginal effects of the digital and traditional usage indices (Model 1 with interaction).

Effect	AME (pp)	SE	p-value
Digital usage +1 SD, traditional usage at −1 SD	12.75	1.80	<0.001
Digital usage +1 SD, traditional usage at 0 (mean)	13.45	1.66	<0.001
Digital usage +1 SD, traditional usage at +1 SD	14.11	1.92	<0.001
Traditional usage +1 SD, digital usage at −1 SD	0.64	1.87	0.732
Traditional usage +1 SD, digital usage at 0 (mean)	1.49	1.82	0.414
Traditional usage +1 SD, digital usage at +1 SD	2.47	1.32	0.063
Difference: digital effect at traditional +1 SD minus −1 SD	1.37	1.73	0.429
Difference: traditional effect at digital +1 SD minus −1 SD	1.83	1.49	0.221

Note: Average marginal effects in percentage points from Model 1 augmented with the digital × traditional interaction, combined across the 30 imputed datasets (Rubin's rules) with replicate-weight variance. The indices are standardized (one SD = one unit). The last two rows are the differences between the effect at +1 SD and at −1 SD of the other index, that is, the interaction effect on the probability; neither difference is statistically significant, consistent with the non-significant interaction coefficient (Probit: 0.022, SE = 0.047, p = 0.642; Wald F(1, 993.3) = 0.22, p = 0.642). A linear probability model with the same specification gives a different result

(interaction = 3.35 percentage points, SE = 1.26, p = 0.008); we report both and treat H8 as not supported in the primary specification (Section 4.1.2, 5.7).

Table A4. Sensitivity of the usage-index associations to index construction (Model 1).

Specification	Probit digital	Probit trad.	LPM digital (pp)	LPM trad. (pp)	AME digital (pp)	AME trad. (pp)	Oster δ (dig. / trad.)
(a) EFA factor scores, six indicators (main specification)	0.533*** (0.072)	0.081* (0.044)	10.57*** (1.26)	8.33*** (1.27)	13.02*** (1.70)	1.86* (1.01)	1.19 / 1.16
(b) EFA factor scores, non-bank credit card use excluded	0.362*** (0.082)	0.188*** (0.056)	2.99* (1.67)	14.89*** (1.75)	8.80*** (2.04)	4.46*** (1.35)	0.25 / 1.39
(c) Fixed assignment, non-bank credit card use in digital index	0.465*** (0.054)	0.242*** (0.034)	10.89*** (1.15)	12.36*** (1.10)	11.00	5.57	2.90 / 2.80
(d) Fixed assignment, non-bank credit card use excluded	0.351*** (0.051)	0.256*** (0.034)	8.00*** (1.06)	13.09*** (1.10)	8.52	6.13	2.42 / 3.00

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Specification	Probit digital	Probit trad.	LPM digital (pp)	LPM trad. (pp)	AME digital (pp)	AME trad. (pp)	Oster δ (dig. / trad.)
(e) As (d), with non-bank credit card use as a separate regressor	0.306*** (0.051)	0.244*** (0.034)	6.47*** (1.01)	12.33*** (1.10)	7.09	5.60	1.69 / 2.84

Note: Model 1 (survey-adjusted Probit and linear probability model, LPM) re-estimated under alternative constructions of the usage indices. Rows (a) and (b) use standardized Thurstone factor scores from the exploratory solution (maximum likelihood, oblimin rotation); row (b) repeats the factor analysis after excluding non-bank credit card use, the retained indicator with the lowest communality (0.207). Rows (c) to (e) use rotation-free indices: standardized unweighted sums of debit card, bank transfer, and prepaid card use (digital; row (c) also includes non-bank credit card use) and of check and automatic bill payment use (traditional). In row (e), non-bank credit card use enters Model 1 as a separate binary regressor (Probit coefficient 0.607***, SE = 0.074). Coefficients are combined across the 30 imputed datasets (Rubin's rules), with replicate-weight variance from the first five imputations; standard errors in parentheses. LPM coefficients are in percentage points. AMEs are percentage-point changes in the probability of usage for a one-SD increase in each index; in rows (c) to (e) they are point estimates averaged across imputations. Oster (2019)-type δ is the relative degree of selection on unobservables needed to drive the coefficient to zero (LPM, first imputed dataset, $R^2max = 1.3 \times R^2$ with controls). Because a factor defined by two indicators is weakly identified, the exploratory loadings of the traditional factor shift from checks (row a) to automatic bill payment (row b) when a single indicator is removed, which also increases the overlap between the two indices. Under fixed assignment, both indices remain positive and significant, with δ above 1, in every construction, whereas the relative size of the digital and traditional associations depends on the weighting. In a model entering the six indicators separately, debit card use is not significant (Probit 0.096, SE = 0.213), while non-bank credit card use (0.610***), bank transfers (0.566***),

and automatic bill payment (0.510***) show the largest coefficients. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

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What Is Associated with Bank Credit Card Usage? The Role of Digital Engagement and Relationship Integration

Highlights:

- Digital payment use is associated with bank credit card usage beyond income.
- Traditional banking use matters, but its size depends on how it is measured.
- Homeownership is negatively associated with bank credit card usage in Chile.
- No robust evidence that digital and traditional engagement reinforce each other.
- Design-based Probit with replicate weights and 30 imputations (EFH 2024).

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Declaration of interests

☐ The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

☒ The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

Jairo Dote-Pardo reports a relationship with Temuco Catholic University that includes: employment. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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