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Heterogeneity in Service Fee Sensitivity: Evidence from ATM Surcharges

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Abstract

Service fees continue to proliferate in a wide range of markets, from retail to payments, generating questions about their impact on consumer choice, competition, and fairness. This paper explores how sensitivity to such fees varies across consumers, use cases, and competitive settings, and whether it is affected by consumer learning. I am able to conduct this in-depth empirical analysis thanks to a uniquely detailed, high-frequency panel data set on surcharged ATM cash withdrawals. Results show that average elasticity estimates mask substantial heterogeneity in consumer sensitivity to service fees. I explore ways in which market and behavioral mechanisms can help explain this heterogeneity. Finally, I investigate whether consumers strategically adjust their behavior in response to service fees.

1 Introduction

Over the past several decades, service fees have proliferated across a wide range of markets. Consumers routinely encounter ATM surcharges, overdraft fees, ticketing and convenience charges, cash-out fees, delivery app fees, late payment penalties, and a growing variety of other small charges associated with accessing goods, services, and payments. While consumers often view such fees as a regrettable cost, they are frequently accepted as unavoidable in exchange for convenience, immediacy, or access. In some settings, these charges are highly salient and directly disclosed at the moment of purchase; in others, they are less transparent or only imperfectly understood by consumers. Equally importantly, consumers differ substantially in the extent to which they can

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avoid such charges by changing their behavior, searching for alternatives, or substituting toward other products and payment methods.

At the same time, service fees and related charges have become an increasingly important source of revenue for firms. Such fees can help businesses recover fixed costs, price discriminate across consumers, manage congestion, or monetize convenience and immediacy. The extent to which firms can profitably impose these charges depends critically on consumers' willingness to pay them and on how sensitive different groups of consumers are to changes in fee levels. Understanding this sensitivity is important not only for firms setting prices, but also for policymakers concerned about competition, consumer welfare, and the potentially unequal burden these charges impose across socioeconomic groups.

Despite the growing importance of service fees in modern consumer markets, relatively little is known about how consumers' sensitivity to such charges varies across contexts and populations. Existing evidence suggests that consumer responses to prices and fees depend on factors such as salience, financial sophistication, liquidity constraints, search costs, and competitive conditions (Chetty, Looney, and Kroft, 2009; Ellison and Ellison, 2009). Yet measuring heterogeneity in sensitivity to service fees remains difficult in practice. Survey and opinion data are often unreliable measures of actual behavior, especially for small and frequently repeated decisions. Meanwhile, sufficiently detailed transaction-level data that directly observe both fee levels and consumer decisions are rare.

This paper studies heterogeneity in consumers' sensitivity to service fees using ATM withdrawal surcharges as an empirical setting. ATM surcharges provide a particularly useful environment for studying these questions. First, the surcharge is highly salient and directly observed by consumers at the moment of decision. Second, ATM withdrawal decisions are frequent and repeated, allowing consumers opportunities to learn and adjust their behavior over time. Third, consumers often face meaningful tradeoffs between convenience, immediacy, and the cost of avoiding fees. Finally, the ATM market exhibits substantial variation across locations, demographics, and competitive environments, allowing for detailed analysis of how sensitivity to service fees varies across different contexts.

To study these issues, I use a uniquely detailed high-frequency panel data set containing daily information on surcharged withdrawals across thousands of ATMs over nearly three years. The richness of the data allows me to directly estimate consumers' sensitivity to ATM surcharges using observed behavioral responses rather than survey evidence or strong structural assumptions. More importantly, the data allow me to document substantial heterogeneity in surcharge sensitivity across demographic groups, location types, and competitive environments.

To extract broader lessons beyond the ATM market itself, I interpret the estimation results through the lens of fundamental mechanisms common to markets with service fees. First, the results suggest that consumers are considerably more sensitive to service fees when making planned

purchases, as opposed to urgent or spur-of-the-moment ones. Second, consumer learning emerges as an important mechanism, with consumers in settings that support repeated interactions and learning exhibiting much greater sensitivity to service fees. Third, I find that consumers who have greater choice in more competitive markets are much more sensitive to service fees. Fourth, the results suggest that more sophisticated consumers are more sensitive to service fees, as are those with lower search costs. Finally, considering the nature of the fee itself, consumers appear to be less sensitive to fees that are less salient.

The findings in this paper speak to debates surrounding financial inclusion, consumer protection, and competition policy. Variation in fee sensitivity across groups may reflect differences in financial literacy, information frictions, liquidity constraints, or access to substitutes, raising questions about whether service-fee pricing disproportionately affects certain consumers. Furthermore, the results provide insight into whether improving consumer information, increasing competition, or expanding access to lower-cost alternatives could influence the distributional consequences of service fee pricing.

2 Related Literature

This paper contributes to several broader strands of literature on consumer response to financial frictions, service fees, and the link between search costs and market power. In addition, the paper contributes to more setting-specific strands of literature, including ATM pricing and deployment, payment choice, and cash demand.

First, the paper contributes to a broader literature studying how consumers respond to fees, add-on charges, and other forms of service fee pricing. A growing body of research shows that consumers' responses to prices depend importantly on salience, complexity, search costs, and opportunities for learning and optimization. Chetty et al. (2009) show that consumers underreact to taxes when they are less salient, while Ellison and Ellison (2009) demonstrate how firms can exploit search frictions and obfuscation through add-on pricing in online markets. Related theoretical work highlights how firms may use contingent charges, shrouded attributes, and partitioned pricing to price discriminate across consumers or monetize convenience and immediacy (Gabaix and Laibson, 2006; Armstrong and Vickers, 2012). More broadly, research in industrial organization and behavioral economics has documented that consumer sophistication, attention, and search behavior play important roles in determining firms' pricing power and market outcomes.

This paper contributes to that literature by studying heterogeneity in consumers' sensitivity to a clear service fee. In particular, the paper documents substantial variation in fee sensitivity across demographic environments, competitive conditions, and consumer use cases that differ in the extent to which consumers are likely to engage in repeated interaction, learn about available substitutes, or face urgency-driven consumption environments. The findings suggest that sensitivity to service fee pricing depends not only on the level of the fee itself, but also on consumers' opportunities to

optimize behavior over time.

Second, the paper contributes to a literature on repeated consumer decision-making, financial sophistication, and behavioral adjustment to small financial frictions. Existing work shows that consumers often fail to optimize in environments characterized by repeated low-stakes financial decisions, including gym memberships, insurance contracts, overdraft fees, and nonlinear pricing schemes (DellaVigna and Malmendier, 2006; Handel, 2013; Grubb, 2015). Consumer responses in such settings often depend on learning opportunities, information frictions, and the availability of substitutes. Similarly, work on household finance and consumer financial behavior highlights substantial heterogeneity in financial sophistication and sensitivity to fees and contractual terms (Stango and Zinman, 2009; Agarwal, Driscoll, Gabaix, and Laibson, 2009).

The findings in this paper complement that literature by providing direct evidence on how consumers behaviorally adjust to service fees in a setting with repeated real-time decisions. In particular, the results show that consumers respond to higher surcharges not only by reducing withdrawal frequency, but also by increasing withdrawal amounts, suggesting active adjustment of liquidity-management behavior in response to financial frictions. The paper further shows that such adjustment varies systematically across different use cases and demographic environments.

Third, the paper contributes to literature studying competition, search costs, and pricing power in consumer markets. Existing work demonstrates that the availability of substitutes and the ease with which consumers can search across alternatives play central roles in shaping firms' ability to impose fees and markups (Brown and Goolsbee, 2002; Hortaçsu and Syverson, 2004). This paper contributes to that literature by documenting that consumers are substantially more sensitive to surcharges in environments with greater availability of nearby ATMs, suggesting that local competitive conditions materially affect willingness to pay service fees.

More specifically, the paper contributes to the literature on ATM withdrawals, payment choice, and cash demand. Early work by Humphrey, Kim, and Vale (2001) estimates consumers' sensitivity to payment instrument prices using Norwegian banking data, including fees associated with ATM withdrawals. Gowrisankaran and Krainer (2011), Ferrari, Verboven, and Degryse (2010), Knittel and Stango (2011), Karoubi (2013), Magnac (2017), and Ardizzi and Cologgi (2025) estimate consumers' sensitivity to ATM surcharges or broader ATM pricing structures using aggregate, low-frequency, or structural approaches. Relative to this literature, the central contribution of this paper is that it directly estimates consumers' behavioral response to ATM surcharges using high-frequency transaction-level panel data, while also documenting substantial heterogeneity in surcharge sensitivity across use cases, demographic environments, and competitive conditions.

The paper also contributes to literature on ATM networks and payment infrastructure more broadly. A large theoretical literature studies how ATM deployment, surcharge pricing, and network structure depend on consumers' willingness to pay for convenience and access (Matutes and Padilla, 1994; Massoud and Bernhardt, 2002; Croft and Spencer, 2003; Chioveanu, Faulí-Oller,

Sandonís, and Santamaría, 2009; Donzé and Dubec, 2009). In many of these models, consumer heterogeneity in convenience valuation plays a central role in determining equilibrium pricing, deployment incentives, and welfare outcomes. The empirical evidence in this paper provides direct support for the importance of such heterogeneity and helps illuminate the mechanisms through which repeated interaction, learning opportunities, and local competition shape willingness to pay service fees.

Finally, the paper contributes to literature studying cash demand, payment behavior, and household liquidity management. Existing theoretical work explores how consumers determine optimal cash holdings and how transaction costs affect cash usage (Alvarez and Lippi, 2009; Briglevics and Schuh, 2020). Empirical work further examines how consumers' payment choices vary across demographic groups and economic environments (Attanasio, Guiso, and Jappelli, 2002; Schuh and Stavins, 2012; Bagnall, Bounie, Huynh, Kosse, Schmidt, Schuh, and Stix, 2016; Greene, Perry, and Stavins, 2024). This paper complements that literature by providing direct evidence on how consumers dynamically adjust cash withdrawal behavior in response to changes in the cost of accessing liquidity.

3 The ATM Setting and Consumer Decision Environment

ATM withdrawals provide a particularly useful setting for studying consumers' sensitivity to service fees and other small financial frictions.

First, ATM surcharges are highly salient for most consumers, who observe the exact fee immediately before deciding whether to proceed with a withdrawal. In particular, I focus the analysis on fixed surcharges, whose absolute value is clearly presented to the consumer in dollar terms.[1] Moreover, because ATM cash withdrawal transactions are quick, consumers can consider whether to accept the fee without having to contend with a perceived sunk time cost (in contrast to, for example, customers who spent a lot of time picking items from the menu only for the food delivery app to present them with multiple service fees at checkout).

Second, the effective "use cases" and the circumstances in which consumers make ATM withdrawal are highly varied, which makes the resulting data especially useful for studying heterogeneity in consumers' sensitivity to service fees. In particular, consumers often face meaningful differences in the urgency of obtaining cash, the availability of nearby alternative sources of cash, and the extent to which withdrawal behavior is repeated over time. In many instances, consumers regularly use the same ATM near their home, workplace, or routine shopping locations, allowing substantial opportunity for learning, comparison across alternatives, and behavioral optimization. At other times, consumers can be confronted with unusual or urgency-driven situations, such as while trav-

[1] Language barriers may be one potential exception, especially for older ATMs that make it hard to choose a language different than English, if at all.

eling, attending entertainment venues, or facing immediate liquidity needs. In such environments, consumers may have limited ability or incentive to search for alternatives or optimize around fees. Furthermore, some consumers face dense ATM markets with many nearby substitutes, while others face more limited choice sets. This variation provides a useful empirical environment for studying how repeated interaction, learning opportunities, convenience valuation, and substitute availability shape sensitivity to service fees.

Third, the ATM market is well-developed and stable, while debit cards are widely used. This makes the market well-suited for studying long-term changes in consumer behavior. In particular, this setting makes it easier to study what role consumer learning plays over a longer period of time, without identification contamination from other changes in the market, such as ongoing adoption from new consumer groups, or entry from new alternatives. Moreover, it allows me to identify whether consumers adapt their behavior in other ways, such as by strategically adjusting their average withdrawal amount.

Fourth, from an estimation perspective, the ATM setting is very well-suited for empirical analysis. In particular, while the data set at my disposal provides detailed, high-frequency information about consumer decisions, the surcharges themselves typically remain fixed for extended periods of time and do not adjust dynamically in response to short-run demand fluctuations. Moreover, most banks set uniform surcharges for all their ATMs, further reducing potential feedback from demand levels to prices. Combined with high-frequency and panel structure of the data, I am able to use rich fixed effects to identify specific drivers of heterogeneity in consumers' sensitivity to surcharges.

Finally, ATM surcharges also represent a meaningful source of revenue for ATM operators and financial institutions. Surcharges may help recover fixed operating costs, compensate for deployment in high-cost or high-convenience environments, or monetize consumers' willingness to pay for immediacy and access. At the same time, surcharges have long attracted policy attention because of concerns regarding competition, consumer welfare, and the unequal burden that service fees may impose across different groups of consumers (Neely, 1997; McAndrews, 1998). Understanding how consumers respond to surcharges is therefore important both for firms designing pricing strategies and for policymakers evaluating the effects of service fee pricing in financial markets more broadly.

4 Data

4.1 Primary and Secondary Data Sources

The primary data used in this paper are a proprietary data set from a U.S. ATM network. For confidentiality reasons, I cannot provide the usual set of descriptive statistics, but I nonetheless try to provide enough information to convey the richness of the data and how I use it for identification purposes.

The data span a period of almost three years, from November 2014 to June 2017, a period of relative stability in the U.S. ATM industry.[2] The data capture withdrawals from thousands of ATMs deployed in a variety of locations and spread over a wide geographic area. The ATMs in the data set represent around a third of all ATMs in the area I use in my empirical analysis.

ATM cash withdrawal information in the data set is captured at a disaggregate, higher-frequency level than in data sets used by previous empirical studies of the ATM industry. In particular, each observation captures the *Number of withdrawals* and *Total withdrawal amount* across all withdrawals for a particular (a) ATM, (b) day, and (c) surcharge combination. To study consumers' sensitivity to service fees, I focus the analysis exclusively on surcharged withdrawals. In total, the data set contains millions of observations over the three years. In addition, the primary data include ATM-level information as the address, location type (such as bank, retail store, or casino), and location name (such as bank name or gas station chain).

To construct the data set for the empirical analysis, I combine the primary data with information from a few other sources. First, I bring in annual demographic information at the county level from the U.S. Census. Second, I use information from multiple online ATM locators to produce a detailed map of all ATMs in the state. I match these secondary data to the main data set using the information available. The matching algorithm primarily uses address information, which I standardize and geocode using the U.S. Census and OpenStreetMap Data APIs. I then use other information, including location type and name, to check for false negatives and positives.

Thus constructed, the data set has both breadth and depth to support a robust empirical analysis. The disaggregate level at which the information is captured allows for a detailed analysis of ATM cash withdrawal patterns not previously possible. The long, high-frequency panel structure of the primary data set is crucial to the identification strategy because it allows for the econometric model to easily control for unobserved factors that affect consumers' cash withdrawal decisions across locations and over time. The controls afforded by such a high-frequency panel data set allow me to directly estimate consumers' sensitivity to surcharges, without need for a structural model.

The information from secondary sources allows me to make the analysis both richer and more robust. Thanks to the demographic information, I not only can better understand how demand for ATM cash withdrawals varies between areas with different socio-economic factors, but can for the first time explore how consumers' willingness to pay surcharges varies as well. The detailed map of all ATMs in the area allows me to bring in further information into the analysis, including

[2]Although consumers were gradually shifting to electronic payments, cash and ATM use was widespread and aggregate withdrawal activity changed only slowly during the sample period (Board of Governors of the Federal Reserve System, 2026; Federal Reserve Bank Services, 2018). Moreover, following a period of rapid expansion in the 1990s and early 2000s, ATM deployment had entered a steady phase by the mid-2010s, before the number of ATM began declining in the 2020s. Finally, the last major regulatory change targeting consumer choice, updates to Regulation E, occurred before the sample period (Consumer Financial Protection Bureau, 2013). The only meaningful development during the sample period, the rollout of chip EMV cards, affected the technology rather than the consumer choice set or surcharge pricing.

capabilities of individual ATM machines, as well as market measures capturing local alternatives to a particular ATM.

There are nonetheless limitations to the data, which limit the type of analysis I can perform. Because the data do not track customers directly, I am not able to directly capture the way in which their cash withdrawal decisions are influenced by who they bank with or how much cash they have on them. More broadly, because I only have withdrawal information for a subset of ATMs in the area, I am not able to investigate operators' supply-side decisions, such as ATM deployment.

4.2 Summary Statistics

Figure 1: Variation in *Number of withdrawals, Total withdrawal amount* and *Average withdrawal amount* daily averages across ATMs – percentile distribution



Figure 1 shows the daily averages for two dependent variables analyzed in this paper, *Number of withdrawals* and *Average withdrawal amount*, as well as *Total withdrawal amount*, and how they vary across ATMs in the final data set. As expected, *Number of withdrawals* and *Total withdrawal amount* both demonstrate substantial variation across ATMs, illustrating how a mature and relatively affordable technology such as the ATM is deployed in both high- and relatively low-traffic locations. In particular, even the median ATM sees only 12 daily withdrawals while the median total withdrawals are just over $700, while the ATM at the fifth percentile sees only a few transactions totaling less than $200 daily.

The final panel in figure 1 shows the variation in *Average withdrawal amount* across ATMs. While not as large as variation in *Number of withdrawals* and *Total withdrawal amount*, the variation in *Average withdrawal amount* across ATMs is nonetheless substantial. This is interesting, because while the former two measures speak to *what* quantities of cash people withdraw, *Average withdrawal amount* speaks more directly to *how* people withdraw cash over time.

Figure 2 shows the distribution of surcharges observed in the main data set. As expected, round surcharge figures are most common, with the $2.00 surcharge accounting for almost half of all observations.

Figure 2: Variation in surcharges across ATMs (proportion of all observations)

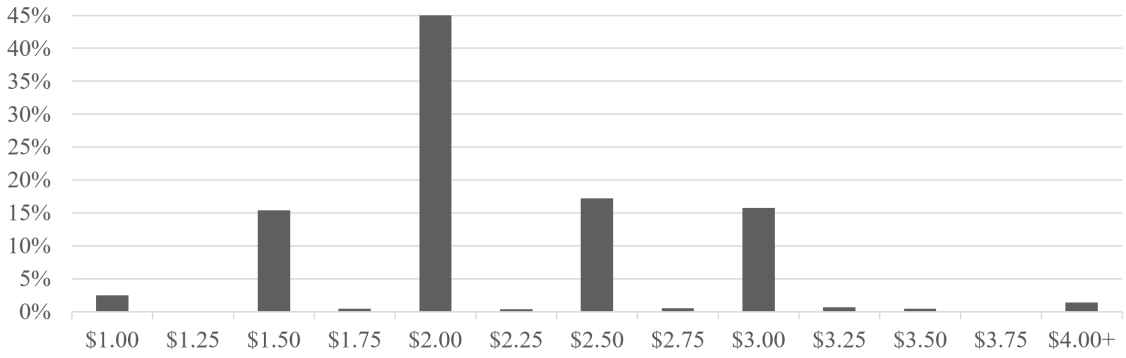
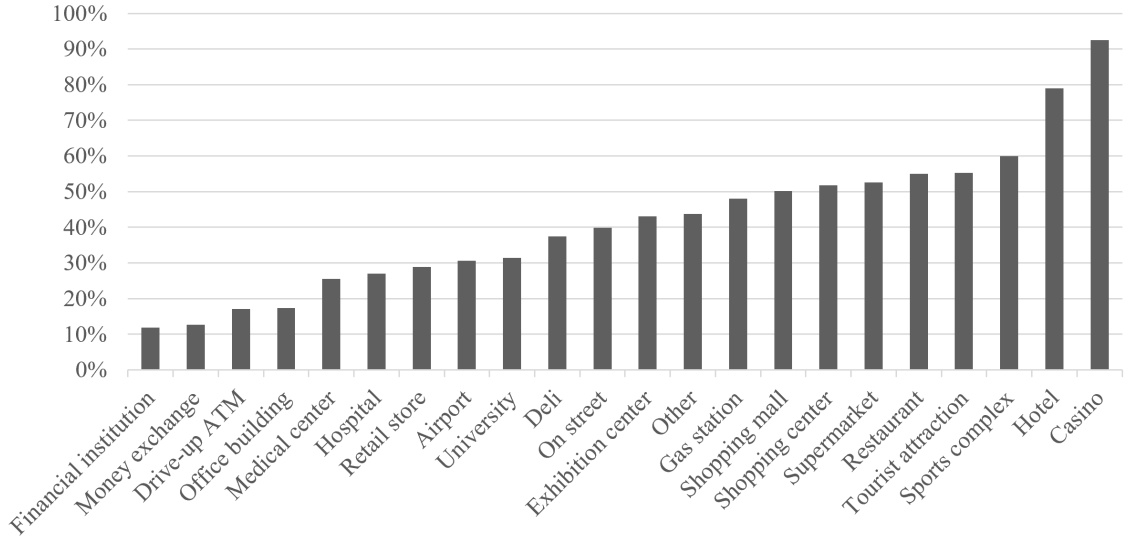


Figure 3: Variation in proportion of all withdrawals that are surcharged across location types



Finally, figure 3 illustrates the proportion of all cash withdrawals at ATMs that are surcharged, and how this measure varies across location types. As expected, ATM locations in or next to banks see relatively few surcharged, out-of-network withdrawals, as do locations for which most withdrawals are likely made by a relatively small number of repeat customers, such as *Office building, Medical center,* or *University*. On the other end of the spectrum are locations which see a large number of tourists and where people are likely to be less price sensitive, such as *Tourist attraction, Hotel,* or *Casino*. Other notable trends include the relatively high proportion of surcharged with-

drawals at *Supermarkets*, suggesting shoppers either have strong preference for paying with cash or have no alternative available to them, as well as *Restaurants*, potentially driven by desire to leave a cash tip.

5 Empirical Approach

5.1 The Demand Model

In my analysis, I employ a variant of the static log-log demand model:

$$ln(Q_{it}^d) = \beta^d \ln(P_{it}) + \zeta_{g(t)}^d + \xi_{h(i)}^d + \epsilon_{it}^d \tag{1}$$

where i denotes the ATM terminal, t denotes the date, and $d \in \{n, av\}$ indexes the measures I analyze in the paper. In particular, in my analysis I focus on two dependent variables: Q_{it}^n, the *Number of withdrawals* at ATM i on day t and Q_{it}^{av}, the corresponding *Average withdrawal amount* for those withdrawals. Many specifications employ fixed effects which take advantage of the panel structure of the data set: $\zeta_{g(t)}^d$ denotes time-fixed effects associated with date t, where $g(t)$ generates indexes for weekdays, weeks, and years, while $\xi_{h(i)}^d$ denotes location-fixed effects associated with ATM i, either for ATM subgroupings $h(i)$ such as *Location type* and *Bank*, or directly for each terminal. Finally, ϵ_{it}^d is the idiosyncratic error term.

The main variable of interest, P_{it}, is the surcharge for out-of-network withdrawals. In the log-log specification, the corresponding coefficient of interest, β^d, captures the homogeneous price elasticity of measure d. Specifically, β^n captures how sensitive demand for ATM cash withdrawals is to the surcharge P_{it}, while β^{av} captures how the surcharge affects consumers' withdrawal behavior, as measured by the *Average withdrawal amount*.

$$ln(Q_{it}^d) = \beta^d \ln(P_{it}) + \beta_{f(i)}^d \ln(P_{it}) f(i) + \zeta_{g(t)}^d + \xi_{h(i)}^d + \epsilon_{it}^d \tag{2}$$

Equation (2) represents more advanced specifications, where I explore the extent to which sensitivity to the surcharge varies across observable different factors associated with a particular ATM, including local demographics, location type, and the availability of other ATMs nearby. For continuous variables, such as percentage of local population that is male, or the number of ATMs per 10,000 inhabitants, $f(i)$ is the value of the variable for ATM i, and $\beta_f^d = \beta_{f(i)}^d \forall i$ is the measure of how sensitivity to the surcharge changes with value of $f(i)$. For categorical variables, such as location type, $f(i)$ are index variables representing different categories, and $\beta_{f(i)}^d$ are the corresponding measures of surcharge sensitivity.

5.2 Estimation Sample and Variable Construction

In order to analyze consumers' sensitivity to ATM surcharges, I restrict the data used in the empirical analysis to only withdrawals for which the ATM surcharge applies. I am able to do this because the primary data set distinguishes between surcharge-free and surcharged withdrawals at each ATM. Accordingly, throughout the empirical analysis, the number and average amount of withdrawals refer only to surcharged withdrawals, unless otherwise stated.

The source data do not contain a transaction record when an ATM had no withdrawals on a particular day, for both surcharged and surcharge-free withdrawals. To avoid conditioning the sample on positive withdrawal activity, I expand the data to include all ATM-days during which each terminal is active, and set both Q^n_{it} and $Q^v{}_{it}$ to zero on those days.[3] Doing this expands the number of ATM-days in the estimation sample by 15.1 percent.

Because the logarithm of zero is undefined, in regressions examining how sensitive the *Number of withdrawals* is to surcharges, I construct the dependent variable as $\ln(Q^n_{it} + 0.1) \forall Q^n_{it} \geq 0$. I conduct a robustness check of this approach, and find that the key findings remain unchanged. I report the full set of results for the robustness analysis in Table 6.

By contrast, on days when no surcharged withdrawals took place, *Average withdrawal amount* is not defined. When estimating regressions examining how sensitive *Average withdrawal amount* is to surcharges, I therefore use the non-expanded estimation sample that only includes ATM-days during which at least one surcharged transaction occurred.

To measure the availability of potential alternatives to a particular ATM, I construct the variable $ATMper10k$ at the ZIP-code level. I am able to do this using the comprehensive map of ATM locations described in the previous Section. Higher $ATMper10k_i$ values indicate that ATM i operates in a local market with more potential ATM alternatives relative to the resident population.

$$ATMper10k_i = 10,000 \times \frac{\text{Number of ATMs in ZIP code } z(i)}{\text{Population of ZIP code } z(i)}$$

5.3 Dealing with Surcharge Endogeneity

Price endogeneity is a canonical challenge in demand estimation. In the context of (1), if Q_{it} and P_{it} are simultaneously determined based on supply and demand in the market, P_{it} and ϵ_{it} will be correlated. Simple OLS estimates of (1) may thus be biased and inconsistent. The extent of such bias depends on just how often firms adjust prices to reflect changing market conditions, and the extent to which such adjustments consistently lag or even anticipate changes in conditions. In

[3] The primary data do not contain information about whether an ATM was active on a particular day. When creating the estimation sample, I use the following two-step algorithm: (1) consider all ATM-days with non-zero number of surcharged or surcharge-free withdrawals, and (2) mark as "active" all ATM-days between two ATM-days identified in the previous step that are no more than one week apart.

industries where such adjustments are both frequent and closely track changes in market conditions, a simple OLS estimate of the price elasticity of demand will likely be positive, reflecting how firms increase prices in times of high demand. By contrast, such simultaneity bias will be smaller or even negligible in industries where firms change prices infrequently or when price changes are only to a small extent driven by factors that influence local demand for the product. Such is the case in the ATM industry, where surcharge changes are very infrequent and banks typically set a single surcharge for all their ATMs in a variety of locations.

I develop a strategy to address potential endogeneity of the surcharge P_{it} in my analysis, which take advantage of the rich, high-frequency panel data set at my disposal and the unique manner in which ATM surcharges are set. I use the panel data set structure to account for potential surcharge endogeneity directly using fixed effects, similar to Levin, Lewis, and Wolak (2017). In particular, I use detailed terminal fixed effects ξ_i^d to absorb all local factors that could affect both Q_{it}^d and P_{it}.

For this to achieve identification and successfully correct for potential price endogeneity, a few conditions need to be satisfied. First, the surcharge P_{it} needs to change over time for a large number of ATMs – this is true for around a quarter of ATMs in the data set. Second, the panel data set needs to be long; that is, there should be a large number of observations for each ATM. In my data set, I observe the vast majority of ATMs daily over the course of almost three years, such that the median number of daily observations for an ATM is 832, and even the ATM at the 10^{th} percentile still has 233 observations.

Finally, the unobserved local factors that could affect both demand and surcharges should not vary substantially over time for a given ATM, and to the extent that they do, such variation should not directly translate into changes in the surcharge at this ATM. The institutional details of the ATM market make a compelling case for this to be true. In particular, while I observe a large number of ATMs in the data set for which the surcharge changes, 98 percent of those ATMs see only a single surcharge change over the course of the three years. In light of this, it is reasonable to think that higher-frequency fluctuations in unobserved factors affect only the dependent variable Q_{it}^d, but do not affect P_{it}. Equally importantly, the majority of ATMs in the data set are associated with banks, which set uniform prices for all their ATMs based on conditions in all markets, rather than directly based on conditions specific to a particular ATM.

6 Results

In the first part of this section, I present results for the core specifications which explore consumers' average sensitivity to service fees. Estimates for these specifications are not the focus of this paper; rather, they establish a base for the main analysis of heterogeneity in sensitivity to surcharges. I also consider whether potential endogeneity of the surcharge is likely to have a substantial impact on my analysis.

Having established a core set of results, the parts that follow explore in depth the different sources of variation in sensitivity to service fees. First, I consider how sensitivity to fees varies across consumer use cases and across environments with different potential for learning. Then, I explore how market competition and availability of substitutes affect consumers' sensitivity to fees. Finally, I look at how sensitivity to service fees varies across different demographic factors and consider the potential distributional implications.

In the final part of this section, I explore how changes in convenience fees can elicit a behavioral response from consumers. Put another way – rather than focusing on *how much* demand changes, I explore *how* consumers adjust their behavior in response to fee changes.

6.1 Average Sensitivity to Convenience Fees

Table 1: Average surcharge elasticity of *Number of Withdrawals*

	1	2	3	4	5
$ln(P_{it})$	-0.205	-0.328	-0.316	-0.363	-0.311
	(0.0055)	(0.0055)	(0.0054)	(0.0089)	(0.0143)
Demographic Variables		X	X	X	
Time FEs			X	X	X
Location type FE, Bank FE				X	
Terminal FE					X
R^2	0.001	0.044	0.081	0.255	0.565

Note: Dependent variable: $\ln(Q^n_{it} + 0.1)$. Estimation Sample: surcharged withdrawals, including days when ATM was active, but no surcharged withdrawals took place. To preserve anonymity of the data source, number of observations and ATMs are not reported.

Table 1 presents the estimation results for the core specifications. Specification (1) is the simplest OLS specification, with only one explanatory variable, $\ln(P_{it})$. While the R^2 for this specification is predictably low, the estimated β coefficient is negative, as expected, and statistically significant at the 1 percent level. This suggests that even this base specification is able to capture how consumers reduce their demand in response to higher service fees. Moreover, this result also suggests that the extent of price endogeneity in the ATM market may not be as severe as in other settings, where the simplest specification could result in a positive price elasticity of demand estimate.

Specification (2) builds on specification (1) by adding local demographic variables. Controlling for these additional variables substantially increases the R^2, suggesting that demand for ATM cash withdrawals varies considerably across socioeconomic groups. Controlling for local demographics makes the β coefficient estimate more negative, suggesting socioeconomic factors not only affect demand for cash withdrawals, but also influence the surcharge levels.

Specification (3) expands on specification (2) by adding time fixed effects to control for how

demand for ATM withdrawals varies throughout the week, seasonally week-by-week over the course of the year, and how demand for cash withdrawals changes with time. The addition of these control variables further increases R^2, however the estimated β coefficient does not change much.

Specification (4) adds further two sets of fixed effects to specification (3). First, *Location type* fixed effects help account for the different withdrawal patterns depending on where the ATM is located, for example at a bank, in a supermarket, or at a university. Second, *Bank* fixed effects help account for factors such as better placement or appeal of ATMs affiliated with certain banks. Controlling for these additional variables more than triples R^2, suggesting demand for cash withdrawals differs substantially across ATMs based on their location and affiliation. Despite this substantial increase in the model's explanatory power, the estimated β coefficient is only slightly more negative for specification (4) than for specification (3).

Specification (5) also builds on specification (3) but goes a step further by adding fixed effects for each *Terminal* observed in the data, instead of *Location type* and *Bank* fixed effects. Doing so substantially increases R^2 relative to both specifications (3) and (4). This suggests that there are considerable unobserved factors that affect demand for cash withdrawals across individual ATMs, for example proximity to other ATMs/bank branches or to businesses that prefer cash payments, the ease with which customers can access the ATM, or how safe they feel withdrawing cash.

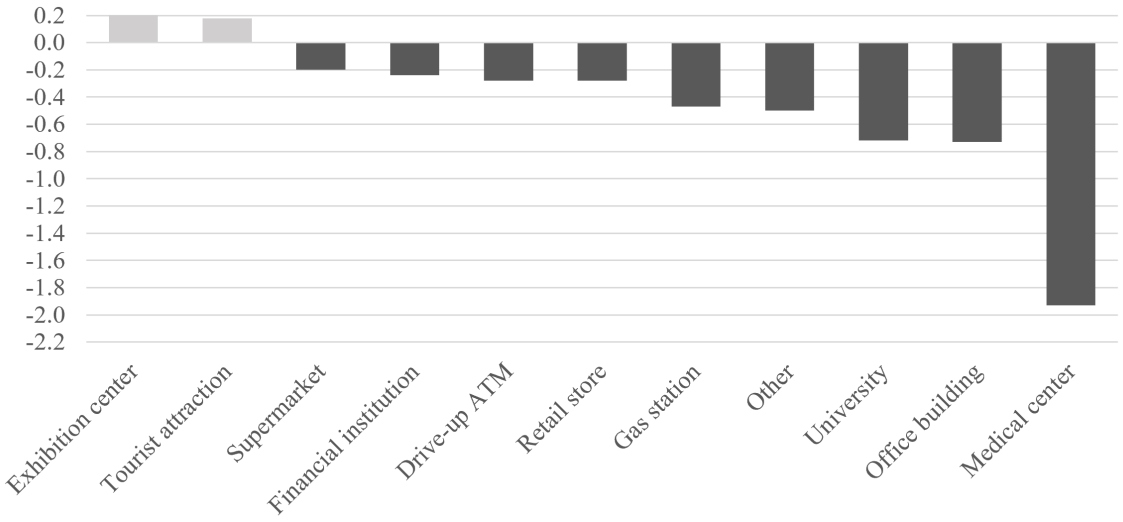
Finally, comparing specifications (1) through (5) gives insight into whether, as expected, the unique institutional setting and data quality mean that price endogeneity affects my analysis considerably less than analyses focused on different markets. In particular, the fact that the estimated β coefficient for specification (5) is no more negative than estimates for specifications (2) through (4) suggests that the extent of price endogeneity and its effect on my analysis is limited, thanks to the combination of steady pricing strategies used by ATM operators and a high-frequency panel data set. Importantly, this provides further support to why ATM cash withdrawals are an advantageous setting to investigate in detail the different sources of variation in sensitivity to service fees.

6.2 Heterogeneity Across Consumer Use Cases, Role of Learning

I first consider how sensitivity to fees varies across consumer use cases and across environments with different potential for learning. This analysis is possible thanks to the number of location types captured in the data set, and the variation in use cases and degree of repeated interaction between them. The specification underpinning this analysis builds on specification (5), replacing $\ln(P_{it})$ with interaction terms between $\ln(P_{it})$ and *Location type*. The estimated location-specific coefficients on $\ln(P_{it})$ are illustrated in figure 4 for location types with sufficient variation in surcharges observed in the data.

The first takeaway from figure 4 is that consumers' sensitivity to service fees varies substantially across location types. While the estimated coefficient on $ln(P_{it})$ of -0.31 from specification (5)

Figure 4: Variation in surcharge elasticity of *Number of Withdrawals* across location types



Note: Dark columns represent estimates that are statistically significant at the 10 percent level or higher; lighter columns represent estimates that are not statistically significant at the 10 percent level.

paints a picture of an average consumer that is relatively insensitive to service fee levels, figure 4 shows how different environments range from those where consumers practically don't respond to the level of service fees, to places where consumers are in fact very sensitive to such fees.

In order to draw from the findings lessons that are broadly applicable in other markets and settings, I look at where the different locations captured in the data set fall on a two-dimensional space. First, consider use cases ranging from urgent and in-the-moment, likely to exhibit lower fee sensitivity, to fully planned decisions, where consumers are likely to be much more sensitive to fee levels. Second, consider potential for consumer learning, ranging from environments with limited repeated interactions where consumers are likely to be less sensitive to fees, to environments where repeated interactions give consumers ample opportunities to learn and adjust, resulting in considerably greater sensitivity to service fees.

Results presented in figure 4 align with this broad, intuitive formulation. Consider first consumers in urgent need of cash. If such consumers are *also* in a location that is new to them – as is likely to happen at, for example, an *Exhibition center* or a *Tourist attraction* – they are insensitive to convenience fees, almost to the point of not being sensitive at all.[4] If such consumers can make their way to a familiar location they have experience with – for example, make an urgent withdrawal at a familiar *Financial institution, Drive-up ATM*, or *Gas station* – they are more sensitive to service fees.

[4]The estimated coefficients on *Exhibition center* and *Tourist attraction* are not statistically different from zero.

Consider now consumers who plan to make a cash withdrawal. If such consumers are in an unfamiliar location – for example, consumers who prefer to pay cash visiting a new *Supermarket*, *Retail Store,* or *Gas Station* – they are less sensitive to convenience fees (albeit more than if their needs were urgent). Finally, consumers most sensitive to service fees are those planning to make withdrawals at a location they are very familiar with – for example, ATMs in places of work such as a *University, Office building,* or *Medical center*.

6.3 Effect of Competition and Substitute Availability on Fee Sensitivity

Another mechanism I am able to investigate using the ATM data is how market competition and availability of substitutes affect consumers' sensitivity to service fees. Using variation in market composition across ATMs in the data set combined with a detailed map of all ATMs in the marketplace, I am able to investigate the extent to which consumers who have convenient alternatives nearby are less willing to pay higher fees. The specification underpinning this analysis builds on specification (5) by adding interaction terms between $\ln(P_{it})$ and $ATMper10k$, which measures the number of ATMs per 10,000 inhabitants in the local market (ZIP code). The estimated coefficients are illustrated in table 2, alongside results for specification (5).

Table 2: Variation in surcharge elasticity of *Number of Withdrawals* across competitive environments

	5	6
$ln(P_{it})$	-0.311	-0.106
	(0.0143)	(0.0465)
$ln(P_{it}) * ATMper10k$		–1.139
		(0.2469)
Demographic Variables		X
Time FEs		
Location type FE, Bank FE		
Terminal FE	X	X
R2	0.565	0.565

Note: Dependent variable: $\ln(Q_{it}^n + 0.1)$. Estimation Sample: surcharged withdrawals, including days when ATM was active, but no surcharged withdrawals took place. To preserve anonymity of the data source, number of observations and ATMs are not reported.

As expected, the statistically significant negative coefficient on $\beta^{ATMper10k}$ confirms that customers are less willing to pay higher fees when there are more alternatives available nearby. This finding provides a good illustration of the mechanism through which competition exerts downward pressure on service fees – by providing greater choice to consumers, competition makes them more sensitive to fees at any one location.

The large absolute value of the $\beta^{ATMper10k}$ coefficient illustrates the important role that availability of alternatives can play in determining consumers' willingness to pay service fees. In the ATM setting, the estimates imply that a consumer at an ATM in the 10^{th} percentile of competitiveness will be about half as sensitive to surcharges than a consumer at an ATM in the 90^{th} percentile of competitiveness.[5] Broadly, these findings make clear how important it is for businesses setting service fees to understand the competitive landscape, and to understand how greater availability of competing alternatives makes potential consumers more sensitive to service fees.

6.4 Further Analysis of Fundamental Mechanisms that Determine Consumers' Fee Sensitivity

Finally, I look to gain further insights into importance of key mechanisms by investigating how consumers' sensitivity to convenience fees depends on socioeconomic factors. This analysis is possible thanks to the size of the data set available to me and broad adoption of ATMs across a wide range of locations. Taken together, these factors mean that I achieve crisp identification in this section thanks to substantial variation in local demographics across the thousands of ATMs in the data set. The specification underpinning this analysis builds on specification (5) by adding interaction terms between $\ln(P_{it})$ and socioeconomic factors measured by the U.S. Census. The estimated coefficients are illustrated in figure 5.

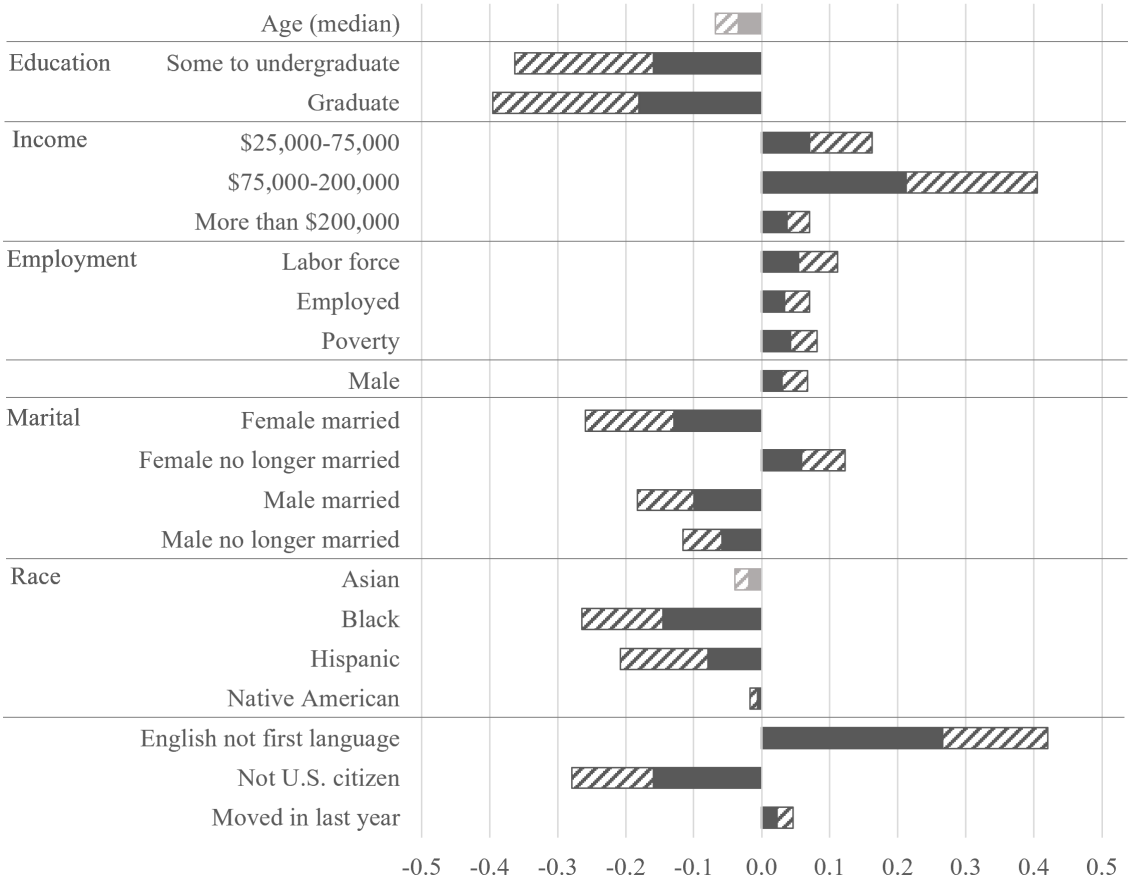
The first general mechanism I consider is whether more sophisticated consumers are more sensitive to service fees than less sophisticated consumers. In figure 5, the strongly negative coefficients on education suggest consumers in more highly educated communities exhibit greater fee sensitivity. This result is consistent with consumers with higher financial sophistication exhibiting greater sensitivity to service fees.

Another related mechanism is how information barriers can make service fees less salient, which in turn can result in consumers being considerably less sensitive to such fees. A result in figure 5 that is consistent with this mechanism is how ATMs in areas with a greater share of the population whose primary language is not English exhibit substantially less sensitivity to surcharges. One potential reason for this is that while all ATMs are required to display surcharges to consumers, this information is presented in English by default, making it harder to process for consumers whose primary language isn't English.

Opportunity cost plays an important role in consumer decisions, and consumers whose time is more valuable are more likely to accept higher service fees. Results in figure 5 suggest that consumers in areas with higher income levels are less sensitive to fee levels, potentially because such consumers view their time as more valuable. Similarly, if working people value their free time more than those out of work, this is consistent with the findings that areas with a greater share of

[5] $\ln(P_{it}) = \beta + \beta^{ATMper10k} * ATMper10k$ = -0.22 at the 10^{th} percentile, and -0.41 at the 90^{th} percentile

Figure 5: Variation in surcharge elasticity of *Number of Withdrawals* across demographic characteristics



Note: Solid (hatched) bars represent difference between estimated coefficients at the 75th and 25th (90th and 10th) percentiles of each characteristic's distribution.
Categorical coefficients are normalized relative to base categories (Education: None; Income: Less than $25,000; Marital: Single; Race: White). Dark bars represent estimates that are statistically significant at the 10 percent level or higher; lighter columns represent estimates that are not statistically significant at the 10 percent level.

people who are currently employed or in the labor force exhibit lower fee sensitivity.

Finally, results in figure 5 suggest ways in which learning can play an important role in shaping consumers' sensitivity to service fees. For example, areas with a greater share of households who have only recently moved in exhibit lower fee sensitivity, potentially since such consumers have had less time to learn about ways in which they could locally acquire cash without paying fees. To the extent that people learn from one another, it is reasonable to expect for such learning to have a lasting effect. The finding that areas with a greater share of the population that are no longer

married exhibit fee sensitivity patterns that are counter to men being less sensitive to fee on average (also shows in figure 5) is one potential illustration of such long-term effects of learning, if men who were once married continue to be more sensitive to fees, and vice versa for women.

6.5 Behavioral Adjustment to Higher Convenience Fees

Table 3 presents the estimation results for specifications where the dependent variable is *Average withdrawal amount*. This analysis provides an illustration of how changes in service fees can elicit broader behavioral responses from consumers.

Table 3: Average and heterogeneous surcharge elasticity of *Average Withdrawal Amount*

	1	2	3	4	5	6
$ln(P_{it})$	0.092	0.101	0.099	0.058	0.027	0.012
	(0.0028)	(0.0029)	(0.0028)	(0.0048)	(0.0094)	(0.0303)
$ln(P_{it}) * ATMper10k$						0.081
						(0.1604)
Demographic Variables		X	X	X		
Time FEs			X	X	X	X
Location type FE, Bank FE				X		
Terminal FE					X	X
R^2	0.001	0.011	0.031	0.154	0.225	0.225

Note: Dependent variable: $\ln(Q_{it}^{av})$. Estimation sample: surcharged withdrawals, ATM-days when $Q_{it}^{n} > 0$. In specification (6), the coefficients on $ln(P_{it})$ and $ln(P_{it}) * ATMper10k$ are jointly significant at the 5 percent level (p-value = 0.0147). To preserve anonymity of the data source, number of observations and ATMs are not reported.

The results for specifications in table 3 are all consistent with the idea that consumers may adjust their behavior in response to higher service fees. In particular, the findings suggest that higher ATM surcharges result in at least some consumers withdrawing more cash than they would otherwise, as captured in the consistently statistically significant and positive estimated β coefficient in specifications (1) through (5) and the jointly significant positive β and $\beta^{ATMper10k}$ coefficients in specification (6). Intuitively, a possible explanation is that as fixed surcharges increase in *absolute* terms, consumers choose to withdraw more cash each time to decrease the *relative* cost of gaining access to cash.

The findings presented here have potential implications that go beyond the ATM setting. Looking at payments broadly, the findings shine a light on the underlying tradeoff consumers face between holding cash for making payments and keeping their money in the safety of interest-bearing checking accounts (Allais, 1947; Baumol, 1952; Tobin, 1956; Romer, 1986; Alvarez and Lippi, 2017). As the cost of gaining access to cash goes up, consumers strategically choose not only to withdraw more cash each time they visit an ATM, but also to hold more of their money as cash than they

would otherwise. Higher costs of obtaining cash resulting from higher surcharges can therefore have far-ranging effects on heavy cash users such as older people, potentially exposing them to greater risks from carrying cash, or imposing a greater opportunity cost of holding cash in a high inflation environment.

These findings further illustrate how service fees can potentially affect consumer behavior, and why it is important for businesses and economists to pay close attention to these seemingly small but widely prevalent fees. In particular, the findings show how consumers can respond to even small changes in service fees by changing not only *how much* they consume, but also strategically adjust their behavior and alter *how* they consume goods and services.

7 Conclusion

This paper studies heterogeneity in consumers' sensitivity to service fees using ATM surcharges as an empirical setting. Using a uniquely detailed, high-frequency panel data set of daily withdrawals across thousands of ATMs, I directly estimate the effect of surcharges on demand for cash withdrawals. Importantly, by taking full advantage of the rich data and unique institutional pricing structure, I am able to document substantial variation in fee sensitivity across consumer demographics, settings with varying degrees of repeat consumers, and competitive conditions.

The results show clearly how higher surcharges reduce the number of ATM cash withdrawals, and that such demand is fairly inelastic at observed fee levels, in line with prior findings. In addition, I document how consumers adapt their behavior in other important ways: as surcharges rise, consumers withdraw cash less frequently but in larger amounts, suggesting they actively adjust their cash-management behavior in response to greater financial frictions. These findings illustrate that even relatively small fee changes can meaningfully affect how consumers access and manage liquidity.

A central contribution of the paper is the documentation of substantial heterogeneity in sensitivity to service fees. Importantly, not only are ATM surcharges a unique and clean empirical setting to conduct this analysis, but the documented heterogeneity patterns can also be linked to fundamental mechanisms in a way that makes the findings applicable to a wide variety of markets, products, and services. Consumers appear considerably more price-sensitive in environments characterized by repeated interaction or greater availability of substitutes, and substantially less sensitive in settings where convenience, immediacy, or informational frictions are likely to dominate decision-making. The results also show how sensitivity to surcharges varies across demographic characteristics, illustrating ways in which the burden imposed by service fees can differ meaningfully across groups.

The findings in this paper paint a clear picture of consumers' general sensitivity to small but salient financial frictions and speak to how such frictions may shape market outcomes and consumer

welfare. The findings illustrate ways in which firms' ability to impose convenience fees depends on variation in consumer preferences and sophistication, the one-off or repeated nature of consumer interactions, and competitive pressure from alternatives.

Substantial heterogeneity in fee sensitivity documented in the paper points to ways in which convenience-fee pricing can impose unequal burdens across consumers, potentially reflecting differences in financial literacy, information frictions, liquidity constraints, or access to substitutes. Importantly, the results also suggest that increasing competition, improving transparency, and enhancing financial education could reduce such burdens.

Several avenues for future research on service fees remain. Linking transaction-level fee responses to individual consumer characteristics and payment behavior would allow for an even richer understanding of how fee sensitivity varies across the population. A structural model estimated using individual decisions between fee-charging services and alternatives could paint a full picture of how consumers weigh the fees against convenience provided by products and services. Combined with supply-side costs of providing convenience, such a model could shed light on welfare implications of controversial offerings such as allowing for account overdrafts / overdraft fees, unbundling airline tickets and charging fees for seat choice and on-board food, or ticketing fees charged by major event and hotel booking services.

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8 Appendix

Table 4: Full results, dependent variable: *Number of withdrawals*

	1	2	3	4	5	6	7	8
$ln(P_{it})$	-0.205	-0.328	-0.316	-0.363	-0.311	-0.106		
	(0.0055)	(0.0055)	(0.0054)	(0.0089)	(0.0143)	(0.0465)		
Age (median)		-0.852	-0.693	0.494			-0.958	
		(0.0245)	(0.0242)	(0.0298)			(0.1297)	
Some to undergraduate		0.439	0.419	-0.565			-0.378	
		(0.0287)	(0.0282)	(0.0329)			(0.0674)	
Graduate		1.655	1.393	0.817			-0.017	
		(0.0323)	(0.0321)	(0.0373)			(0.0987)	
Labor force		-0.173	-0.364	0.461			0.130	
		(0.0163)	(0.0165)	(0.0197)			(0.0431)	
Employed		-0.206	0.009	0.040			0.343	
		(0.0144)	(0.0149)	(0.0162)			(0.0261)	
$25,000-75,000		0.511	0.519	-0.019			0.378	
		(0.0207)	(0.0203)	(0.0229)			(0.0375)	
$75,000-200,000		1.336	1.620	1.148			1.305	
		(0.0220)	(0.0224)	(0.0259)			(0.0608)	
More than $200,000		-0.513	-0.391	-0.350			0.532	
		(0.0204)	(0.0201)	(0.0226)			(0.0523)	
Poverty		0.705	0.802	0.909			0.193	
		(0.0173)	(0.0171)	(0.0191)			(0.0298)	
Male		0.210	0.194	0.228			0.212	
		(0.0158)	(0.0155)	(0.0172)			(0.0385)	
Female married		0.567	0.544	1.687			-0.523	
		(0.0329)	(0.0323)	(0.0356)			(0.0649)	
Female no longer married		1.282	1.205	1.228			0.017	
		(0.0223)	(0.0219)	(0.0239)			(0.0471)	
Male married		0.520	0.283	–1.105			-0.502	
		(0.0346)	(0.0343)	(0.0387)			(0.0581)	
Male no longer married		0.707	0.634	-0.018			-0.127	
		(0.0176)	(0.0173)	(0.0199)			(0.0330)	
English not first language		-0.778	-0.781	–1.460			1.406	
		(0.0441)	(0.0432)	(0.0506)			(0.1256)	
Not U.S. citizen		-0.962	-0.917	–2.381			–1.482	
		(0.0401)	(0.0393)	(0.0445)			(0.1117)	
Moved in last year		0.802	0.842	0.604			0.133	
		(0.0159)	(0.0156)	(0.0179)			(0.0346)	
Asian		1.194	1.241	1.932			0.395	
		(0.0244)	(0.0239)	(0.0273)			(0.0726)	
Black		-0.241	-0.215	0.149			0.013	
		(0.0104)	(0.0102)	(0.0117)			(0.0505)	

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Table 4 – *Continued from previous page*

	1	2	3	4	5	6	7	8
Hispanic		1.608	1.599	2.601			3.246	
		(0.0263)	(0.0258)	(0.0322)			(0.2770)	
Native American		1.710	1.712	0.540			0.294	
		(0.0148)	(0.0145)	(0.0215)			(0.0981)	
Interaction with $ln(P_{it})$								
$ATMper10k$						–1.139		
						(0.2469)		
Drive-up ATM							-0.282	
							(0.0664)	
Exhibition center							0.245	
							(0.1598)	
Financial institution							-0.240	
							(0.0176)	
Gas station							-0.473	
							(0.0636)	
Medical center							–1.934	
							(0.1304)	
Office building							-0.734	
							(0.0692)	
Other							-0.501	
							(0.1724)	
Retail store							-0.282	
							(0.0390)	
Supermarket							-0.203	
							(0.0605)	
Tourist attraction							0.179	
							(0.1784)	
University							-0.717	
							(0.1224)	
Age (median)								-0.117
								(0.0953)
Some to undergraduate								-0.601
								(0.0668)
Graduate								-0.938
								(0.0801)
Labor force								0.196
								(0.0486)
Employed								0.141
								(0.0315)
$25,000-75,000								0.299
								(0.0432)
$75,000-200,000								0.873
								(0.0642)

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Table 4 – *Continued from previous page*

	1	2	3	4	5	6	7	8
More than $200,000								0.219
								(0.0573)
Poverty								0.187
								(0.0357)
Male								0.215
								(0.0414)
Female married								-0.537
								(0.0751)
Female no longer married								0.223
								(0.0564)
Male married								-0.366
								(0.0704)
Male no longer married								-0.224
								(0.0404)
English not first language								1.380
								(0.1551)
Not U.S. citizen								-0.700
								(0.1244)
Moved in last year								0.121
								(0.0398)
Asian								-0.089
								(0.0805)
Black								-0.469
								(0.0391)
Hispanic								-0.738
								(0.1089)
Native American								-0.317
								(0.1207)
Demographic Variables		X	X	X				
Time FEs			X	X	X	X	X	X
Location type FE, Bank FE				X				
Terminal FE					X	X	X	X
R^2	0.001	0.044	0.081	0.255	0.565	0.565	0.566	0.565

Note: Dependent variable: $\ln(Q_{it}^n + 0.1)$. Estimation sample: surcharged withdrawals, including days when ATM was active, but no surcharged withdrawals took place. To preserve anonymity of the data source, number of observations and ATMs are not reported.

Table 5: Full results, dependent variable: *Average withdrawal amount*

	1	2	3	4	5	6	7	8
$ln(P_{it})$	0.092	0.101	0.099	0.058	0.027	0.012		
	(0.0028)	(0.0029)	(0.0028)	(0.0048)	(0.0094)	(0.0303)		
Age (median)		0.082	0.035	-0.062			-0.076	
		(0.0126)	(0.0126)	(0.0159)			(0.0858)	
Some to undergraduate		0.234	0.243	0.449			0.056	
		(0.0144)	(0.0143)	(0.0174)			(0.0446)	
Graduate		0.056	0.133	0.185			0.195	
		(0.0164)	(0.0164)	(0.0199)			(0.0652)	
Labor force		-0.241	-0.189	-0.255			0.021	
		(0.0083)	(0.0085)	(0.0106)			(0.0286)	
Employed		0.004	-0.049	-0.032			-0.019	
		(0.0073)	(0.0076)	(0.0086)			(0.0173)	
$25,000-75,000		0.028	0.028	0.014			-0.081	
		(0.0107)	(0.0106)	(0.0124)			(0.0251)	
$75,000-200,000		-0.055	-0.131	-0.081			-0.099	
		(0.0112)	(0.0115)	(0.0138)			(0.0409)	
More than $200,000		0.321	0.287	0.182			-0.042	
		(0.0103)	(0.0103)	(0.0121)			(0.0347)	
Poverty		-0.080	-0.103	0.078			0.076	
		(0.0089)	(0.0088)	(0.0103)			(0.0200)	
Male		-0.165	-0.154	-0.144			-0.086	
		(0.0079)	(0.0079)	(0.0092)			(0.0257)	
Female married		0.128	0.131	0.036			0.139	
		(0.0166)	(0.0165)	(0.0190)			(0.0437)	
Female no longer married		-0.049	-0.026	0.007			-0.014	
		(0.0115)	(0.0114)	(0.0128)			(0.0317)	
Male married		-0.296	-0.224	-0.020			-0.138	
		(0.0175)	(0.0175)	(0.0206)			(0.0385)	
Male no longer married		0.029	0.051	0.082			0.012	
		(0.0089)	(0.0088)	(0.0106)			(0.0219)	
English not first language		0.227	0.223	0.110			-0.192	
		(0.0225)	(0.0222)	(0.0273)			(0.0845)	
Not U.S. citizen		0.130	0.123	0.574			0.488	
		(0.0201)	(0.0199)	(0.0235)			(0.0740)	
Moved in last year		0.129	0.117	0.103			-0.015	
		(0.0080)	(0.0080)	(0.0095)			(0.0230)	
Asian		-0.298	-0.309	-0.200			0.002	
		(0.0122)	(0.0121)	(0.0143)			(0.0479)	
Black		-0.056	-0.064	-0.105			0.085	
		(0.0053)	(0.0053)	(0.0063)			(0.0336)	
Hispanic		0.266	0.270	-0.039			-0.092	
		(0.0132)	(0.0131)	(0.0170)			(0.1843)	
Native American		-0.559	-0.557	-0.088			-0.184	

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Table 5 – *Continued from previous page*

	1	2	3	4	5	6	7	8
		(0.0073)	(0.0072)	(0.0113)			(0.0651)	
Interaction with $ln(P_{it})$								
$ATMper10k$						0.081		
						(0.1604)		
Drive-up ATM							-0.008	
							(0.0418)	
Exhibition center							0.414	
							(0.1185)	
Financial institution							0.012	
							(0.0116)	
Gas station							0.065	
							(0.0390)	
Medical center							-0.084	
							(0.0909)	
Office building							0.099	
							(0.0467)	
Other							0.093	
							(0.1075)	
Retail store							0.002	
							(0.0257)	
Supermarket							0.207	
							(0.0397)	
Tourist attraction							-0.374	
							(0.1241)	
University							-0.072	
							(0.0891)	
Age (median)								0.055
								(0.0638)
Some to undergraduate								-0.044
								(0.0442)
Graduate								-0.040
								(0.0530)
Labor force								0.102
								(0.0324)
Employed								0.027
								(0.0208)
$25,000-75,000								-0.084
								(0.0291)
$75,000-200,000								-0.094
								(0.0431)
More than $200,000								0.005
								(0.0382)
Poverty								0.089

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Table 5 – *Continued from previous page*

	1	2	3	4	5	6	7	8
								(0.0239)
Male								-0.081
								(0.0275)
Female married								0.171
								(0.0506)
Female no longer married								0.004
								(0.0378)
Male married								-0.148
								(0.0467)
Male no longer married								-0.000
								(0.0268)
English not first language								-0.254
								(0.1049)
Not U.S. citizen								0.419
								(0.0818)
Moved in last year								-0.014
								(0.0266)
Asian								-0.014
								(0.0532)
Black								0.002
								(0.0259)
Hispanic								0.119
								(0.0728)
Native American								-0.316
								(0.0805)
Demographic Variables		X	X	X				
Time FEs			X	X	X	X	X	X
Location type FE, Bank FE				X				
Terminal FE					X	X	X	X
R^2	0.001	0.011	0.031	0.154	0.225	0.225	0.225	0.225

Note: Dependent variable: $\ln(Q_{it}^n)$. Estimation sample: surcharged withdrawals, including days when ATM was active, but no surcharged withdrawals took place. To preserve anonymity of the data source, number of observations and ATMs are not reported.

Table 6: Full results, dependent variable: *Number of withdrawals*, robustness check: $ln(Q_{it}^n + 1)$

	1	2	3	4	5	6	7	8
$ln(P_{it})$	-0.068	-0.149	-0.142	-0.168	-0.210	-0.001		
	(0.0032)	(0.0031)	(0.0031)	(0.0048)	(0.0072)	(0.0233)		
Age (median)		-0.447	-0.347	0.310			-0.624	
		(0.0138)	(0.0136)	(0.0161)			(0.0651)	
Some to undergraduate		0.201	0.182	-0.437			-0.217	
		(0.0162)	(0.0159)	(0.0178)			(0.0338)	
Graduate		1.014	0.852	0.502			0.014	
		(0.0183)	(0.0181)	(0.0202)			(0.0495)	
Labor force		-0.060	-0.175	0.265			0.147	
		(0.0092)	(0.0093)	(0.0106)			(0.0216)	
Employed		-0.256	-0.130	-0.015			0.157	
		(0.0081)	(0.0084)	(0.0088)			(0.0131)	
$25,000-75,000		0.331	0.336	-0.083			0.180	
		(0.0117)	(0.0114)	(0.0124)			(0.0188)	
$75,000-200,000		0.882	1.056	0.679			0.674	
		(0.0125)	(0.0126)	(0.0140)			(0.0305)	
More than $200,000		-0.346	-0.273	-0.303			0.205	
		(0.0115)	(0.0113)	(0.0122)			(0.0262)	
Poverty		0.395	0.453	0.476			0.124	
		(0.0098)	(0.0096)	(0.0104)			(0.0150)	
Male		0.140	0.127	0.134			0.099	
		(0.0089)	(0.0087)	(0.0093)			(0.0193)	
Female married		0.315	0.307	1.047			-0.287	
		(0.0186)	(0.0182)	(0.0193)			(0.0325)	
Female no longer married		0.743	0.698	0.693			0.049	
		(0.0126)	(0.0123)	(0.0129)			(0.0236)	
Male married		0.332	0.184	-0.673			-0.306	
		(0.0196)	(0.0193)	(0.0209)			(0.0291)	
Male no longer married		0.395	0.348	-0.028			-0.114	
		(0.0099)	(0.0097)	(0.0107)			(0.0166)	
English not first language		-0.365	-0.367	-0.832			0.883	
		(0.0249)	(0.0243)	(0.0274)			(0.0630)	
Not U.S. citizen		-0.763	-0.737	–1.722			-0.929	
		(0.0227)	(0.0222)	(0.0241)			(0.0560)	
Moved in last year		0.407	0.432	0.253			0.104	
		(0.0090)	(0.0088)	(0.0097)			(0.0174)	
Asian		0.799	0.828	1.250			0.146	
		(0.0138)	(0.0135)	(0.0148)			(0.0364)	
Black		-0.075	-0.059	0.174			-0.167	
		(0.0059)	(0.0058)	(0.0063)			(0.0253)	
Hispanic		0.983	0.976	1.712			1.609	
		(0.0149)	(0.0145)	(0.0174)			(0.1389)	
Native American		1.371	1.372	0.308			0.068	

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Table 6 – *Continued from previous page*

	1	2	3	4	5	6	7	8
		(0.0084)	(0.0082)	(0.0116)			(0.0492)	
Interaction with $ln(P_{it})$								
$ATMper10k$						–1.170		
						(0.1239)		
Drive-up ATM							-0.240	
							(0.0333)	
Exhibition center							0.095	
							(0.0801)	
Financial institution							-0.162	
							(0.0088)	
Gas station							-0.344	
							(0.0319)	
Medical center							-0.986	
							(0.0654)	
Office building							-0.437	
							(0.0347)	
Other							-0.269	
							(0.0865)	
Retail store							-0.185	
							(0.0196)	
Supermarket							-0.185	
							(0.0303)	
Tourist attraction							0.160	
							(0.0895)	
University							-0.536	
							(0.0614)	
Age (median)								-0.062
								(0.0478)
Some to undergraduate								-0.290
								(0.0335)
Graduate								-0.458
								(0.0402)
Labor force								0.233
								(0.0244)
Employed								0.057
								(0.0158)
$25,000-75,000								0.142
								(0.0217)
$75,000-200,000								0.454
								(0.0322)
More than $200,000								0.037
								(0.0288)
Poverty								0.133

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Table 6 – *Continued from previous page*

	1	2	3	4	5	6	7	8
								(0.0179)
Male								0.106
								(0.0208)
Female married								-0.311
								(0.0377)
Female no longer married								0.176
								(0.0283)
Male married								-0.259
								(0.0353)
Male no longer married								-0.194
								(0.0202)
English not first language								1.049
								(0.0778)
Not U.S. citizen								-0.468
								(0.0624)
Moved in last year								0.090
								(0.0200)
Asian								-0.123
								(0.0404)
Black								-0.417
								(0.0196)
Hispanic								-0.533
								(0.0546)
Native American								-0.289
								(0.0606)
Demographic Variables		X	X	X				
Time FEs			X	X	X	X	X	X
Location type FE, Bank FE				X				
Terminal FE					X	X	X	X
R^2	0.001	0.011	0.031	0.154	0.225	0.225	0.225	0.225

Note: Dependent variable: $\ln(Q_{it}^n + 1)$. Estimation sample: surcharged withdrawals, including days when ATM was active, but no surcharged withdrawals took place. To preserve anonymity of the data source, number of observations and ATMs are not reported.