Rising Rents and Consumer Debt*

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PRELIMINARY

Abstract

In the aftermath of the COVID-19 pandemic, house prices and rents surged. While research has shown clear links between house prices, consumption, and the financial conditions of home owners, there is little evidence on how rising rents affect renter households. To help address this gap, we construct a new dataset which links administrative credit card data to asking rents at the apartment-building level in order to study the borrowing, spending, and mobility response to rising rents. Exploiting within-county variation in rent growth across apartment buildings, we find that renters buffer rent shocks with increased spending and borrowing on credit cards, especially for those who were already rent burdened. We also find that credit limits rise as rents increase, suggesting that renters request additional borrowing capacity when rents go up. At the same time, renters are more likely to become delinquent on their credit cards after a rise in rents. Finally, we find evidence that some renters move out of their building as rents go up, although moving does not appear to eliminate the effects of rising rents on credit card borrowing and delinquency. All told, our results provide new insight into the distributional effects of shelter inflation and how renters cope financially with rising housing costs.

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1 Introduction

In 2023 year-over-year housing services inflation exceeded 8 percent.[1] This inflation was not borne equally. For home owners with fixed rate mortgages, monthly housing payments were unaffected and the value of their asset rose. Most renters, on the other hand, faced substantial increases in their monthly housing payments when their leases came up for renewal. A flurry of media reports point to the burden rising rents are placing on renters.[2] While there is a large body of work in economics examining how home owners are affected by rising house prices[3], less is known about how renters –who comprise about 40 percent of the US population– respond to rising rents.

When renters face higher rents, there are many margins along which they may adjust. One margin is to substitute away from housing consumption by moving to a smaller or lower-quality unit, or to a lower-amenity neighborhood or city. If moving is costly or suitable lower-cost housing is difficult to find, renters may instead reduce non-housing consumption to help finance higher housing costs. Yet another possibility is that renters may borrow, for example on credit cards, to maintain non-housing consumption and pay the higher rent. Although such borrowing is expensive, this may be a rational response if moving is especially costly or if reducing non-housing consumption is especially difficult. This paper will examine how renters respond to rising rents on each of these dimensions.

To study these responses, we leverage a unique panel dataset on thousands of apartment buildings across the U.S. that tracks how landlords are changing asking rents on a monthly basis, merged to administrative credit card account data for all major credit card banks in the U.S.. We merge credit card accounts to the specific building in which account holders live, such that for each apartment in our data we observe both how rents are changing in that building as well as the credit card activity of the account holders who live in that building. Our empirical strategy is to follow the experience of renters who moved into a building before 2019, and how their spending, borrowing, and moving choices were affected by their landlord raising rent in that same building over the

[1] See: https://data.bls.gov/dataViewer/view/timeseries/CUUR0000SAH1

[2] See, for example, https://www.nbcnews.com/data-graphics/data-shows-middle-class-renters-increasingly-burdened-housing-costs-rcna176189.

[3] See, for example, Mian and Sufi 2009; Mian, Rao, and Sufi 2013; Kaplan, Mitman, and Violante 2016; Bhutta and Keys 2016; Aladangady 2017; Stroebel and Vavra 2019; Cloyne et al. 2019.

subsequent period of high rent inflation from 2019 through 2024. Specifically, we estimate panel fixed effects models relating credit card account outcomes to own-building asking rents, controlling for both account and county-by-month fixed effects. Our models thus narrow in on comparisons between individuals who lived in the same county at the same time –thus experiencing similar labor and housing market conditions– but whose landlords raised rents more or less aggressively and/or at different times during the recent inflationary episode.

We find that renters use credit card borrowing to buffer rising rents. As building asking rents rise, credit card balances rise as well, with a 10 percent rise in rents raising balances by 3.8 percent. Most of the rise in balances reflects extra borrowing: For each 10 percent rise in asking rents, revolving balances (i.e. balances that accrue interest) rise by 2.4 percent. We also find that higher rents lead to higher rates of credit card delinquency, indicating that some renters delay credit card payments to finance rising rents. Finally, we find that renters obtain higher credit limits when rents rise, suggesting they requested additional borrowing capacity. All told, this behavior is costly: we find that a 10 percent rise in rents leads to a 2.4 percent rise in finance charges.

Buffering rising rents via credit cards may be especially likely among "rent-burdened" families. These families are likely to already have low levels of discretionary spending, making it difficult to find ways to cut spending. We proxy for such households as those whose own income is relatively low compared to pre-pandemic average local rents. Indeed, we find that rent-burdened account-holders exhibit a three times larger increase in a balances than not rent-burdened account-holders when rents rise. Furthermore, rising rents raise credit limits and revolving balances only for rent-burdened account holders.

Rising rents also induce some renters to move. In particular, we find that a 10 percent rise in rents raises the probability a renter will leave their building by 0.8 percentage points (or 7 percent at the mean moving rate). Most of these moves are local, but there is also a smaller increase in cross-county and cross-state moves. Moving does not appear to fully eliminate the borrowing response to rising rents. In particular, we find that revolving balances and delinquencies increase for those who move during the sample period as well as those who stay, which may reflect costs incurred to move.

Importantly, while we find that credit card borrowing rises with rising rents, this borrowing is not one-for-one with the rise in rents: for each \$100 increase in rents card spending increases by at least \$9. This suggests that renters are also likely absorbing the rise in rents in other ways, for example, by reducing their cash purchases, spending down savings, or adjusting their labor supply, all outcomes we cannot observe in our data. Still, given that about 70 percent of all retail spending is done on credit cards, it is notable that we do not see credit card spending fall when rents rise as would be consistent with a decline in spending among convenience credit card users.[4]

We confirm these patterns and extend our analysis using individual credit report data linked to county-level asking rent indexes that we construct from the building-level data. These data permit us to conduct two key extensions of our main results. First, we examine whether consumers open additional credit card accounts as rents rise. We find that they do, which, combined with the account-level evidence that consumers request credit line increases on existing lines, collectively highlights how consumers seek additional borrowing capacity in response to inflationary rent pressure. Second, in these data we can observe home ownership (as proxied by the existence of a mortgage on their credit file) and use homeowners as a falsification check. We show that homeowners, as expected, are not affected by rising county-level rents.

This paper adds to the literature on the distributional effects of inflation (e.g. Doepke and Schneider 2006; Kaplan and Schulhofer-Wohl 2017; Jaravel 2021; Del Canto et al. 2023). We show that during the most recent episode of housing inflation renters increased their costly credit card indebtedness and had higher delinquencies. These negative outcomes contrast with the effects of housing inflation on homeowners, as past research typically shows that home owners benefit from rising house prices due to wealth and collateral effects (e.g. Mian and Sufi 2009; Mian, Rao, and Sufi 2013; Kaplan, Mitman, and Violante 2016; Bhutta and Keys 2016; Aladangady 2017; Stroebel and Vavra 2019; Cloyne et al. 2019)

Our work also connects to the literature on how high rent burdens can affect the consumption of basic necessities and childrens' wellbeing (e.g. Angst et al. 2025; Newman and Holupka 2015; Newman and Holupka 2016; Collinson and Ganong 2018). This literature typically focuses on the

[4] See, for example, research by Capital One on the share of retail spending on credit cards `https://capitaloneshopping.com/research/cash-vs-credit-card-spending-statistics/`.

low-income housing-voucher eligible population and studies how vouchers can improve household wellbeing. We add to this literature by examining a broader set of renters, as compared to earlier studies that have focused on a single city or housing voucher recipients, and provide new evidence on how renters buffer rent increases by borrowing on credit cards.

Finally, our paper contributes to the literature on how consumers respond to income and expense shocks, and in particular households' use of credit cards to smooth income or expense shocks (e.g. Agarwal, Liu, and Souleles 2007; Gelman et al. 2015). Our findings may also be related to the literature on the optimality of credit card borrowing (e.g. Zinman 2015; Keys and Wang 2019. Ponce, Seira, and Zamarripa 2017). Indeed, despite the costliness of credit card borrowing (due to high finance charges and fees) and the permanent nature of higher rents, we find that renters use cards in response to rising rents.

2 Data and Descriptive Statistics

In this paper we link administrative data from several sources to construct a panel of monthly (or quarterly) by account (or person) data on consumer borrowing and own-building (or county) rents. This section describes and summarizes the data.

2.1 Rental Data

2.1.1 Data Description

This paper uses apartment building data from RealPage, a company that provides property management software to apartment building owners and managers. For each apartment building in the data, there are several static variables describing the structure of the building (e.g., number of stories, number of units, building quality, address) as well as dynamic variables updated on a monthly basis, such as asking rents (i.e., the price for a new lease) and occupancy rates. [5]

From 2019 to 2024, the RealPage data includes information on about 50,000 buildings each

[5] Asking rents, reported at the building-month level, reflect the asking rent for the average unit in the building in a given month.

month across the U.S.[6] Almost all buildings in the data have at least 20 units and collectively contain about 10 million units, implying that that these data reflect nearly the universe of 20+ unit buildings and about one-quarter of all rental units in the U.S.[7]

For our main empirical exercise, we merge credit card account data to the RealPage data at the building level, as we describe in more detail below. In a second, complementary exercise we construct county-level "repeat rent" indexes from the building-level data and merge them to credit record data.[8] For this analysis we focus on 511 of the largest counties across the U.S. where we estimate that RealPage covers at least 10 percent of the rental housing stock for that county (on average, RealPage covers about one-third of rental units in these counties).

Figure 1 shows how county-level rents evolved from 2018 through late 2024. The blue line shows that the median of the county rent indexes jumped sharply by about 20% from the beginning of 2021 to late 2022. The shaded area plots the 10th through 90th percentiles of the rent indexes, highlighting considerable heterogeneity across counties in rent growth. In the bottom 10% of counties, rents grew by less than 10% between February 2020 and July 2022, while in the top 10% of counties rents grew by over 30% during this period.

2.1.2 The relationship between asking rents and contract rents

Importantly, in the RealPage data we observe asking rents rather than contract rents. Asking rents are the spot price for a new lease, but at any given point in time most renters will be mid-lease and will not experience a price change until lease renewal. Even then, landlords may not fully adjust rents to market rates at lease renewal.[9] Moreover, the RealPage data reflect asking rents in larger professionally managed buildings, whereas many renters live in smaller buildings or in single-family rentals. A key question is to what extent the changes in rent we observe at the

[6] The data have coverage in almost all major metro areas in the U.S. One notable exception is New York City.

[7] Census estimates, based on the 2021 American Community Survey, that there about 10 million rental units in 20+ unit buildings in the U.S., and about 43 million rental units across all building sizes, including single-family units. See https://data.census.gov/table/ACSDT5Y2021.B25032?q=b25032.

[8] We construct repeat rent indexes at the county level by calculating monthly rental growth using consecutively observed buildings (which is most buildings). Specifically, we calculate monthly rent growth (g_{ct}), for county c at time t, as $(\sum_i rent_{ict})/(\sum_i rent_{ict-1}) - 1$, where $rent_i$ is the asking rent for building i, and all i are observed in both t and $t-1$. We then use these monthly rent growth series to create county-level indexes.

[9] One reason for limited adjustments is that in some jurisdictions, landlords may be constrained by rent control laws.

building level translate into rents paid by a typical tenant.

To assess the relationship between growth in asking rents and growth in contract rents reported by the typical renter family, we regress self-reported gross monthly rent from the American Communities Survey (ACS) microdata on our county-level rent indexes based on the RealPage building data. Table 3 shows the results. In column 1, contract rents are regressed on contemporaneous asking rents, controlling for year and county fixed effects (the ACS data are annual, so we use the June values of asking rents). The coefficient on $AskingRentIndex$ indicates that a \$100 increase in asking rents is associated with a \$28 increase reported contract rents. In column 2, we use a 1-year lag of asking rents, and coefficient increases to 0.41, consistent with a rise in asking rents passing through to contract rents with a lag (Adams et al. 2024). In column 3, we simultaneously include contemporaneous, 1-year lag, and 2-year lag asking rents. Adding up these coefficients implies roughly a \$60 increase in contract rents over 2 years from a \$100 rise in asking rents. In columns 4 and 5, we show that these results are robust to adding in individual demographic controls and to limiting the sample to ACS respondents living in large buildings (at least 20 units), which would be the closest to the sample of renters used in our building rent analysis. Overall, these results indicate that our asking rent data from RealPage are strongly correlated with contract rents reported by renters in the ACS, that asking rents pass through to contract rents with a lag, and that pass-through is less than one-for-one.

2.2 Credit Card Data

Our primary source of data on consumer borrowing is administrative data derived from the FR Y-14M. The FR Y-14M has monthly, detailed data on the portfolios of bank holding companies, savings and loan holding companies, and intermediate holding companies which are subject to annual capital assessments and stress testing.[10] We focus on the FR Y-14M credit card data, which provide us with account-month level panel data on balances, purchases, payments, fees, finance charges, and delinquency status on credit cards, all recorded at the end of the billing cycle (i.e., what appears on a credit card statement). The FR Y-14M credit card data cover roughly 90

[10] More details on the FR Y-14M can be found at `https://www.federalreserve.gov/apps/reportingforms/Report/Index/FR_Y-14M` and `https://www.philadelphiafed.org/surveys-and-data/y14-methodology`

percent of the US credit card market.

A key advantage of the FR Y-14M data for this paper is that about half of lenders report the account-holders nine-digit ZIP code. Nine-digit ZIP codes represent small areas and, for most large apartment buildings, uniquely identify a single apartment building (in fact, large apartment buildings generally have *multiple* unique 9-digit ZIP codes within a single building). We use these 9-digit ZIP codes to match credit card accounts with the RealPage rent data at the building level. (We do not observe unit numbers within buildings or any other personally identifiable information, so account-holders remain anonymous.) To do so, we use a file provided by the U.S. Postal Service that has all addresses and 9-digit ZIP codes. We merge these data to the RealPage data using the building address field in the RealPage data and identify the 9-digit ZIP codes that are uniquely associated with a single RealPage building. All told, we are able to merge about 35,000 RealPage buildings with accounts in the FR Y-14M data.

There are several other advantages of the FR Y-14M over other commonly used alternative data sources on consumer borrowing, such as consumer credit report data. The Y-14M data are monthly and recorded at statement end; by comparison, credit report data typically are recorded on a particular date and thus reflect an arbitrary point in each account's billing cycle. Because the FR Y-14M data records the statement balance, new purchases, and payments made at the end of the billing cycle, we can distinguish between new purchases and revolving debt balances — that is, balances which accrue interest. In particular, we can determine if a borrower is revolving and the size of the revolving balance by comparing their current month's payments to last month's statement. The revolving balance is the difference between last month's balance and this month's payment. Measuring revolving balances is not possible in credit report data. The FR Y-14M data also include more account-level information than is typical in other data sources. For example, we can observe finance charges and fees assessed, the retail APR for the card, balance transfers and cash withdrawals, and, of particular note, self-reported income. We also observe credit limits, the borrower's FICO credit score, the number of days the account has been past due, if the account is joint and/or has authorized users, and the year the account was opened.

To construct our main analysis sample we extract a 30 percent random sample of personal credit card accounts that were considered active by the lender in January 2019 and where the borrower resided in a nine-digit ZIP code uniquely associated with a building in the RealPage data.[11] We then follow those accounts through the end of 2024. We drop accounts that do not appear in the data continuously through the end of 2024.[12] We also drop accounts where the 9-digit ZIP code changes during 2019, which ensures the account-holder was living in the RealPage building for at least a year. We do, however, follow accounts where the nine-digit ZIP code changes anytime after the end of 2019 (presumably because the individual moved, which is one of our outcomes of interest). Our final sample includes 278,140 credit card accounts and 19.5 million account-month observations, in about 19,000 apartment buildings.

We use the FR Y-14M to construct the following outcome variables to capture changes in spending and borrowing. These include (all in nominal dollars): New purchases, the statement balance, current credit limit, and revolving balances (defined as last month's statement balance less this month's payments made), and finance charges. We also examine an indicator for 60-day delinquency, whether the account is revolving (defined as a positive revolving balance), and moving (defined as residing in a different 9-digit ZIP code than the previous month).

We also use these data to define different types of borrowers to examine whether there is a heterogeneous response to rising rents, based on their behavior in early 2019. One particular variable of interest is whether the individual is "rent burdened", which we define based on whether the ratio of county average rents to their own income is above or below the median in January 2019. In appendices, we also examine heterogeneous responses by credit utilization (balances divided by limit less than or greater than 30 percent), by whether their credit score is subprime, and by whether their income is above or below the median in our sample.

Table 1 summarizes our merged Y-14M RealPage sample. The average account statement balance is just over $2000, while average monthly purchase volume is almost $500. Nearly half of these renter accounts revolve, and the average revolving balance is nearly $1700. The past due

[11] Active accounts have had some debt, credit, or balance activity in the prior 12 months.

[12] There are two reasons an account would exit the data and not be included in our sample. The primary reason is that only institutions with sufficiently large portfolios are required to submit the FR Y-14M data. As a result, smaller institutions and their associated accounts will not continue to be reported if the institutions' portfolio falls below the reporting threshold in a particular year. Second, a much smaller number of account-holders will close their accounts. Though we cannot examine it in the FR Y-14M, we examine account closure and opening in the CCP/Equifax data, described below.

(over 60 days late) fraction of accounts is less than 1%, the monthly moving probably is about 1%, and average stated income just over $50,000. Towards the bottom of the table we show three variables drawn from the Quarterly Census of Employment and Wages (QCEW) published by the Bureau of Labor Statistics (BLS). These data provide county-by-quarter information on wages, employment, and establishments, and we merge them to the Y-14M data using the county associated with accounts in 2019. Finally, the last three rows of Table 1 show rent statistics from RealPage. Average asking rent across accounts in matched RealPage buildings over 2019 to 2024 is $1737.[13] Finally, average growth in asking rents over the observation period is nearly 24%, and the standard deviation of 16.7% indicates considerable variation in rent growth.

2.3 Credit Report Data

We supplement the Y-14 analyses with the Federal Reserve Bank of New York Consumer Credit Panel/Equifax (henceforth CCP/Equifax) data.[14] The CCP/Equifax is an individual-level quarterly panel dataset based on a five percent random sample of US consumers with credit histories. The data include detailed information drawn from credit reports, including balances and delinquency status on credit card accounts. The data also includes each borrowers' Equifax Risk Score (a type of credit score), age, and the zip code (5-digit) and county of residence.

These data have a few advantages over the FR Y-14M data which we use to bolster and extend our main analysis. First, we can observe both renters and home owners, as proxied by the presence of mortgage debt. This allows us to conduct falsification analyses of the effects of rising rents on home-owners. Second, we can observe person-level credit card debt (whereas the FR Y-14M data are at the account level and we cannot link borrowers across accounts), which allows us to observe credit card opening and closing behavior as well as any substitution between cards. One disadvantage of the the CCP data, however, is that they do not include 9-digit ZIP codes or other location identifiers that would allow us to merge in rent data at the building level. Therefore, for

[13]Average asking across all buildings in the RealPage data (i.e. regardless of whether the building is matched to the Y-14M data) over this period, weighted by the number of units in each building, is somewhat lower at just under $1600. In 2024Q2, the median asking rent across all buildings, weighted by the total number of units, is about $1600, which compares to a median asking rent for all vacant rental units in the U.S. across all structure types in 2024Q2 of $1481, as reported in the Census Housing Vacancy Survey.

[14]More details on the CCP/Equifax can be found in Lee and van der Klaauw 2010

these analyses, we use the county-level rent indexes derived from the RealPage building data, and merge them to the CCP using individuals' county of residence in 2019.

We use a 10% sample of the CCP data and construct a balanced panel of individuals from 2019Q1 through 2024Q2 who, as of 2019Q4, live in the 511 counties mentioned above where RealPage covers a significant portion of the rental housing stock. Furthermore, we focus on individuals born between 1959 and 1994 (i.e. ages 25-59 in 2019). Finally, we infer renter and owner status from each consumer's history of having a mortgage as of 2019Q1: Owners are identified as those with a mortgage as of 2019Q1, while renters are identified as those without a mortgage as of 2019Q1 and whom have no history of ever having a mortgage. We exclude from the sample other individuals, i.e. those do not have a mortgage in 2019Q1 but have had a mortgage at some point in the past.

Table 2 provides summary statistics by tenure status. Renters in our sample have average credit card balances of nearly $3000 across of their cards (including zero balances for those without any credit cards), while home owners' average balances are closer to $7000. Renters and owners have, on average, about 2 and 3 credit card accounts, respectively. We can also see from this table that renters are more likely than owners to move, have lower credit scores, and are younger.[15]

3 Do Rising Rents Affect Credit Card Borrowing?

3.1 Descriptive Patterns

Figure 2 shows trends in asking rents, credit card balances, and credit card delinquencies using the RealPage data and our CCP data sample. Rents began surging in early 2021 and credit card balances among renters soon followed, much more so than for home owners.[16] After declining during the early part of the pandemic, the fraction of renters with a credit card delinquency also increased for renters relative to home owners after rents started rising. These patterns are suggestive that renters responded to rising rents in part by borrowing more on their credit cards, and that rising rents may have contributed to increased financial stress and delinquency. The rest

[15]Credit scores in the CCP refer to the Equifax Risk Score.

[16]We construct a national repeat rent index, similar to the county rent indexes described above in Section 2.1.

of our paper attempts to uncover if these credit card trends are causally related to rising rents.

3.2 Analysis of Building-Credit-Card Merged Data

Using Y-14M credit card account data merged to own-building asking rent data, we estimate models using ordinary least squares (OLS) models of the following form:

$$y_{itbc} = \beta ln(rent)_{bt} + \alpha_i + \rho_{ct} + \epsilon_{itbc} \tag{1}$$

where i refers to the card account, t refers to the statement month, b refers to the building (9-digit zipcode) of residence in January 2019, and c refers to the county where the building is located. $ln(rent)_{bt}$ refers to the log of building asking rent, measured as the average over month $t-11$ through month t.[17] α_i refers to an account fixed effect and ρ_{ct} is a county by month fixed effect. In some models, we alternatively replace α_i with building fixed effects (δ_b) and $\mathbf{X}_i$, a vector of account-level characteristics including: 2019 borrower income quartile, 2019 credit score quintile, lender, and year of origination fixed effects, and an indicator for whether the account is joint or has authorized users. Some models also replace ρ_{ct} with time fixed effects (η_t) and $\mathbf{E}_{ct}$ a vector of county-quarter economic variables from the QCEW including average weekly wages, the number of establishments, and the number of employees in the county. In all models we adjust standard errors for clustering by county.

In these models, the identifying assumption for a causal interpretation of β is that asking rents in the building are conditionally orthogonal to borrowing outcomes. The use of county-month fixed effects (ρ_{ct}) allow us to interpret β as net of any common national and county-month shocks to economic conditions that might be correlated with both rents and credit card borrowing. This would include, for example, changes in labor market conditions which might affect both housing demand (and thus market rents) and borrowing behavior. We can thus interpret β as the effect of within-county-month changes in rents. In other words, the identifying variation is not whether a particular county experienced faster rent growth than another, but rather, whether a particular

[17] In Appendix Table A1, we present results using a variety of alternative definitions, averaging over months $t-2$ or $t-6$ through t, month t, and using different lags of rents.

building's rent grew faster than other buildings in the same county.

Our models also employ account fixed effects (α_i), which allow us to interpret β as net of any person-specific correlation between the level of rent in a building and borrowing behavior; for example, if borrowers who live in more expensive buildings tend to also spend more or are more likely to revolve credit card debt. Also recall that we fix the building of residence to January 2019. Thus, β will not reflect the effects of changes in rent which would be endogenous to borrower choices on where to live after 2019 (in particular, if they move to a new building with a different level of rents). Instead, the models identify the effects of within-building growth in rents for the building in which the borrower lived in 2019 — well before the pandemic and widespread rental inflationary episode began.

Table 4 shows the results of estimating equation 1 for four measures of credit card use: balances, purchases, and indicator for revolving, and revolving balances, where balances and purchases are expressed in logs. The odd-numbered columns display results replacing α_i and and ρ_{ct} with δ_b, η_t, $\mathbf{X}_i$, and $\mathbf{E}_{ct}$, and the even-numbered columns display the main specification, as noted in the table. Table 4, column 2 indicates that a 10 percent increase in building asking rents leads to a 3.8 percent increase in credit card balances (statistically significant at the one percent level). Credit card purchases increase by a similar amount (3.2 percent, column 4). Column 8 indicates revolving balances increase by 2.4 percent following a 10 percent rise in rents.

In dollar terms, these results imply that for every \$100 increase in monthly asking rent, credit card purchases increase by \$9, balances by about \$45, and revolving balances by \$24. Moreover, recall from our analysis of ACS data in 2.1.2 that asking rents may not fully pass through to contract rents. Thus, these results on the extent to which renters buffer rent increases using their credit cards are likely understated. We do not find a statistically meaningful increase in the propensity for borrowers to revolve (column 6), indicating that this borrowing response is concentrated among those who already revolved on credit cards.

Comparing the effects on total balances and revolving balances implies that much of the rise in balances reflects additional borrowing, rather than additional spending which is paid off at the end of the month (often referred to as "convenience use" of credit cards). That said, the results do not rule out higher convenience spending on credit cards in response to rising rents, which may reflect a shift away from cash spending, or perhaps — surprisingly — higher overall non-housing spending. This might occur if, for example, the rise in rents triggers moving costs; we discuss this possibility in more detail below. Still, without more complete data on spending, we cannot fully trace out the spending dynamics in response to rising rents.

3.2.1 Heterogeneous effects by rent burden

Table 5 shows the results of estimating a modified version of equation 1 that includes interactions between asking rents and our measure of whether an account-holder is "rent burdened," which is a dummy variable set to one if the account holder lives in a county where average rents in 2019 relative to the account holder's own income are above the median. Those who already faced high rents relative to their income before rents started rising rapidly may have less financial slack to absorb rising housing costs, and may turn more strongly toward credit cards.

Indeed, we find that rent burdened account-holders exhibit a stronger borrowing response to higher rents. In particular, for a rent burdened account-holder, a 10 percent rise in building rents raises balances by 6.0 percent, compared to a 1.5 percent increase for non-rent burdened account-holders. The rise in balances for rent burdened account-holders can be explained by a larger rise in purchases (4.5 percent), a rise in the propensity to revolve (by 1.9 percentage points), and a rise in revolving balances (4.1 percent). For non-rent burdened account-holders, rents only lead to a rise in purchases of 1.8 percent and there is no statistically significant change in revolving balances.[18] In other words, for rent burdened account-holders, rising rents lead to more credit card *borrowing*, while for non rent burdened account holders, rising rents lead to more credit card *spending*.

Table 6 shows other margins by which credit card account-holders might respond to rising rents. Table 6, Panel A, Column 1 shows that a 10 percent rise in rents leads to a 1.3 percent increase in credit limits. This would be consistent with renters requesting additional access to credit to allow them to spend and borrow more on their credit card to buffer rising rents. Table 6, Panel B, Column 1 shows these effects are driven by rent burdened account holders. This is consistent with

[18] Appendix table A3 examines heterogeneity by credit-related characteristics, including utilization rates, income, and credit scores in 2019. The results show that account-holders with higher utilization rates, lower incomes, and lower credit scores exhibit a stronger borrowing response to rising rents and are more likely to revolve.

the evidence from Table 5 of a larger spending and borrowing response for this group, and the notion that these renters may have less financial slack to absorb rising rents outside borrowing.

Table 6, Panel A, Column 2 indicates that rising rents lead to rising delinquencies: a 10 percent rise in rents raises delinquency rates by by 0.04 percentage points, or 9 percent at the mean of the dependent variable. These effects are similar across both rent burdened and non burdened account-holders. In other words, in addition raising credit card spending and borrowing, another way renters buffer rising rents is to delay paying their credit cards.

Finally, Table 6, Panel A, Column 3 indicates that a final margin by which renters respond to rising rents is to move. A 10 percent rise in rents raising moving rates rise by 0.08 percentage points, or 7 percent at the mean of the dependent variable. These effects are similar by rent burden. When we look at where people move, we find that most of the rising rent-induced moves are local (within county), although there is also a smaller increase in moving to a new county or state (not shown).

In addition to the rise in borrowing, Table 5 indicated a rise in purchases, with not rent burdened renters in particular displaying a purchase response without a rising in revolving balances. This would appear to be inconsistent with a reduction in non-housing consumption due to higher housing expenditures. One possibility is this at least partially reflects moving costs. Table 7 examines heterogeneity in the spending and borrowing response according to whether the renter moved at some point after 2019 or not. This is of course an endogenous choice and could simply reflect differences in the changing financial position of movers versus stayers, so we interpret these results with some caution. Still, the split is consistent with substantial moving costs. In particular, the spending response to rising rents is about double for movers compared to stayers. For stayers, the rise in balances almost entirely reflects rising revolving balances (column 4). That said, revolving balances (column 4) and delinquencies (column 6) do rise for movers, so moving does not appear to mitigate the borrowing effects of rising rents.

3.3 Analysis of County Rents linked to Credit Report Data

In this section, we draw on the CCP data merged to county rent indexes built from the RealPage building data to study how credit card activity responds to changes in countywide rents. We estimate OLS models of the following form:

$$y_{itzc} = \beta ln(rent)_{ct} + \theta \mathbf{X_i} + \gamma \mathbf{E_{ct}} + \alpha_z + \rho_t + \epsilon_{itzc} \tag{2}$$

where $\mathbf{X_{it}}$ includes person characteristics (credit score, age) and $\mathbf{E_{ct}}$ refers to county-level quarterly employment and wages from the QCEW. α_z and ρ_t are zip code and month fixed effects, respectively. Unlike the previous building-level analysis, we cannot include county-month fixed effects to control for local economic conditions, since the rent variation is at the county-month level. Therefore, we attempt to control for county economic conditions using quarterly QCEW data. Although this identification may be less convincing, since we observe homeowners in the CCP, we can conduct falsification tests using the sample of homeowners (i.e. they should not respond to rising rents, conditional on house prices).

Table 8 shows the results for the sample of renters. Similar to the building-level analysis, we find that rising rents raise balances. The top row of column 1 indicates that each 10 percent rise in county rents raising balances by 6.2 percent. Column 2 adds house prices to the model, and indicates that renter balances are responsive to rental price inflation, but not house price inflation.

Table 8 also shows that renters respond to rising rents by opening new credit card accounts. Column 4 of the top panel shows that a 10 percent increase in rents leads to 0.46 more card accounts. Combined with the earlier result that customers request line increases, this suggests renters respond to rising rents by seeking additional credit.

The bottom panel of 8 shows the results for delinquencies and moving. There is a positive of effect of rising rents on delinquencies, although the results are only statistically significant when we look at one-year lagged rents. There is also a positive effect on moving which is similar in magnitude to the building-level results, although it is not statistically different from zero. Moving may not respond as clearly to countywide rent increases compared with building-level rent changes since cross-county moves are potentially more costly than within-county moves.

Table 9 shows the results for home-owners, which as noted above can serve as a type of falsification check on our results. We do not find any evidence that owners balances rise with rising rents (columns 1-3). We also do not find evidence of an increase in the number of card accounts once we control for house prices increases (column 5).

4 Conclusion

Using a new linked dataset of apartment building rents and credit card accounts, we document the spending, borrowing, and moving response to rising rents. We show that renters buffer rising rents by borrowing on credit cards, with rising rents leading to higher credit card balances, revolving balances, credit limits, and delinquency rates. These effects are largest for renters who were already rent-burdened. We also find that some renters move when rents go up, although moving does not appear to fully mitigate the borrowing response to rising rents. All told, our paper adds new insight into the effects of rising housing costs on households. Housing inflation has very different distributional implications for renters and homeowners: unlike home owners, which most research shows benefit from rising house prices, renters are negatively affected by rising rents. We shed new light on how renters cope financially when housing costs go up.

References

Adams, Brian et al. (2024). “Disentangling rent index differences: data, methods, and scope”. In: *American Economic Review: Insights* 6.2, pp. 230–245.

Agarwal, Sumit, Chunlin Liu, and Nicholas S Souleles (2007). “The reaction of consumer spending and debt to tax rebates—evidence from consumer credit data”. In: *Journal of political Economy* 115.6, pp. 986–1019.

Aladangady, Aditya (2017). “Housing wealth and consumption: Evidence from geographically linked microdata”. In: *American Economic Review* 107.11, pp. 3415–3446.

Angst, Sean et al. (2025). “How do renters survive unaffordability? Household-level impacts of rent burden in Los Angeles”. In: *Journal of Urban Affairs* 47.5, pp. 1639–1662.

Bhutta, Neil and Benjamin Keys (2016). “Interest Rates and Equity Extraction during the Housing Boom”. In: *American Economic Review* 106.7, pp. 1742–1774. DOI: 10.1257/aer.20140040.

Cloyne, James et al. (2019). “The effect of house prices on household borrowing: A new approach”. In: *American Economic Review* 109.6, pp. 2104–2136.

Collinson, Robert and Peter Ganong (2018). “How do changes in housing voucher design affect rent and neighborhood quality?” In: *American Economic Journal: Economic Policy* 10.2, pp. 62–89.

Del Canto, Felipe et al. (2023). *Are inflationary shocks regressive? a feasible set approach*. Tech. rep. National Bureau of Economic Research.

Doepke, Matthias and Martin Schneider (2006). “Inflation and the redistribution of nominal wealth”. In: *Journal of Political Economy* 114.6, pp. 1069–1097.

Gelman, Michael et al. (2015). *How individuals respond to a liquidity shock: Evidence from the 2013 government shutdown*. NBER Working Paper 21025. National Bureau of Economic Research.

Jaravel, Xavier (2021). “Inflation inequality: Measurement, causes, and policy implications”. In: *Annual Review of Economics* 13.1, pp. 599–629.

Kaplan, Greg, Kurt Mitman, and Giovanni Violante (2016). “Consumption and House Prices in the Great Recession: Model Meets Evidence”. In: *Journal of Public Economics* 130, pp. 66–81. DOI: 10.1016/j.jpubeco.2015.07.008.

Kaplan, Greg and Sam Schulhofer-Wohl (2017). “Inflation at the household level”. In: *Journal of Monetary Economics* 91, pp. 19–38.

Keys, Benjamin and Jialan Wang (2019). “Minimum payments and debt paydown in consumer credit cards”. In: *Journal of Financial Economics* 131.3, pp. 528–548.

Lee, Donghoon and Wilbert van der Klaauw (2010). “An Introduction to the FRBNY Consumer Credit Panel”. In: *Federal Reserve Bank of New York Staff Reports* 479.

Mian, Atif, Kamalesh Rao, and Amir Sufi (2013). “Household Balance Sheets, Consumption, and the Economic Slump”. In: *Quarterly Journal of Economics* 128.4, pp. 1687–1726. DOI: 10.1093/qje/qjt020.

Mian, Atif and Amir Sufi (2009). "The Consequences of Mortgage Credit Expansion: Evidence from the U.S. Mortgage Default Crisis". In: *Quarterly Journal of Economics* 124.4, pp. 1449–1496. DOI: 10.1162/qjec.2009.124.4.1449.

Newman, Sandra and Scott Holupka (2015). "Housing affordability and child well-being". In: *Housing Policy Debate* 25.1, pp. 116–151.

— (2016). "Housing affordability and children's cognitive achievement". In: *Health Affairs* 35.11, pp. 2092–2099.

Ponce, Alejandro, Enrique Seira, and Guillermo Zamarripa (2017). "Borrowing on the wrong credit card? Evidence from Mexico". In: *American Economic Review* 107.4, pp. 1335–1361.

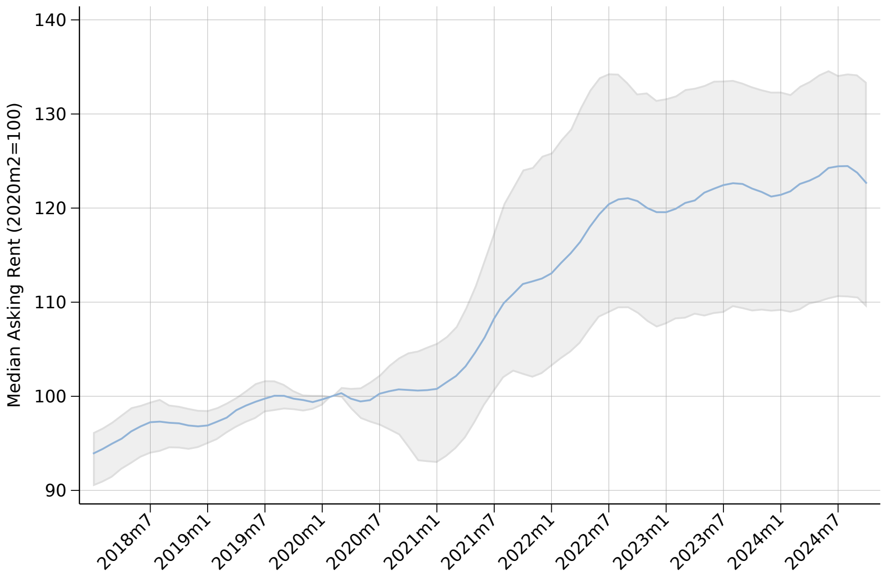
Ruggles, Steven et al. (2025). *IPUMS USA: Version 16.0 [dataset]*. Minneapolis, MN. DOI: 10.18128/D010.V16.0. URL: https://doi.org/10.18128/D010.V16.0.

Stroebel, Johannes and Joseph Vavra (2019). "House Prices, Local Demand, and Retail Prices". In: *Journal of Political Economy* 127.1, pp. 139–177. DOI: 10.1086/700722.

Zinman, Jonathan (2015). "Household debt: Facts, puzzles, theories, and policies". In: *Annual review of Economics* 7.1, pp. 251–276.

Figures and Tables

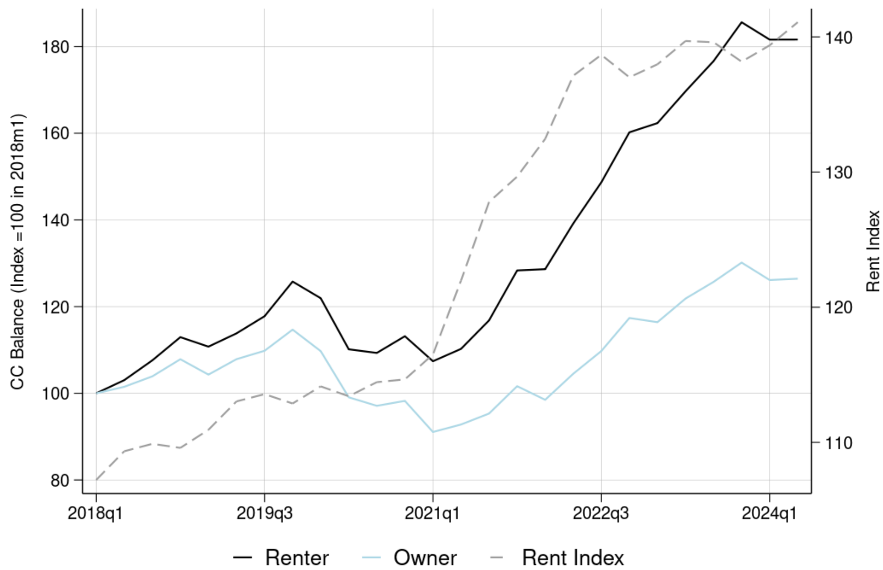
Figure 1: Rent Growth from 2019-2024



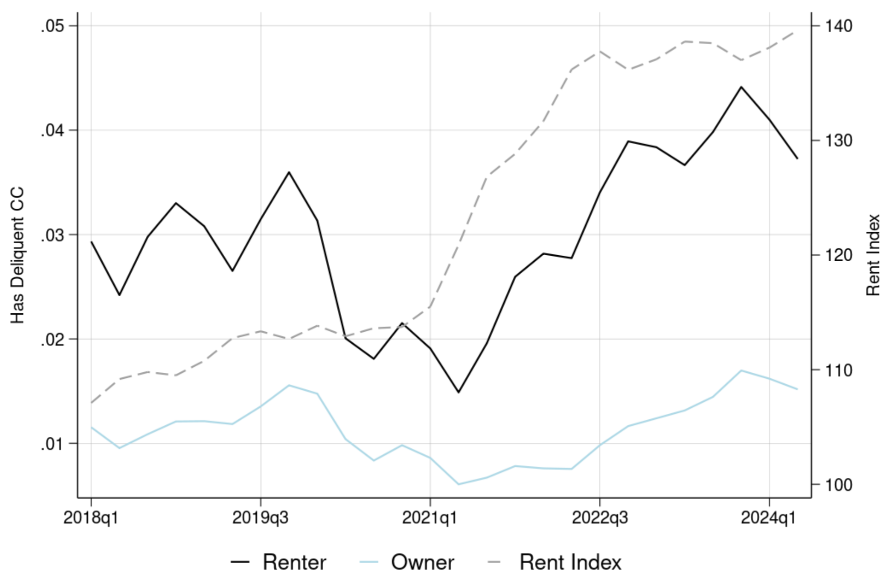
Notes: Blue line represents the median building asking rent of the median county. Shaded region spans 10th to 90th percentile counties. Data source: RealPage

Figure 2: Rents and Credit Card Borrowing

(a) Balances



(b) Delinquencies



Notes: Left axis in panel a displays credit card balances (index to 2018m1) and in panel b displays credit card delinquency (60+ days past due) rates, both separately for owners (blue line) and renters (black line). Right axis is the building rents, indexed to 2018m1 (dashed line). Data sources: CCP/Equifax and RealPage

Table 1: Summary Statistics

	Mean	SD
Balance	2077.8	3759.0
Purchases	488.2	1413.7
Revolves (=1)	0.494	0.500
Revolving Balance	1690.0	3533.7
Credit Limit	7780.0	7510.8
High Utilization, 2019 (=1)	0.507	0.500
Past Due (=1)	0.005	0.072
Moves (=1)	0.011	0.106
Income	53763	183603
FICO Score	720.9	80.6
Subprime FICO Score, 2019 (=1)	0.316	0.465
Joint Acct or Auth. Users (=1)	0.117	0.322
Year Acct Opened	2014	3
County Avg Weekly Wage	1462.0	476.5
County Employment (1000s)	1018.2	1021.4
County Establishments (1000s)	73.4	105.4
Rent Burdened, 2019 (=1)	0.501	0.500
Building Asking Rent (t)	1736.6	735.1
Building Asking Rent (t-11,t)	1709.8	728.6
Building Rent Growth, 2019m1-2024m1	0.239	0.167
Observations	19469800	
No. of Accounts	278140	

Data sources are FR Y-14M, RealPage, and BLS QCEW.

Table 2: CCP Summary Statistics

	Renters	Owners	All
Credit card balance ($)	2,934.70	6,933.61	4,557.66
Number cards	1.88	2.97	2.32
Has a delinquent card	0.03	0.01	0.02
County asking rent ($)	1,680.28	1,591.52	1,644.25
Move in next year	0.14	0.08	0.12
Credit score in 2019	645.95	746.54	688.30
Birth year	1,980	1,974	1,978

Data sources: FRBNY Consumer Credit Panel/Equifax; RealPage; BLS; Zillow

Table 3: Relationship between Askings Rents and Contract Rents

	(1)	(2)	(3)	(4)	(5)
Asking Rent Index ($)	0.283**		0.188**	0.183**	0.160*
	(0.083)		(0.057)	(0.051)	(0.059)
1-Year Lag Asking Rent Index ($)		0.410**	0.313**	0.318**	0.322**
		(0.086)	(0.067)	(0.065)	(0.050)
2-Year Lag Asking Rent Index ($)			0.094*	0.090*	-0.008
			(0.038)	(0.035)	(0.056)
Sample	All renters	All renters	All renters	All renters	Large buildings
County FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Demog Controls				Yes	Yes
N	528129.00	528129.00	528129.00	528129.00	149351.00
Adj R-sq	0.21	0.21	0.21	0.38	0.32

Standard errors clustered at state level; * $p < 0.05$, ** $p < 0.01$

Notes: Reports results from OLS regressions individual-level gross monthly rent reported in the ACS on county-level asking rent indexes constructed by the authors from RealPage building level data. Control variables and sample listed in column notes. Large buildings refers to those ACS respondents who rent a unit in a building with at least 20 units.
Data sources: RealPage; 2021-2023 ACS (Ruggles et al. 2025)

Table 4: Building Rents and Credit Card Use

	Ln(Balance)		Ln(Purchases)		Revolves		Ln(Rev. Balance)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ln(Building Rent)	0.3224	0.3839	0.4204	0.3165	-0.0114	0.0098	0.1585	0.2433
	(0.0535)***	(0.0517)***	(0.0480)***	(0.0375)***	(0.0058)*	(0.0063)	(0.0533)***	(0.0612)***
Account Controls	X		X		X		X	
County Econ Controls	X		X		X		X	
Month FE	X		X		X		X	
Building FE	X		X		X		X	
Account FE		X		X		X		X
County-Month FE		X		X		X		X
N	18222699	19467210	18222699	19467210	17946137	19189107	17946137	19189107

Estimated using equation 1. Account controls refer to income group, credit score group, lender, account opening year, and joint/authorized user card fixed effects. County economic controls are employment, number of establishments, and weekly average wages. Building and account characteristics measured in January 2019. Building asking rent is average from month t-11 to month t. Standard errors in parentheses adjusted for clustering at county-level. *p<0.1 **p<0.05 ***p<0.01. Data sources are FR y-14M, Real Page, BLS.

Table 5: Building Rents and Credit Card Use, by Rent Burden

	(1) ln(Balance)	(2) ln(Purchases)	(3) Revolves	(4) ln(Revolving Balance)
ln(Building Rent)				
X Not Rent Burdened	0.1528	0.1781	0.0007	0.0718
	(0.0618)**	(0.0418)***	(0.0073)	(0.0715)
X Rent Burdened	0.6029	0.4547	0.0187	0.4101
	(0.0565)***	(0.0383)***	(0.0073)**	(0.0701)***
N	18072180	18072180	17814006	17814006

Estimated using equation 1. All models include account and county-month fixed effects. Building, county, and rent burden status measured in January 2019. Building asking rent is average from month t-11 to month t. Standard errors in parentheses adjusted for clustering at county-level. *p<0.1 **p<0.05 ***p<0.01. Data sources are FR y-14M, Real Page, BLS.

Table 6: Building Rents and Other Outcomes

	(1) ln(Credit Limit)	(2) Past Due	(3) Moves
A. All			
ln(Building Rent)	0.1258	0.0044	0.0082
	(0.0136)***	(0.0013)***	(0.0010)***
N	19467210	19467210	19189107
B. By Rent Burden			
ln(Building Rent)			
X Not Rent Burdened	-0.0132	0.0043	0.0099
	(0.0169)	(0.0016)***	(0.0011)***
X Rent Burdened	0.2487	0.0044	0.0071
	(0.0165)***	(0.0014)***	(0.0010)***
N	18072180	18072180	17814006

Estimated using equation 1. All models include account and county-month fixed effects Building, county, and rent burden status measured in January 2019. Building asking rent is average from month t-11 to month t. Standard errors in parentheses adjusted for clustering at county-level. *p<0.1 **p<0.05 ***p<0.01. Data sources are FR y-14M, Real Page, BLS.

Table 7: Building Rents and Credit Card Borrowing, by Moving

	(1) Ln(Balance)	(2) Ln(Purchases)	(3) Revolves	(4) Ln(Rev. Balance)	(5) ln(Credit Limit)	(6) Past Due
A. Never Moves						
ln(Building Rent)	0.2951	0.1512	0.0158	0.2450	0.1055	0.0012
	(0.0768)***	(0.0558)***	(0.0105)	(0.0937)***	(0.0229)***	(0.0021)
N	4728500	4728500	4660950	4660950	4728500	4728500
B. Moves						
ln(Building Rent)	0.4216	0.3464	0.0107	0.2677	0.1480	0.0057
	(0.0594)***	(0.0431)***	(0.0070)	(0.0661)***	(0.0151)***	(0.0016)***
N	14732060	14732060	14521602	14521602	14732060	14732060

Estimated using equation 1. All models include account and county-month fixed effects. Building and county refer to January 2019 residence. Building asking rent is average from month t-11 to month t. Standard errors in parentheses adjusted for clustering at county-level. *p<0.1 **p<0.05 ***p<0.01. Data sources are FR y-14M, Real Page, BLS.

Table 8: County Rents and Credit Card Use (Renters)

	ln(balance)			No. Cards		
	(1)	(2)	(3)	(4)	(5)	(6)
ln(rent index, 12mo MA)	0.621***	0.697**		0.458***	0.334**	
	(0.184)	(0.284)		(0.089)	(0.132)	
lnprice		-0.094			0.152	
		(0.257)			(0.134)	
ln(lag rent index)			0.612***			0.460***
			(0.164)			(0.087)
N	1088644	1088616	1088644	1088644	1088616	1088644
Adj R-square	0.20	0.20	0.20	0.18	0.18	0.18

	Has DQ			Moved		
	(1)	(2)	(3)	(4)	(5)	(6)
ln(rent index, 12mo MA)	0.008	0.005		0.012	0.030	
	(0.007)	(0.009)		(0.021)	(0.025)	
lnprice		0.005			-0.024	
		(0.006)			(0.018)	
ln(lag rent index)			0.021***			0.014
			(0.007)			(0.020)
N	1088644	1088616	1088644	890348	890320	890348
Adj R-square	0.04	0.04	0.04	0.06	0.06	0.06

*p<0.1 **p<0.05 ***p<0.01. Data sources are FRBNY CCP/Equifax, Real Page, Zillow, BLS.

Table 9: County Rents and Credit Card Use (Owners)

	ln(balance)			No. Cards		
	(1)	(2)	(3)	(4)	(5)	(6)
ln(rent index, 12mo MA)	-0.264*	-0.779***		0.319***	-0.098	
	(0.158)	(0.235)		(0.112)	(0.180)	
lnprice		0.675***			0.547***	
		(0.191)			(0.156)	
ln(lag rent index)			-0.213			0.302***
			(0.142)			(0.105)
N	791641	791607	791641	791641	791607	791641
Adj R-square	0.18	0.18	0.18	0.21	0.21	0.21

	Has DQ			Moved		
	(1)	(2)	(3)	(4)	(5)	(6)
ln(rent index, 12mo MA)	0.003	-0.005		0.005	0.001	
	(0.005)	(0.007)		(0.020)	(0.022)	
lnprice		0.010			0.006	
		(0.006)			(0.015)	
ln(lag rent index)			0.009*			-0.002
			(0.004)			(0.018)
N	791641	791607	791641	647393	647359	647393
Adj R-square	0.06	0.06	0.06	0.07	0.07	0.07

*p<0.1 **p<0.05 ***p<0.01. Data sources are FRBNY CCP/Equifax, Real Page, Zillow, BLS.

Appendix

Table A1: Building Rents and Credit Card Borrowing, Alternate Rent Measures

	(1) Ln(Balance)	(2) Ln(Purchases)	(3) Revolves	(4) Ln(Rev. Balance)	(5) ln(Credit Limit)	(6) Past Due
A. Rent Measured as Average of t-11,t						
ln(Building Rent)	0.3839	0.3165	0.0098	0.2433	0.1258	0.0044
	(0.0517)***	(0.0375)***	(0.0063)	(0.0612)***	(0.0136)***	(0.0013)***
N	19467210	19467210	19189107	19189107	19467210	19467210
B. Rent Measured as Average of t-5,t						
ln(Building Rent)	0.3102	0.2539	0.0082	0.1943	0.0965	0.0033
	(0.0431)***	(0.0343)***	(0.0052)	(0.0504)***	(0.0112)***	(0.0011)***
N	19467210	19467210	19189107	19189107	19467210	19467210
C. Rent Measured as Average of t-2,t						
ln(Building Rent)	0.2627	0.2104	0.0073	0.1653	0.0782	0.0030
	(0.0371)***	(0.0312)***	(0.0044)*	(0.0428)***	(0.0096)***	(0.0010)***
N	19467210	19467210	19189107	19189107	19467210	19467210
D. Rent Measured at t						
ln(Building Rent)	0.2235	0.1741	0.0068	0.1426	0.0639	0.0024
	(0.0317)***	(0.0275)***	(0.0037)*	(0.0360)***	(0.0083)***	(0.0008)***
N	19467210	19467210	19189107	19189107	19467210	19467210
E. Rent Measured at t-3						
ln(Building Rent)	0.2241	0.1855	0.0059	0.1408	0.0715	0.0024
	(0.0326)***	(0.0269)***	(0.0040)	(0.0376)***	(0.0084)***	(0.0008)***
N	19467210	19467210	19189107	19189107	19467210	19467210
F. Rent Measured at t-12						
ln(Building Rent)	0.2443	0.2024	0.0052	0.1496	0.0866	0.0030
	(0.0328)***	(0.0234)***	(0.0042)	(0.0402)***	(0.0095)***	(0.0009)***
N	19466078	19466078	19189107	19189107	19466078	19466078

Estimated using equation 1. All models include account and county-month fixed effects. Building and county refer to January 2019 residence. Building asking rent is average from month t-11 to month t. Standard errors in parentheses adjusted for clustering at county-level. *p<0.1 **p<0.05 ***p<0.01. Data sources are FR y-14M, Real Page, BLS.

Table A2: Building Rents and Credit Card Borrowing, by Time Period

	(1) Ln(Balance)	(2) Ln(Purchases)	(3) Revolves	(4) Ln(Rev. Balance)	(5) ln(Credit Limit)	(6) Past Due	(7) Moves
A. 2019-2024							
ln(Building Rent)	0.3986	0.3277	0.0093	0.2512	0.1303	0.0058	0.0115
	(0.0464)***	(0.0379)***	(0.0059)	(0.0569)***	(0.0134)***	(0.0012)***	(0.0010)*
N	30087330	30087330	29657511	29657511	30087330	30087330	2965751
B. 2019-2021							
ln(Building Rent)	0.2649	0.4326	-0.0153	-0.0001	0.0912	-0.0025	0.0185
	(0.0534)***	(0.0491)***	(0.0066)**	(0.0551)	(0.0130)***	(0.0007)***	(0.0021)*
N	15473484	15473484	15043665	15043665	15473484	15473484	1504366
C. 2022-2024							
ln(Building Rent)	0.1366	0.0458	0.0088	0.1202	0.0183	0.0070	0.0014
	(0.0453)***	(0.0351)	(0.0062)	(0.0485)**	(0.0060)***	(0.0021)***	(0.0006)
N	14613846	14613846	14613846	14613846	14613846	14613846	1461384

Estimated using equation 1. All models include account and county-month fixed effects. Building and county refer to January 2019 residence. Building asking rent is average from month t-11 to month t. Standard errors in parentheses adjusted for clustering at county-level. *p<0.1 **p<0.05 ***p<0.01. Data sources are FR y-14M, Real Page, BLS.

Table A3: Building Rents and Credit Card Borrowing, by Credit Behavior

	(1) Ln(Balance)	(2) Ln(Purchases)	(3) Revolves	(4) Ln(Rev. Balance)	(5) ln(Credit Limit)	(6) Past Due
A. High Utilization						
ln(Building Rent)	0.6456	0.1949	0.0606	0.7021	0.0905	0.0026
	(0.0700)***	(0.0456)***	(0.0090)***	(0.0877)***	(0.0134)***	(0.0023)
N	9861600	9861600	9720720	9720720	9861600	9861600
B. Low Utilization						
ln(Building Rent)	0.4123	0.3630	0.0133	0.1840	0.0925	0.0045
	(0.0800)***	(0.0474)***	(0.0094)	(0.0817)**	(0.0137)***	(0.0009)***
N	9599380	9599380	9462246	9462246	9599380	9599380
C. Revolver						
ln(Building Rent)	0.6227	0.1511	0.0715	0.7616	0.0937	0.0035
	(0.0744)***	(0.0421)***	(0.0094)***	(0.0904)***	(0.0124)***	(0.0020)*
N	11021640	11021640	10864188	10864188	11021640	11021640
D. Non-Revolver						
ln(Building Rent)	0.5766	0.3805	0.0438	0.3623	0.1260	0.0030
	(0.0902)***	(0.0486)***	(0.0117)***	(0.0974)***	(0.0195)***	(0.0010)***
N	8438850	8438850	8318295	8318295	8438850	8438850
E. Below Median Income						
ln(Building Rent)	0.4424	0.2731	0.0239	0.3519	0.1159	0.0052
	(0.0638)***	(0.0435)***	(0.0090)***	(0.0753)***	(0.0142)***	(0.0017)***
N	9287110	9287110	9154437	9154437	9287110	9287110
F. Above Median Income						
ln(Building Rent)	0.2572	0.3450	-0.0081	0.0755	0.0938	0.0036
	(0.0809)***	(0.0673)***	(0.0091)	(0.0851)	(0.0175)***	(0.0016)**
N	8898610	8898610	8771487	8771487	8898610	8898610
G. Subprime						
ln(Building Rent)	0.3709	0.1100	0.0333	0.3759	0.0491	0.0045
	(0.0685)***	(0.0484)**	(0.0099)***	(0.0847)***	(0.0171)***	(0.0023)*
N	6152720	6152720	6064824	6064824	6152720	6152720
D. Not Subprime						
ln(Building Rent)	0.3877	0.3509	0.0091	0.2000	0.0993	0.0037
	(0.0592)***	(0.0451)***	(0.0070)	(0.0668)***	(0.0122)***	(0.0014)**
N	13308750	13308750	13118625	13118625	13308750	13308750

Estimated using equation 1. All models include account and county-month fixed effects. Building and county refer to January 2019 residence. Building asking rent is average from month t-11 to month t. Standard errors in parentheses adjusted for clustering at county-level. *p<0.1 **p<0.05 ***p<0.01. Data sources are FR y-14M, Real Page, BLS.