Behavioral Cross-Selling: Evidence from Retail Credit Cards*

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Abstract

Why do some non-financial firms rely on revenue from consumer financial products? At several large U.S. retailers, direct revenues from credit card partnerships exceed total operating income. This paper proposes a theory of *behavioral cross-selling*, in which firms use their access to customers to cross-sell products that capitalize on behavioral biases, such as inattention or forgetfulness. We test our theory in the retail credit card market using data from a major credit bureau. Although retail cards account for only 17% of balances in our sample, they generate 45% of missed minimum payments, triggering late fees. Liquidity constraints cannot fully explain missed minimums: among individuals with multiple cards, nearly half of missed payments on retail cards could have been avoided by reallocating excess payments from other cards. Consistent with the theory, firms in locations with more avoidable missed payments are more likely to offer retail cards and provide larger sign-up incentives. We discuss how behavioral cross-selling can help explain practices in industries such as airlines, auto dealerships, tax preparation services, and sports entertainment.

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1 Introduction

In early 2024, federal regulators proposed capping credit card late fees at \$8, down from \$30. Although the rule targeted credit card issuers, some of its most consequential effects were expected to fall on an unlikely group: department stores. Morgan Stanley analysts estimated the cap could cut average EBIT for department store chains by 30%, highlighting these firms' dependence on profits from consumer financial products.[1]

Department stores are not alone. While non-financial firms have long offered financial services to support their core business, some use them as a direct source of revenue. Major airlines, for instance, earn substantial income from co-branded credit cards: Delta received \$7.4 billion from American Express in 2024.[2] Walmart has partnered with Lenders One to offer in-store mortgages and is expanding their portfolio of financial products.[3] By one estimate, over half of franchise auto dealer profits come from finance and insurance activities.[4]

This paper examines why and when non-financial firms profit directly from consumer financial products, even without an apparent comparative advantage, with a focus on retail credit cards. Behavioral biases, such as inattention or overoptimism, can create opportunities for firms to extract rents. When non-financial firms' consumer interactions give them an advantage in acquiring certain customers for financial products, these rents may not be fully competed away. We call this phenomenon "behavioral cross-selling." For retail credit cards, we provide evidence that firms exploit consumer forgetfulness to profit from late fees.

We begin with a simple model of behavioral cross-selling, in which non-financial firms in segmented markets may cross-sell financial products and consumer behaviors make this cross-selling profitable. The model yields two intuitive predictions. First, firms with a more behaviorally biased customer base are more likely to cross-sell. Second, the incentives offered to take up the financial product (e.g., discounts) increase with customer bias. These predictions differ from classic price discrimination (e.g., Berg *et al.*, 2025), and are more closely related to models with loss-leader pricing (e.g., Gabaix and Laibson, 2006).

We examine our model's predictions in the context of retail (also known as private label) credit cards, which can be used only at one merchant or a small group of affiliated merchants.[5] Total outstanding retail credit was over \$130 billion at the end of 2023 and retail credit cards

[1] See Straton *et al.* (2024). Appendix A.4 includes additional estimates and information on the rule.

[2] Delta's 2024 operating income was \$6 billion. See, https://www.sec.gov/ix?doc=/Archives/edgar/data/0000027904/000002790425000004/dal-20241231.htm. See also, Marketplace (2019); Sitaraman (2023); Isidore (2024).

[3] See, e.g., Furlan Nunes (2022); PYMNTS (2025).

[4] See, Davis (2012).

[5] As in Flagg *et al.* (2024), our definition excludes co-branded credit cards which carry a retailer's branding, but can be used broadly, irrespective of retailer.

make up more than one-fourth of all open credit card accounts.[6] For some retailers, these cards are a major source of profits: at Macy's, Nordstrom, and Kohl's, for example, average credit card revenues from 2022 to 2024 exceeded operating income.

We study the retail credit card market using a monthly, tradeline-level panel from a major credit bureau with actual payments for one million U.S. consumers. We construct a measure of missed minimums from actual payments data that closely aligns with the incidence of late fees by credit score observed in bank supervision data. We find that missed minimum payments—and therefore late fees—are common on retail cards and account for a disproportionate share of card revenue. In particular, retail cards represent 17% of total outstanding credit card balances in our sample, but account for 45% of missed minimum payments. As a result, late fees significantly increase card revenue: for example, we estimate that for every $1,000 in spending, clothing store cards will generate around $65 in late fees.

We next provide evidence that consumer biases contribute to retail card late fees. Among consumers with multiple credit cards, missed minimum payments on retail cards frequently coincide with overpayments on other cards in the same month. In consumer-months where borrowers held two or more cards in our sample, nearly half of missed retail card payments could have been avoided using excess payments made elsewhere. This pattern suggests that many missed payments do not arise from liquidity constraints alone. We further show that these avoidable missed minimums are more frequent when the retail card is used less often, suggesting that inattention or forgetting may contribute to repayment behaviors.

Firms respond to these consumer behaviors in ways consistent with the behavioral cross-selling framework. We construct a firm-level measure of consumer behavioral bias using store locations and the local frequency of avoidable missed minimum payments. Firms in areas with more behaviorally biased consumers are more likely to offer retail credit cards: within industry, a one standard deviation increase in local consumer bias is associated with a nine percentage point increase in the probability of offering a card. Conditional on offering a card, firms with higher levels of local bias are also more likely to offer larger discounts for card uptake. These patterns align with the model's comparative statics and suggest that firms strategically monetize access to behavioral consumers.

Additional evidence supports the behavioral cross-selling framework in this setting. While firms might offer cards to extend credit to financially constrained customers, we provide evidence that this is unlikely to drive retail card offerings. In our sample, 77% retail card holders have one or more general purpose cards and of these consumers, 91% could have financed their first month of spending using the remaining credit limit on other cards.

While our analysis focuses on retail credit cards, the logic of behavioral cross-selling

[6] See Flagg *et al.* (2024) and CFPB (2023a).

applies more broadly. In the final section of the paper, we discuss how the concept can help explain practices across a range of contexts, including airlines, big-box retailers, auto dealers, tax preparation services, and sports entertainment. Each example is unified by the model's core mechanism: behavioral frictions dampen consumer sensitivity to the true cost of the financial product. When consumers choose financial products based on factors other than price, non-financial firms that lack an apparent comparative advantage in financial services may possess an acquisitional advantage through access to their existing customers.

Related Literature We contribute to several strands of literature related to the credit card market, cross-selling, and consumer behavioral biases. Despite the importance and prevalence of retail credit cards, relatively little has been written about them. Exceptions include recent work by the Federal Reserve Board (Flagg *et al.*, 2024) and CFPB (CFPB, 2024), which document the structure and size of the retail credit market, and Hall (2024), which provides a historical account of the shift from in-house to bank credit in the late 20th century. We add to this literature by providing new evidence on consumer behavior and a framework for understanding firm incentives in this setting.

Behavioral cross-selling relies on frictions or mistakes in consumer financial decision-making that can generate profits for firms. We provide evidence of a new type of mistake common on both general purpose and retail cards: misallocating card payments within a month, resulting in avoidable missed minimums. Prior work has documented several other anomalies in credit card repayment, including failure to prioritize payments on the higher APR product (e.g., Ponce *et al.*, 2017; Gathergood *et al.*, 2019; Katz *et al.*, 2024) and incurring avoidable overdraft or credit card late fees (Stango and Zinman, 2009; Scholnick *et al.*, 2013; Jørring, 2024).[7] We further examine the mechanisms behind repayment behaviors and how they influence firms' incentives.

Our focus on firms offering financial products alongside their base good relates to an extensive literature on cross-selling and "add-ons." In finance, recent work on cross-selling focuses on how to make customer relationships more valuable to banks (e.g., Puri and Rocholl, 2008; Santikian, 2014; Basten and Juelsrud, 2023), and existing work on add-ons often studies pricing (e.g., Lal and Matutes, 1994; Verboven, 1999; Ellison, 2005; Gabaix and Laibson, 2006; Shulman and Geng, 2013; Savioli and Zirulia, 2020). In other literatures, there has been some work on consumer dynamics and firm incentives associated with cross-selling. For example, in marketing, Li *et al.* (2005) and Li *et al.* (2011) study the optimal time to introduce new products in the customer lifecycle.

[7] More broadly, we contribute to a literature that measures the incidence of consumer financial mistakes (e.g., Calvet *et al.*, 2009; Agarwal *et al.*, 2017).

This paper differs from the cross-selling and add-on literature two key ways. First, we study firms selling products that are unrelated to the utility and functionality of the base good. Unlike room service in hotels, or ink for printers, a credit card sold by a clothing company does not affect the utility or functionality of a t-shirt. Second, we focus on behavioral (rather than competitive) frictions that make financial products profitable; and unlike banks cross-selling checking accounts and mortgages, we study a non-financial firm's decision to sell a separate financial product in which they have no apparent comparative advantage.

Our paper also relates to longstanding literatures on non-financial firms and financial products, including work on captive finance, vertical integration, trade credit, and, more recently, "buy now, pay later." Firms could use financing to support sales, engage in price discrimination, exploit or overcome information frictions, manage liquidity constraints, or mitigate enforcement challenges (e.g., Brennan *et al.*, 1988; Stroebel, 2016; Smith, 1987; Cunat, 2007; Benetton *et al.*, 2022; Russel *et al.*, 2024; Berg *et al.*, 2025).

In contrast to this literature, we focus on financial products offered by non-financial firms through off–balance sheet arrangements. Retail credit cards are uncollateralized, typically involve small consumer purchases, and underwriting is handled by a partner bank. In these cases, traditional explanations for captive finance are less likely to apply. Instead, we emphasize that profitability arises from behavioral frictions in financial decision-making and firms' acquisitional advantage. More broadly, this idea connects to a literature on "financialization," which examines the growing participation of non-financial firms in financial markets (Fischer, 2021; Palladino, 2017).

Our model is similar in spirit to the shrouded attributes model, where behavioral biases affect how firms disclose information about add-ons (Gabaix and Laibson, 2006). Related research, including DellaVigna and Malmendier (2004) and Heidhues and Kőszegi (2010), show that firms can design contracts to exploit biased consumers. We build on this work, studying firm decisions to cross-sell a separate financial product when faced with differentially biased consumers.

2 A Model of Behavioral Cross-Selling

We begin with a simple model where non-financial firms produce a base good and can also cross-sell consumer financial products. Markets are segmented by brand preferences and some consumers exhibit behavioral biases (e.g., overoptimism or inattention) which dampen their sensitivity to the true cost of financial products. The model predicts that firms with more behavioral customers are more likely to cross-sell and offer large discounts on the base good to customers who take up the financial product. We refer to using access to biased customers in order to generate revenue from financial products as *behavioral cross-selling.* We highlight how the model's predictions differ from classic price discrimination (e.g., Berg *et al.*, 2025) and relate to models of loss-leader pricing (e.g., Gabaix and Laibson, 2006).

2.1 Setup

Suppose there are K industries, each defined by a distinct type of base good (e.g., t-shirts vs. sandwiches). Within each industry, non-financial firms offer goods that vary in brand quality b. Each brand is supplied by a single representative firm. Firms choose the price $p_{k,b}$ of their base good and decide whether to offer an add-on financial product.

If a firm offers the financial product, it may provide an uptake-contingent discount, $d_{k,b}$, to incentivize sign up.[8] Other features of the product are taken as given.[9] Offering the financial product incurs a cost C_k, which varies across industries. This reduced-form parameter captures the plausibility and logistical burden of cross-selling in a particular industry. For example, a department store cross-selling a credit card is more natural, and easier to implement, than a sandwich shop cross-selling a mortgage.

Environment. Consumers are unaware of any financial product offers when deciding whether to purchase the base good. Firms face a downward-sloping demand curve in price for the base good, $D_{k,b}(p_{k,b})$. We assume that markets for the base good are segmented by brand quality, so that pricing decisions across industries and quality tiers do not interact. This segmentation reflects the limited substitutability across quality tiers (e.g., a designer vs no-name handbag) and allows us to focus on firm-level decisions without modeling strategic interactions across firms or industries.

If a consumer is offered the financial product after agreeing to buy the base good, they accept if the financial benefit of the product exceeds their reservation utility $\overline{U}_i$, which reflects the "hassle" of accepting.[10] The financial benefit is $d_{k,b}$ (e.g., discounts) less any revenue expected to be paid to the firm. A share of consumers, $\alpha_{k,b}$, exhibit behaviors that generate ex-post financial revenue R for the firm. The key behavioral friction is that they naively behave as if $R = 0$ ex-ante due to, for example, overoptimism or inattention. In the case of retail credit cards, some consumers may incur late fees or interest charges but misjudge the likelihood. The remaining share $1 - \alpha_{k,b}$ holds accurate beliefs and generates no financial

[8] In this static model, d is a one-time discount. We discuss this further in Section 2.2.3.

[9] In practice, these features are often determined by a financial industry partner, due to regulatory and capital constraints.

[10] For example, for a retail card, this could be the time and credit score-related costs of opening an additional credit card.

revenue.[11] Uptake probabilities are therefore $\gamma(d) = P(d \geq \overline{U}_i)$.[12] The parameter $\alpha_{k,b}$ is known to the firm.

Timing. First, in each industry k, firms post their base good prices publicly $p_{k,b}$, and privately decide whether to offer a financial product $\mathcal{F}_{k,b} = (\mathbb{I}(\text{Offer}), d_{k,b})$. Second, the market for the base good clears: the firm earns $p_{k,b} - c_{k,b}$ for each good sold, where $c_{k,b}$ is the marginal cost of production. Finally, if the firm offers a financial product, consumers take it with probability $\gamma(d_{k,b})$. For each financial product sold, the firm receives $\alpha_{k,b}R - d_{k,b}$, where $\alpha_{k,b}R > 0$ is the ex-post revenue generated by behaviorally biased consumers, and $d_{k,b}$ is the discount paid regardless of bias. The firm therefore maximizes:

$$\max_{p_{k,b}, \mathcal{F}_{k,b}} \Pi = \underbrace{D_{k,b}(p_{k,b})(p_{k,b} - c_{k,b})}_{\Pi_{base}(p)} + \mathbb{I}(\text{Offer}) \cdot \left[\underbrace{D_{k,b}(p_{k,b}) \cdot \gamma(d_{k,b}) \cdot (\alpha_{k,b}R - d_{k,b})}_{\Pi_{card}(p,d)} - C_k \right] \tag{1}$$

2.2 Solution & Predictions

We solve the model and examine the determinants of the firm's two key decisions: (i) whether to offer a financial product, and if so, (ii) how to set uptake-contingent discounts. All proofs are in Appendix A.1.

2.2.1 The Decision to Cross-Sell Financial Products

The non-financial firm will choose to cross-sell a financial product when:

$$C_k + \underbrace{\Pi_{base}(p^*_{\not c}) - \Pi_{base}(p^*_c)}_{>0} \leq \Pi_{card}(p^*_c, d^*_c) \tag{2}$$

where subscripts $\not c$ and c indicate whether the firm does not or does offer a card, respectively. Equation 2 captures the trade-off a firm faces when deciding whether to offer a financial product. The net profits on the card (including discounts), must be greater than the fixed cost $C_k \geq 0$ and also offset any losses on the base good, since firms with financial products may lower prices to attract customers.

The fixed cost C_k varies across industries and reflects factors such as the ease of reaching consumers during the transaction. As discussed above, this may depend on the nature of

[11]Some consumers may expect their behaviors to generate financial revenue R (and may or may not actually generate R). These consumers never take up the financial product so are irrelevant for the firm's cross-selling decision.

[12]We model this as independent of consumer naivete. If less sophisticated consumers also have less elastic demand, it would generally increase the firm's incentives to cross-sell financial products.

consumer interactions in a given setting (e.g., department vs sandwich stores). Within each industry, firms differ only in the behavioral composition of their customer base, denoted by $\alpha_{k,b}$. The model then yields two empirical predictions:

Prediction 2.1. *Extensive margin decisions are influenced by the following:*

(a) Holding all else constant, there exists a threshold $\overline{\alpha}$ such that if $\alpha < \overline{\alpha}$ no cross-selling occurs. If $\alpha \geq \overline{\alpha}$, the firm chooses to cross-sell.

(b) Let $s_k = \frac{1}{N_k} \sum_{b \in k} \mathbb{I}(Offer)$ be the share of firms within industry k who offer the financial product. Then, $s_k \to \{1, 0\}$ as $C_k \to \{0, \infty\}$.

When consumers are naive, firms can generate revenue by cross-selling a product that exploits this naivete—a mechanism we refer to as *behavioral cross-selling*. However, because naive consumers subsidize all users of the financial product, the product is only profitable when a large share of a firm's customers are naive. Part (b) says that when cross-industry variation in the costs C_k is large relative to within industry variation in profitability, firms within an industry will tend to make similar decisions about whether to cross-sell. Institutional factors like customer interactions or operational constraints, can create variation in C_k.

2.2.2 Discounts for Financial Product Uptake

If the non-financial firm chooses to cross-sell a financial product, it offers discounts to consumers who take up the product according to:

$$d^* = -\frac{\gamma(d^*)}{\gamma'(d^*)} + \alpha R \tag{3}$$

Intuitively, a larger discount increases the probability that consumers adopt the financial product but reduces the firm's margin on each successful uptake. Sensitivity to the discount is governed by $\gamma'(d)$ which determines the pass-through of α to d^*. The share of naive consumers, α, shapes the firm's willingness to subsidize uptake:

Prediction 2.2. *For firms that cross-sell, discounts offered to consumers to sign-up for the financial product, d, are increasing in the share of consumers who are naive α, $\frac{\partial d^*}{\partial \alpha} > 0$.*

When a greater share of consumers are naive, the expected revenue from each uptake increases, strengthening the firm's incentive to induce uptake through larger discounts.

2.2.3 Potential Additional Dynamic Considerations

Our single-period model is intended to illustrate the key forces across settings. In environments where firms interact repeatedly with consumers, additional dynamic considerations may shape firm decisions. We briefly discuss two such forces in the context of retail credit cards (which will be our main empirical setting).

Ex-Post Responses to R. If the non-financial firm interacts repeatedly with consumers, the behaviors that generate R—such as incurring late fees—may reduce future demand for the base good among naive consumers. For example, a consumer who incurs a late fee after opening a retail card may decrease subsequent spending. Appendix Figure A.3 shows that the likelihood of making purchases on the card remains stable following a missed minimum payment, suggesting limited negative feedback from R on future spending in this setting.

Discounts Over Different Horizons. While our static model includes a one-time uptake-contingent discount, firms that repeatedly interact with consumers may choose how to allocate incentives over time. Appendix Table A.2 shows that in the retail card context, firms offer both upfront bonuses (e.g., 20% off a first purchase) and ongoing benefits (e.g., rewards tied to continued spending). Each may serve to attract new users and encourage retention.

2.3 Relationship to Price Discrimination & Loss-Leader Pricing

In this section, we highlight how some of the model's predictions relate to classic price discrimination and loss-leader pricing.

2.3.1 Price Discrimination

Aside from behavioral biases, why else might non-financial firms provide financing? One reason could be to price discriminate among consumers (typically high- and low-income) who differ in their willingness to pay. In Appendix A.1, we develop a simple model of price discrimination, based on Berg *et al.* (2025) and Brennan *et al.* (1988). Prediction 2.3 highlights the model's key predictions.

Prediction 2.3. *In a model with price-discrimination (Appendix A.1):*

(a) Liquidity-constrained consumers with low willingness-to-pay use the financial product.

(b) Firms are more likely to offer the financial product if the base good has high margins.

These predictions differ from our model of behavioral cross-selling. In particular, with behavioral biases, both naifs and sophisticates (who expect $R = 0$ ex-ante) will select into the financial product. Sophistication could be uncorrelated, or, if anything, negatively correlated with income or willingness-to-pay. Prediction 2.3(b) says that price discrimination is more likely when margins are high, because selling to low-income consumers is more profitable than raising prices and only selling to high-income consumers. This contrasts with Prediction 2.1(a) and the idea that firms are likely to sell a financial product only if the financial product *itself* is profitable (e.g., α and R are large).

2.3.2 Loss-Leader Pricing

Our model also relates to models with "loss-leader" pricing, in which firms may sell a base product below cost to attract behavioral customers, as in Gabaix and Laibson (2006). In our model, firms set prices according to:

$$p^* = -\frac{D(p)}{D'(p)} + c - \gamma(d)\frac{\gamma(d)}{\gamma'(d^*)} \tag{4}$$

When a financial product is offered, the firm has an incentive to lower the base-good price to draw consumers into the store. Firms can then monetize their customer base by selling consumers the financial product.

Prediction 2.4. *For firms that cross-sell, consumers who take the financial product only pay $p - d$ for the base good. The base good is thus sold as a loss leader ($p - d < c$) if:*

$$-\frac{D(p^*)}{D'(p^*)} + [1 - \gamma(d^*)]\frac{\gamma(d^*)}{\gamma'(d^*)} - \alpha R < 0 \tag{5}$$

Margins on the base good are lower when the financial product is more profitable ($\uparrow \alpha R$), when demand is more elastic in the base-good market ($\downarrow -\frac{D(p)}{D'(p)}$), and when demand for the financial product is highly elastic in discounts ($\downarrow \frac{\gamma(d)}{\gamma'(d)}$). In a model with perfectly elastic demand for discounts, the firm would fully offset financial-product revenue with base-good losses and earn zero profits from the financial product, similar to Gabaix and Laibson (2006).[13] Unlike Gabaix and Laibson (2006), we analyze a setting in which firms have access to different consumer groups that vary in their degree of behavioral bias.

[13]While we do not test this loss-leader mechanism directly in the context of retail cards, there is some suggestive evidence consistent with this logic. Appendix Table A.2 shows that most clothing and department stores offer sign-up discounts of 10 to 20 percent. By comparison, estimated net profit margins in the apparel and general retail sectors are just 3.0% and 4.6%, respectively (see: `https://pages.stern.nyu.edu/~adamodar/New_Home_Page/datafile/margin.html`).

3 Retail Credit Cards: Background & Data

We examine our model's predictions in the context of retail credit cards. Retail cards account for more than a quarter of all credit cards and generate significant direct revenue for many non-financial firms. For instance, industry analysts have projected that proposed regulations on credit card late fees could reduce EBIT at retail stores by as much as 30%, highlighting the financial importance of cards to these firms.[14] This raises the central question of the paper: why is it so profitable for non-financial firms to cross-sell these financial products? This section introduces key institutional details of the retail card market and describes our data. Despite their importance, retail cards remain an understudied segment of the consumer credit market (see, Flagg *et al.*, 2024).

3.1 Institutional Details

We focus our analysis on retail (or private-label) credit cards that can be used only at one merchant or a small group of affiliated merchants. These cards are typically offered through a partnership between a non-financial merchant and a financial institution. Merchants market the card to customers, and the partner financial institution funds the receivables and manages servicing (CFPB, 2024). Earnings from interest and fees, net defaults, are generally shared between the two parties.[15] While some department stores offered revolving credit as early as the 1930s, these products generally did not become a direct source of profit for merchants until the rise of specialized credit card lenders in the late twentieth century.[16]

Market Size. Retail credit is a substantial part of the consumer credit market. Flagg *et al.* (2024) estimate that retail credit outstanding totaled $130 billion at the end of 2023, with roughly one-third of U.S. adults (with a credit record) holding at least one open retail credit account.[17] Although the share of retail cards in the total credit card market has declined in recent years, they continue to represent more than a quarter of all credit card accounts (CFPB, 2023a). Over 60 percent of outstanding retail card balances are held by consumers with credit scores below 720 (Flagg *et al.*, 2024).

[14]See Straton *et al.* (2024). Appendix A.4 includes additional estimates and information on the rule.

[15]Specific details on the exact structure of the compensation sharing are redacted in documents reported to the SEC. See, for example, https://www.sec.gov/Archives/edgar/data/27419/000110465913057305/a13-17284_1ex10dx.htm and https://www.sec.gov/Archives/edgar/data/39911/000003991121000063/exhibit104.htm. Some analysts suggest that these arrangements vary, with some more revenue sharing and others more profit sharing (see, e.g., Straton *et al.*, 2024).

[16]For discussion, see Hyman (2011); Hall (2024); CFPB (2024).

[17]These Flagg *et al.* (2024) estimates include both credit cards and other nonrevolving credit holdings of sales finance companies. However, they note that retail credit is "more than 90 percent revolving in nature."

Importance of Credit Card Revenue for Stores. Retail credit cards are a significant revenue source for many non-financial firms. Among the 100 largest U.S. retailers, 50 maintain a credit card partnership (CFPB, 2024). Although these programs may also support brand loyalty or consumer spending, net revenue from interest and fees is a direct and meaningful contributor to many merchants' profitability. Figure 1 reports the share of gross profit and operating income attributable to credit card revenues in 2022–24 for a sample of publicly traded retail firms that disclose this information in their 10-K filings. For some firms—Macy's, Nordstrom, and Kohl's—credit card revenues exceeded total operating income, suggesting they may have operated at a loss absent this source of income.

Marketing. Retail credit cards are typically marketed by the non-financial merchant, often at the point of sale. Consumers are encouraged to sign up with both upfront bonuses and ongoing benefits.[18] Anecdotal reports suggest that store employees may be rewarded for promoting cards, or penalized for failing to do so.[19]

3.2 Data and Summary Statistics

Credit Bureau Data. Our primary data source contains monthly, tradeline-level information on a panel of one million US consumers from a major credit bureau, as described by Katz *et al.* (2024). The dataset includes industry code indicators which allow us to distinguish between retail and general-purpose credit cards.[20] It also includes information on actual payments (unlike traditional credit bureau data) and all of an individual's debts (unlike bank supervision data or data from a single financial institution). Between 2017 and 2018, the dataset includes approximately 1.2 million unique retail card tradelines and 2.5 million unique general purpose card tradelines.[21] Actual payment data is available only from a subset of issuers,[22] and we focus our analysis on tradelines with this information—covering about two-thirds of retail cards.

Table 1 summarizes our 2017-2018 sample.[23] On average, retail cards are associated with borrowers that have lower credit scores than general purpose card holders (718 vs 731).

[18]See Appendix Section A.6 for details on card rewards.

[19]See, for example, Woodruff-Santos (2015). See also numerous firsthand accounts on the online forum Reddit, e.g., here, here, here, here, and here.

[20]In particular, we follow Flagg *et al.* (2024) and define retail cards as those in the following industry code groups: AP, AT, and AZ are automotive parts; CG, CS, and CZ are clothing stores; DC, DM, DV, and DZ are department stores; HA, HF, HM, HT, and HZ are home furnishings; JA and JC are jewelry; LA, LH, LZ, TN, and TZ are contractors; OC is oil companies; and SG, SZ, and SM are sporting goods.

[21]We define general purpose cards as all credit cards that can be used more widely across merchants, including both co-branded cards and all other credit cards.

[22]See CFPB (2020); Katz *et al.* (2024).

[23]Our full data is a decade-long panel from 2013-2022. In most analysis we use the 2017-2018 sample.

68% of retail cards are held by women, compared to 53% of general purpose cards. General purpose cards are 21 percentage points more likely to have positive balances than retail cards and carry (revolving) balances that are (three) four times higher, consistent with retail cards' more narrow acceptance at specific merchants. Despite this, delinquency in a two year period is similar across the card types.

Table 1 also disaggregates retail cards by industry. There is substantial variation in consumer credit scores across industries: holders of sporting goods cards have average scores around 670, compared to over 730 for those with home improvement or contractor cards. Jewelry and home cards have relatively high balances and a greater share of months with revolving balances, consistent with these cards being used to finance larger purchases. In contrast, department and clothing store cards have lower balances and slightly less frequent zero-balance months, suggesting use for smaller, frequent purchases.

Text from 10-K SEC Filings. Firms disclose information about their credit card partnerships in their SEC 10-K filings. We collect data on these disclosures using the edgar-crawler (Loukas *et al.*, 2021), analyzing all 10-K filings from fiscal year 2023 and retail, food, and accommodation industries from 2000 to 2024. We identify credit card partnerships using a predefined set of terms. Appendix A.5 provides additional details on our methodology. Overall, 4% of publicly traded firms (16% when revenue-weighting) mention credit card partnerships. Some industries have much higher shares; for example, 31% of firms in retail trade (NAICS 44-45) mention partnerships (87% revenue-weighted).[24]

Credit Card Rewards Data. We collect credit card rewards data from a variety of online sources, primarily from the websites of firms and their issuers. According to CFPB (2024), Synchrony, Citi, Capital One, and Bread Financial, collectively issue more than 80% of retail cards. We therefore focus on these four issuers and supplement missing cards from NerdWallet reviews. The final dataset includes 221 stores with information on sign-up bonuses and other rewards. Appendix Table A.2 provides summary statistics by industry. Our full methodology is described in Appendix A.6. We make our data publicly available for other researchers here.

Dun & Bradstreet Data. We use data from Dun & Bradstreet to identify the store locations of public firms in retail, food and accommodation industries. We merge these data with 10-K filings to study how variation in local consumer behavior relates to firms' decisions

[24] Figure A.1 shows that the share of firms in retail, food, and accommodation that mention credit card partnerships in their annual 10-K has been increasing since 2000.

to offer retail cards. The merged dataset includes 194 firms with over 160,000 store locations. We use this data for our extensive margin analysis because it better tracks parent-company level store locations, which aligns with the 10-K filings, compared to other data sources.

SafeGraph Data. We use data from SafeGraph to identify the locations of stores in our rewards sample, which includes both public and private firms. We use this data source instead of Dun & Bradstreet because our rewards sample includes subsidiaries and non-public firms, which can be more clearly identified in the SafeGraph data.[25] We match these firm locations to the rewards data to study the determinants of rewards.

4 Empirical Evidence: Consumer Behaviors

This section provides evidence that retail credit card users exhibit behavioral biases that could make cross-selling profitable for firms. We show that late fees from missed payments are a key source of revenue for retail cards. Among consumers with multiple credit cards, missed minimum payments on retail cards frequently coincide with overpayments on other cards in the same month, suggesting that many missed payments do not arise from liquidity constraints alone. This consumer behavior may allow firms to extract fees from retail cards, consistent with the behavioral cross-selling framework.

4.1 Missed Payments and Retail Cards

Missing a credit card minimum typically results in a late fee of \$20-\$40. Across all credit cards, these fees totaled \$14 billion in 2019—11% of total credit card interest and fees (CFPB, 2022). While our data does not report late fees directly, we infer missed payments from actual payment records. Appendix A.7 details our procedure and shows that the incidence of minimums missed in our data align with late fee incidence in bank supervision data.[26]

Missed Minimums on Retail Cards Are Common. Table 2 shows that missed minimums on credit cards are common: 38% of active general purpose cards and 37% of active retail cards have at least one missed minimum over two years. Because retail cards are used less frequently, this annual measure understates differences in months when borrowers *could*

[25] For example, in Dun & Bradstreet data, Gap and its subsidiaries (Banana Republic, Athleta, Old Navy) share a parent identifier, and some store fronts are only labeled as the parent company, Gap. Safegraph instead labels each storefront by its actual name but provides no parent identifier.

[26] If the minimum payment is made within 30 days, the delinquency is not reported to credit bureaus. Our data allow us to observe both missed minimums that trigger a late fee but not a reported delinquency, and those that do result in a delinquency.

have missed a minimum. Conditioning on months with a positive balance, missed payments are 25% more common on retail cards than on general purpose cards. Across all credit score groups, borrowers are more likely to miss minimums on retail cards.

Table 3 shows that missed minimums are more common on retail cards even *within an individual*. Column (3), which includes individual-by-time fixed effects, shows that consumers are 1.4 percentage points (17%) more likely to miss a minimum on their retail card than on their general purpose card.

Late Fees Are More Important for Retail Card Revenue. Figure 2 shows that, although retail cards account for 45% of missed minimums in our sample, they represent just 17% of total outstanding balances.[27] This implies that missed payments, and the associated late fees, are a disproportionately important revenue stream for retail cards.[28] We next estimate the scale of this revenue and its contribution to total issuer profits.

Quantifying Importance of Late Fees. Figure 3 presents estimates of credit card revenue for newly opened accounts, disaggregated by card type and revenue source. We track each card for two years following account opening; Appendix A.8 details the methodology.

Panel (a) shows that, per dollar of spending, retail cards generate substantially more late fee revenue than general purpose cards. For example, clothing cards generate $65 in late fees per $1,000 of spending, over four times the $15 for general purpose cards. Panel (b) shows how these differences shape revenue composition. Late fees are 18% of interest revenue for general purpose cards, but are 118% of interest revenue for clothing cards. Appendix A.8 shows late fee differences are not offset by higher default losses. Overall, our results suggest that late fees are an important source of revenue for retail cards.

Additional Evidence on Importance of Late Fees. Two additional pieces of evidence highlight the importance of late fees to the profitability of retail cards. First, as noted above,

[27] As shown in Table 1, retail cards are somewhat more likely than general purpose cards to have reported actual payments. In Figure 2, as in our other analyses, we restrict the sample to cards with actual payments, so comparisons are made on a consistent set of accounts. Because our sample includes a slightly higher share of retail cards, our estimates of the shares of balances and missed minimums on retail cards may both be higher than those based on a sample of all cards. However, using Y-14 regulatory data on large banks, CFPB (2022) estimates that private label cards account for 46% of late fees, in line with our estimates. CFPB (2022) also estimates that late fees accounted for 91% of all consumer fees and 25% of total interest and fees on private label cards—both substantially higher than for general purpose cards.

[28] While additional missed minimums may be associated with additional collection costs, CFPB (2023b) finds that, in regulatory data, "revenue from late fees has consistently far exceeded pre-charge-off collection costs over the last several years." This is consistent with our evidence in Section 4.2 that many missed minimums seem to result from behaviors, rather than liquidity constraints.

financial analysts projected that the CFPB's proposed cap of $8 on late fees would significantly reduce the profitability of retail stores. Appendix A.4 provides a number of analyst estimates. Second, private label card providers appear to structure minimum payments to ensure they can charge the maximum late fee. Regulations cap late fees at the greater of a fixed amount or the missed minimum payment.[29] Katz *et al.* (2024) show that private label cards are more likely than general purpose cards to set minimum payment floors near the regulatory threshold, increasing the frequency of maximum late fees. Appendix Figure A.2 shows an example contract from Synchrony Financial, the largest provider of retail credit cards in the U.S., in which minimum floors exactly mirror the regulatory thresholds.[30]

4.2 Behavioral Drivers of Missed Payments

Why do consumers miss minimum payments—and incur late fees—on retail credit cards? One possibility is financial distress: consumers may lack the liquidity to make payments, and lenders charge high late fees to compensate for default risk. Alternatively, missed minimums could reflect behavioral frictions such as forgetting or inattention. To distinguish between these explanations, we identify missed payments that could have been met using excess payments to other credit cards in the same month. This approach provides a lower bound on the share of late fees driven by avoidable misallocations rather than liquidity constraints.

Liquidity Constraints Alone Don't Explain Missed Minimums. Table 4 shows that in consumer-months where borrowers hold two or more cards, nearly 50% of missed minimums could have been avoided using excess payments on other cards in the same month.[31] This share of "avoidable missed minimums" is increasing in credit score, consistent with liquidity constraints being less important for higher credit score consumers: among superprime borrowers, 63% of missed minimums on general purpose cards, and 70% of missed minimums on retail cards, were avoidable. Overall, these results suggest that behavioral frictions such as forgetting or inattention—rather than liquidity constraints alone—shape aggregate consumer late fees.[32]

[29] See 12 CFR § 1026.52 (Regulation Z).

[30] In particular, as of 2022Q4, the regulation allowed lenders to charge a $30 late fee after a first miss and a larger late fee, $41, if the borrower had already missed a payment in the prior six months. The contract minimums, from the CFPB Credit Card Agreement Database 2022Q4, exactly reflect these two thresholds.

[31] Across all consumer-months, conditional on a consumer having a balance on at least one open credit card, they have balances on two or more cards 63% of the time.

[32] Because debts may fall due on different days, unexpected *within-month* liquidity shocks could, in principle, contribute to this result. However, we find it unlikely that such timing effects alone could explain the magnitudes we document. Supporting this view, Jørring (2024) shows that at a large U.S. financial institution, two-thirds of consumers incurred at least one avoidable late or overdraft fee over a five-year period, where "avoidable" is conservatively defined as having sufficient liquidity on the fee day to cover both

Costs of Behaviors. Table 5 quantifies the late fee costs of avoidable missed minimum payments. Conditional on having at least one avoidable missed minimum, the average annual cost is $63 in fees. While modest at the individual level, these fees imply a 25 percentage point increase in APR due to the typically small balances. A simple aggregation across the market suggests that avoidable missed minimums cost consumers $3.3 billion annually, a substantial potential source of revenue for firms.[33] These estimates are a lower bound, as they only include cases where excess payments were made to other cards in the same month.

"Forgetting" as a Mechanism. Table 6 shows that less frequently used cards are more likely to have a missed payment, helping explain the higher incidence of missed minimums on retail cards. Column (2) shows that the share of prior-year months without spending strongly predicts missed payments, and including this measure reduces the retail card coefficient by about half. Column (4) shows a similar relationship among consumers making excess payments, who are unlikely to be liquidity constrained. These results are consistent with some missed payments arising from "forgetting" or inattention to infrequently used cards.[34]

Additional Mechanisms. Appendix A.9 presents additional evidence and discussion of other potential mechanisms contributing to more missed minimum payments on retail cards. One alternative explanation is intra-household frictions: retail cards may be used by a household member who is not the primary financial decision-maker, leading to coordination failures.[35] Appendix Table A.4 shows that, among individuals with excess payments, those who are married are more likely to miss avoidable minimums, consistent with this interpretation playing some role. Another mechanism is strategic deprioritization: liquidity-constrained households may prioritize repaying general purpose cards due to their broader usability. However, due to large late fees, this mechanism does not explain the incidence of *avoidable* missed minimums that could have been paid with excess payments on other cards.

the required payment and a full month of consumption expenditures.

[33]Our estimate is the $63.53 average annual cost conditional on holding two or more cards and having at least one avoidable missed minimum (Table 5) $\times$ 39% of consumers that have at least one avoidable missed minimum in a year $\times$ 258 million US adults $\times$ 82% of adults with at least one credit card (U.S. Government Accountability Office, 2023) $\times$ 63% of consumer-months with 2+ cards, conditional on 1+.

[34]If borrowers are also present-biased, this can amplify the effects of forgetting Ericson (2017): cardholders procrastinate in repaying a card until the deadline, and then forget.

[35]For instance, if a card is rarely used and one household member makes a purchase without informing the other, the bill may be overlooked, resulting in a late fee.

5 Empirical Evidence: Firms & Behavioral Cross-Selling

This section tests whether firm behavior aligns with the behavioral cross-selling framework. We construct a firm-level measure of consumer bias using store locations and geographic variation in avoidable missed minimum payments (as defined in Section 4). We find that firms operating in areas with more behavioral consumers are more likely to offer retail credit cards. Conditional on offering a card, these firms are also more likely to provide larger rewards at their store. These patterns are consistent with the model's comparative statics.

Importantly, firms need not replicate this exercise when deciding whether to offer cards. In practice, they may learn about customer bias indirectly (e.g., by observing late fees) and adjust their card offerings and discounts over time in coordination with partner banks.

5.1 Measuring Firm-Level Customer Behavioral Bias

To construct firm-level measures of customer behavioral bias, we combine county-level variation in avoidable missed minimum payments with store-level location data.

We first construct a county-level measure of avoidable missed minimums on general purpose cards. For each card-month in 2017-18 with a positive balance, we record whether an individual missed a payment that could have been made with excess payments on other cards in the same month (as in Section 4.2). Among borrowers with two or more cards, we define α_c as the share of card-months in county c with an avoidable missed minimum, conditional on a positive balance and total actual payments exceeding total minimum payments.[36] To map this measure to firms, for each firm b in industry k, we use 2019 Dun & Bradstreet establishment data to calculate the share of the firm's stores located in each county c, denoted λ_{bkc}, with $\sum_c \lambda_{bkc} = 1$.

Combining these measures, we calculate the firm-level α_{bk} as:

$$\alpha_{bk} \equiv \sum_{c=1}^{N} \lambda_{bkc} \cdot \alpha_c \tag{6}$$

where N is the total number of counties. We construct this estimate using general purpose cards to avoid reverse causality from firm behavior. In particular, a retail card–based version of α_{bk} could be higher for firms that offer cards *because* of their cards. General purpose cards mitigate this concern and provide an ex-ante proxy for card profitability.

Figure 4 shows substantial spatial variation in missed minimum behavior. The 25th and

[36] We exclude months in which borrowers did not make sufficient payments to cover their minimums to avoid capturing variation driven by liquidity constraints. We also exclude counties in which our credit bureau sample has less than ten unique borrowers.

75th percentile of county-level α_c are 5.4% and 10.5%, respectively. The map displays patterns at the commuting zone level, with avoidable missed minimums less common in parts of the Upper Midwest and more common in the South. To better understand these patterns, Table 7 regresses county-level avoidable missed minimums on a set of county covariates.[37] More densely populated areas are predicted to have higher rates of avoidable missed minimums, but local levels of income, college education, and labor force participation are not strongly predictive. There is a strong negative relationship between credit scores and avoidable repayments: a one standard deviation increase in a county's average credit score is associated with a 0.1 standard deviation decrease in the share of months with an avoidable missed minimum. These results are broadly consistent with Agarwal *et al.* (2022), who find that credit scores, rather than income, predict optimal repayment and the net rewards borrowers earn on credit cards.[38]

We construct a second measure of consumer behavior that better captures the *ex-post* profitability of retail cards. This will be used for understanding how firms set rewards on the intensive margin. As before, we use firm-level store locations, λ_{bkc}, but now construct this using Safegraph data, which is better for identifying subsidiaries within a parent company and non-public firms. In addition, we combine firm-level locations with a county-by-industry average of avoidable missed minimums, $\overline{M}_{kc}$.

This measure differs from α_c in two key ways. First, $\overline{M}_{kc}$ is defined at the industry-county level, whereas α_c is measured only at the county level. We link firms to credit bureau industries using four-digit NAICS codes.[39] Second, $\overline{M}_{kc}$ reflects the unconditional average number of avoidable missed minimums across cards, whereas α_c captures their conditional frequency in card-months with a positive balance and with total payments exceeding total minimums. In short, α_c measures the likelihood of a mistake when a borrower is able to make one, whereas $\overline{M}_{kc}$ also accounts for differences in usage and liquidity across industries and counties.

We construct the firm-level ex-post profitability measure as:

$$\overline{M}_{bk} \equiv \sum_{c=1}^{N} \lambda_{bkc} \cdot \overline{M}_{kc} \tag{7}$$

where λ_{bkc} is the share of stores in a given county c for firm b in industry k measured using SafeGraph data. We prefer this measure for the intensive margin analysis, as it better

[37] Appendix Table A.1 presents analogous results for all missed minimums.

[38] The geographic patterns we document also broadly align with the spatial distributions of credit scores and card rewards presented in Agarwal *et al.* (2022).

[39] If a NAICS code does not link to an industry, then the firms are dropped from the sample. Details on how with filter this data can be found in Appendix A.6.

captures differences in both behaviors and usage patterns which drive profitability.[40]

5.2 Customer Behaviors and Extensive Margin Card Offerings

We first test whether, within industry, firms with more stores in places with behaviorally biased consumers are more likely to offer a retail card (Prediction 2.1). We scrape 10-K filings for mentions of credit card partnerships, and a firm is classified as having a credit card if they ever mention a partnership between 2000-2024. Appendix A.5 has more details.

Table 8, Column (1), shows that a one standard deviation increase in the firm-level avoidable missed minimum probability, α_{bk}, is associated with a nine percentage point increase in the probability of offering a card. By contrast, Column (2) shows that the overall missed minimum rate, regardless of avoidability, is not predictive of card offerings. These results suggest that it is specifically behavioral mistakes—rather than missed payments more broadly, which may reflect financial distress—that drive the profitability of offering retail credit cards. Columns (3) and (4) show that avoidable missed minimums remain a strong predictor even after controlling for local income per capita.[41] This again suggests that firms respond to behavioral mistakes, rather than to other factors correlated with income.

5.3 Customer Behaviors and Rewards

We next use our second measure, $\overline{M}_{bk}$, to test whether firms with more behaviorally profitable consumers offer larger rewards on their cards (Prediction 2.2). To measure rewards, we collect data from online sources; see Appendix A.6 for details. We focus primarily on ongoing rewards that apply to all purchases and one-time sign-up percentage discounts.

Table 9 shows that firms with more expected missed minimums over a two-year period tend to offer higher ongoing rewards at the main store. Table 9, Column (1), shows that a one standard deviation increase in the number of avoidable missed minimums predicts a rewards rate increase of 0.6 percentage points. This result holds when controlling for local income per capita. Conditioning on a non-zero sign-up bonus, Table 10, Column (1) shows that a one standard deviation increase in avoidable missed minimums predicts a 9 percentage point increase in sign-up percentage discount.[42]

[40] In relation to our model, $\overline{M}_{bk}$ is analogous to αR whereas α_{bk} is analogous to α.

[41] Specifically, we re-estimate Equation 6, replacing α_c with county-level income.

[42] Appendix Figures A.6 and A.7 show scatter plots of our results.

5.4 Additional Evidence on Firm Decisions

Most Retail Card Borrowers are Not Credit Constrained. Firms may offer retail cards to relax consumers' credit constraints, as in our model of price discrimination (Prediction 2.3). However, of borrowers who opened at least one store card in the 2017-2018 sample, 77% had one or more general purpose cards, which have lower interest rates on average (CFPB, 2024). Table 11 shows that conditional on having a general purpose card, 91% could have financed their first month of store-card spending using the remaining credit limit on other non-store cards. Even among borrowers with the lowest credit scores this share is 70%. Overall, average utilization on other cards is only 35%. Thus, credit constraints are unlikely to be the primary driver of store card issuance.

Card Offerings are Homogeneous Across Industries. Our model predicts that fixed costs of offering a financial product, C_k, could drive cross-industry differences in the likelihood of card adoptions, and that as these differences grow, firms' decisions within an industry should become more uniform (Prediction 2.1b). Figure 5 supports this: within most industries, the market-cap-weighted share of firms offering a card is either close to zero or close to one, consistent with substantial variation in C_k.[43] These fixed costs may reflect logistical and reputational frictions. In fast-food restaurants or convenience stores, there is often limited opportunity for staff to promote a financial product, and doing so may frustrate customers expecting speed and convenience. In other settings, such as those with infrequent repeat visits, non-durables, or smaller basket sizes, the introduction of a credit card product may seem poorly matched to the setting and operationally challenging.

Firms Appear to Obfuscate Rewards. In our model, firms treat uptake probabilities conditional on a discount, $\gamma(d)$, as given. In practice, firms may design reward programs to change these probabilities. For example, they may structure rewards so that perceived rewards ex-ante are larger than realized rewards ex-post, or so that rewards are difficult to compare across stores, reducing price sensitivity and increasing $\frac{\gamma(d)}{\gamma'(d)}$.[44] Anecdotally, the structure of many programs is consistent with these incentives. Firms often design points that have low or changing values, expire quickly, redeem automatically into small (e.g., $10)

[43] Figure 5 focuses on retail, food, and accommodation (two-digit NAICS: 44, 45, 71, 72), which are more likely to offer a card. Appendix Figure A.4 shows the distribution of the market-cap-weighted share of firms that offer a card across all three-digit NAICS industries. Consistent with our prediction, the distribution is bimodal, with a large number of industries at zero and a substantial (but smaller) number near one.

[44] This idea is consistent with works on price obfuscation (Ellison and Ellison, 2018) and comparison complexity (Shubatt and Yang, 2025).

certificates, redeem only once a threshold is met, or redeem only after a phone call.[45]

5.5 Consumer Welfare & Evidence of Cross-Subsidization.

What are the implications of these patterns for consumer welfare? On the one hand, as noted in Section 2.3.2, if consumers are fully elastic to rewards, firms will pass all late-fee revenue back to them in the form of discounts. Our results in Section 5.3 suggests that firms *do* pass some of the late fees back to behavioral consumers. On the other hand, if consumers are not fully elastic, firms can extract surplus from them. The fact that analysts predicted proposed regulations on credit card late fees could reduce EBIT at retail stores by up to 30% (Appendix A.4) suggests it is unlikely that all surplus is passed back.

Moreover, as in our model, firms practically cannot perfectly price discriminate between rational and behavioral consumers on either the base good or on discounts. Because of this, there will be some degree of cross-subsidization between rational and behavioral cardholders. This cross-subsidization is important from the perspective of a social planner interested in distributional effects. To illustrate this, Table 12 shows that 64% of store-cardholders pay zero late fees over two years, whereas 20% miss at least two minimums, paying at least $52 in late fees.[46] A cardholder at the 10th percentile of late fees per dollar of spending does not incur fees, whereas one at the 90th percentile pays $24 in late fees per $100 spent. Borrowers who incur more late fees are disproportionately low income and low credit score.

6 Discussion & Conclusion

We conclude by examining how behavioral cross-selling—firms using consumer access to cross-sell financial products that are profitable due to behavioral frictions—applies across a range of contexts. Each example is unified by the model's core mechanism: behavioral frictions dampen consumer sensitivity to the true cost of the financial product. In the case of retail cards, this would result from inattention to, or overoptimism about, late fees. When consumers choose financial products based on factors other than price, non-financial firms that lack an apparent comparative advantage in financial services may possess an acquisitional advantage through access to their customers.

[45]For instance, AMC awards 50 points per dollar, but each point is worth only 0.1 cents (far below the 1-cent industry norm). Ashley Stewart cardholders receive 20% off their first purchase only if used within 15 minutes. For further examples, see our rewards data here. Point expiration, auto-redemption, and threshold-redemption are all common, with these major stores all having at least one of the three practices: DSW, Petco, Crate & Barrel, Meijer, Belk, JC Penney, Eddie Bauer, Saks, Sephora, Sheetz, Best Buy, Kohls.

[46]We assume that all late fees are $26.

Airlines & Co-Branded Credit Cards. Major U.S. airlines offer co-branded credit cards through partnerships with banks such as American Express and Chase. While these cards may foster loyalty and increase ticket sales, they also provide substantial direct revenue for airlines. For example, Delta, United, and American Airlines each earn billions annually by selling frequent flyer miles to their bank partners.[47] Unlike retail credit cards, co-branded cards can be used broadly and generate substantial revenue from interchange fees and revolving balances, rather than late fees. Nevertheless, many aspects of the industry still align with the model. Consumers may overestimate the value of rewards (Liston-Heyes, 2002), consistent with estimates that airlines sell miles for roughly three times their cost.[48] Airlines may contribute to misperceptions by restricting redemption options and devaluing miles over time.[49] Many miles also go unredeemed: by one estimate, 15-30% of all airline miles go unspent and expire.[50] While the behavioral frictions differ from retail cards, the core mechanism of behaviors dampening effective price sensitivity remains.

Big-Box Retailers & Mortgages. Some big-box retailers have participated in efforts to offer mortgage products to their customers. For example, Walmart, though a 2022 partnership with Lenders One, opened in-store mortgage kiosks.[51] While this effort represents a small share of overall revenue, it is an instance of cross-selling a financial product with little obvious comparative advantage beyond customer acquisition. A number of studies show mortgage borrowers fail to shop: over 75% apply to only one lender, despite large potential savings.[52] One estimate suggests that insufficient search may cost consumers up to $9 billion annually (Alexandrov and Koulayev, 2018). These behavioral frictions again reduce effective price sensitivity, potentially making mortgages profitable to cross-sell, consistent with the core mechanism of behavioral cross-selling.

Auto Dealers & Financing Products. Auto dealers frequently act as intermediaries in vehicle financing, earning compensation by marking up interest rates arranged through third-party lenders. Davis (2012) estimates that finance and insurance activities account for over half of franchise dealer profits. The structure of mark-up compensation would allow dealers to generate profits through less salient components of the transaction (Grunewald *et al.*,

[47] See footnote 2.

[48] See `https://www.bloomberg.com/news/articles/2017-03-31/airlines-make-more-money-selling-miles-than-seats`.

[49] See discussion in Saxon and Spickenreuther (2023).

[50] Saxon and Spickenreuther (2023).

[51] See `https://www.housingwire.com/articles/welcome-to-walmart-heres-your-mortgage/`.

[52] See CFPB (2018), citing Alexandrov and Koulayev (2018); Fannie Mae (2022); CFPB (2015). See also Woodward and Hall (2012); Bhutta *et al.* (2024).

2020; Momeni, 2024). For instance, consumers who negotiate lower prices may unknowingly accept higher interest rates. Indeed, Grunewald *et al.* (2020) notes that their empirical evidence is consistent with a model in which consumer utility is more sensitive to changes in car price than loan price.

Tax Services & Refund Anticipation Loans. In the mid-2000s tax preparation services such as H&R block commonly offered refund anticipation loans—short-term financing against expected tax refunds. By one estimate, this type of product accounted for 21% of H&R Block's tax services revenue, and the firm's stock fell 7% following regulatory pressure to end the program.[53] While these loans may have addressed short-term liquidity needs, a settlement with the California Attorney General alleged they were deceptively marketed as early refunds rather than high-cost loans, raising concerns about consumer misunderstanding.[54] This case reflects the logic of behavioral cross-selling: leveraging customer access to cross-sell financial products where behavioral frictions reduce effective price sensitivity.

Sports TV Networks & Sports Gambling. In recent years, sports networks have increasingly partnered with sportsbooks as legalized betting has expanded. ESPN launched ESPN Bet in 2023 through a $2 billion licensing agreement with Penn Entertainment,[55] and several regional sports networks that carry live professional games now feature the FanDuel brand through naming partnerships.[56] While some consumers may gamble rationally for entertainment value, evidence of adverse impacts on certain households suggests that this is not always the case (Baker *et al.*, 2024). Either way, these partnerships enable networks to promote gambling products that are designed to achieve substantial profits (Levitt, 2004). Consistent with behavioral cross-selling, networks cross-sell to product where consumers appear insensitive to true costs.

[53] See `https://www.creditslips.org/creditslips/2010/12/hr-block-blocked-from-refund-anticipation-loans.html`.

[54] See `https://web.archive.org/web/20110812140525/http://oag.ca.gov/news/press_release?id=1645`.

[55] See `https://www.nytimes.com/2023/08/08/business/espn-penn-entertainment-gambling.html`.

[56] See `https://www.businesswire.com/news/home/20241018023472/en/Diamond-Sports-Group-and-FanDuel-Announce-Broad-Commercial-Partnership`.

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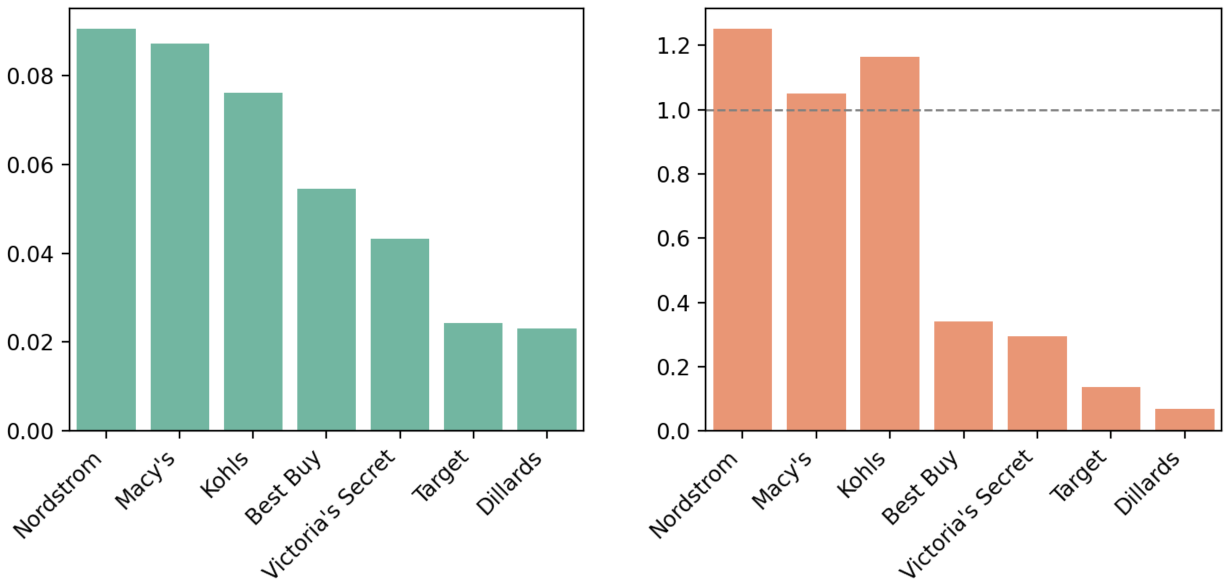
Figures

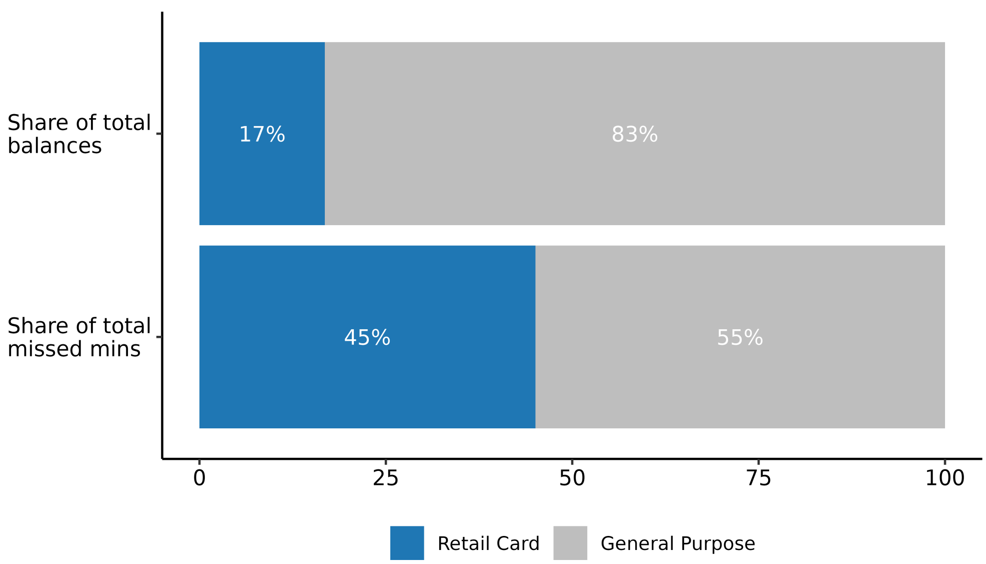
Figure 1: *Importance of Retail Cards For Select Stores*

(a) *Average Card Revenue/Gross Profit 2022-24* **(b)** *Average Card Revenue/Operating Income 2022-24*



Note: Figure shows card revenue normalized by gross profit or operating income, averaged from 2022-2024. Data Source: 10-K reports.

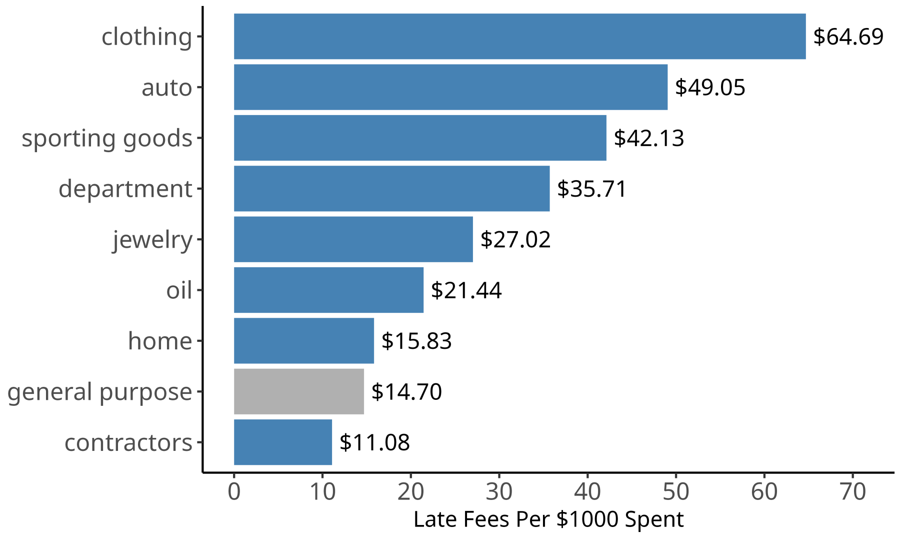
Figure 2: *Retail Cards Incur Disproportionate Share of Late Fees*



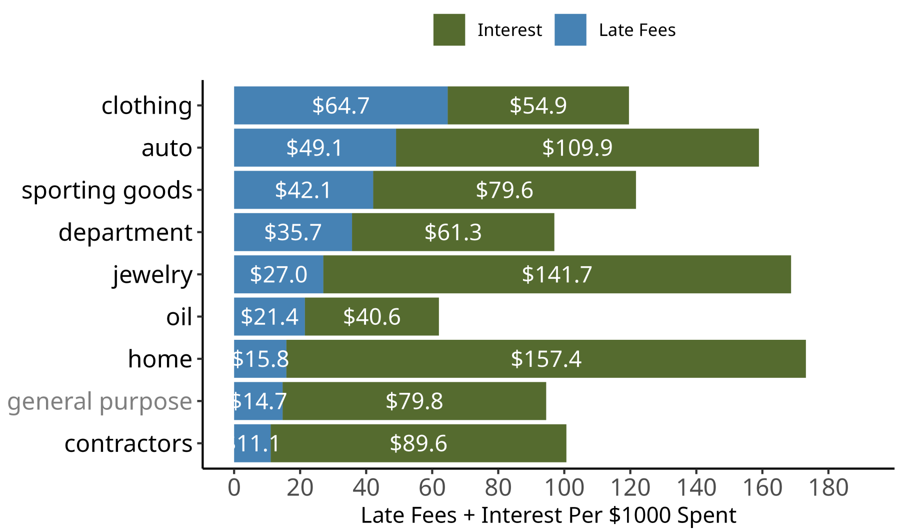
Note: Figure shows the share of total balances and missed minimums incurred by retail versus general purpose cards. The sample restricts to cards with actual payments and balances. Data Source: Credit Bureau Data.

Figure 3: *Estimated Revenue by Card Type within Two Years of Card Opening*

(a) *Late Fee Revenue*

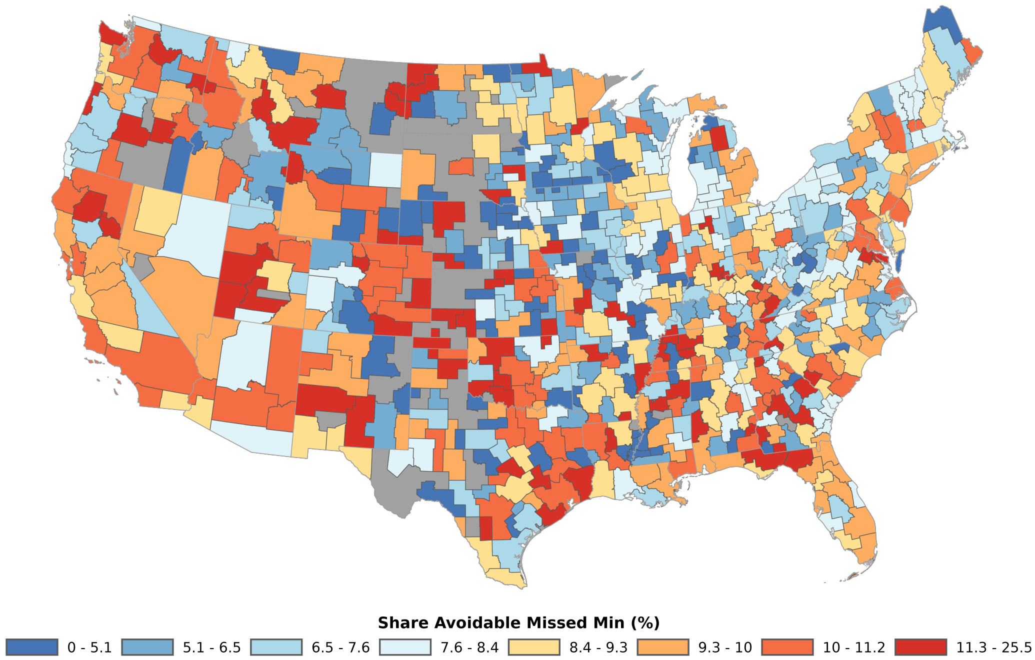


(b) *Late Fee and Interest Revenue*



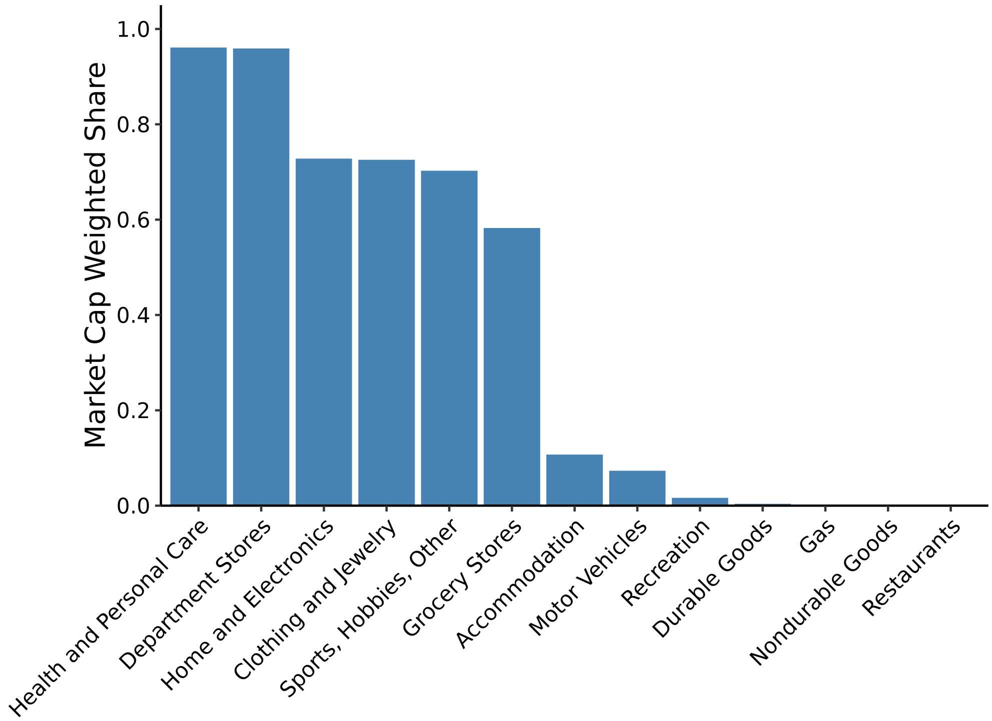
Note: Figure shows the expected revenue from late fees and interest by card type (or industry) per $1000 spent. We calculate the expected revenue within two years of a card opening using the 2013-2022 sample. Details on the methodology can be found in Appendix A.8. Data Source: Credit Bureau Data.

Figure 4: *Variation in α at the Commuting Zone Level*



Note: Figure shows the probability of an avoidable missed minimum by commuting zone as defined in Section 5.1, in the 2017-2018 sample. Data Source: Credit Bureau Data.

Figure 5: *Card Offerings by Industry*



Note: Figure shows the market-capitalization weighted share of firms that offer a credit card for select three-digit NAICS industries within retail, food, and accommodation (two-digit NAICS: 44, 45, 71, 72). Data Source: 10-K filings; Compustat.

Tables

Table 1: *Summary Statistics By Card Type*

Statistic	General Purpose	Private Label	Department	Clothing	Contractors	Home	Jewelry	Oil	Auto	Sporting Goods
Usage Characteristics										
Share Non-Zero Balance	0.64	0.43	0.42	0.43	0.45	0.46	0.35	0.57	0.45	0.50
Share Revolving	0.57	0.44	0.42	0.40	0.51	0.60	0.65	0.29	0.51	0.65
Average Balance If Non-Zero	2,250	562	453	267	1,147	1,164	1,472	269	610	599
Average Revolving Balance If Rev	2,048	626	529	288	1,333	1,238	1,408	383	561	587
Share Delinquent Within 2 Years	0.05	0.06	0.06	0.09	0.02	0.05	0.08	0.02	0.07	0.12
Average Card Age (Yr)	7	7	8	5	6	3	3	19	4	3
Credit Scores										
Average Credit Score	731	718	723	699	741	731	687	724	713	670
Share Deep Subprime ($<$ 580)	0.08	0.10	0.09	0.13	0.05	0.06	0.14	0.08	0.09	0.17
Share Subprime (580-619)	0.05	0.06	0.06	0.08	0.03	0.05	0.09	0.05	0.06	0.11
Share Near-prime (620-659)	0.08	0.09	0.09	0.11	0.07	0.09	0.13	0.08	0.10	0.18
Share Prime (660-719)	0.15	0.17	0.16	0.18	0.16	0.18	0.23	0.15	0.19	0.22
Share Superprime (720+)	0.64	0.58	0.61	0.49	0.69	0.61	0.41	0.65	0.55	0.33
Demographics										
Share Female	0.53	0.68	0.69	0.86	0.46	0.60	0.39	0.48	0.40	0.38
Share Homeowner	0.63	0.64	0.64	0.58	0.75	0.65	0.55	0.70	0.64	0.58
Average Income ($k)	63	57	57	53	61	64	54	60	56	56
Sample Size										
N Cards	2,454,534	1,227,734	695,114	261,692	86,884	86,485	39,192	27,695	27,060	3,612
N Cards W/ Balance	2,347,093	924,405	489,264	187,695	84,538	72,259	36,918	27,128	23,883	2,720
N Cards W/ Actual Payments	686,484	610,479	333,825	143,272	53,795	31,780	19,123	14,429	12,328	1,927

Note: Table shows summary statistics at the card-level for the 2017-2018 sample. Measures were first constructed at the card-level (e.g., averaged over card-month observations), then averaged over cards. The card age is as January 2018. Demographics are imputed by the Credit Bureau. Data Source: Credit Bureau Data.

Table 2: *Frequency of Missed Minimums*

	% of Months w/ Missed Min		% of Cards w/ Missed Min (2 yrs)	
	General Purpose	Retail Card	General Purpose	Retail Card
1) Superprime	4.5	4.9	29.3	24.6
2) Prime	8.0	8.9	43.1	42.3
3) Near-prime	10.1	11.3	48.3	48.9
4) Subprime	13.7	15.7	54.4	56.8
5) Deep Subprime	19.7	22.9	62.4	65.8
Overall	7.7	9.8	38.4	37.3

Note: Table shows the frequency of missed minimums for the 2017-2018 sample. The percentage of months with a missed minimum is constructed as the total number of missed minimums across all cards divided by the total number of card months with a non-zero balance in a given credit score category. The percentage of cards with a missed minimum is calculated as the share of cards that have missed at least one minimum over the 2017-2018 period, conditional on the card having at least one month with a non-zero balance. Data Source: Credit Bureau Data.

Table 3: *Missed Minimums are More Common on Retail Cards*

	Missed Min. (0 or 1) x 100		
	(1)	(2)	(3)
Retail Card	2.550***	1.775***	1.364***
	(0.020)	(0.016)	(0.017)
Mean Outcome	7.87	7.87	7.87
Sample	Positive Baln	Positive Baln	Positive Baln
R2 Adj.	0.002	0.100	0.176
FE Controls		Individual	Individual x Month
Observations	79367940	79367940	79367940

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: Table shows the likelihood of missing minimums on retail cards for the 2013-2022 sample. The regressions include only card-month observations with balance greater than zero. Standard errors are clustered at the individual level. Data Source: Credit Bureau Data.

Table 4: *Frequency of Avoidable Missed Minimums Among 2+ Card Holders*

	% of Missed Mins That are Avoidable		*% of Cards w/ Avoidable Misses (2 yrs)*	
	General Purpose	Retail Card	General Purpose	Retail Card
1) Superprime	62.9	70.4	19.3	18.0
2) Prime	50.3	55.0	27.1	28.4
3) Near-prime	43.4	46.4	29.3	31.4
4) Subprime	37.1	39.6	31.0	34.8
5) Deep Subprime	31.4	32.4	33.6	38.2
Overall	47.4	48.5	23.9	24.9

Note: Table shows the frequency of avoidable missed minimums for the 2017-2018 sample, restricting to card-month observations where the borrower has at least two open card lines. The percent of missed minimums that are avoidable is constructed as the number of missed minimums in which the minimum could have been made based on excess payments across cards divided by the total number of missed minimums. The percentage of cards with an avoidable missed minimum is calculated as the share of cards that have missed at least one avoidable minimum over the 2017-2018 period, conditional on the borrower having at least two open card lines. Data Source: Credit Bureau Data.

Table 5: *Annual Costs of Missing Avoidable Minimum*

	Mean	SD	p50	p75	p90
N Makeable Missed Mins	2.44	2.44	2	3	5
Total Cost	63.53	63.47	52	78	130
Effective Annual IR Increase	24.56	66.19	3.17	13.06	63.24

Note: Table shows the annual costs of missing an avoidable minimum over the 2018 sample for borrowers who have at least two cards open in a given month and had at least one avoidable missed minimum. We assume that the late fee is $26. The effective annual interest rate increase at the borrower-level is calculated as the total costs from an avoidable missed minimum over the average monthly revolving balance. Data Source: Credit Bureau Data.

Table 6: *Evidence of "Forgetting" to Repay Retail Cards*

	Missed Min. (0 or 1) x 100			
	(1)	(2)	(3)	(4)
Retail Card	1.191***	0.631***	1.461***	0.772***
	(0.021)	(0.021)	(0.020)	(0.020)
Months w/ zero spend		0.375***		0.381***
(of last year)		(0.002)		(0.003)
Mean Outcome	7.49	7.49	2.7	2.7
Sample	Positive Baln	Positive Baln	Excess Pymnts	Excess Pymnts
FE Controls	Individual	Individual	Individual x Month	Individual x Month
Observations	47766391	47766391	32330324	32330324

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: Table shows the relationship between missing a minimum and the share of months over the past year with zero spending over the 2013-2022 sample. Column (1) and (2) condition on card-month observations with a positive balance and with a non-missing value of months over the past year with zero spending. Column (3) and (4) condition on card-month observations with excess payments and with non-missing values of months over the past year with zero spending. Standard errors are clustered at the individual level. Data Source: Credit Bureau Data.

Table 7: *Correlation Between α and County-Level Characteristics*

	α: Share Avoidable Missed Min. (SD)			
	(1)	(2)	(3)	(4)
Pop. Density (1000s ppl per mi)	0.04***	0.04**	0.04**	0.02^{+}
	(0.01)	(0.01)	(0.01)	(0.01)
Log Per Capita Income	0.22*	0.06	0.06	0.34
	(0.10)	(0.20)	(0.21)	(0.23)
Prop. College Educ. (%)		0.00	0.00	0.00
		(0.00)	(0.00)	(0.00)
Prop. Labor Force (%)			0.00	0.00
			(0.00)	(0.00)
Avg Credit Score (SD)				−0.12***
				(0.04)
Mean Outcome	1.57	1.57	1.57	1.57
Observations	1978	1978	1978	1978
R2	0.004	0.004	0.004	0.011

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: Table shows the correlation between the county-level share of avoidable missed minimums and various county demographics. The population, income, education, and labor force variables are from the American Community Survey (ACS), and average credit score is calculated as the average of all borrowers within a county in the 2017-2018 credit bureau sample. The share of avoidable missed minimums and the average credit score are normalized by the standard deviation of each measure. Standard errors are robust to heteroskedasticity. Data Source: Credit Bureau Data and ACS.

Table 8: *Extensive Margin of Card Offerings*

	Ever Mentions Card (0 or 1) x 100			
	(1)	(2)	(3)	(4)
Wgt Avoidable Missed Min Prob. (SD)	9.107**		7.070*	6.347*
	(3.062)		(3.269)	(3.002)
Wgt Missed Min Prob. (SD)		3.680		
		(3.014)		
Log (total stores)	6.266*	5.263^{+}	10.961***	8.807**
	(2.642)	(2.722)	(2.900)	(2.697)
Firm-Wght Income Per Capita (SD)			−9.855*	-8.177^{+}
			(4.741)	(4.203)
Mean Outcome	32.47	32.47	32.47	32.47
Observations	194	194	194	194
FE Controls	2-Digit Naics	2-Digit Naics	2-Digit Naics	2-Digit Naics
Weights	By Stores	By Stores	By Stores	
R2	0.195	0.172	0.220	0.208

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: Table shows the relationship between firms card offering and the probability of borrowers making an avoidable missed minimum on general purpose cards for firms within retail, food, and accommodation industries. The county-level measure is aggregated to the firm-level using store locations. The weighted avoidable missed minimum probability, the unconditional missed minimum probability, and income per capita are normalized by the standard deviation of each measure. Standard errors are robust to heteroskedasticity. Data Source: Credit Bureau Data; Dun & Bradstreet; 10-K filings.

Table 9: *Relationship Between Rewards Offered and Late Fees*

	Rewards at Main Store (%)			
	(1)	(2)	(3)	(4)
Expected N Avoidable Missed Min (SD)	0.575*		1.250*	0.910*
	(0.064)		(0.196)	(0.204)
Expected N Missed Min (SD)		0.817**		
		(0.037)		
Log (total stores)	0.404	0.447^{+}	0.229*	0.164^{+}
	(0.140)	(0.140)	(0.039)	(0.050)
Firm-Wght Income Per Capita (SD)			0.769	0.877
			(0.541)	(0.667)
Mean Outcome	5.51	5.51	5.51	5.51
Observations	65	65	65	65
FE Controls	2-Digit Naics	2-Digit Naics	2-Digit Naics	2-Digit Naics
Weights	By Stores	By Stores	By Stores	
R2	0.159	0.158	0.163	0.168

$^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: Table shows the relationship between the rewards rate at the main store in percentage terms and firm-level variables. Details on how we collect and filter rewards data can be found in Appendix A.6, and details on the construction of the firm-level expected missed minimums can be found in Section 5.1. The weighted number of avoidable missed minimums, the number of unconditional missed minimums, and income per capita are normalized by the standard deviation of each measure. Standard errors are robust to heteroskedasticity. Data Source: Credit Bureau Data; NerdWallet; Firm Websites; SafeGraph; ACS.

Table 10: *Relationship Between Introduction Percentage Offered and Late Fees*

	Intro Offer at Main Store (%)			
	(1)	(2)	(3)	(4)
Expected N Avoidable Missed Min (SD)	9.008**		7.693*	9.738*
	(0.359)		(1.104)	(1.062)
Expected N Missed Min (SD)		7.245***		
		(0.136)		
Log (total stores)	0.038	−0.065	1.817	0.443
	(0.932)	(0.860)	(1.099)	(1.562)
Firm-Wght Income Per Capita (SD)			−5.259	−2.075
			(4.812)	(4.185)
Mean Outcome	18.85	18.85	18.85	18.85
Observations	39	39	39	39
FE Controls	2-Digit Naics	2-Digit Naics	2-Digit Naics	2-Digit Naics
Weights	By Stores	By Stores	By Stores	
R2	0.126	0.120	0.154	0.163

$^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: Table shows the relationship between the one-time sign-up bonus in percentage terms and firm-level variables. Details on how we collect and filter rewards data can be found in Appendix A.6, and details on the construction of the firm-level expected missed minimums can be found in Section 5.1. The weighted number of avoidable missed minimums, the number of unconditional missed minimums, and income per capita are normalized by the standard deviation of each measure. Standard errors are robust to heteroskedasticity. Data Source: Credit Bureau Data; NerdWallet; Firm Websites; SafeGraph; ACS.

Table 11: *Credit Constraints at Time of Store Card Opening*

	% of Borrowers w/ Other Card	*% that Could Finance First Month on Other Cards*	*Avg Utilization on Other Cards (%)*
1) Superprime	93.1	98.5	15.7
2) Prime	71.6	90.3	43.5
3) Near-prime	67.6	83.6	57.2
4) Subprime	62.9	76.9	63.9
5) Deep Subprime	52.0	69.9	67.9
Overall	76.7	90.8	34.7

Note: Table shows a snapshot of the availability of general purpose cards for borrowers at the time of opening a store card in the 2017-2018 sample. Each observation is at the borrower and card opening month level, so if a borrower opens two store cards within the 2017-2018 sample, then they are represented twice at the time of each card opening. Columns (2) and (3) are conditional having at least one other card. All statistics are calculated using general purpose cards only. Data Source: Credit Bureau Data.

Table 12: *Distribution of Missed Minimums on Store Cards In Two Year Period*

	Zero Missed Mins (%)	*One Missed Min (%)*	*Two+ Missed Mins (%)*
1) Superprime	76.2	15.2	8.6
2) Prime	58.5	19.2	22.3
3) Near-prime	51.6	19.2	29.2
4) Subprime	43.7	18.6	37.7
5) Deep Subprime	34.8	16.7	48.5
Overall	63.6	16.7	19.6

Note: Table shows the distribution of missed minimums across credit score within the 2017-2018 sample. Observations are at the borrower-card level for store cards. All store cards are included regardless of whether or not they were used in the two year period. Data Source: Credit Bureau Data.

A Appendix

A.1 Proofs

Proof of Prediction 2.1

Proof. (a) Let $\overline{\alpha}$ be such that $\Pi(p^*_{\not{c}})|\text{No Offer} = \Pi(p^*_c, d^*_c, \overline{\alpha})|\text{Offer}$. By the envelope theorem, Π conditional on offering the financial product is non-decreasing in α, so for all $\alpha \geq \overline{\alpha}$, $\Pi|\text{No Offer} \leq \Pi(\alpha)|\text{Offer}$ and cross-selling occurs. Identical logic holds for $\alpha < \overline{\alpha}$.

(b) This follows almost immediately from inspecting Equation 2. When $C_k = 0$, all firms within an industry will cross-sell since the optimization problem with cross-selling perfectly nests the optimization with no cross-selling (same solution can be achieved with $d_{k,b} = 0 \Rightarrow \gamma(d_{k,b}) = 0$). When C_k becomes large, it will no longer be profitable for any store in industry k to cross-sell.

□

Proof of Prediction 2.2

Proof. The derivative, $\frac{\partial d^*}{\partial \alpha} = R > 0$, follows directly from Equation 3. To show that Equation 3 holds, we can take first order conditions. Conditional on cross-selling, the two first order conditions are:

$$[p] : p = -\frac{D(p)}{D'(p)} + c - \gamma(d)(\alpha R - d) \tag{A.1}$$

$$[d] : d = -\frac{\gamma(d)}{\gamma'(d)} + \alpha R \tag{A.2}$$

□

Proof of Prediction 2.3

Proof. Consider a simple model of price discrimination, adapted and using similar notation to Berg *et al.* (2025). There are two types of consumers. High income consumers have WTP: $w^{high} = 1$ and low income consumers have (lower) WTP: $w^{low} = 1 - \Delta$. The share of low income consumers is η. Marginal costs for the store are $1 - \Delta - m$, where m is the margin on the base good, if sold to a low income consumer at their willingness-to-pay.

Assume that high income consumers (and firms) have a discount rate equal to 1, but due to liquidity constraints, low income consumers have a lower discount rate $\delta = \frac{1}{1+r_b}$. Let

$$(1-\eta)(\Delta + m) > m$$

so without in-store financing, firms set $p^* = 1$ and only sell to high-income consumers. Intuitively, if the high-income consumers' WTP is a lot higher (Δ is large), the store will profit-maximize by only selling to high-income consumers, rather than lowering prices for everyone. In this case, with no in-store financing, profits are $(1-\eta)(\Delta + m)$.

With in-store financing, if the price p is set such that both types of consumers buy the base good and $r < r_b$ (stores offer "cheap" financing), profits are given by:

$$\eta \cdot [(1+r)p - (1-\Delta-m)] + (1-\eta) \cdot [p - (1-\Delta-m)]$$

The participation constraints are:

$$\begin{aligned} 0 < r < r_b \qquad & \text{[Cheap financing]} \\ p \le 1 \qquad & \text{[High income buys good]} \\ \delta(1+r)p \le 1-\Delta \qquad & \text{[Low income buys good]} \end{aligned}$$

Suppose the store sets $r = \frac{1-\Delta}{\delta} - 1 < \frac{1}{\delta} - 1 = r_b$ and $p^* = 1$. Then, they make profits of:

$$\eta \cdot [(1-\Delta)/\delta - (1-\Delta-m)] + (1-\eta) \cdot [\Delta + m] = \left(\frac{1-\Delta}{\delta} - 1\right)\eta + \Delta + m$$

This will be higher than profits with no in-store financing if

$$\Delta\left(1 + \frac{1}{\delta}\right) + m > \frac{1}{\delta} - 1$$

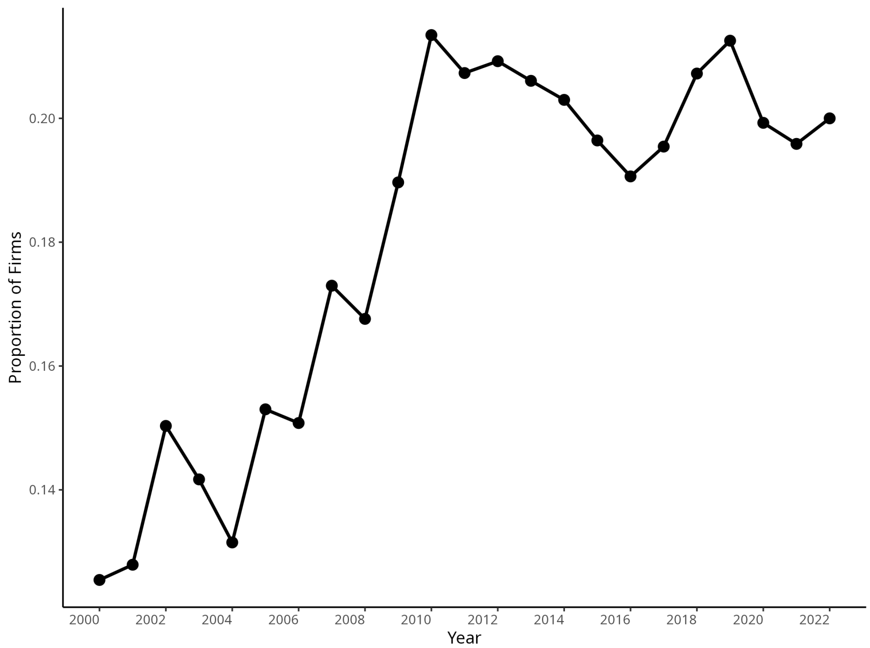
Intuitively, when margins are high, it is worth offering the bundled good-financing package since this allows low-income consumers to buy the good (receiving a discount on financing) instead of being locked out of the market. Only low income, low discount rate consumers take up the financial product since high income consumers have high discount rates. □

Proof of Prediction 2.4

Proof. Plugging the FOC for p into the FOC for d (Equations A.1 and A.2) gives us Equation 4. Equation 4 minus Equation A.2 yields the price consumers who take the financial product pay. □

A.2 Additional Figures

Figure A.1: *Retail, Food, & Accommodation Card Mentions over Time*



Note: Figure plots the share of firms in retail, food, and accommodation that mention credit card partnerships in their 10-K in a given year. Details on the methodology used to identify these partnerships can be found in Appendix A.5. Data Source: 10-K filings.

Figure A.2: *Example Synchrony Credit Card Agreement*

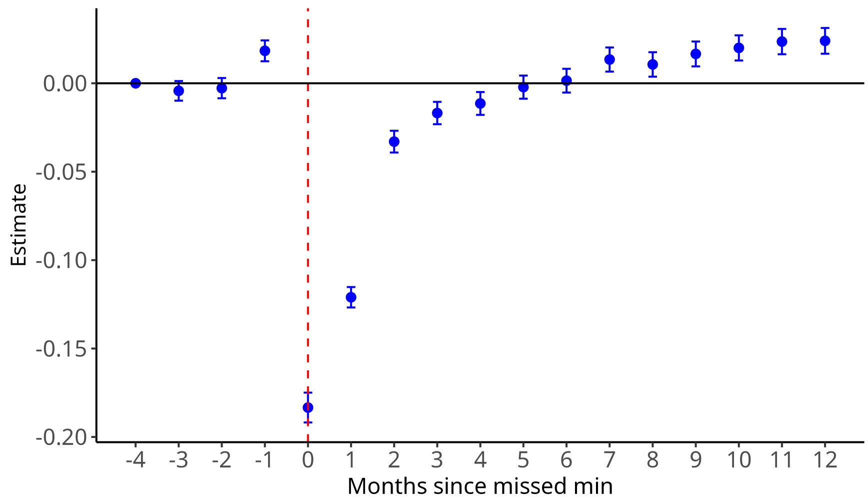
Minimum Payment Calculation
Your total minimum payment is calculated as follows.
The greater of:

1. $30, or $41 (which includes any past due amounts) if you have failed to pay the total minimum payment due by the due date in any one or more of the prior six billing cycles.
   OR
2. The sum of:
   a. Any past due amounts; PLUS
   b. 1% of your new balance (excluding any balance in connection with a special promotional purchase with a unique payment calculation) shown on your billing statement; PLUS
   c. Any late payment fees charged in the current billing cycle; PLUS
   d. All interest charged in the current billing cycle; PLUS
   e. Any payment due in connection with a special promotional purchase with a unique payment calculation.

We round up to the next highest whole dollar in figuring your total minimum payment. Your total minimum payment will never be more than your new balance. Payments required in connection with a special promotional purchase with a unique payment calculation will not be increased to, but may be included in the $30 or $41 minimum amount otherwise due on your account.

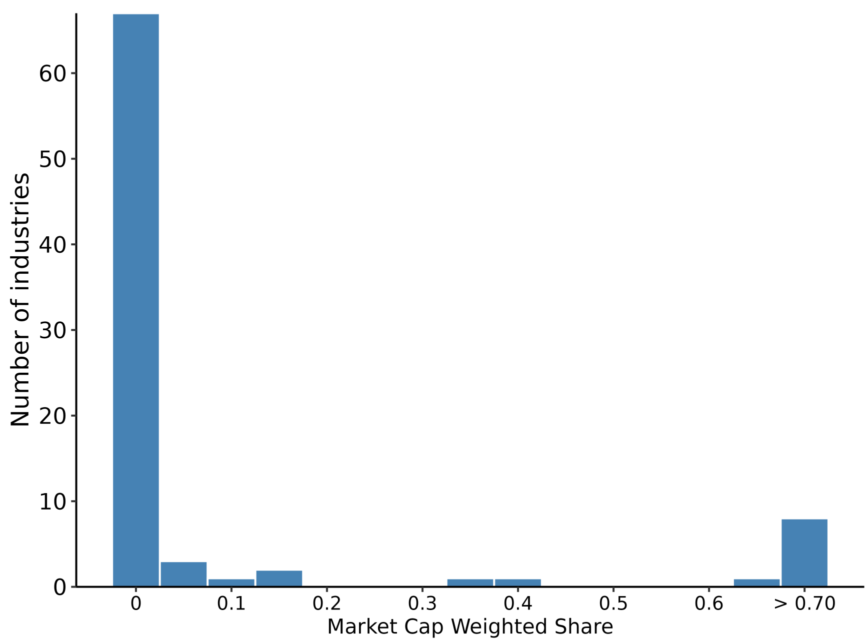
Note: Figure shows example minimum payment formula for Synchrony Financial (Premier World Mastercard) from the CFPB Credit Card Contract Database 2022Q4. At the time, 12 CFR § 1026.52 (Regulation Z) allowed lenders to charge a $30 late fee after a first miss and a larger late fee, $41, if the borrower had already missed a payment in the prior six months. The minimum payment floor exactly reflects these two thresholds.

Figure A.3: *Consumer Spending After Missing an Avoidable Minimum*



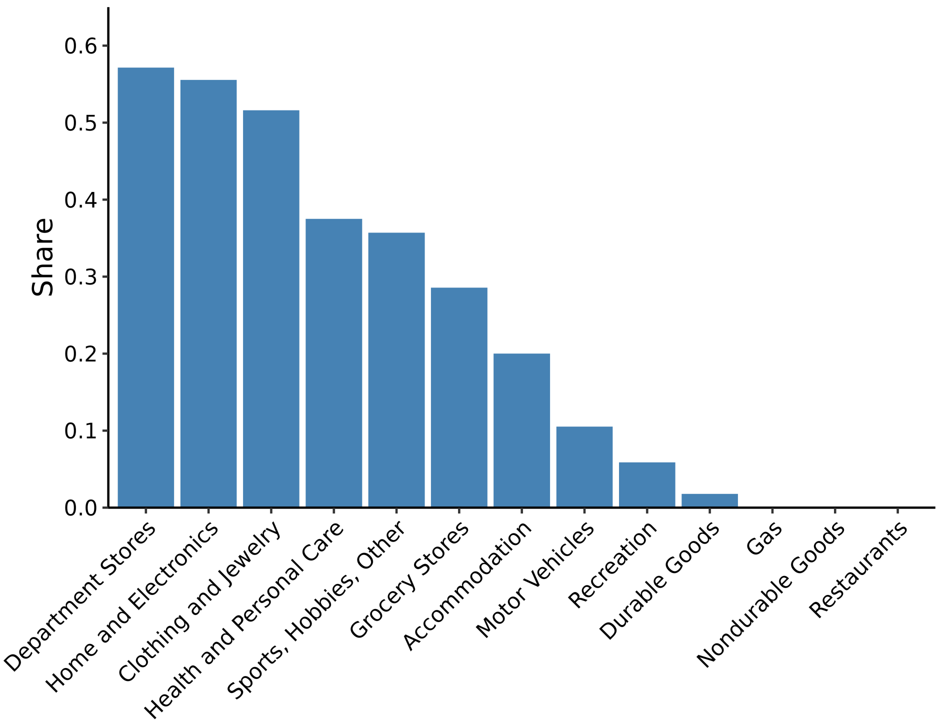
Note: Figure shows the probability that a consumer spends on a card in the months after an avoidable missed minimum over the 2013-2022 sample. The avoidable missed minimum occurs in month 0, and estimates are relative to the probability of spending on the card four months prior to an avoidable missed minimum. The sample is restricted to consumers who don't miss an additional minimum between month 1 and month 12. Data Source: Credit Bureau Data.

Figure A.4: *Distribution of Card Offering Share By Industry*



Note: Figure shows the distribution of the market capitalization weighed share of firms that offer cards within all three-digit NAICS industries. Each observation is a three-digit NAICS industry in the 2023 fiscal year sample of firm 10-Ks. In this figure, credit card partnerships are identified using only the 2023 snapshot. Details on the methodology can be found in Appendix A.5. Data Source: 10-K filings and Compustat.

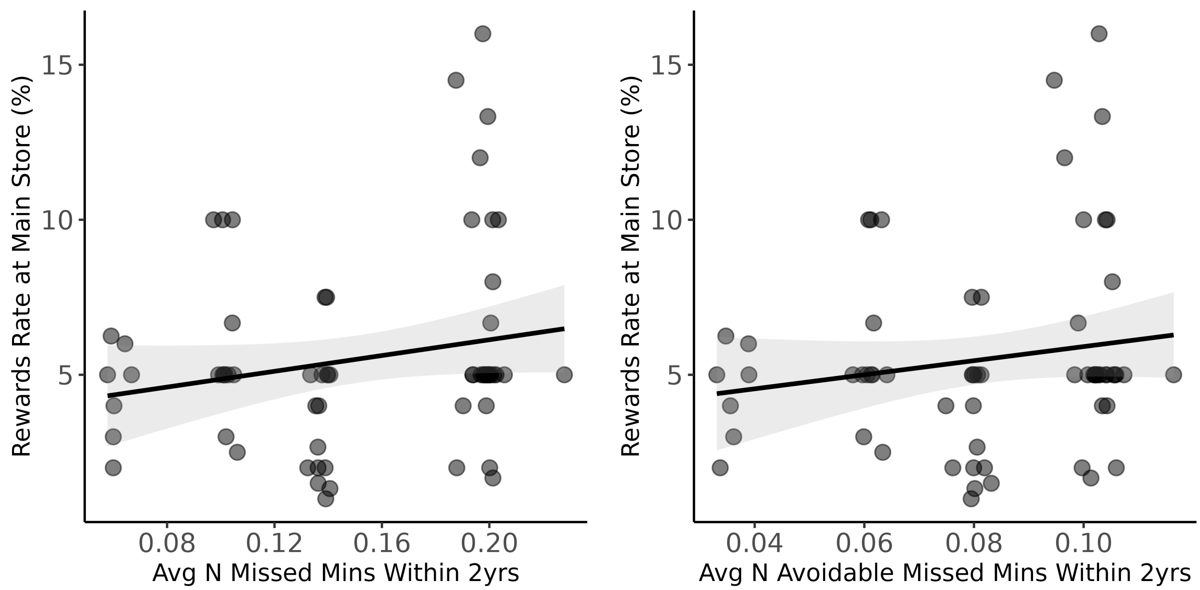
Figure A.5: *Unweighted Card Offerings by Industry*



Note: Figure shows the unweighted share of firms that offer a credit card for select three-digit NAICS industries within retail, food, and accommodation (two-digit NAICS: 44, 45, 71, 72). Data Source: 10-K filings; Compustat.

Figure A.6: *Missed Minimums and Rewards*

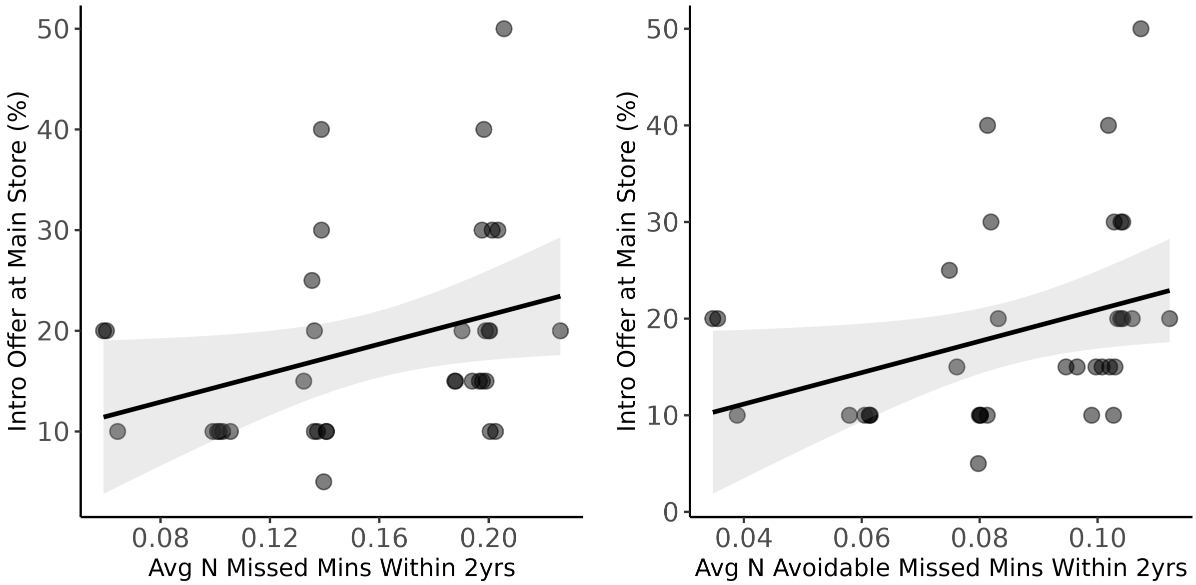
(a) *Missed Minimums* **(b)** *"Avoidable" Missed Minimums*



Note: Figure shows a scatterplot of the rewards rate at the main store in percentage terms on the firm-level expected number of missed minimums within two years over the 2013-2022 credit bureau sample. Details on how we collect rewards data can be found in Appendix A.6, and details on the construction of the firm-level expected missed minimums can be found in Section 5.1. Data Source: Credit Bureau Data; NerdWallet; Firm Websites; SafeGraph.

Figure A.7: *Missed Minimums and Introduction Offer*

(a) *Missed Minimums* **(b)** *"Avoidable" Missed Minimums*



Note: Figure shows a scatterplot of the one-time sign-up bonus in percentage terms on the firm-level expected number of missed minimums within two years over the 2013-2022 credit bureau sample. Only firms with intro offer percentages greater than zero are included. Details on how we collect rewards data can be found in Appendix A.6, and details on the construction of the firm-level expected missed minimums can be found in Section 5.1. Data Source: Credit Bureau Data; NerdWallet; Firm Websites; SafeGraph.

A.3 Additional Tables

Table A.1: *Correlation Between Share of Missed Minimums and County-level Characteristics*

	Share Missed Min. (SD)			
	(1)	(2)	(3)	(4)
Pop. Density (1000s ppl per mi)	0.08***	0.08***	0.08***	0.04*
	(0.02)	(0.02)	(0.02)	(0.02)
Log Per Capita Income	−0.18+	−0.21	−0.19	0.49*
	(0.11)	(0.21)	(0.21)	(0.23)
Prop. College Educ. (%)		0.00	0.00	0.00
		(0.00)	(0.00)	(0.00)
Prop. Labor Force (%)			0.00	0.00
			(0.00)	(0.00)
Avg Credit Score (SD)				−0.30***
				(0.04)
Mean Outcome	2.1	2.1	2.1	2.1
Observations	1981	1981	1981	1981
R2	0.004	0.004	0.004	0.039

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: Table shows the correlation between share of card-months with a missed minimum (conditional on a positive balance) in percentage terms and various county demographics. The population, income, education, and labor force variables are from the American Community Survey (ACS), and average credit score is calculated as the average of all borrowers within a county in the 2017-2018 credit bureau sample. The share of missed minimums and the average credit score are normalized by the standard deviation of each measure. Standard errors are robust to heteroskedasticity. Data Source: Credit Bureau Data and ACS.

A.4 Analyst Reports on Effects of CFPB Late Fee Regulation

In early 2024 the Consumer Financial Protection Bureau finalized a rule to lower the safe harbor threshold for credit card late fees. The prior rule allowed a \$30 late fee for the first missed payment and \$41 for any subsequent misses within six months, both adjusted upward with the Consumer Price Index (CPI) over time. The proposed rule would have lowered the safe harbor to \$8 for all misses and removed the CPI adjustment.[57] The rule was stayed, and eventually voided, by a federal judge.[58]

Below, we provide examples of analyst reports that discussed the potential effects of the regulation on non-financial firms in retail credit card partnerships.

[57] https://www.federalregister.gov/documents/2024/03/15/2024-05011/credit-card-penalty-fees-regulation-z.

[58] https://www.nytimes.com/2025/04/16/business/credit-card-late-fee-limit-cfpb.html.

Morgan Stanley Analyst Report, Feb. 2024 (Straton *et al.*, 2024)

> Our analysis shows the proposed credit card late fee regulation change could negatively impact Dept. Store '25e EBIT by $\sim$ 30% on average. We highlight outsized downside risk for those with higher 1) private label credit card exposure (where a larger % of revenue is generated from late fees), & 2) low-income consumer exposure (the cohort that tends to disproportionately pay late fees).

UBS Analyst Report, Jan. 2024 (Sole *et al.*, 2024)

> Our analysis indicates Department Stores such as KSS, JWN, and M likely experience the greatest negative impact to EPS if the CFPB rule change on credit card late fees is implemented. The CFPB has proposed a $\sim$ 75% reduction in credit card late fee revenue. KSS could see a -100% to -34% (-\$2.01 to -\$0.67) impact on EPS vs. our FY23 estimate, all else equal. The EPS impact for M and JWN could be in the -37% to -6% range vs. our FY23 forecast. GPS and DDS could experience an EPS impact in the -12% to -1% range vs. our FY23 EPS estimate (Fig. 1). We believe downside risk from the potential reduction in credit card late fees is not fully priced into these stocks. Credit income reduction risk is one reason we rate KSS, JWN, M, GPS, and DDS Sell.

BofA Global Research Analyst Report, Nov. 2023 (Hutchinson and Xiao, 2023)

> We remain concerned about GPS' exposure to credit income and the potential impact of CFBP's [sic] regulation to reduce late fees. Although GPS no longer discloses its credit card revenues, in 2017 it recognized \$412mn from its credit card revenue sharing programs with then-partner Synchrony. This was 2.6% of sales and 29% of EBIT in 2017; keeping credit at 2.6% of sales in F2024 would equate to 73% of EBIT. 2024 is the earliest the late fee changes could occur, and management is working with current credit partner Barclays to mitigate potential impacts.

BofA Global Research Analyst Report, Sep. 2023 (Hutchinson *et al.*, 2023)

> Credit agreements are all different, and we have no visibility on the breakout of income. Historical JWN financials show that 12-14% of credit revenue came from late fees. This is likely higher for M/KSS given the customer demographics and could be different depending on the structure of these deals. Because of this lack of clarity, we used a wide range of outcomes for our scenario analysis (late fees

between 14% and 30% of credit revenue). Assuming late fees decline 75% and costs remain the same, we estimate M/JWN would lose 6%/11% of F24 EPS at the better end of the scenario. We model KSS credit income as 68% of total EBIT in F24, making the change more severe. Under the 14% revenue contribution, KSS' EPS would drop 29%.

A.5 Additional Details on Text from 10-K SEC Filings

In order to systematically identify firms with credit cards, we analyze firm 10-Ks using the edgar-crawler. We use two samples of 10-Ks: (a) retail, food, and accommodation firms from 2000-2024; and (b) all public firms in 2023. In order to identify whether or not a firm has a credit card partnership, we search the 10-K text for mentions of the following phrases associated with credit card partnerships: "private-label credit card", "private label credit card", "proprietary credit card", "credit card agreement", "credit card arrangement", "credit card partner", "credit card relationship", "credit card issued by", "credit cards issued by", "credit card program", "credit card profit", "credit card revenue", "credit card operations", "credit card member", "company's credit card", "loyalty credit card", "private label and co-branded credit card", "private-label and co-branded credit card", "co-branded and private-label credit card", "co-branded and private label credit card."

If one of these phrases are mentioned, then we use this as a proxy for the firm having a credit card. Figure A.8 provides examples of excerpts from firm 10-Ks in which a credit card-related phrase was mentioned.

Figure A.8: *Examples of Credit Card Mentions in Firm 10-Ks*

(a) *Excerpt from Gap's 2023 10-K*

Old Navy, Gap, Banana Republic, and Athleta each have a private label credit card program and a co-branded credit card program through which customers receive benefits. Private label and co-branded credit cards are provided by a third-party financing company, with associated revenue sharing arrangements reflected in Gap Inc. operations. We also have an integrated loyalty program across the U.S. and Puerto Rico that aims to attract new customers and create enduring relationships by turning customers into lifelong loyalists. We are focused on increasing the lifetime value of our loyalty members through greater personalization, including leveraging first party data and increasing promotions with targeted content, offers, and experiences. Although each brand expression has a different look and feel, customers can earn and redeem rewards across all of our brands. All of our brands issue and redeem gift cards.

(b) *Excerpt from Home Depot's 2020 10-k*

We help our customers finance their projects by offering PLCC products through third-party credit providers. Our PLCC program includes other benefits, such as a 365-day return policy and, for our Pros, commercial fuel rewards and extended payment terms. In fiscal 2019, our customers opened approximately 4.8 million new The Home Depot private label credit accounts, and at the end of fiscal 2019 the total number of The Home Depot active account holders was approximately 16.7 million. PLCC sales accounted for approximately 23% of net sales in fiscal 2019.

Note: Figure shows excerpts from firm 10-Ks that mention at least one of our credit card-related phrases. Data Source: 10-K filings.

We exclude general mentions of "credit cards", as this term is mentioned in other contexts (e.g., interchange fees paid). For the 2000-2024 sample of retail, food, and accommodation firms, if one of these phrases is mentioned at any point in the sample, then the firm is classified as offering a card. We do this in order to avoid cases where in a particular year, a firm fails to mention their credit card partnership.

A.6 Additional Details on Credit Card Rewards Data

Manual Collection of Rewards Data. We make our data publicly available for other researchers here. The "Read Me" contains the methodology and data dictionary. We collected information on source, card type, annual fees, rewards at store (excluding intro offers), co-branded rewards, intro offers, and financing.

Cleaning the Data. Our rewards data includes 318 co-branded and private label cards. We collapse rewards to the firm-level, so if a firm has both a co-branded and private-label card, they are in our regression sample as one observation. In many cases, the rewards rate and the sign-up bonus are the same on both cards, but if they aren't, we take the average across cards at the firm. We only include firms that have a percentage rewards rate. For example, if a gas store card offers a rewards rate of $0.13 per gallon off, then it is excluded from our sample.[59] With these two restrictions, our sample is reduced to 221 firms that we are able to match to Safegraph data.

Given our measure of ex-post profitability of retail cards, $\overline{M}_{bk}$, (described in Section 5.3) relies on geographic variation, we only include firms with at least 10 or more stores in the Safegraph data. This means we exclude firms like Wayfair that have a predominately online presence. With this restriction, we are left with 182 firms. In order to construct $\overline{M}_{bk}$, we match firms to credit bureau industries using four-digit NAICS codes. If a NAICS code doesn't fit into a credit bureau industry, then the code is excluded. We are able to match 150 remaining firms to an industry.[60] We also only include firms that have sufficient county-level borrower by industry information covering at least 60% of store locations. This is important to ensure that our aggregated firm-level avoidable missed minimums measure is representative of actual firm locations. We are left with 110 firms after accounting for this.

Some cards in our sample are used entirely as financing tools. These products offer no rewards but provide favorable terms for financing large purchases. We exclude such cards because offering cheaper financing to behavioral customers represents a different form of cross-selling. Therefore, including these firms as zeros in our rewards regression could be misleading. After excluding these cards, our final sample consists of 65 firms.

Table A.2: *Summary Statistics of Retail Card Rewards Data*

Industry	N Firms	Avg. Rewards (%)	Avg. Sign-up (%)	Avg. Sign-up ($)	Share No Annual Fee	Share w/ Financing
Auto	29	4.4	6.7	262	100	76
Clothing	35	6.3	21.9	39	100	3
Contractors	19	5.1	16.7	38	100	90
Department	19	4	17.5	41	100	26
Home	33	6.5	10	62	100	97
Jewelry	12	-	-	100	100	100
Sporting Goods	16	5.3	15	40	94	44
Unclassified	47	4.9	16.3	79	89	45

Note: Table shows rewards summary statistics at the *store* level. "Avg. Rewards" is the average discount offered (excluding the sign-up bonus) conditional on non-zero. The value of rewards was manually converted to percentages if reported in points. "Avg. Sign-Up" is the average sign up bonus (i.e., one-time discount) conditional on non-zero, depending on whether the discount is offered in percentages or dollars. "Share w/ Financing" is the share of stores who offer any form of special financing on their cards (e.g., promotional APR, deferred interest). We restrict to the 210 firms with NAICS codes and websites. Data Source: Rewards data and Safegraph.

[59]We exclude these because imputing a rewards rate as a percentage of spending would imply making judgments about how much customers spend on a given card.

[60]An example of a NACIS code excluded includes Health and Personal Care Stores (4461), which doesn't match to any of the credit bureau industries.

A.7 Identifying Missed Minimum Payments

In our credit bureau data, missing payments data and zero payment are often both reported as missing. To separate between the two, we assign a month a zero payment when there are months within the two-year period both before and after that have non-missing payment information. We also require the credit limit to be non-missing in that particular month. Table A.3 shows our approach generates missed payment frequencies that generally align well with Y-14 data on the frequency of credit card late fees.

Table A.3: *Comparison of Imputed Missed Minimums and Y-14 Data*

Group	Share Cards Miss Min (1yr)	CFPB: Share Late Fee
1) Superprime	20%	15%
2) Prime	35%	32%
3) Near-prime	42%	43%
4) Subprime	52%	53%
5) Deep Subprime	63%	70%

Note: Table shows a comparison of our imputed share of cards with a missed minimum over one year and the CFPB's Y-14 estimate of the share of cards with a late fee. Data Source: Credit Bureau Data and CFPB (2022) Figure 4.

A.8 Details on Quantification Exercise

We estimate expected revenue and profit within two years of opening by card type. To do so, as in Agarwal *et al.* (2018), we assume average realized and expected profits are the same during our time period. We first identify card openings using the opening date in the credit bureau data. We calculate the expected revenue from late fees in industry k as:

$$\mathbb{E}\left[R_k^{lf}\right] = \sum_{t=1}^{23} \delta^{t-1} \sum_{n=1}^{N_k} \frac{1}{N_k} \left(F \cdot \mathbf{1}\{\text{Missed Minimum}\}_{knt}\right) \tag{A.3}$$

where N_k is the number of observed card openings in industry k; F is the dollar amount of the late fee which we set to \$26;[61] and δ is the monthly discount factor which we set to 0.995 (consistent with a 0.95 annual discount factor). We do a similar exercise when calculating the expected revenue from interest costs.

$$\mathbb{E}\left[R_k^{int}\right] = \sum_{t=1}^{23} \delta^{t-1} \sum_{n=1}^{N_k} \frac{1}{N_k} \left(\text{int}_{knt}\right) \tag{A.4}$$

[61] This conservative estimate reflects the average first-time general purpose late fee in CFPB (2022); average private label (\$27) and repeat fees (\$34–\$35) are higher.

To estimate interest costs, we multiple the revolving balance by the annual percentage rate, which we set to 20%.

$$\mathbb{E}\left[\text{int}_{knt}\right] = \underbrace{\left(\text{Balance}_{t-1} - \text{Amount Paid}_t\right)}_{\text{Revolving Balance}_t} \times \frac{\text{APR}}{100} \tag{A.5}$$

In Figure 3, we normalize by the level of spending, s_t. Since we don't directly observe spending, we impute it as follows:

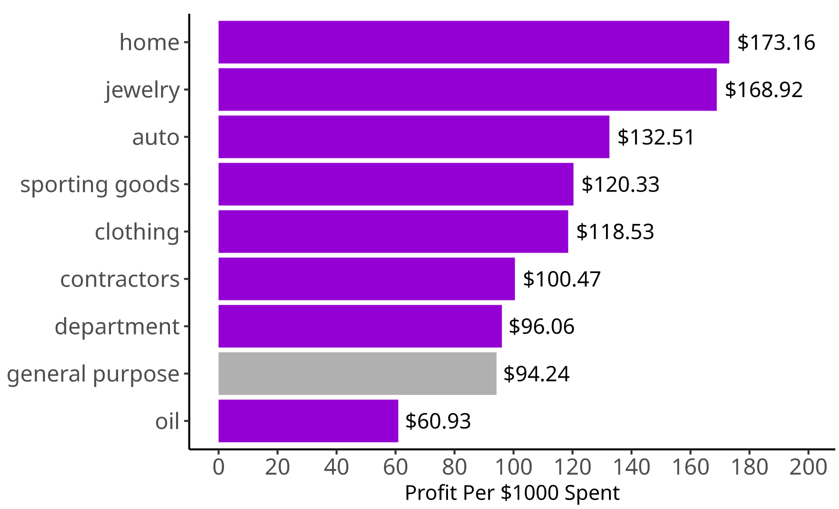
$$s_{knt} = \text{Balance}_{knt} - \text{Revolving Balance}_{knt} - \text{int}_{knt} - F \cdot \mathbf{1}\{\text{Missed Minimum}\}_{knt} \tag{A.6}$$

In words, we impute spending as the change in balance that isn't explained by the previous revolving balance and fees. Finally, we calculate total expected profits from card openings by industry which includes expected default costs.

$$\mathbb{E}[\pi_k] = \sum_{t=1}^{23} \delta^{t-1} \sum_{n=1}^{N_k} \frac{1}{N_k} \left(F \cdot \mathbf{1}\{\text{Missed Minimum}\}_{knt} + \text{int}_{knt} - \text{def}_{knt}\right) \tag{A.7}$$

To calculate the default costs, we use delinquency information from the credit bureau data which includes the month of delinquency, if one occurred, and the chargeoff amount. Figure A.9 shows the expected card profits by card type per $1000 spent. This estimate represents the profits that retail firms share with the partner bank.

Figure A.9: *Card profits by card type*



Note: Figure shows the expected profits by card type (or industry) per $1000 spent. We calculate expected profits within two years of a card opening using the 2013-2022 sample. Data Source: Credit Bureau Data.

A.9 Additional Evidence on Mechanisms for Missed Minimums

In section 4.2, we highlight one mechanism that may help explain the higher incidence of missed minimum payments on retail cards: borrowers are more likely to miss payments on cards they use less frequently (e.g., because they "forgot" non-salient cards). In this appendix, we discuss two additional potential mechanisms.

One possibility is intra-household frictions.[62] Because retail cards are typically limited to a single merchant, they are less likely to serve as a household's primary credit card. This may lead to coordination failures if the household's main financial decision-maker is not the card's primary user.

Table A.4 provides suggestive evidence consistent with this interpretation. Column (1) shows that, unconditionally, marriage is negatively associated with missed payments—consistent with married individuals having higher incomes and greater financial stability. To account for these differences, column (2) controls for credit score and finds that, conditional on creditworthiness, married individuals are more likely to miss minimum payments. Column (3) further shows that, among card-months with positive balances, the interaction between being married and having excess payments is associated with a two percentage point increase in the likelihood of a missed minimum. This pattern supports the hypothesis that intra-household coordination frictions contribute to missed payments on retail cards.

Table A.4: *Household Frictions and Missed Minimums*

	Missed Min. (0 or 1) x 100		
	(1)	(2)	(3)
Is Married	−0.117***	0.131***	−1.075***
	(0.005)	(0.005)	(0.016)
Credit Score		−0.010***	−0.026***
		(0.000)	(0.000)
Has Excess Pymts			−17.921***
			(0.014)
Is Married x Has Excess Pymts			1.971***
			(0.017)
Mean Outcome	2.93	2.93	7.87
Sample	Excess Pymnts	Excess Pymnts	Postive Baln
R2 Adj.	0.008	0.012	0.096
Observations	55673770	55673770	79367940

[62] For additional discussion of intra-household frictions in credit, see (Kim, 2021; Vihriälä, 2022).

Note: Table shows the relationship between household frictions and missing minimums over the 2013-2022 sample. We classify a borrower as being married using demographic information provided in the credit bureau data, and having excess payments is a binary variable based on whether or not the borrower has observed excess payments across cards in a given month. Standard errors are robust to heteroskedasticity. Data Source: Credit Bureau Data.

A second potential explanation is strategic deprioritization. Because general purpose cards can be used more broadly, liquidity-constrained households may prioritize payments on these cards over retail cards to preserve access to credit. In contrast, the consequences of missing a payment on a retail card—usable only at a single store—may be perceived as less costly. The notion that households strategically prioritize which debts to fall behind on is consistent with findings from Conway and Plosser (2017) and Arnesen *et al.* (2021), who show that households are more likely to become delinquent on debts with lower or no collateral value. However, in this setting, strategic deprioritization is less consistent with the high incidence of avoidable missed minimums, which occur despite available liquidity.