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# **Measuring Consumption with Credit Card Data: Benchmarking and Beyond**

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# Measuring Consumption with Credit Card Data: Benchmarking and Beyond\*

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**Abstract:** We introduce a novel monthly county-level consumption dataset constructed from spending data on over 350 million credit cards in the Federal Reserve’s Y-14M reports, covering over 3,000 U.S. counties since 2014. We first show that the data closely track traditional consumption measures, explaining 92 percent of the variation in monthly adjusted personal consumption expenditures (PCE) growth at the national level, capturing meaningful cross-sectional variation in annual adjusted PCE growth at the state level, and reproducing the impulse response of official consumption measures to identified monetary policy shocks. We then use the county-month panel to estimate heterogeneous consumption responses to monetary policy shocks across the county-level income distribution, an analysis infeasible with traditional consumption data. We find suggestive evidence that low-income counties exhibit larger spending declines than high-income counties, consistent with heterogeneous-agent New Keynesian models. Finally, we provide practical guidance for researchers working with similar data, discussing coverage, sample composition, and the approximation of credit card spending from credit bureau data.

**Keywords:** Measurement and Data, Consumption, Credit Card Spending

**JEL Codes:** D12, E01, E21

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# 1 Introduction

National accounts, published by government statistical agencies, provide the central measurement system for macroeconomic analysis. Consumption, for example, is measured comprehensively in the National Income and Product Accounts (NIPA), yet official consumption statistics are available only with a delay and, at subnational levels, at relatively low frequency or limited geographic granularity. These limitations are especially consequential when researchers and policymakers want to assess rapidly evolving shocks or heterogeneous responses across local areas and household groups. At the same time, the widespread use of credit cards generates large volumes of data on household spending. A growing literature shows that, when organized and benchmarked carefully, such data can be transformed into economic statistics that complement official accounts, offering more timely, higher-frequency, and more geographically detailed measures of consumer spending (Vavra, 2021; Aladangady et al., 2022; Buda et al., 2023; Andersen et al., 2026). Despite these advantages, credit card spending may differ from aggregate consumption along important dimensions. Credit card users may not be representative of consumers without credit cards, and even among cardholders, only a subset of purchases are made by credit card. Thus, it is *ex ante* not obvious how closely credit card spending tracks aggregate consumption.

In this paper, we use credit card data from the Federal Reserve’s Y-14M reports to construct high-frequency, geographically granular measures of household spending and evaluate their usefulness as consumption measures. Our paper makes three contributions. First, we systematically benchmark Y-14M credit card spending against traditional consumption measures, establishing its strengths and limitations as a proxy for consumption in both the national time series and the geographic cross-section. Second, we introduce a novel monthly county-level consumption dataset and illustrate its research value by studying heterogeneous monetary policy transmission across the county-level income distribution, an analysis that is infeasible with traditional consumption data. Finally, we provide a guide for researchers using credit card data to measure consumption, discussing key caveats related to consumption-category coverage, sample representativeness, changes in card adoption and sample composition, and the use of credit bureau data to approximate credit card spending.

The Y-14M reports, collected for regulatory stress-testing purposes, require large bank holding companies with at least \$100 billion in total assets to provide detailed, de-identified monthly data on individual credit card accounts. Covering over 350 million U.S. credit cards over the period from 2014 to 2026, the data represent a significant share of the market, accounting for approximately 66 percent of outstanding consumer credit card balances (CFPB, 2025). We obtain a card’s monthly net purchase dollar volume, which serves as our measure

for credit card spending, as well as a card’s ZIP code, which allows for a geographically granular attribution of spending.<sup>1</sup> Throughout the paper, our baseline spending measure is growth in average purchase volume among cards with positive purchase volume. This measure abstracts from changes in the total number of cards in the Y-14M sample. We discuss the construction of our spending measure in Section 2 and examine how changes in card counts and the entry and exit of active cards affect measured spending growth in Section 7.

We start by benchmarking monthly year-over-year growth in average credit card spending against personal consumption expenditures (PCE) growth and retail sales growth at the national level. For our baseline PCE measure, we exclude a number of components that are not true out-of-pocket expenditures by households, such as spending by the nonprofit sector, healthcare expenditures paid by insurance, and imputed rental equivalent consumption by households who own their homes. We refer to this baseline measure as *adjusted PCE*.

We find that credit card spending growth approximates both adjusted PCE growth and retail sales growth very well, both during normal times and during the extraordinary circumstances of the COVID-19 pandemic. In a simple univariate time-series regression, variation in credit card spending growth explains 92 percent of the variation in monthly adjusted PCE growth and 71 percent of the variation in monthly retail sales growth over our sample period. We then study the cross-section and benchmark annual credit card spending growth against annual PCE growth at the state level. Credit card spending growth is strongly associated with adjusted PCE growth in pooled state-year regressions and captures meaningful variation in state-level consumption growth, although the within-year cross-sectional relationship is more uneven. Finally, we compare Y-14M credit card spending to several private-sector high-frequency spending measures and show that, over comparable sample periods, the Y-14M series more closely approximates adjusted PCE growth than the alternative transaction-based datasets we examine.

Having shown that credit card spending closely tracks traditional consumption measures, we introduce a novel monthly county-level consumption dataset constructed from the Y-14M credit card data. Traditional consumption measures are available either at high frequency but with limited geographic detail or at finer geographic disaggregation but lower frequency. Our dataset helps break this trade-off by allowing us to track consumption at the county level at a monthly frequency, a combination of frequency and geographic detail unavailable in traditional public consumption data. We validate the county-level series in several ways. First, we show that counties’ shares of aggregate Y-14M credit card spending are strongly

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<sup>1</sup>Compared to transaction-level credit card datasets, the Y-14M data do not report individual purchases but only monthly account-level spending totals. We therefore cannot distinguish between spending categories.

related to their shares of spending in the Economic Census. Second, we document that county-level spending dynamics align closely with well-documented economic developments: counties with higher COVID-19 intensity in the early stages of the pandemic experienced markedly sharper consumption declines in April 2020, while neighboring counties within the same metropolitan area exhibit similar spending dynamics throughout the sample period. Finally, county-level consumption as measured by credit card spending is positively associated with local income growth and negatively associated with increases in the local unemployment rate. Covering more than 3,000 counties since 2014, this dataset opens the door to research designs that require both high-frequency and granular geographic variation in consumption.

We present a proof-of-concept research application that illustrates the value of monthly county-level consumption data for studying heterogeneous monetary policy transmission. Using local projections, we first estimate the impulse responses of credit card spending and traditional consumption measures to contractionary monetary policy shocks at the national and state level. Credit card spending declines gradually, troughs at medium horizons, and partially mean-reverts, closely tracking the response of retail sales and supporting its use as a consumption proxy in dynamic settings. We then exploit the geographic granularity of our dataset to estimate heterogeneous responses across counties with different income levels, an analysis infeasible with traditional public consumption data at monthly frequency. Heterogeneous-agent New Keynesian models predict that monetary policy transmits more strongly to lower-income and liquidity-constrained households, but direct evidence at fine geographic resolution has been limited by data availability. We find that lower-income counties exhibit larger consumption declines than higher-income counties, a differential that is suggestive rather than precisely estimated but consistent with these predictions and with account-level evidence on credit-score heterogeneity in the same data.

We conclude with a researcher’s guide for using credit card data to measure consumption. This section highlights the strengths of the Y-14M data, discusses the main caveats involved in interpreting credit card spending as a consumption measure, and provides practical guidance for researchers working with similar credit card or credit bureau data. We first show that the relationship between credit card spending and PCE varies meaningfully across PCE consumption categories, underscoring the importance of choosing an appropriate benchmark when evaluating card-based spending measures. Next, we decompose credit card spending growth in two ways: first into average-spending and card-count components, and then into intensive- and extensive-margin components of average spending growth. These decompositions show that both the number and composition of active cards are important for interpreting measured spending growth over time. We further document substantial het-

erogeneity across banks, showing that individual bank-level spending series can be noisy even when the aggregate Y-14M series closely tracks consumption. Finally, we evaluate whether researchers can approximate credit card spending using the types of variables commonly available in credit bureau data. We find that spending can be approximated reasonably well using changes in balances and payments, but that approximation quality varies across borrower groups and deteriorates for lower-FICO accounts. Together, these results provide a set of caveats and best practices for researchers seeking to use credit card data as a consumption measure.

**Related literature and contribution.** First, we contribute to the growing literature on how naturally occurring private-sector data can be harnessed to construct high-frequency, geographically detailed measures of economic activity that complement official statistics. Most closely related to our paper are studies that develop transaction-based consumption datasets and benchmark them against established consumption measures. [Aladangady et al. \(2022\)](#) construct real-time consumer spending indexes from Fiserv payment-processor data that closely track Census retail sales at the national, state, and metropolitan statistical area (MSA) levels, while [Buda et al. \(2023\)](#) use BBVA retail bank-account transactions to construct a representative consumption panel that reproduces national-account consumption aggregates in Spain. More broadly, related work uses private-sector and administrative micro data to build real-time measures of economic activity ([Chetty et al., 2024](#)) and disaggregated economic accounts ([Andersen et al., 2026](#)). We contribute to this literature by constructing a novel monthly county-level dataset based on U.S. credit card spending and by showing how these data can be used to approximate official consumption statistics. Unlike many existing transaction-based datasets, our data are not drawn from a single bank, fintech, or payment processor, but from comprehensive supervisory data covering a large share of the U.S. credit card market, allowing us to benchmark card spending against official consumption across time, categories, and geographies.

Our paper further relates to work that uses transaction-based spending data to study household consumption dynamics and responses to shocks. The COVID-19 pandemic highlighted the usefulness of these data, with researchers drawing on spending data from JP-Morgan Chase ([Cox et al., 2020](#)), BBVA ([Carvalho et al., 2021](#)), and the fintech company SaverLife ([Baker et al., 2020](#)) to study high-frequency, disaggregated spending dynamics. Earlier work also used payment-processor and credit card data to study the consumption consequences of housing, income, wealth, and monetary policy shocks ([Mian et al., 2013](#); [Ganong and Noel, 2019, 2020](#); [Buda et al., 2025](#)). [Vavra \(2021\)](#) provides an overview of this literature and highlights the broader role of administrative micro data in real-time business-cycle analysis. We evaluate the measurement assumptions underlying these applications.

Specifically, we provide the first systematic assessment of the validity and limitations of credit card spending as a proxy for consumption dynamics and offer practical guidance for researchers working with similar data.

Finally, we contribute to research on heterogeneous-agent macroeconomic models and their implications for household consumption. In HANK models, the transmission of monetary policy and other aggregate shocks depends on the distribution of household income, liquidity, balance sheets, and marginal propensities to consume (Kaplan et al., 2018; Auclert, 2019). Related empirical work shows that monetary policy can have heterogeneous effects across households and regions, including through balance-sheet positions and mortgage refinancing channels (Beraja et al., 2019). Our data provide a way to study these mechanisms at high frequency and fine geographic detail using a broad measure of household spending. As an illustration, we use our credit-card-based consumption measures to estimate local consumption responses to contractionary monetary policy shocks and show that low-income counties exhibit substantially larger spending declines.

The remainder of the paper is structured as follows. Section 2 discusses our data and Section 3 presents summary statistics. In Section 4, we benchmark credit card spending against traditional data sources of consumption and in Section 5 we present our novel monthly county-level consumption dataset. Section 6 presents our research application and studies the transmission of monetary policy to consumption. In Section 7, we discuss caveats and best practices and provide a guide for researchers working with credit card spending data. Section 8 concludes.

## 2 Data

### 2.1 Y-14M Credit Card Data

We obtain monthly account-level data on U.S. consumer credit cards from the Federal Reserve’s supervisory FR Y-14M reports. These reports require large bank holding companies, which are subject to supervisory stress tests, to report detailed information on individual credit card accounts on a monthly basis. The data are available from June 2013 and include, depending on the month and on prevailing reporting requirements, between 16 and 20 banks, covering a large portion of the credit card market and accounting for 66 percent of aggregate outstanding balances on consumer credit cards (CFPB, 2025).

Our main variables of interest are a card’s purchase volume, defined as “the net purchase dollar volume during the current month’s cycle” and the account ZIP code, defined as the nine-digit or five-digit ZIP code “the cardholder reported as their billing address” (FRB,

2024). These variables allow us to track monthly credit card spending at the ZIP-code level. We map account ZIP codes to counties using standard ZIP-code crosswalks. Thus, our data record spending by the place of residence of the consumer (household-based data), rather than by the location of expenditure (point-of-sale data).

We focus on general-purpose and private-label consumer credit cards that, in any given month, had any account activity within the previous twelve months. To ensure consistency over time, we further restrict the sample to 13 banks that are present throughout the entire sample period from 2014 to 2026. Finally, in each month, we only consider cards with nonzero purchase volume. This restriction focuses the analysis on cards used for purchases in a given month and avoids mechanically diluting average spending with dormant or unused accounts. This leaves us with a dataset of 142 to 249 million credit cards per month.

From these data, we construct three datasets: (A) monthly data at the national level, (B) annual data at the state level, and (C) monthly data at the county level. For each dataset, we calculate credit card (CC) spending growth as growth in average credit card spending among cards with positive purchase volume. Let

$$\overline{CCSpending}_{r,t} = \frac{1}{N_{r,t}} \sum_{i=1}^{N_{r,t}} CCSpending_{i,r,t}$$

denote average credit card spending in region  $r$  and period  $t$ , where  $i$  indexes individual cards and  $N_{r,t}$  is the number of cards with positive purchase volume in region  $r$  and period  $t$ . We calculate credit card spending growth as

$$g_{r,t}^{CC} = \left( \frac{\overline{CCSpending}_{r,t} - \overline{CCSpending}_{r,t-\tau}}{\overline{CCSpending}_{r,t-\tau}} \right) \times 100, \quad (1)$$

where  $\tau = 12$  for the monthly datasets and  $\tau = 1$  for the annual dataset.

Our baseline measure is growth in average spending among cards with positive purchase volume, rather than growth in total credit card spending. This choice is intended to abstract from changes in the number of cards observed in the Y-14M data, which can reflect secular growth in card adoption and bank portfolio growth in addition to changes in household consumption. However, average spending growth can still be affected by changes in the composition of cards with purchase activity, since the set of active cards is not constant over time. We investigate both of these issues in Section 7.2 by decomposing total credit card spending growth into changes in average spending and changes in the number of cards, and by decomposing average credit card spending growth into intensive-margin spending changes among continuing cards and extensive-margin changes due to card entry and exit.

## 2.2 Benchmarking Data

We use two types of benchmarking data. First, we compare Y-14M credit card spending to official consumption and retail sales statistics produced by federal statistical agencies. These data provide the most widely used benchmarks for aggregate consumption, but they are available at limited geographic granularity or relatively low frequency and are released with some delay. Second, we also compare Y-14M credit card spending to several alternative private-sector high-frequency transaction datasets. These datasets are closer in spirit to our credit card measure as they are constructed from card transactions, electronic payments, or household purchase records rather than from surveys or national-accounting source data.

### 2.2.1 Official Consumption Statistics

**PCE:** Our primary official consumption benchmarks are national PCE from the NIPA and annual state-level PCE from the BEA Regional Accounts, both published by the Bureau of Economic Analysis (BEA). National PCE comprises about 68 percent of U.S. GDP and includes all expenditures by households and nonprofit institutions serving households (NPISH). BEA constructs PCE using a variety of source data, which often arrive with a lag and are available only at an aggregated level. As a result, preliminary monthly PCE estimates for the nation are typically released about four weeks after the end of the reference month and are subject to revision as additional source data become available.

BEA also publishes estimates of PCE at the state level, reflecting spending by households and nonprofits residing in each U.S. state.<sup>2</sup> Estimating PCE at the state level presents an additional challenge as much of the underlying source data identify the location of the business rather than the residence of the consumer. BEA therefore adjusts point-of-sale expenditures for interstate consumer flows, such as spending associated with tourism, cross-border shopping, and transportation hubs. To identify and correct such flows, BEA compares state expenditure patterns with population and disposable income and uses household expenditure information from the Consumer Expenditure Survey (CE). These adjustments necessarily involve some imputation. The CE is not designed to be representative at the state level, and the residency adjustment factors are based on average expenditure patterns over 2015–2019 and are held fixed over time. As a result, unusual or changing patterns of interstate spending may be difficult to allocate precisely across states in a given year.

Both national and state-level PCE include components that are not true out-of-pocket

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<sup>2</sup>State-level PCE is available annually rather than monthly and is released with a longer delay than national PCE. Details on the construction of National PCE are available [here](#) and details on State PCE [here](#).

expenditures by households, such as spending by the nonprofit sector, healthcare expenditures paid by insurance, and imputed rental equivalent consumption by owner-occupied households. They also include categories of spending that are often not paid for using credit cards, such as motor vehicle purchases and rents. For our main analysis, we construct an adjusted PCE measure designed to be more comparable to credit-card-based household spending. Specifically, we start from total PCE and subtract six broad components: motor vehicles and parts; housing and utilities; health care; financial services and insurance; other services; and final consumption expenditures of NPISH:

$$\begin{aligned} \widetilde{\text{PCE}}_t = & \text{PCE}_t - \text{Motor Vehicles}_t - \text{Housing and Utilities}_t - \text{Health Care}_t \\ & - \text{Financial Services}_t - \text{Other Services}_t - \text{NPISH}_t, \end{aligned} \quad (2)$$

where  $\widetilde{\text{PCE}}_t$  denotes adjusted PCE. We exclude motor vehicles and parts as these purchases are large, infrequent expenditures that are rarely paid for primarily by credit card. We exclude housing and utilities, health care, and financial services as these categories include substantial expenditures that are imputed, paid by third parties, or otherwise not directly comparable to card-based household purchases. We exclude final consumption expenditures by NPISH as our credit card data measure consumer spending by cardholders rather than expenditures by nonprofit institutions. Finally, we exclude other services as this residual services category contains several components that are less directly comparable to the purchase-volume concept in the Y-14M data. We refer to the resulting aggregate as *adjusted PCE*.<sup>3</sup>

**Census Retail Sales.** We further benchmark our credit card spending data against Census retail and food services sales, one of the main source datasets used by the BEA in constructing PCE. These data capture spending on retail goods and food services, categories in which credit cards are a common method of payment. The data come from a monthly survey of establishments known as the Monthly Retail Trade Survey. Since January 2019, the Census Bureau has also published experimental Monthly State Retail Sales (MSRS) estimates, which report modeled year-over-year percentage changes by state and retail subsector and provide an additional subnational benchmark for credit card spending. Sampled establishments report revenues, which are then weighted and aggregated to the industry level and published at a monthly frequency by the U.S. Census Bureau, typically about two weeks after the end of the reference month.

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<sup>3</sup>Total credit card spending in our Y-14M sample rose from 32 percent of adjusted PCE in 2014 to 45 percent in 2026. Relative to total PCE, the corresponding share rose from 14 percent to 19 percent over the same period.

### 2.2.2 Private Sector High-Frequency Data

**Fiserv:** Fiserv is one of the largest electronic payment processors in the United States. The data are merchant-based and record the dollar amount, timing, and merchant location of card and electronic transactions at merchants that use Fiserv’s payment-processing network. Following [Aladangady et al. \(2022\)](#), the raw transaction data are filtered to construct constant-merchant spending indexes, mapped to Census retail categories using merchant category codes, and benchmarked to Economic Census levels. The resulting series provide high-frequency measures of retail spending by industry and geography. Relative to the Y-14M data, Fiserv is merchant-based rather than cardholder-based, making it conceptually close to Census retail sales but less directly comparable to residence-based consumption measures.

**Affinity Solutions.** Affinity Solutions aggregates anonymized credit and debit card transactions from financial institutions. We use the Affinity Solutions spending indexes distributed through the Opportunity Insights Economic Tracker ([Chetty et al., 2024](#)). The data are cardholder-based and can be aggregated by geography, industry, day, and ZIP-code income quartile, allowing researchers to track spending across local areas and income groups. Relative to Fiserv, Affinity is closer to the household-spending concept in the Y-14M data because transactions are assigned to cardholders rather than merchants; relative to the Y-14M data, however, it includes both credit and debit cards and is available only through processed spending indexes rather than account-level records.

**Numerator:** Numerator is a consumer panel dataset that records detailed household purchases from submitted paper receipts, online receipts, and linked loyalty or membership transactions ([Hacıoğlu Hoke et al., 2025](#)). The data include item-level information, retailer information, transaction timing, and household characteristics, and are weighted to match Census demographics and major retailer sales aggregates. Numerator therefore provides richer information on spending categories and household characteristics than the Y-14M data, but it is based on a selected consumer panel rather than administrative account-level card records.

**Verisk Analytics:** Verisk Analytics aggregates credit and debit card transactions at the ZIP-code-by-week level ([Aladangady et al., 2025](#)). Transactions are assigned to the ZIP code of the card owner’s billing address rather than to the location where the transaction occurred. This residence-based geographic assignment makes Verisk conceptually close to the Y-14M data, while its weekly frequency and ZIP-code-level demographic information provide additional flexibility. Relative to Y-14M, however, Verisk includes both credit and debit cards and is available only as an aggregated spending product.

Table 1: Descriptive Statistics

This table reports summary statistics for the three main analysis samples. Panel A reports statistics for the monthly national sample from June 2014 to June 2026. Panel B reports statistics for the annual state-level sample from 2015 to 2024. Panel C reports statistics for the monthly county-level sample from June 2014 to June 2026. Monthly growth rates in credit card (CC) spending, adjusted PCE, and retail sales are reported as year-over-year (YoY) growth rates.

|                                         | Obs.    | Mean   | Median | p(1)   | p(99)  |
|-----------------------------------------|---------|--------|--------|--------|--------|
| <i>Panel A. Monthly National Level.</i> |         |        |        |        |        |
| Number of Cards (in m)                  | 145     | 192.97 | 186.30 | 142.43 | 248.93 |
| Number of Banks                         | 145     | 12.90  | 13     | 12     | 13     |
| Monthly YoY CC Spending Growth (in %)   | 145     | 3.66   | 2.92   | -20.44 | 36.12  |
| Monthly YoY Adjusted PCE Growth (in %)  | 145     | 5.33   | 4.34   | -13.15 | 29.39  |
| Monthly YoY Retail Sales Growth (in %)  | 145     | 5.11   | 3.88   | -6.20  | 28.88  |
| <i>Panel B. Annual State Level.</i>     |         |        |        |        |        |
| Number of Cards (in m)                  | 510     | 3.68   | 2.12   | 0.27   | 25.34  |
| Number of Banks                         | 510     | 12.99  | 13     | 13     | 13     |
| Annual CC Spending Growth (in %)        | 510     | 3.77   | 2.59   | -8.31  | 18.26  |
| Annual Adjusted PCE Growth (in %)       | 510     | 5.06   | 3.92   | -7.29  | 21.07  |
| <i>Panel C. Monthly County Level.</i>   |         |        |        |        |        |
| Number of Cards (in k)                  | 454,285 | 61.37  | 9.84   | 0.38   | 916.45 |
| Number of Banks                         | 454,285 | 11.62  | 12     | 8      | 13     |
| Monthly YoY CC Spending Growth (in %)   | 454,285 | 3.95   | 3.22   | -15.16 | 30.34  |

### 3 Descriptive Statistics

Table 1 reports summary statistics for the datasets used in our main analysis: monthly data at the national level (Panel A), annual data at the state level (Panel B), and monthly data at the county level (Panel C). The 145 monthly observations in Panel A span nearly twelve years of data; the 510 state-year observations in Panel B correspond to 10 years across 51 states (including the District of Columbia); and the 454,285 county-month observations in Panel C cover more than 3,000 counties over approximately the same period. The national-level data include, on average, about 193 million credit cards from 13 banks per month; the state-level data include about 3.7 million credit cards from 13 banks per state-year; and the county-level data include about 61 thousand credit cards per county-month. While all 13 banks are represented in the national- and state-level datasets, bank coverage varies across counties, with the smallest counties covered by at least eight banks.

As shown in Panel A, monthly year-over-year credit card spending growth is, on average, slightly lower than both monthly year-over-year adjusted PCE growth and monthly year-over-year retail sales growth, a pattern that also holds for annual credit card spending growth relative to adjusted PCE growth at the state level (Panel B). Credit card spending growth

also exhibits greater volatility than adjusted PCE growth: the first percentile of monthly credit card spending growth is (-20.4) percent, compared with (-13.2) percent for adjusted PCE, while the 99th percentile is 36.1 percent, compared with 29.4 percent. This wider range is consistent with the fact that credit card transactions disproportionately capture discretionary expenditures, which are more sensitive to economic conditions. Nonetheless, as we show in the next section, credit card spending growth closely tracks the time-series movement of both adjusted PCE growth and retail sales growth.

## 4 Benchmarking

We benchmark Y-14M credit card spending against two types of consumption measures. We first compare the data to official consumption and retail sales statistics produced by the BEA and Census Bureau, focusing on both monthly national time-series dynamics and annual state-level cross-sectional variation. We then compare Y-14M spending to several private-sector high-frequency spending measures, which are closer in spirit to credit card data but differ in coverage, transaction concept, payment instruments, and geographic attribution. These comparisons allow us to assess both how closely Y-14M credit card spending approximates traditional consumption benchmarks and whether our results reflect broader patterns also present in other transaction-based spending data.

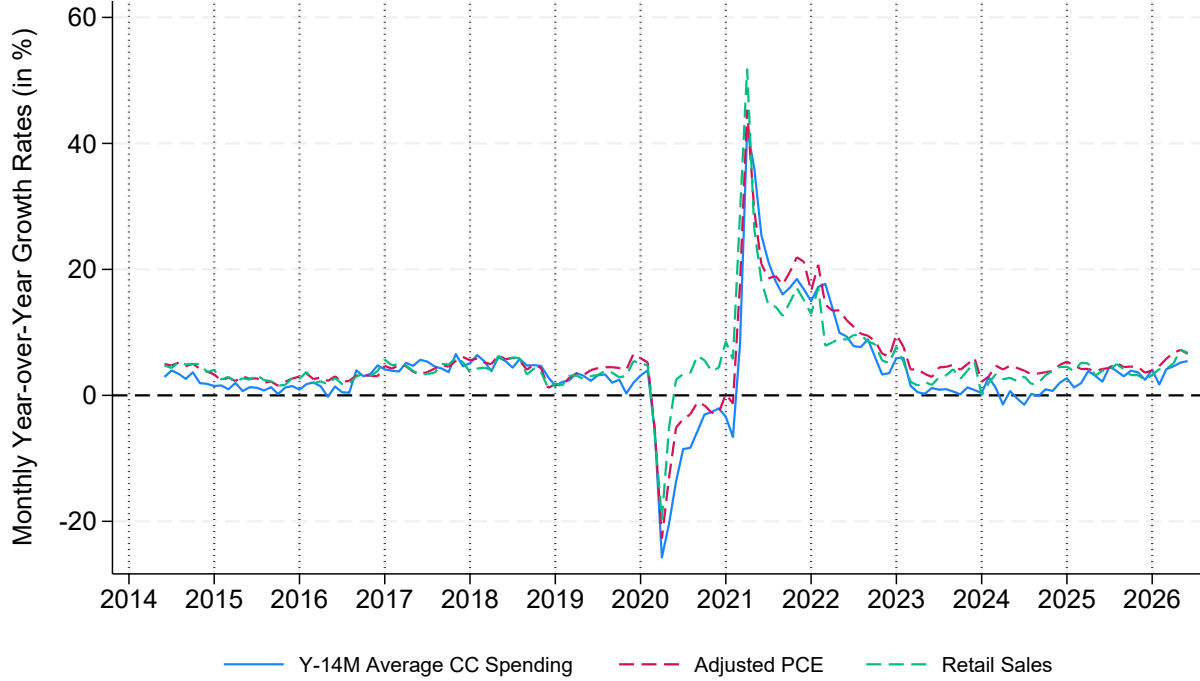
### 4.1 Monthly National Benchmarks

Figure 1 plots monthly year-over-year growth in credit card spending (solid blue line) alongside monthly year-over-year growth in adjusted PCE (dashed red line) and retail sales (dashed green line). Credit card spending closely tracks both benchmark series over time, including during relatively stable periods and during the extraordinary circumstances of the COVID-19 pandemic. From 2014 to 2020, the three series fluctuate in a narrow range and exhibit very similar dynamics, with only modest differences in growth rates across the measures.

Importantly, the sharp decline in credit card spending at the onset of the COVID-19 pandemic closely mirrors the declines in adjusted PCE and retail sales. Credit card spending fell by 25.7 percent at its trough in April 2020, compared with declines of 22.7 percent in adjusted PCE and 19.7 percent in retail sales. While retail sales recovered more rapidly in the months following the initial shock, credit card spending continued to provide a close approximation to adjusted PCE growth. From 2021 through 2023, credit card spending also tracks the normalization of consumption growth in the post-pandemic period. Beginning in 2023, credit card spending growth again falls slightly below both adjusted PCE and retail

Figure 1: Monthly National Consumption Growth: Official Benchmarks

This figure plots monthly year-over-year growth rates in average credit card (CC) spending (solid blue line), adjusted personal consumption expenditures (adjusted PCE; dashed red line), and retail sales (dashed green line) from June 2014 to June 2026.



sales growth, before the three series converge once more by 2025.<sup>4</sup>

Table 2 reports simple time-series regressions of monthly year-over-year growth in adjusted PCE and retail sales on credit card spending growth. Columns (1)–(3) use adjusted PCE growth as the dependent variable. In the full sample, credit card spending growth is strongly associated with adjusted PCE growth, with a slope coefficient of 0.88 and an adjusted  $R^2$  of 0.92. Because the COVID-19 pandemic generated unusually large movements in all three series, the strong full-sample fit may disproportionately reflect their common contraction and rebound during this period. We therefore examine whether the relationship remains strong when the pandemic period is excluded. Excluding the narrow COVID period from March 2020 through March 2021 leaves the relationship virtually unchanged. The slope coefficient is 0.89 and the adjusted  $R^2$  is 0.91. Because year-over-year growth rates continue

<sup>4</sup>For comparison, Figure A1 plots credit card spending alongside both adjusted and total PCE, illustrating how the adjustment changes the aggregate PCE growth series.

to use pandemic-period observations as their comparison base for an additional year, Column (3) applies a broader exclusion through March 2022. Under this specification, the slope coefficient declines to 0.69 and the adjusted  $R^2$  to 0.58. Thus, the exceptional pandemic and normalization dynamics contribute to the headline full-sample fit, but credit card spending continues to explain a substantial share of adjusted PCE growth outside this period.<sup>5</sup>

Columns (4)–(6) report the analogous results for retail sales growth. Credit card spending explains 71 percent of its variation in the full sample. The fit rises to 86 percent when the narrow COVID period is excluded and declines to 59 percent under the broader exclusion. Taken together, the results indicate that the close relationship between credit card spending and traditional consumption benchmarks is not driven solely by the initial pandemic contraction and rebound, although the broader pandemic period accounts for part of the exceptionally strong full-sample relationship.

One notable exception to the close correspondence between the series is the 2023–24 period, when credit card spending growth falls below PCE growth and, to a lesser extent, retail sales growth. This divergence coincides with the sharp monetary tightening that began in 2022. As most credit card APRs are indexed to the bank prime rate, which closely follows the federal funds rate, higher policy rates directly increase borrowing costs for cardholders carrying balances. Consistent with this mechanism, we show particularly weak spending growth among revolvers during that period (Section 5.3).<sup>6</sup>

## 4.2 State-Level Benchmarks

We next examine whether credit card spending closely tracks consumption not only at the national level, but also across states. We benchmark our state-level spending measures against two official sources: annual PCE from the BEA, the broadest available measure of state-level consumption, and Census’s experimental Monthly State Retail Sales estimates, a higher-frequency but narrower measure of retail activity.

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<sup>5</sup>Table A1 reports the analogous regressions using total PCE growth as the dependent variable. Credit card spending also tracks total PCE closely in the full sample, although the fit is weaker than for adjusted PCE, particularly when the broader COVID period is excluded.

<sup>6</sup>A possible alternative explanation is that strong population growth driven by immigration increased aggregate PCE relative to average credit card spending. Figure A2 compares credit card spending with population-adjusted PCE, providing little evidence that population growth accounts for the gap.

Table 2: Benchmarking Monthly National Consumption

This table reports monthly national time-series regressions from June 2014 to June 2026. All variables are measured as monthly year-over-year growth rates. Columns (1)–(3) use adjusted PCE growth as the dependent variable, and Columns (4)–(6) use retail sales growth as the dependent variable. The explanatory variable in all columns is average credit card (CC) spending growth. Columns (1) and (4) use the full sample. Columns (2) and (5) exclude observations from March 2020 through March 2021, while Columns (3) and (6) exclude observations from March 2020 through March 2022. Standard errors are reported in parentheses. \*\*\*, \*\*, and \* denote statistical significance at the 1, 5, and 10 percent levels, respectively.

|                      | $\Delta$ Adjusted PCE |                                |                               | $\Delta$ Retail Sales |                                |                               |
|----------------------|-----------------------|--------------------------------|-------------------------------|-----------------------|--------------------------------|-------------------------------|
|                      | Full Sample<br>(1)    | Excl. COVID<br>(Narrow)<br>(2) | Excl. COVID<br>(Broad)<br>(3) | Full Sample<br>(4)    | Excl. COVID<br>(Narrow)<br>(5) | Excl. COVID<br>(Broad)<br>(6) |
| $\Delta$ CC Spending | 0.88***<br>(0.02)     | 0.89***<br>(0.02)              | 0.69***<br>(0.05)             | 0.70***<br>(0.04)     | 0.82***<br>(0.03)              | 0.59***<br>(0.04)             |
| Adjusted $R^2$       | 0.92                  | 0.91                           | 0.58                          | 0.71                  | 0.86                           | 0.59                          |
| Observations         | 145                   | 132                            | 120                           | 145                   | 132                            | 120                           |

#### 4.2.1 Annual State-Level PCE

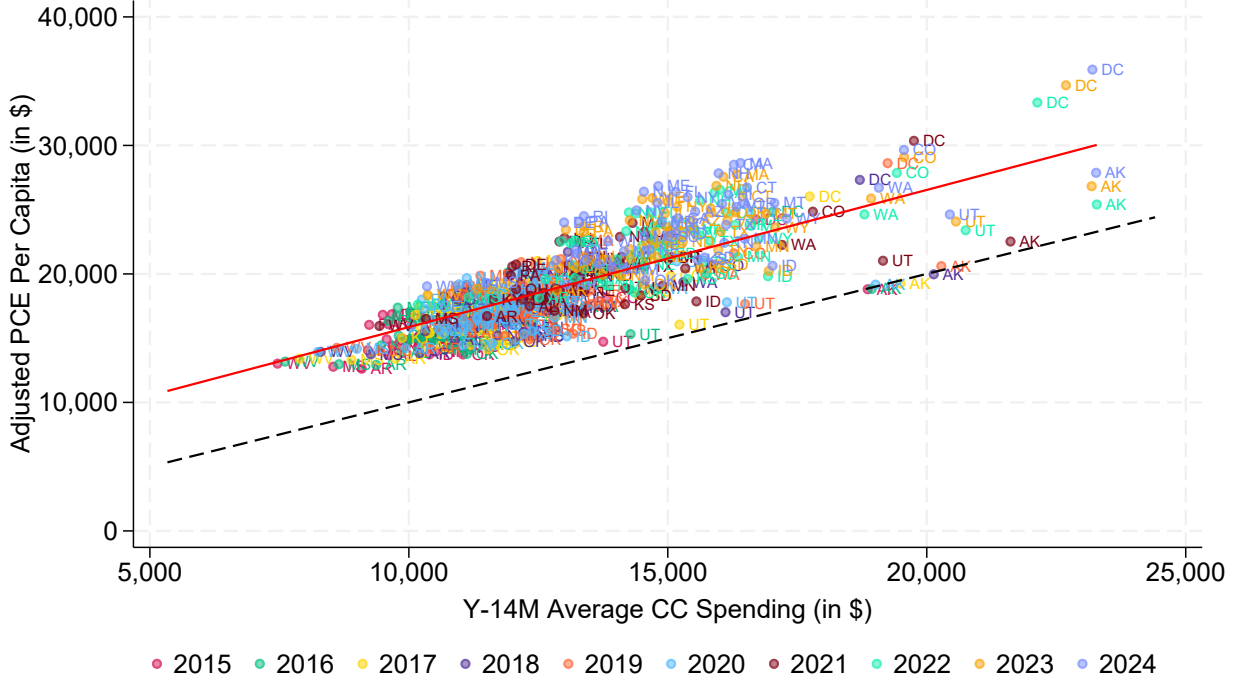
We begin by examining whether variation in credit card spending levels across states is informative about variation in adjusted state PCE. State-level PCE provides the broadest official measure of consumption across states and is therefore a natural benchmark for our state-level credit card spending measure.

Figure 2 plots average annual credit card spending per card against adjusted PCE per capita across states for all years from 2015 to 2024. The figure shows a strong positive relationship: states with higher average credit card spending also tend to have higher per-capita consumption. A univariate regression yields a slope coefficient of 1.16 and an adjusted  $R^2$  of 0.66, indicating that credit card spending captures a substantial share of cross-sectional variation in consumption levels across states.

We then turn from levels to growth rates. Because state-level PCE is available only at an annual frequency, we benchmark annual credit card spending growth against annual adjusted PCE growth. Figure 3 illustrates this relationship for selected years, while Table 3 reports the corresponding regression evidence for the full sample and separately by year. Pooling all state-year observations, annual growth in average credit card spending is strongly associated with annual adjusted PCE growth, with a slope coefficient of 0.93 and an adjusted  $R^2$  of 0.87. This pooled relationship, however, combines both time-series and cross-sectional

Figure 2: Annual State-Level Consumption Levels

This figure plots annual adjusted PCE per capita against average annual Y-14M credit card (CC) spending per card for state-year observations from 2015 to 2024. Each dot represents a state-year observation. The solid red line indicates the fitted regression line, and the dashed black line indicates the 45-degree line.



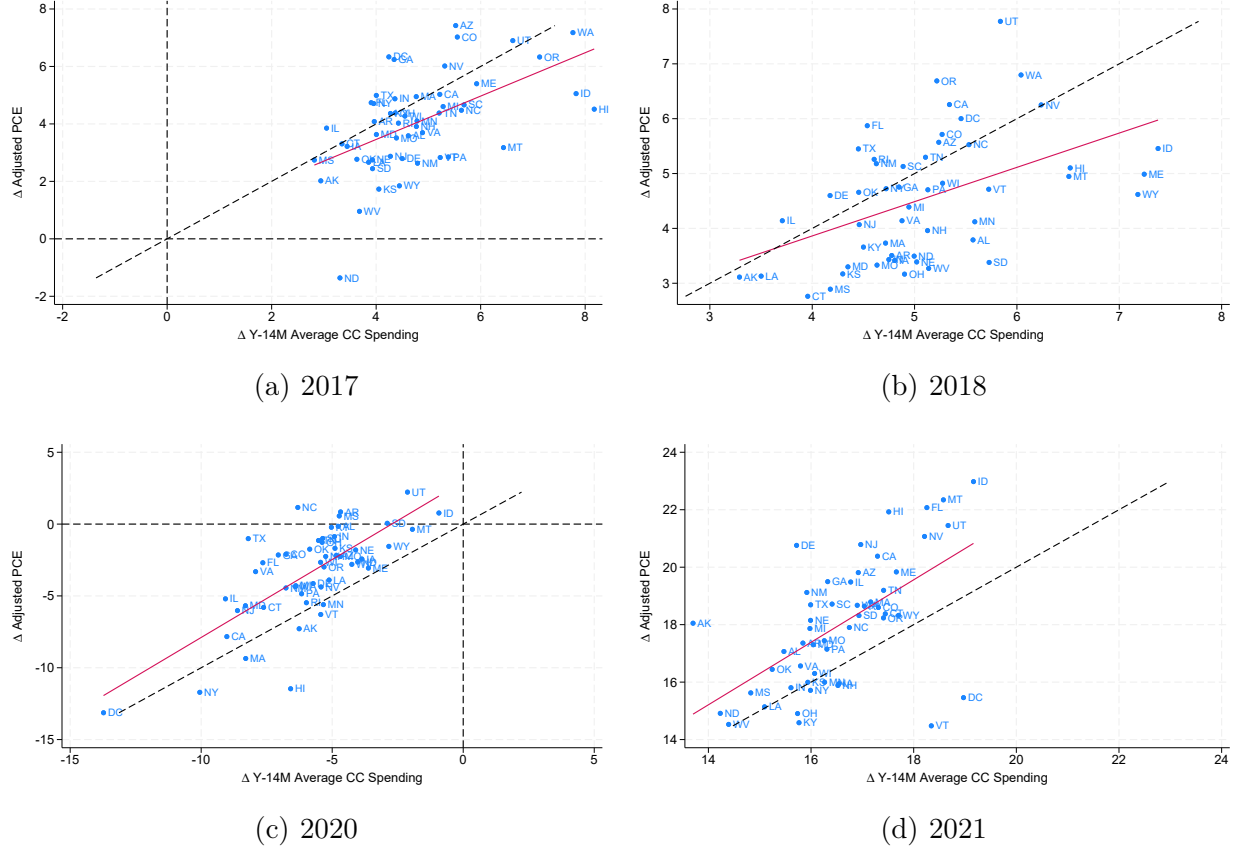
variation and is influenced by years with large aggregate consumption movements, especially the pandemic contraction and rebound in 2020 and 2021. The within-year cross-sectional relationship is more modest. The fit is positive in most years, but weaker in 2019, 2022, and 2023, when annual consumption growth varied less across states and the estimated coefficients are not statistically significant.<sup>7</sup>

Both Y-14M credit card spending and state-level PCE are conceptually household-based measures of consumption. However, the most comprehensive source data for state-level PCE statistics are Economic Census receipts by the state of the business establishment, which measure where purchases occur (point-of-sale data) rather than where purchasers live (household-based data). These point-of-sale data are therefore converted into household-based measures using a residency adjustment procedure. For state-category cells in which

<sup>7</sup>Figure A3 in the appendix further shows selected state-level time series and confirms that credit card spending growth also tracks adjusted PCE growth within individual states over time.

Figure 3: Annual State-Level Consumption Growth: Cross-Sectional Evidence

This figure plots annual growth rates in adjusted PCE against annual growth rates in average credit card (CC) spending at the state level for selected years. Panel (a) shows 2017, Panel (b) 2018, Panel (c) 2020, and Panel (d) 2021. Each dot represents a state. The solid red lines indicate fitted regression lines, and the dashed black lines indicate 45-degree lines.



point-of-sale spending appears distorted by purchases from nonresidents, expenditure shares are adjusted toward Consumer Expenditure Survey-based resident spending shares, with the remaining state shares rescaled to preserve national PCE totals (BEA, 2024). By contrast, Y-14M credit card spending can be assigned directly to the cardholder's state of residence, without the need for an analogous residency adjustment.

This distinction is important when interpreting differences between the two series: discrepancies need not reflect measurement error in credit card spending alone, since the geographic allocation of state-level PCE itself requires inference from multiple source datasets, interpolation procedures, and selective residency adjustments. Consistent with this possibility, the state-level relationship is strongest in 2020 and 2021, precisely when pandemic-related disruptions to travel, commuting, and cross-state shopping likely reduced the importance of

Table 3: Benchmarking Annual State-Level Consumption

This table reports state-level regressions of annual adjusted PCE growth on annual growth in average credit card (CC) spending. The first column pools all state-year observations from 2015 to 2024, and the remaining columns estimate the regression separately by year. Robust standard errors are reported in parentheses. \*\*\*, \*\*, and \* denote statistical significance at the 1, 5, and 10 percent levels, respectively.

|                      | $\Delta$ Adjusted PCE |                   |                   |                   |                   |                   |
|----------------------|-----------------------|-------------------|-------------------|-------------------|-------------------|-------------------|
|                      | All Years             | 2015              | 2016              | 2017              | 2018              | 2019              |
| $\Delta$ CC Spending | 0.93***<br>(0.02)     | 0.53***<br>(0.18) | 0.67**<br>(0.27)  | 0.75***<br>(0.18) | 0.63***<br>(0.15) | -0.07<br>(0.17)   |
| Adjusted $R^2$       | 0.87                  | 0.12              | 0.21              | 0.29              | 0.21              | 0.00              |
| Observations         | 510                   | 51                | 51                | 51                | 51                | 51                |
|                      |                       |                   |                   |                   |                   |                   |
|                      |                       | 2020              | 2021              | 2022              | 2023              | 2024              |
| $\Delta$ CC Spending |                       | 1.08***<br>(0.12) | 1.09***<br>(0.30) | 0.25<br>(0.15)    | 0.20<br>(0.13)    | 0.19***<br>(0.05) |
| Adjusted $R^2$       |                       | 0.52              | 0.33              | 0.02              | 0.03              | 0.16              |
| Observations         |                       | 51                | 51                | 51                | 51                | 51                |

interstate consumer flows and reduced the extent to which purchases occurred outside consumers' state of residence. More generally, weaker correlations in other years may therefore partly reflect differences in how cross-state spending is geographically assigned rather than differences in underlying consumption dynamics.

#### 4.2.2 Monthly State-Level Retail Sales

A limitation of the state-level PCE data is that they are available only at an annual frequency. To evaluate whether Y-14M spending also captures higher-frequency geographic variation in consumption, we compare monthly state-level credit card spending growth to monthly state-level retail sales growth from the Census Bureau.

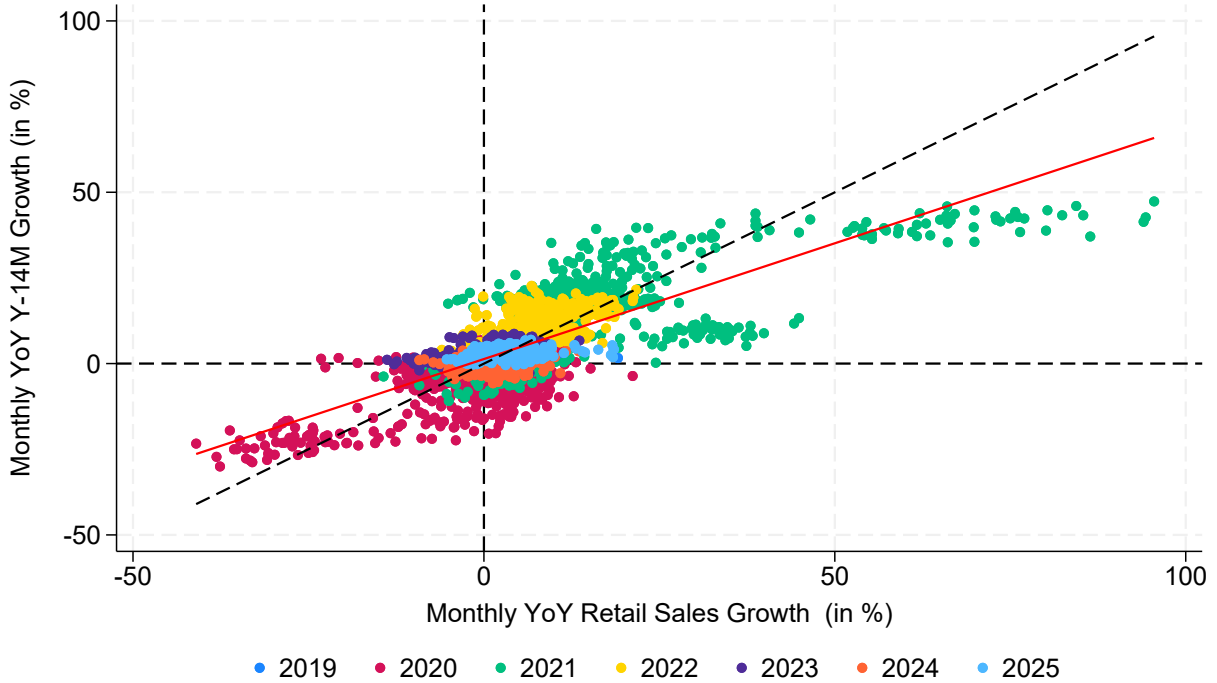
Figure 4 plots monthly year-over-year growth in average Y-14M credit card spending against monthly year-over-year growth in Census retail sales, where each dot represents a state-month observation. The figure shows a positive relationship between the two series, with a slope coefficient of 0.81 and an  $R^2$  of 0.40, indicating that Y-14M spending captures meaningful variation in monthly state-level retail spending growth. Nonetheless, the relationship is weaker than in the annual state-level PCE comparison.<sup>8</sup>

Unlike Y-14M credit card spending, monthly retail sales are a point-of-sale based measure

<sup>8</sup>Figure A4 in the appendix further shows selected state-level time series.

Figure 4: Monthly State-Level Retail Spending Growth: Cross-Sectional Evidence

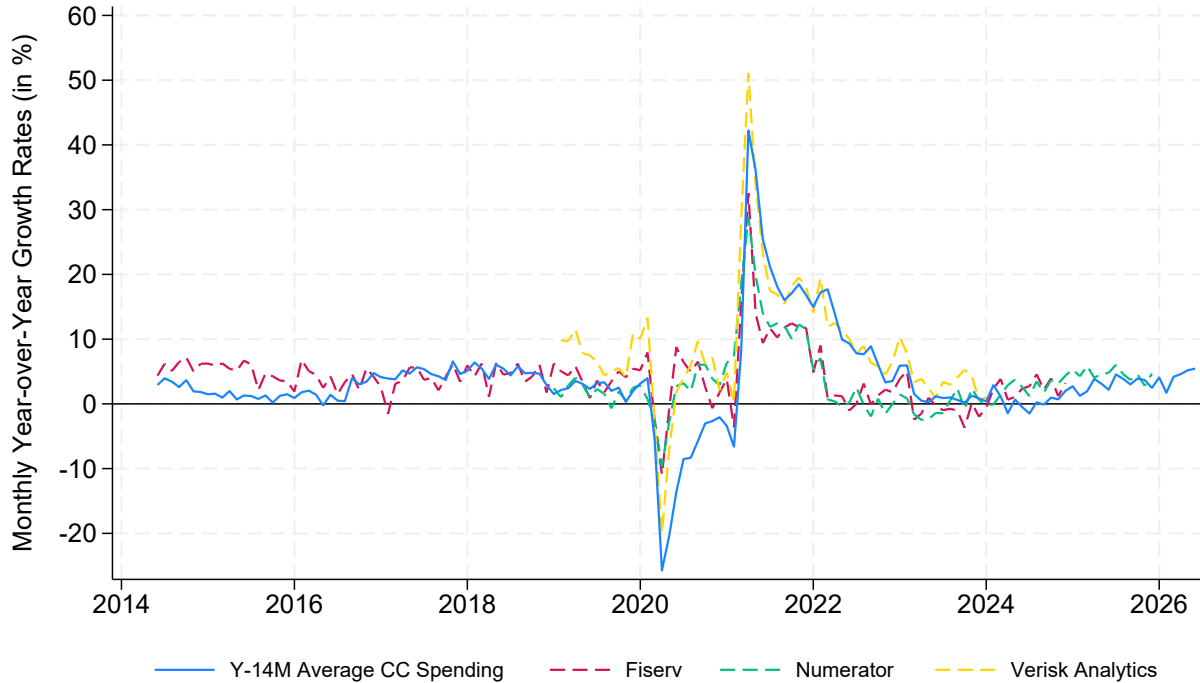
This figure plots monthly year-over-year (YoY) growth in average Y-14M credit card spending against monthly year-over-year growth in Census retail sales at the state level from 2019 to 2025. Each dot represents a state-month observation. The solid red line indicates the fitted regression line, and the dashed black line indicates the 45-degree line.



of retail activity by the state in which sales occur. The MSRS data are an experimental Census Bureau product published since January 2019. The estimates combine two types of information. First, when state-level sales data are not directly observed, national retail sales are allocated to states using each state's share of retail-establishment payroll. Second, where available, the estimates use state-level inputs, including third-party point-of-sale data, retailer survey responses, and modeled sales for establishments that do not report directly (Census Bureau, 2025). Thus, the weaker correlation relative to adjusted PCE likely reflects, at least in part, the fact that state-level Census retail sales are point-of-sale data, whereas Y-14M spending is assigned to cardholders' state of residence.

Figure 5: Monthly National Consumption Growth: Private-Sector Benchmarks

This figure plots monthly year-over-year growth rates in average Y-14M credit card (CC) spending (solid blue line) and private-sector high-frequency indicators (HFIs) based on data from Fiserv (dashed red line), Numerator (dashed green line), and Verisk Analytics (dashed yellow line). The plotted sample varies across benchmark series based on data availability.



### 4.3 Private-Sector High-Frequency Spending Measures

We next compare Y-14M credit card spending to several widely used private-sector high-frequency spending measures. These measures are mostly based on card transaction data and thus conceptually similar to the Y-14M data.

Figure 5 plots monthly year-over-year growth in Y-14M credit card spending alongside high-frequency spending measures from Fiserv, Numerator, and Verisk Analytics.<sup>9</sup> Despite differences in coverage, transaction concept, and sample period, the private-sector series exhibit broadly similar dynamics to the Y-14M measure. In particular, all series capture the sharp decline in spending at the onset of the COVID-19 pandemic and the subsequent

<sup>9</sup>Figure A5 in the appendix reports the analogous comparison for Affinity Solutions, for which the publicly available data are reported as a seasonally adjusted change relative to January 2020 rather than as a monthly year-over-year growth rate.

Table 4: Benchmarking Monthly National Consumption: Private-Sector HFIs

This table reports monthly national time-series regressions of adjusted PCE growth on private-sector high-frequency indicators (HFIs) and Y-14M credit card (CC) spending. All variables are measured as monthly year-over-year growth rates. Columns (1), (3), and (5) regress adjusted PCE growth on spending growth from Fiserv, Numerator, and Verisk Analytics, respectively. Columns (2), (4), and (6) regress adjusted PCE growth on average Y-14M credit card spending growth over the same sample periods as the corresponding HFI regressions. Standard errors are reported in parentheses. \*\*\*, \*\*, and \* denote statistical significance at the 1, 5, and 10 percent levels, respectively.

|                       | $\Delta$ Adjusted PCE |                   |                   |                   |                   |                   |
|-----------------------|-----------------------|-------------------|-------------------|-------------------|-------------------|-------------------|
|                       | Fiserv                |                   | Numerator         |                   | Verisk            |                   |
|                       | (1)                   | (2)               | (3)               | (4)               | (5)               | (6)               |
| $\Delta$ HFI Spending | 0.98***<br>(0.10)     |                   | 1.22***<br>(0.12) |                   | 0.96***<br>(0.06) |                   |
| $\Delta$ CC Spending  |                       | 0.88***<br>(0.02) |                   | 0.88***<br>(0.02) |                   | 0.88***<br>(0.03) |
| Adjusted $R^2$        | 0.41                  | 0.92              | 0.56              | 0.94              | 0.84              | 0.95              |
| Observations          | 128                   | 128               | 84                | 84                | 60                | 60                |
| Sample                | 2014m6–2025m1         |                   | 2019m1–2025m12    |                   | 2019m2–2024m1     |                   |

rebound in 2021. The series differ somewhat in levels and volatility, but the overall pattern suggests that the Y-14M data reflect broad high-frequency spending patterns also visible in other private-sector transaction datasets.<sup>10</sup>

Table 4 evaluates the relationship between adjusted PCE growth and private-sector high-frequency spending measures and compares this relationship to the benchmarking performance of Y-14M credit card spending over the corresponding sample period. The table shows that credit card spending growth based on the Y-14M data explains a substantially larger share of the variation in adjusted PCE growth compared to various private-sector high-frequency spending measures. The adjusted  $R^2$  rises from 0.41 to 0.92 in the Fiserv comparison, from 0.56 to 0.94 in the Numerator comparison, and from 0.84 to 0.95 in the Verisk comparison. These results indicate that, over the corresponding sample periods, Y-14M spending growth is at least as informative about national adjusted PCE growth as the private-sector high-frequency spending measures considered here.

<sup>10</sup>Table A2 in the appendix further evaluates the relationship between Y-14M credit card spending and private-sector high-frequency spending measures in a time-series regression framework. The results show a strong positive association across all four benchmarks.

## 5 Beyond Benchmarking

Official consumption measures are available either at high frequency but with limited geographic detail or at finer geographic disaggregation but lower frequency. In this section, we move beyond these limitations by providing monthly spending measures that can be constructed at fine geographic disaggregation and across detailed cardholder characteristics. We illustrate two dimensions of this granularity. First, we introduce and validate a monthly county-level consumption dataset that allows us to track local consumption dynamics across more than 3,000 counties. Second, we show that the account-level structure of the data allows us to study high-frequency spending dynamics across cardholder characteristics such as credit scores and credit card utilization. These exercises highlight how credit card data can be used not only to approximate traditional consumption measures, but also to facilitate research designs that are infeasible with official consumption statistics.

### 5.1 Validating the County-Level Data

To assess whether county-level credit card spending captures the geographic distribution of spending levels, we first benchmark it against the U.S. Economic Census, an independent source available in 2017 and 2022. Among other things, the Economic Census is used by BEA to benchmark retail sales at five-year intervals, and it provides industry-level measures of revenues at retail establishments in each county in the U.S. For each Census year, we compute each county’s share of aggregate Y-14M credit card spending and its share of aggregate Economic Census spending in retail categories.<sup>11</sup>

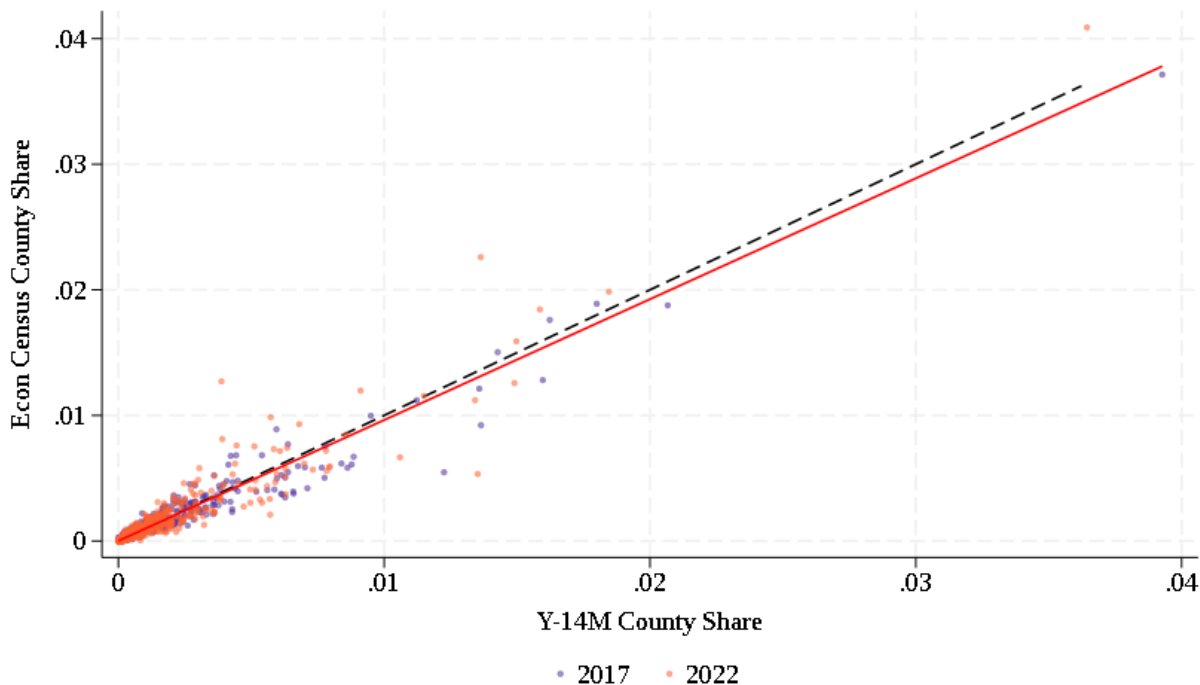
Figure 6 shows that this geographic allocation is very similar in the two datasets. Counties that account for a larger share of aggregate Economic Census spending also account for a larger share of aggregate Y-14M credit card spending, and this relationship is strongly positive in both benchmark years. The fit is especially tight for the bulk of counties, while a small number of very large counties generate some dispersion in the upper tail. A univariate regression yields a slope coefficient of 1.02 and an  $R^2$  of 0.91. The close alignment with Economic Census spending shares indicates that Y-14M credit card spending captures not

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<sup>11</sup>Because the Economic Census collects data on revenues based on the location of the establishment, we focus on retail goods/service NAICS categories that are more likely to be purchased locally. This includes 442 (furniture), 443 (electronics/appliances), 445 (food/beverage), 446 (health/personal care), 448 (clothing), 451 (sporting goods), 452 (general merchandise), 453 (miscellaneous), 722 (food services/restaurants), 811 (repair/maintenance), 812 (personal/laundry), along with equivalent 2022 codes. Figure A6 in the appendix reports the analogous comparison in per-capita levels, which displays greater dispersion owing to cross-county variation in cards per resident but confirms the same positive association.

Figure 6: County-Level Spending Shares: Total Credit Card Spending and Economic Census

This figure plots county shares of aggregate Economic Census spending against county shares of aggregate Y-14M credit card spending for the years 2017 and 2022. Each dot represents a county-year observation. The solid red line indicates the fitted regression line, and the dashed black line indicates the 45-degree line.



only aggregate time-series movements, but also meaningful cross-sectional variation in local spending activity. This provides support for using the county-level series to study high-frequency local consumption dynamics.<sup>12</sup>

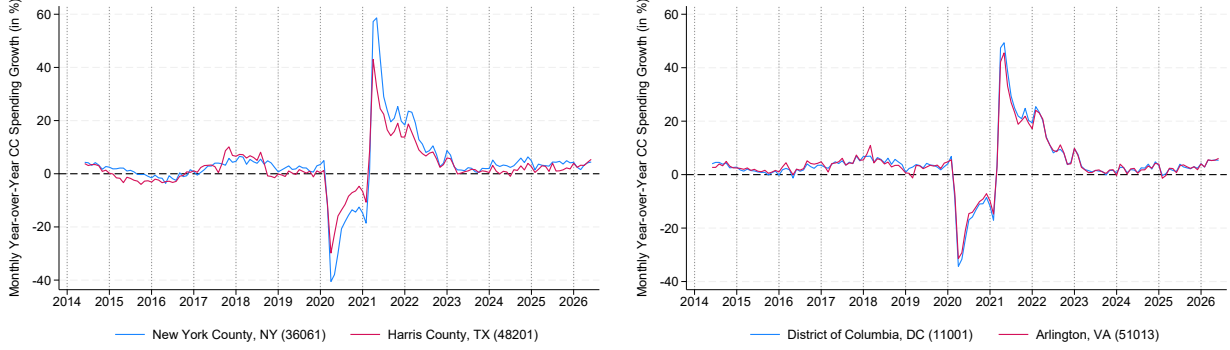
## 5.2 Monthly County-Level Consumption Dynamics

This section showcases our novel monthly county-level consumption dataset, which allows us to track local consumption dynamics at high frequency and fine geographic detail. We present selected time-series evidence and cross-county patterns, and show that county-level consumption growth is closely associated with local economic developments.

<sup>12</sup>As official consumption statistics are unavailable at the county-month level, Appendix Figure A7 provides an additional benchmark using private-sector data from Affinity Solutions, which cover 1,978 counties from January 2020 onward. A regression of Affinity spending changes on the corresponding Y-14M measure yields a slope coefficient of 0.92 and an  $R^2$  of 0.25.

Figure 7: Monthly County-Level Consumption Growth

This figure plots monthly year-over-year growth rates in average credit card (CC) spending for selected counties from June 2014 to June 2026. Panel (a) compares New York County, NY, and Harris County, TX. Panel (b) compares the District of Columbia and Arlington County, VA.



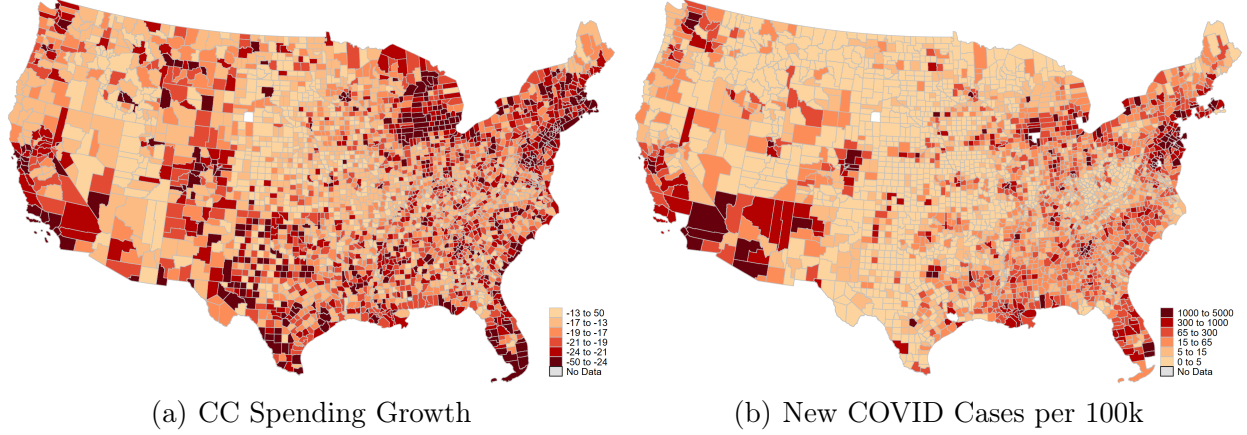
(a) New York County, NY vs Harris County, TX (b) Washington, DC vs Arlington County, VA

Figure 7 plots monthly growth rates of credit card spending for four selected counties. Panel (a) compares spending growth in New York County, NY, and Harris County, TX. New York County experienced a markedly sharper decline in consumption at the onset of the COVID-19 pandemic, consistent with the severe early impact of the pandemic in New York City and with evidence that local pandemic intensity strongly influenced consumer spending during this period (Chetty et al., 2024). Panel (b) compares spending growth in Washington, DC, and Arlington County, VA, two neighboring localities within the Washington metropolitan area. Reflecting their shared economic environment, the two counties exhibit nearly identical spending growth rates throughout the sample period, including during the pandemic contraction and subsequent rebound.

To illustrate the geographic breadth of the dataset, Figure 8 presents county-level maps of credit card spending growth (Panel a) and local pandemic incidence (Panel b) as of April 2020, the first full month of the COVID-19 pandemic. The two maps exhibit strikingly similar spatial patterns. Counties with high COVID-19 incidence, particularly in the Northeast, the Bay Area, and South Florida, experienced the sharpest declines in credit card spending. By contrast, counties in the Mountain West and the rural Midwest, where case counts remained low in the early stages of the pandemic, exhibit substantially milder spending declines. To quantify this relationship, we regress county-level credit card spending growth on log new COVID-19 cases per 100,000 residents in April 2020. The estimated coefficient is  $-1.33$  ( $t = -31.77$ ), with an  $R^2$  of 0.25, confirming that counties with higher pandemic intensity experienced significantly larger declines in consumption. This close spatial correspondence

Figure 8: County-Level Consumption Growth and Pandemic Incidence

This figure maps county-level consumption growth and local pandemic incidence in April 2020, the first full month of the COVID-19 pandemic. Panel (a) shows monthly year-over-year growth in average credit card (CC) spending and darker colors indicate larger spending declines. Panel (b) shows new COVID-19 cases per 100,000 residents and darker colors indicate higher local pandemic incidence.



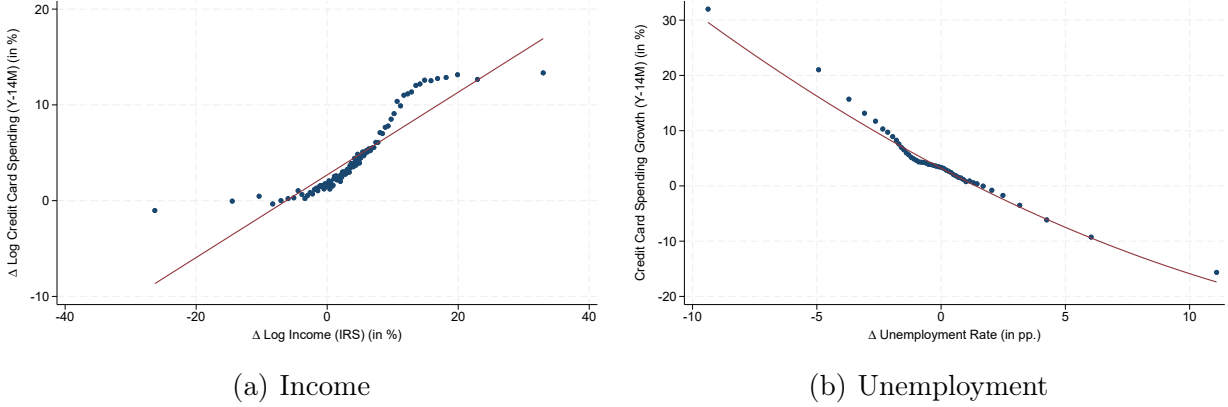
between pandemic intensity and consumption is consistent with evidence that local COVID-19 severity strongly influenced consumer spending during this period (Horvath et al., 2023; Chetty et al., 2024).

We next show that our local consumption measure not only captures intuitive spending patterns in selected counties and periods, but exhibits the expected correlations with local economic conditions. Figure 9 presents a binned scatterplot that shows the correlation between annual credit card spending growth and annual income growth (Panel a) and monthly credit card spending growth and monthly unemployment growth (Panel b) at the county level. Annual consumption growth, as measured by Y-14M credit card spending, is positively associated with annual income growth, yielding a regression coefficient of 0.43 ( $t = 53.24$ ) with an  $R^2$  of 0.32. Conversely, monthly consumption growth is negatively associated with monthly unemployment growth, yielding a regression coefficient of  $-2.29$  ( $t = -407.30$ ) with an  $R^2$  of 0.36. These relationships are not intended as causal estimates, but they show that the Y-14M county series moves in the expected direction with local fundamentals.<sup>13</sup>

<sup>13</sup>Figure A8 presents the analogous relationships after excluding the broader COVID-19 period. The positive association between credit card spending growth and income growth and the negative association between credit card spending growth and unemployment changes remain clearly visible outside this period.

Figure 9: County-Level Consumption Growth and Local Economic Conditions

This figure presents binned scatterplots relating county-level credit card spending growth to local economic conditions. Panel (a) plots annual growth rates in average credit card spending against annual income growth. Panel (b) plots monthly year-over-year growth rates in average credit card spending against monthly year-over-year changes in the unemployment rate. Each dot represents a bin of county-level observations.



Together, the county time series, COVID maps, and correlations with local economic conditions show that Y-14M credit card spending captures meaningful local consumption dynamics in addition to aggregate national movements. Covering more than 3,000 counties at a monthly frequency since 2014, this dataset opens the door to research designs that require both high-frequency and granular geographic variation in consumption. In Section 6, we present one such application and study the heterogeneous transmission of monetary policy to consumption across the county-level income distribution.

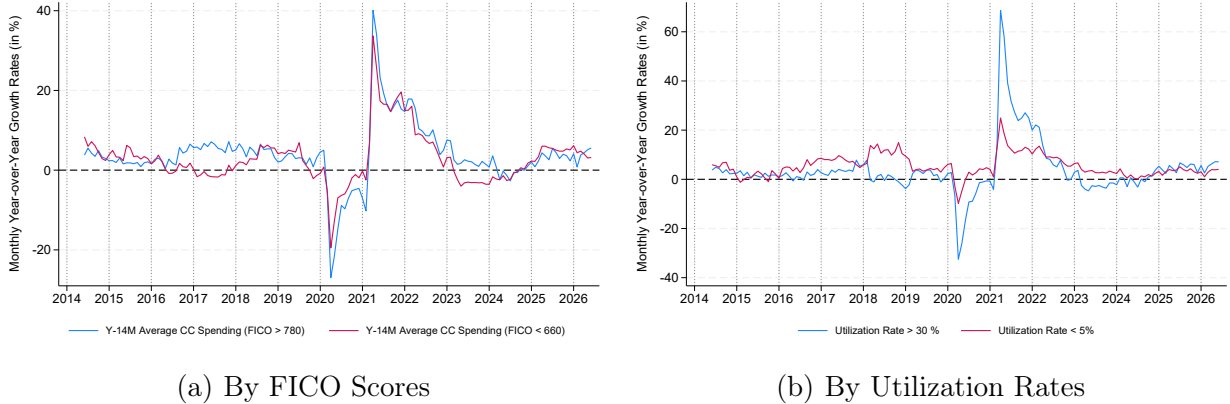
### 5.3 Cardholder-Level Spending Dynamics

The preceding subsection highlights the geographic granularity of the Y-14M data. A second advantage of the data is that the underlying observations are at the account level, which allows us to study spending dynamics not only across places, but also across cardholder characteristics. To illustrate this dimension of the data, Figure 10 plots monthly year-over-year growth in average credit card spending separately by FICO score and credit card utilization.

Panel (a) compares the consumption dynamics of cardholders with FICO scores above 780 and below 660. While spending growth of the two groups follows broadly similar dynamics over most of the sample, including the contraction at the onset of the COVID-19 pandemic and the subsequent rebound, low-FICO cardholders exhibited lower spending growth in

Figure 10: Monthly Credit Card Spending Growth by Cardholder Characteristics

This figure plots monthly year-over-year growth rates in average credit card (CC) spending by cardholder characteristics from June 2014 to June 2026. Panel (a) compares cardholders with FICO scores above 780 and below 660. Panel (b) compares cardholders with utilization rates above 30 percent (revolvers) and below 5 percent (transactors).



2017 and 2023. Analogously, Panel (b) compares cardholders with utilization rates above 30 percent, which we refer to as revolvers, and below 5 percent, which we refer to as transactors. These classifications provide a simple proxy for cardholders with relatively high and low exposure to revolving credit. Revolvers exhibited lower spending growth in 2018 and 2023 and, additionally, a steeper contraction and stronger rebound in spending during and after the pandemic.

Notably, the periods of weaker spending growth among low-FICO cardholders and revolvers coincide with monetary policy tightening episodes in 2017–2018 and 2023. The particularly weak spending growth of revolvers in 2023 is also consistent with the interpretation in Section 4.1 that monetary tightening may have contributed to the 2023–24 gap between credit card spending and PCE growth. While this evidence is descriptive, it illustrates how the account-level structure of the Y-14M data can be used to study heterogeneity in spending dynamics across borrower characteristics.

## 6 Research Application: The Consumption Response to Monetary Policy Shocks

In this section, we use the local projections methodology of Jordà (2005) to study the transmission of monetary policy to consumption. The exercise serves as a proof of concept for

the research value of disaggregated consumption accounts constructed from the Y-14M data. We focus on monetary policy because theory predicts heterogeneous consumption responses across the income and liquidity distribution, while traditional consumption data lack the frequency and geographic granularity needed to study these responses at a local level. We first estimate the impulse responses of credit card spending and traditional consumption measures to contractionary monetary policy shocks at the national and state level, providing a further validation that credit card spending captures economically meaningful consumption dynamics and that it responds to aggregate shocks in the same way as measures built from established sources. We then exploit the high frequency and geographic granularity of the Y-14M data to estimate the heterogeneous effects of monetary policy on consumption across the income distribution at the county level.

## 6.1 Empirical Specification

**Consumption Measures:** We examine four consumption measures: (i) total PCE, the standard aggregate measure; (ii) adjusted PCE, as discussed in Section 2.2; (iii) retail sales from the Census Bureau; and (iv) aggregated credit card spending from the Y-14M data. Comparing responses across these measures allows us to assess both the validity of credit card spending as a consumption proxy and differences in the estimated response across consumption measures. All consumption measures are deflated using the Personal Consumption Expenditures Price Index (PCEPI, base year 2017) to obtain real values:

$$y_{i,t} = \ln \left( \frac{C_{i,t}}{\text{PCEPI}_t/100} \right) \quad (3)$$

where  $C_{i,t}$  denotes nominal consumption in geographical unit  $i$  in period  $t$ . We use PCEPI rather than the consumer price index (CPI) because it is purpose-built for deflating PCE, employs chain-weighting to better account for substitution across consumption categories, and exhibits less volatility than CPI. At the state and county level, we apply the national deflator, since consistent subnational price indices are unavailable at monthly frequency, so the resulting real series abstract from regional variation in prices.

**Monetary Policy Shock:** We measure monetary policy shocks using the high-frequency identification approach of [Jarociński and Karadi \(2020\)](#). We use the posterior median of their information-purged monetary policy shock, identified by sign restrictions on the co-movement of interest rate futures and stock prices around FOMC announcements. Announcement-level surprises are aggregated to the monthly frequency to match our data. To facilitate

interpretation, we normalize the shock so that a one-unit increase corresponds to a 25-basis-point rise in the federal funds rate.<sup>14</sup>

**Specification:** We estimate impulse responses using the following local projection specification:

$$y_{i,t+h} - y_{i,t} = \beta_h \cdot \text{shock}_t + \Gamma'(L)X_{i,t} + \alpha_i + \varepsilon_{i,t+h} \quad (4)$$

where  $y_{i,t+h} - y_{i,t}$  denotes the cumulative log change in real consumption from period  $t$  to horizon  $h$ ,  $\text{shock}_t$  is the monetary policy shock,  $\Gamma'(L)X_{i,t}$  represents a polynomial in the lag operator applied to a vector of controls (including lags of the shock, of log real consumption, and of macroeconomic indicators), and  $\alpha_i$  captures fixed effects. Lags of log real consumption are included following [Montiel Olea and Plagborg-Møller \(2021\)](#), who show that lag augmentation makes local projection inference robust to serial correlation without requiring a HAC adjustment. The coefficient of interest,  $\beta_h$ , traces out the impulse response function at each horizon  $h$ . We implement equation (4) at three levels of aggregation. At the monthly national level, we estimate:

$$y_{t+h} - y_t = \beta_h \cdot \text{shock}_t + \sum_{j=1}^p \gamma_j \cdot \text{shock}_{t-j} + \sum_{j=1}^p \delta_j \cdot y_{t-j} + \phi \cdot \mathbf{1}_{\text{COVID}} + \alpha_m + \varepsilon_{t+h} \quad (5)$$

with  $p = 2$  lags, horizons up to  $h = 12$  months, month-of-year fixed effects  $\alpha_m$  to control for seasonality, and heteroskedasticity-robust standard errors. At the state-year level, we estimate:

$$y_{s,t+h} - y_{s,t} = \beta_h \cdot \text{shock}_t + \sum_{j=1}^p \gamma_j \cdot \text{shock}_{t-j} + \sum_{j=1}^p \delta_j \cdot y_{s,t-j} + \theta' W_{s,t-1} + \alpha_s + \phi \cdot \mathbf{1}_{\text{COVID}} + \varepsilon_{s,t+h} \quad (6)$$

with  $p = 1$  lag, horizons up to  $h = 3$  years, state fixed effects  $\alpha_s$ , one lag of national unemployment and inflation in  $W_{s,t-1}$ , and standard errors two-way clustered by state and year. The state-level specification does not include year fixed effects, as these would absorb all variation in the national monetary policy shock. Identification therefore relies on time-series variation in national monetary policy, with the panel structure providing statistical power

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<sup>14</sup>Formally, we regress the effective federal funds rate on the contemporaneous shock and twelve of its lags, twelve lags of the federal funds rate, and month-of-year fixed effects, and let  $\hat{\gamma}$  denote the impact coefficient of the shock. We then construct the normalized shock as  $\text{shock}_t = \text{shock}_t^{\text{raw}} \times (\hat{\gamma}/0.25)$ , so that a one-unit increase in  $\text{shock}_t$  raises the federal funds rate by 25 basis points on impact.

through cross-sectional variation in consumption levels.<sup>15</sup> Finally, at the county-month level, we estimate:

$$y_{c,t+h} - y_{c,t} = \beta_h \cdot \text{shock}_t + \sum_{j=1}^p \gamma_j \cdot \text{shock}_{t-j} + \sum_{j=1}^p \delta_j \cdot y_{c,t-j} + \Theta'(L)W_{c,t} + \phi \cdot \mathbf{1}_{\text{COVID}} + \alpha_c + \alpha_m + \varepsilon_{c,t+h} \quad (7)$$

with  $p = 2$  lags, horizons up to  $h = 12$  months, county fixed effects  $\alpha_c$ , month-of-year fixed effects  $\alpha_m$ , and controls  $\Theta'(L)W_{c,t}$  that include two lags of national unemployment, inflation, and county-level log house prices, and one lag of county-level log income. Because the monetary policy shock varies only at the national level, identification exploits time-series variation in  $\text{shock}_t$  across the full panel. Standard errors are two-way clustered by county and date. Time fixed effects are excluded for the same reason as in the state-year specification: they would absorb all identifying variation in the national shock.

Our sample includes the COVID-19 pandemic, which induced extraordinary volatility in consumption patterns. In the monthly specifications we follow [Schorfheide and Song \(2024\)](#) and [Buda et al. \(2025\)](#) and set observations from March 2020 through October 2020 to missing, thereby excluding this period from estimation while preserving the time-series structure for computing leads and lags, and we additionally include a COVID indicator spanning March 2020 through June 2022 to absorb residual level shifts associated with fiscal stimulus and the subsequent normalization period. The annual state-level specification cannot accommodate a within-year exclusion, and we therefore leave it unadjusted.

## 6.2 Benchmarking: Monthly National and Annual State-Level

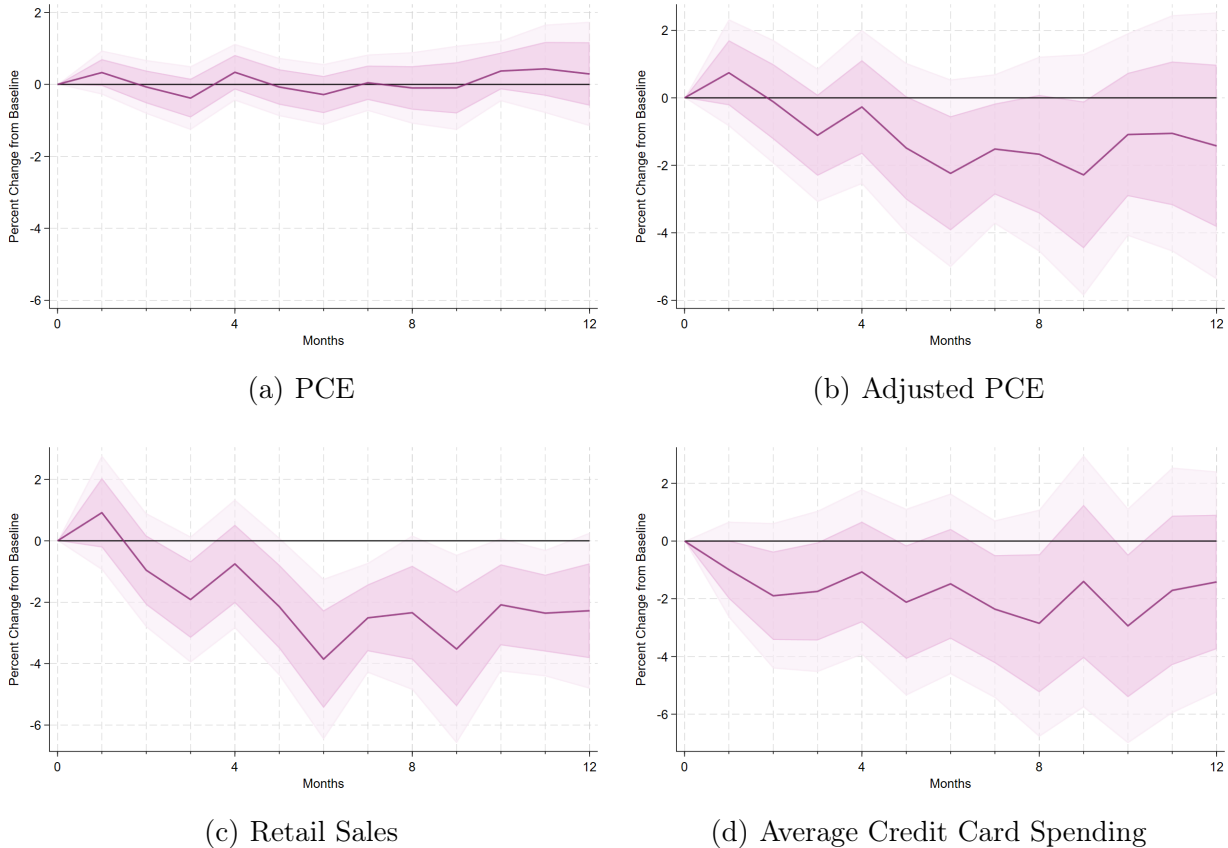
We begin by benchmarking the impulse response of credit card spending against those of traditional consumption measures at the national and state level, assessing whether credit card spending tracks not only the levels and growth rates documented in Section 4, but also the dynamic response of consumption to monetary policy. This is a demanding test of the series: agreement in levels and growth rates need not imply agreement in second moments, and a proxy that co-moves with PCE unconditionally could still respond differently to an identified shock. If the responses line up, this consumption series at a more granular county-month panel can be used to study transmission at frequencies and geographies where official consumption statistics are unavailable.

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<sup>15</sup>An alternative specification with year fixed effects would require interacting the shock with state-level characteristics to study heterogeneous transmission, which we leave for future work.

Figure 11: Monthly National Response to Monetary Policy Shocks

This figure displays impulse responses of real consumption measures to a 25-basis-point contractionary monetary policy shock, estimated by local projections using monthly national data from 2014 to 2025. Panels (a)–(d) show real PCE, real adjusted PCE, real retail sales, and real average credit card spending, respectively. The dependent variable is the cumulative log change from the shock month. All specifications include month-of-year fixed effects, two lags of the shock and dependent variable, and a COVID indicator for March 2020–June 2022, with standard errors clustered by date. Observations from March–October 2020 are set to missing following [Schorfheide and Song \(2024\)](#). The shaded regions represent 68 percent (darker) and 90 percent (lighter) confidence intervals.



**Monthly National Results:** Figure 11 displays the impulse responses of the four consumption measures to a 25-basis-point contractionary monetary policy shock, estimated using monthly national data from 2014 to 2025. The specification includes month-of-year fixed effects, two lags of the shock and the dependent variable, and a COVID indicator spanning March 2020 to June 2022, with heteroskedasticity-robust standard errors.

Three of the four consumption measures exhibit a clear contractionary response. Retail sales decline most sharply, falling to roughly  $-3.8$  percent by month six before fluctuating

between  $-2$  and  $-3$  percent over the remainder of the horizon. Credit card spending follows a similar path, declining gradually to a trough of approximately  $-3$  percent at month eight and recovering toward  $-1.5$  percent by month twelve. Adjusted PCE shows a more moderate response, reaching approximately  $-2$  percent between months seven and nine before mean-reverting toward  $-1.5$  percent. The three series are therefore closely aligned in both timing and magnitude, with the response building over roughly six to eight months in each case.

In contrast, aggregate PCE exhibits a muted response that oscillates around zero throughout the 12-month horizon. This difference reflects the composition of total PCE, which includes large components that are unlikely to respond to monetary policy at this horizon: imputed rent for owner-occupied housing, which adjusts sluggishly by construction, and health care expenditures largely paid by third parties. When these components are excluded, as in adjusted PCE, a contractionary response becomes visible.

The similarity between credit card spending and retail sales is the relevant benchmarking result. Card spending disproportionately captures discretionary, interest-sensitive expenditures such as dining, travel, and retail goods, and its response tracks that of an independently constructed official series measuring broadly the same categories. The magnitudes are also consistent with external evidence: [Bräuning and Stavins \(2026\)](#) estimate a cumulative decline in aggregate Y-14M spending of about 4 percent following a 25-basis-point contractionary shock, while [Buda et al. \(2023\)](#) document a consumption trough of roughly 3 percent using Spanish transaction data and a comparable Euro Area shock identified by [Jarociński and Karadi \(2020\)](#). Our estimates fall within this range.

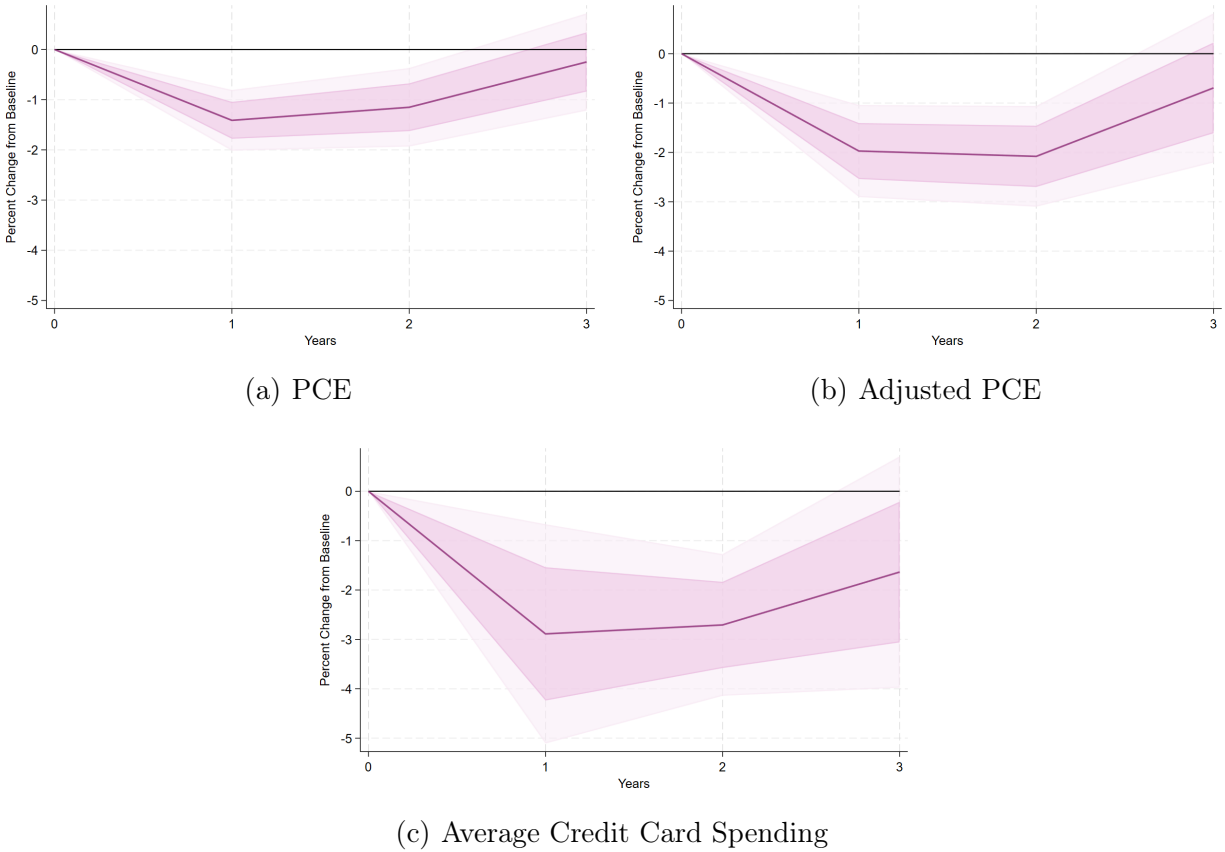
**Annual State-Level Results:** Figure 12 displays the impulse responses of three consumption measures to a 25-basis-point contractionary monetary policy shock, estimated using state-year panel data from 2014 to 2025.<sup>16</sup> The specification includes state fixed effects, one lag of the shock and of the dependent variable, one lag of unemployment and inflation, and an indicator for COVID between 2020 and 2022, with standard errors two-way clustered by state and year. Because the specification includes state but not year fixed effects, the estimated coefficients reflect the average consumption response across states to national monetary policy over time, controlling for time-invariant state characteristics such

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<sup>16</sup>The annual shock is the within-year sum of the monthly high-frequency surprises, and the normalization is re-estimated at annual frequency, where the dependent variable is the annual average federal funds rate. The annual shock is therefore normalized to raise the average funds rate over the year by 25 basis points, which is a different object from the monthly normalization, under which the shock raises the funds rate by 25 basis points on impact. Magnitudes are consequently not directly comparable across Figures 11 and 12, and we compare the shape and relative ordering of the responses rather than their levels.

Figure 12: Annual State-Level Response to Monetary Policy Shocks

This figure displays impulse responses of real consumption measures to a 25-basis-point contractionary monetary policy shock, estimated by local projections using annual state-level data from 2014 to 2025. Panels (a)–(c) show real PCE, real adjusted PCE, and real average credit card spending, respectively. The dependent variable is the cumulative log change from the shock year. All specifications include state fixed effects, one lag of the shock and of the dependent variable, one lag of unemployment and inflation, and an indicator for 2020 through 2022, with standard errors two-way clustered by state and year. The annual shock is the within-year sum of monthly surprises and is normalized at annual frequency; see footnote 16 for comparability with the monthly estimates. The shaded regions represent 68 percent (darker) and 90 percent (lighter) confidence intervals.



as industry composition, demographics, and baseline consumption levels.

All three measures exhibit a similar response pattern: a decline that is largely complete within the first year, persists through year two, and partially recovers by year three. This common dynamic across independently constructed consumption measures validates credit card spending as a proxy in dynamic settings, confirming that it tracks not only the levels and growth rates documented earlier, but also the response to identified shocks.

Notably, unlike at the national monthly level where total PCE was essentially unrespon-

sive, all three measures including total PCE exhibit a clear contractionary response at the state-year level. The magnitudes differ in the expected order. Credit card spending shows the largest sensitivity, declining roughly 3 percent by year one and remaining near that level in year two before recovering to about  $-1.5$  percent by year three. Adjusted PCE exhibits an intermediate response of approximately  $-2$  percent in years one and two. Total PCE displays the most muted reaction, reaching roughly  $-1.5$  percent in year one and recovering steadily thereafter.

The amplified response of credit card spending is consistent with account-level evidence. [Bräuning and Stavins \(2026\)](#) show, using the same underlying data at the account level, that the spending response to interest rate changes is concentrated among revolving accounts and low-credit-score borrowers, with essentially no response among high-score accounts. Credit card purchases therefore over-represent precisely the households whose consumption is most interest sensitive, which is the margin our aggregate series inherits.

### 6.3 Beyond Benchmarking: Monthly County-Level

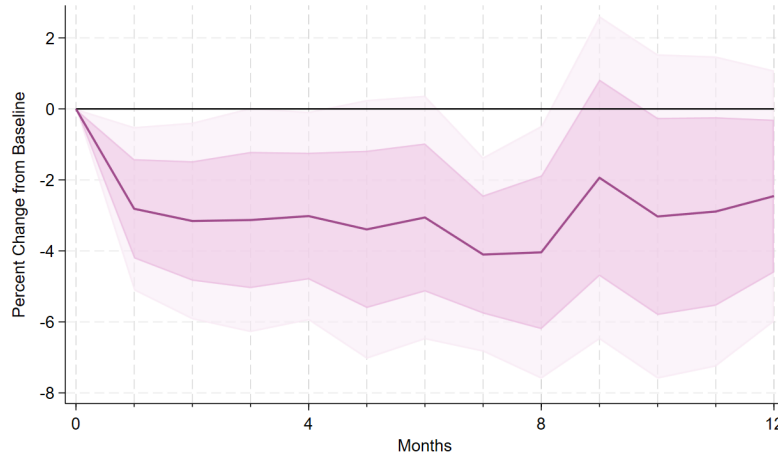
We now turn to the county-month level, where the Y-14M data track consumption at a geographic and temporal granularity unavailable in traditional consumption statistics. We exploit this variation to estimate the heterogeneous effects of monetary policy on consumption across the income distribution at the county level.

**Replication of Aggregate Results:** Figure [13](#) displays the impulse response of real county-level average credit card spending to a 25-basis-point contractionary monetary policy shock, estimated on the panel of more than 3,000 counties from June 2014 to September 2025. The response reproduces the national pattern: spending falls by roughly 3 percent within the first two months, remains near that level through month six, and reaches a trough of approximately  $-4$  percent at months seven and eight before partially recovering. Both the timing of the trough and its magnitude are close to the national estimate in Figure [11](#), panel (d). The estimate is distinguishable from zero at the 90 percent level through month six, after which the confidence bands widen.

**Heterogeneity by County Income:** We next examine whether the transmission of monetary policy to consumption differs systematically across the income distribution. We split counties into above- and below-median groups based on their time-averaged Internal Revenue Service (IRS) income, a classification that is highly stable over time: 91% of counties retain the same classification whether income is measured in 2013 or averaged over the full sample

Figure 13: Monthly County-Level Response to Monetary Policy Shocks

This figure displays the impulse response of real county-level average credit card spending to a 25-basis-point contractionary monetary policy shock, estimated by local projections using monthly county-level data from June 2014 to September 2025. The dependent variable is the cumulative log change in real average credit card spending from the shock month. The specification includes county fixed effects, month-of-year fixed effects, the contemporaneous shock and two of its lags, two lags each of the dependent variable, the national unemployment rate, national inflation, and county-level log house prices, one lag of county-level log income, and a COVID indicator for March 2020–June 2022, with standard errors two-way clustered by county and date. Observations from March–October 2020 are set to missing following [Schorfheide and Song \(2024\)](#). The shaded regions represent 68 percent (darker) and 90 percent (lighter) confidence intervals.



(a) Average Credit Card Spending

period.<sup>17</sup> We estimate equation (7) augmented with an interaction between the monetary policy shock and an indicator for above-median income counties:

$$y_{c,t+h} - y_{c,t} = \beta_h^{\text{low}} \cdot \text{shock}_t + \beta_h^{\Delta} \cdot \text{shock}_t \times \mathbf{1}[\text{High Income}_c] + \Gamma'(L)X_{c,t} + \alpha_c + \alpha_m + \varepsilon_{c,t+h} \quad (8)$$

where  $\beta_h^{\text{low}}$  captures the response of low-income counties and  $\beta_h^{\Delta} = \beta_h^{\text{high}} - \beta_h^{\text{low}}$  identifies the differential response. Because the income classification is based on a within-county average, it is time-invariant and therefore absorbed by the county fixed effects; only the interaction is separately identified. Standard errors for  $\beta_h^{\Delta}$  are obtained directly from the interaction

<sup>17</sup>Figure A9 shows raw monthly credit card spending growth for counties in the top and bottom deciles of the income distribution. The two groups exhibit broadly similar aggregate dynamics, with differences concentrated around the pandemic period. The formal local-projection estimates below isolate heterogeneity in the response to monetary policy shocks.

term rather than from separate regressions, thereby correctly accounting for the covariance between the two group estimators.<sup>18</sup>

Figure 14 presents the results. Panel (a) shows that both groups exhibit a contractionary response, with spending in low-income counties declining by approximately 4.5 percent at the trough compared to roughly 3 percent for high-income counties. Panel (b) shows the difference  $\hat{\beta}_h^\Delta$ , which is positive at every horizon, indicating that high-income counties are less responsive. The differential peaks at around 1.5 percentage points near month four and is distinguishable from zero at the 90 percent level. We therefore read this as suggestive evidence of heterogeneous transmission rather than as a precisely estimated differential.

The direction of this heterogeneity is consistent with account-level evidence from the same underlying data. Bräuning and Stavins (2026) show that the spending response to interest rate changes is concentrated among revolving accounts and borrowers in the lowest credit-score deciles, with essentially no response among high-score accounts, which they attribute to constrained households lacking the liquid resources to pay down balances while maintaining spending. It is also the pattern predicted by heterogeneous-agent New Keynesian models (Kaplan et al., 2018), in which transmission operates disproportionately through households with low liquid wealth who cannot smooth consumption in response to income or interest rate shocks, including the “wealthy hand-to-mouth” households of Kaplan et al. (2014) who hold illiquid assets but negligible liquid buffers.

We emphasize that county-level income is a coarse proxy for the household-level liquidity constraints these models concern. Within-county heterogeneity in income and wealth is substantial, and our estimates average over it, so the differential we recover is likely attenuated relative to the household-level object. What the county-month data establish is that the heterogeneity is detectable at the geographic level at all, which is the relevant question for whether disaggregated consumption accounts can support this class of analysis.

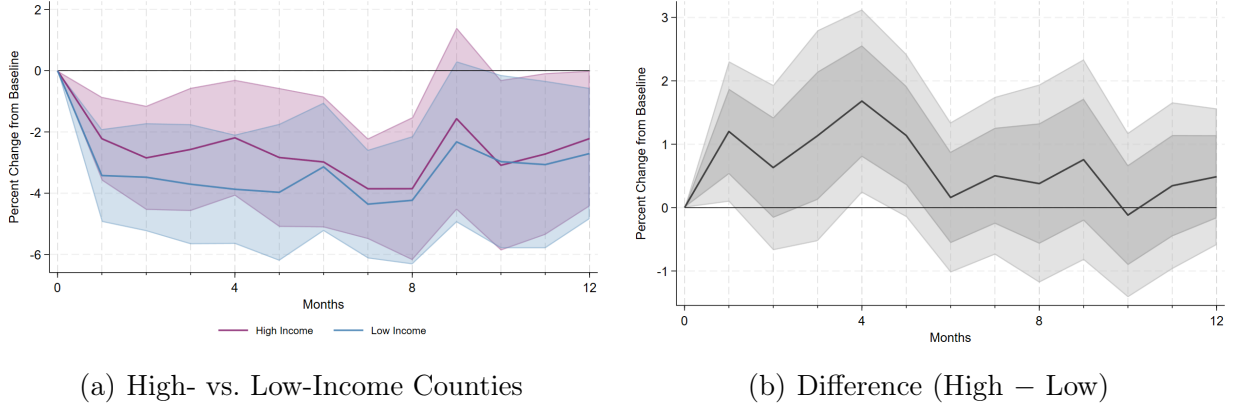
Documenting these patterns requires the geographic and temporal granularity of the Y-14M data. Official consumption measures are available at high frequency only at the national level and at finer geographic disaggregation only at relatively low frequency, making it impossible to detect whether monetary policy transmission varies systematically across the income distribution. The Y-14M data, covering more than 3,000 counties at monthly frequency over more than a decade, provide precisely this variation.

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<sup>18</sup>We also examine heterogeneity by county house price levels using time-averaged Zillow HPI. However, 74% of counties receive the same above/below median classification under income and house prices, reflecting the high correlation between the two measures at the county level. Residualizing house prices on income yields no statistically significant differential response, suggesting that the balance sheet channel operates primarily through the income dimension in our data rather than independently through housing wealth.

Figure 14: Heterogeneous County-Level Response to Monetary Policy by Income

This figure displays impulse responses of real average county-level credit card spending to a 25-basis-point equivalent contractionary monetary policy shock by county income group, estimated from a single interacted local-projection specification using monthly county-level data from 2014 to 2025. Counties are classified as above or below the median based on time-averaged IRS income. Panel (a) shows the impulse responses for high- and low-income counties. Panel (b) shows the difference between high- and low-income counties, with standard errors obtained directly from the interaction term. The dependent variable is the cumulative log change in real average credit card spending from the shock month. The specification includes county fixed effects, month-of-year fixed effects, two lags of the shock and dependent variable, controls for lags of national unemployment, national inflation, county-level house prices, and county-level income, and a COVID indicator for March 2020–June 2022, with standard errors two-way clustered by county and date. Observations from March–October 2020 are set to missing following [Schorfheide and Song \(2024\)](#). The shaded regions represent 68 percent (darker) and 90 percent (lighter) confidence intervals.



## 6.4 Research Application: Summary

Across both monthly and annual specifications, credit card spending exhibits impulse responses that are qualitatively consistent with traditional consumption measures: a decline following contractionary monetary policy that builds over several months, a trough at medium horizons, and partial mean reversion thereafter. At the monthly frequency, the response of card spending is close to that of retail sales in both timing and magnitude, and roughly half again as large as that of adjusted PCE, while headline PCE shows no discernible response. The amplification relative to headline PCE reflects composition rather than measurement error: card transactions disproportionately capture discretionary, interest-sensitive, and postponable expenditures, which are the margin of adjustment for household consumption, whereas headline PCE is dominated by components such as imputed rent and third-party-financed health care that do not respond at these horizons. The close correspondence with retail sales, an independently constructed official series covering

broadly the same categories, is the more informative benchmark.

At the county level, the Y-14M data allow us to go further. Official consumption statistics are not available at both a sufficiently high frequency and a sufficiently granular geographic disaggregation to detect whether monetary policy transmission varies systematically across the income distribution. The Y-14M data, covering more than 3,000 counties at monthly frequency over more than a decade, provide precisely this variation. We find that low-income counties exhibit a larger consumption decline following contractionary monetary policy, a differential that is suggestive rather than precisely estimated but that aligns both with the predictions of HANK models and with account-level evidence on credit-score heterogeneity in the same data (Bräuning and Stavins, 2026). Together, these results suggest that credit card spending not only approximates consumption in levels, growth rates, and dynamic responses to shocks, but also supports research designs that existing consumption statistics cannot.

## 7 A Researcher’s Guide: Caveats and Best Practices

### 7.1 Credit Card Spending and Consumption Subcategories

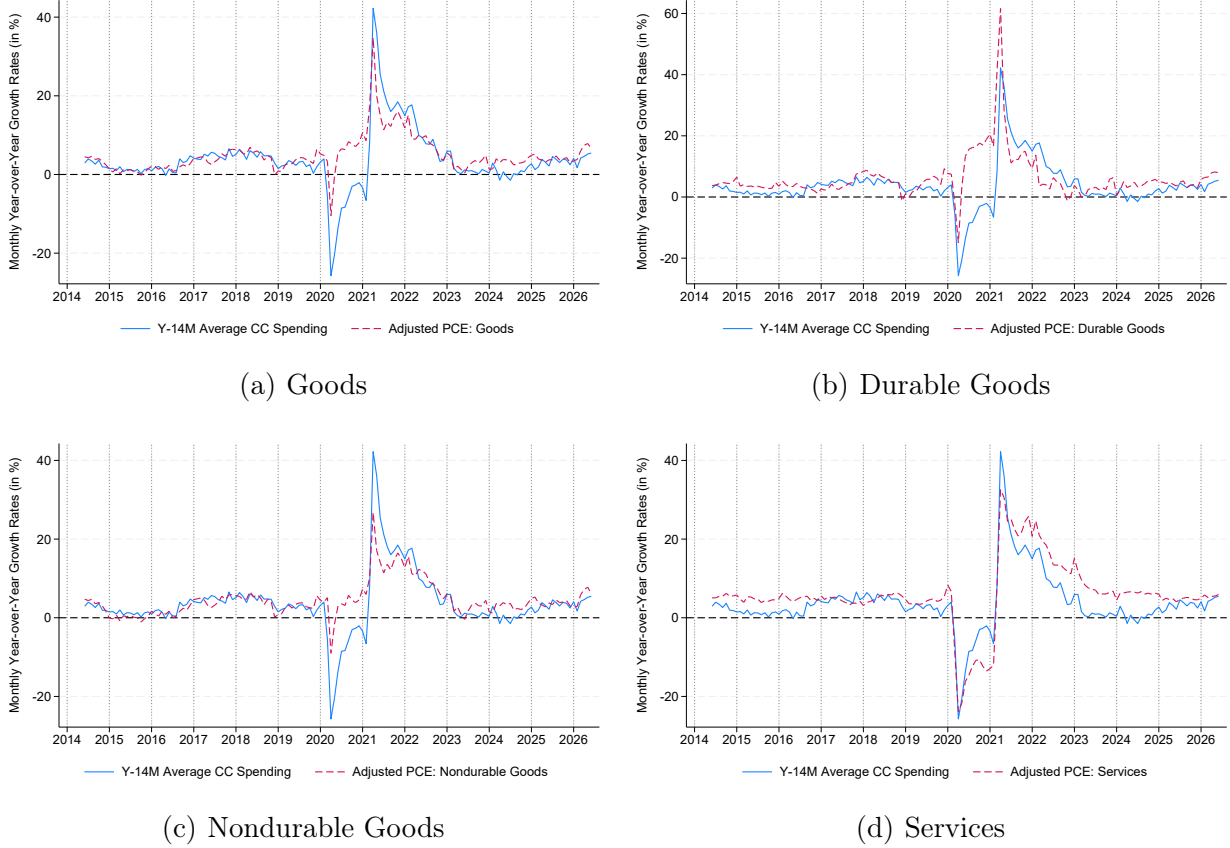
The Y-14M data allow us to observe total credit card spending in a given month, but they do not provide information on the types of goods and services purchased. This limitation represents an important drawback relative to transaction-level data, which allow researchers to track spending patterns across merchant categories.

Credit card spending is likely to capture some components of consumption better than others. Figure 15 compares monthly year-over-year growth rates in credit card spending against growth rates of major PCE subcategories: total goods, durable goods, nondurable goods, and services. In normal times, credit card spending tracks goods consumption reasonably well, both for durable and nondurable goods. During the COVID-19 period, however, credit card spending declined more sharply and recovered less quickly than goods consumption, consistent with pandemic-related shifts in spending composition that cannot be directly decomposed in the Y-14M data. The divergence is particularly visible for services in the post-COVID period, when services PCE growth remained notably higher than credit card spending growth. Thus, as Y-14M spending is not observed at the transaction level, the data are best suited for studying aggregate consumption dynamics rather than shifts across detailed goods and services categories.

A related issue is that broad PCE includes several components that are conceptually less comparable to credit card spending as they either do not reflect out-of-pocket household purchases or are rarely paid for using credit cards. These include housing and utilities, health

Figure 15: Monthly National Consumption Growth: Major PCE Subcategories

This figure plots monthly year-over-year growth rates in average credit card (CC) spending (solid blue line in each panel) and major PCE subcategories (dashed red line in each panel) from June 2014 to June 2026. Panel (a) shows total goods, Panel (b) durable goods, Panel (c) nondurable goods, and Panel (d) services.

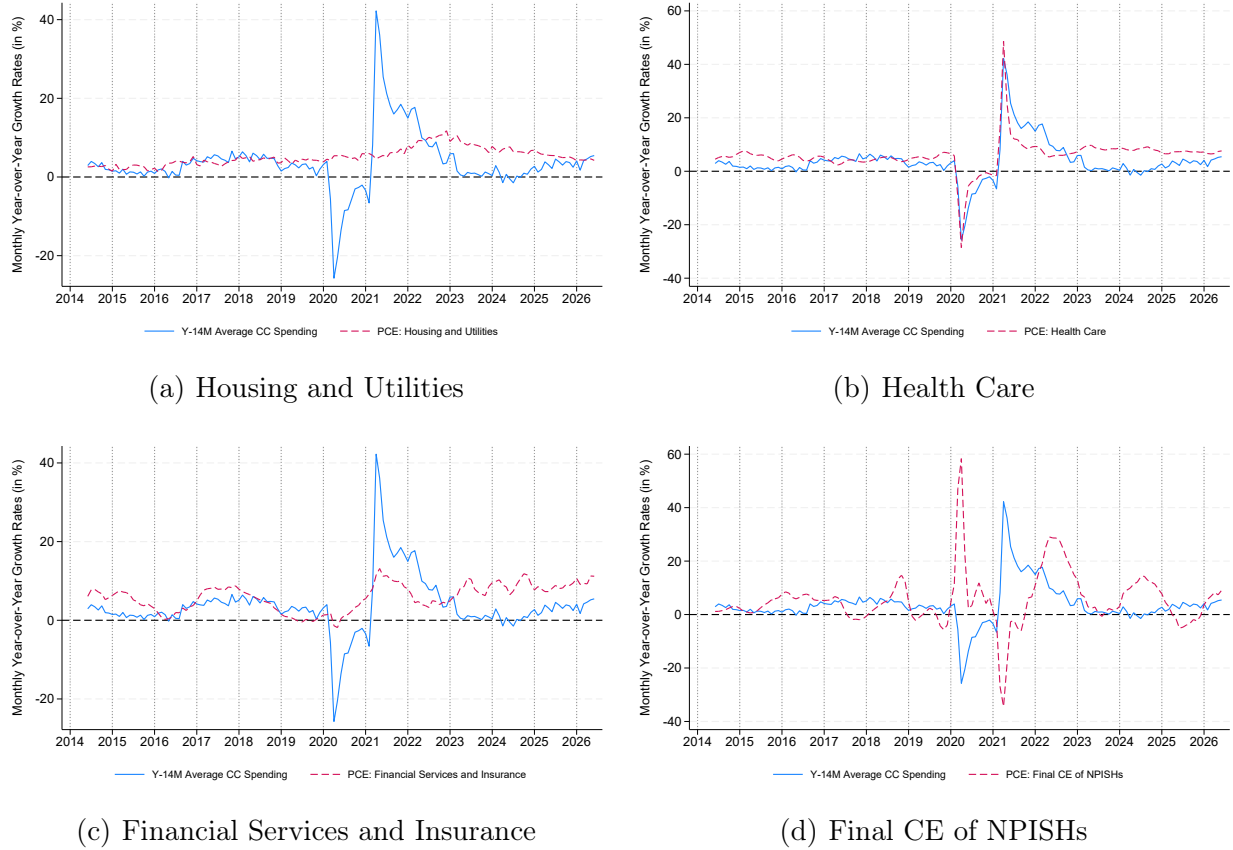


care expenditures paid by insurance, financial services, spending by nonprofit institutions serving households, and some large durable purchases such as motor vehicles. For this reason, our baseline benchmark throughout the paper is adjusted PCE, which excludes categories that are less likely to be captured by credit card spending.<sup>19</sup> Figure 16 illustrates this point and shows that the excluded PCE categories exhibit dynamics that differ markedly from credit card spending and from the adjusted consumption measures analyzed earlier. Housing and utilities are relatively smooth, health care and financial services grow more strongly in the post-pandemic period, and nonprofit consumption displays a distinct pattern

<sup>19</sup>Figure A10 provides complementary evidence from the 2024 Diary of Consumer Payment Choice. Credit card use is highest in categories such as lodging, travel, restaurants, transportation, groceries, gas, and drug stores, and substantially lower for rent, financial services, and transfers.

Figure 16: Monthly National Consumption Growth: Excluded PCE Subcategories

This figure plots monthly year-over-year growth rates in average credit card (CC) spending (solid blue line in each panel) and PCE subcategories excluded from our adjusted PCE measure (dashed red line in each panel) from June 2014 to June 2026. Panel (a) shows housing and utilities, Panel (b) health care, Panel (c) financial services and insurance, and Panel (d) final consumption expenditures of nonprofit institutions serving households.



around the pandemic.

Taken together, Figures 15 and 16 highlight an important caveat for researchers using credit card data to measure consumption. Aggregate card spending is most informative about broad consumption dynamics, especially for out-of-pocket and card-payable expenditures. It is less well suited for measuring categories such as imputed housing services, insurance-financed health care, nonprofit expenditures, or purchases that are rarely made by credit card. Researchers should therefore choose benchmark consumption aggregates that correspond as closely as possible to the spending concept captured in the card data.

## 7.2 Payment-Method Shifts and Sample Composition

A central challenge in interpreting credit card spending is that aggregate spending growth may reflect not only changes in spending per card, but also changes in the number and composition of cards observed in the sample. Credit card usage has increased over time, both within our sample and in the economy overall (Bayeh et al., 2025). As a result, growth in *total* credit card spending can overstate growth in underlying consumption if it partly reflects more cards entering the sample rather than higher *average* spending on existing cards.

Figure 17 illustrates why our baseline analysis focuses on average credit card spending rather than total credit card spending. We decompose year-over-year growth in total credit card spending into growth in average spending per card and growth in the number of cards in the sample.<sup>20</sup> While growth in average credit card spending tracks adjusted PCE growth well over most of the sample (as also shown in Figure 1), growth in total credit card spending is systematically higher in most periods as the number of cards in the sample increases over time. Thus, total card spending growth is not a pure measure of consumption growth but also reflects increasing card adoption and bank portfolio growth, rather than spending growth by existing cardholders alone.

While total credit card spending can be decomposed into changes in average spending per card and changes in the number of cards, average per-card spending can be decomposed into an intensive and an extensive margin. The intensive margin captures year-over-year spending growth among cards observed in both the current month and the same month one year earlier. The extensive margin captures the combined net effect of cards entering and exiting the sample. Figure 18 illustrates this decomposition. The decomposition shows substantial churn in the card population. In most periods, spending growth among continuing cards is close to zero or negative, with a pronounced exception during the post-COVID recovery. By contrast, the net entry/exit margin is positive in most periods and accounts for much of the observed fit between average credit card spending growth and aggregate consumption growth. This pattern indicates that changes in the composition of cards, rather than changes in spending on a fixed set of cards alone, play an important role in the dynamics of average credit card spending.

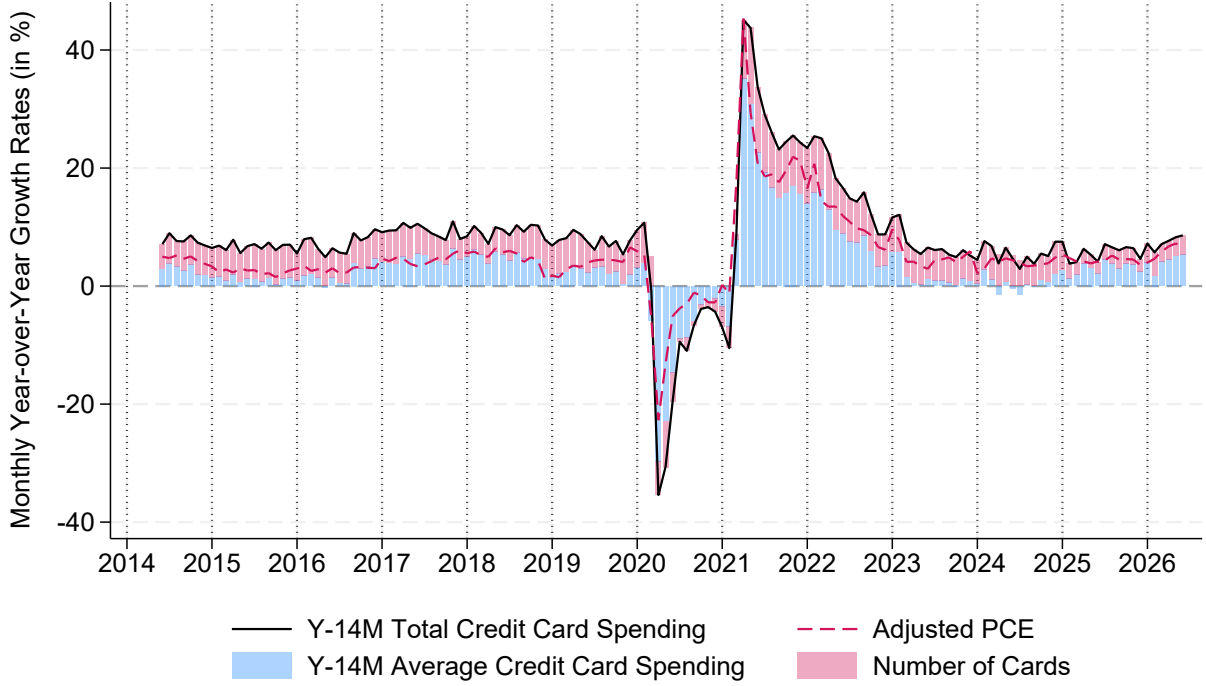
The positive net entry/exit margin should not be interpreted as an extensive margin of cardholder consumption. Credit card accounts experience substantial turnover, as consumers open and close accounts, activate and deactivate secondary cards, and reallocate spending

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<sup>20</sup>Let total credit card spending be  $T_t = \bar{x}_t N_t$ , where  $\bar{x}_t$  denotes average spending per card and  $N_t$  denotes the number of cards. Taking year-over-year log differences gives  $\Delta_{12} \log T_t = \Delta_{12} \log \bar{x}_t + \Delta_{12} \log N_t$ .

Figure 17: Decomposing Total Credit Card Spending Growth

This figure plots monthly year-over-year growth in total credit card spending (solid black line) and its decomposition into growth in average credit card spending (blue bars) and growth in the number of credit cards in the sample (red bars) from June 2014 to June 2026, alongside monthly year-over-year growth in adjusted PCE (dashed red line).



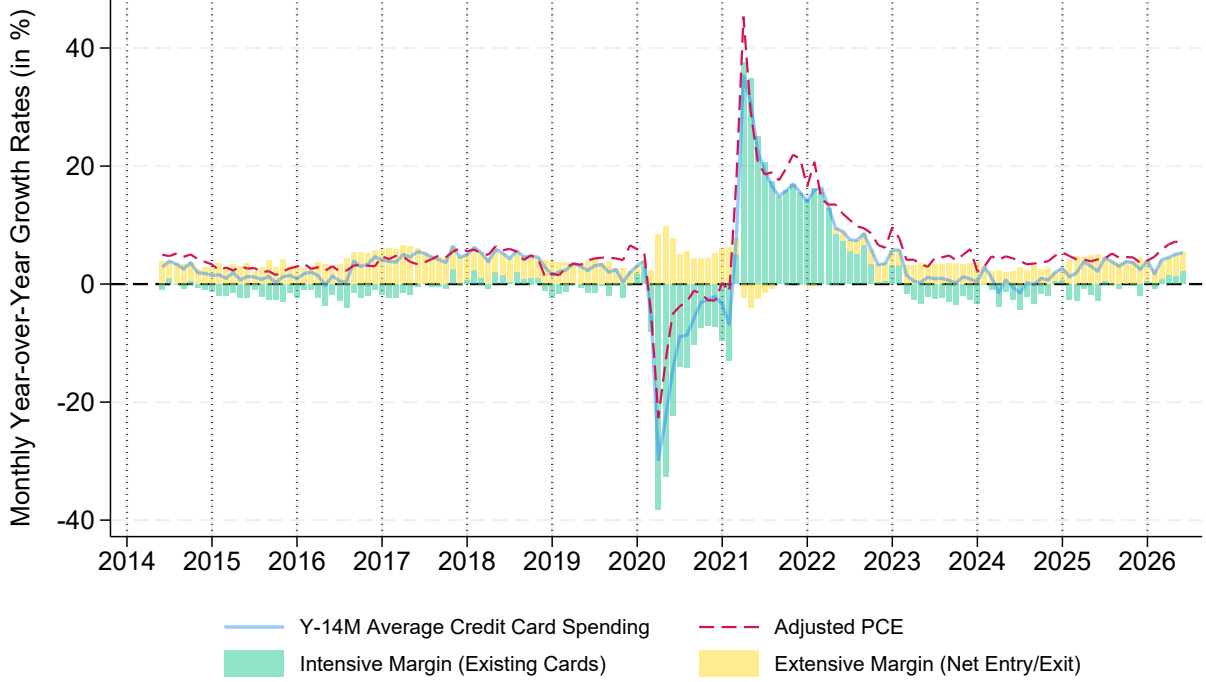
across cards. A positive net contribution means that the increase in average spending caused by relatively low-spending cards leaving the active set exceeds the decrease caused by relatively low-spending cards entering it.<sup>21</sup> Restricting the analysis to continuing cards would therefore condition on a selected, relatively stable set of actively used cards and omit changes in card use that are part of the aggregate credit card spending signal.

Taken together, Figures 17 and 18 show that researchers should carefully distinguish between total credit card spending growth, average per-card spending growth, and the extent to which these dynamics reflect spending changes among continuing cards versus changes in the number or composition of cards.

<sup>21</sup>Figure A11 decomposes the net entry/exit margin into separate entry and exit components. Entering cards are those with positive purchase volume in month  $t$  but not in month  $t-12$ , while exiting cards have positive purchase volume in month  $t-12$  but not in month  $t$ . The positive exit contribution exceeds the negative entry contribution over most of the sample.

Figure 18: Decomposing Average Credit Card Spending Growth

This figure plots monthly year-over-year growth in average credit card spending (solid blue line) and its decomposition into an intensive margin among continuing cards (green bars) and an extensive margin due to net entry and exit (yellow bars) from June 2014 to June 2026, alongside monthly year-over-year growth in adjusted PCE (dashed red line).



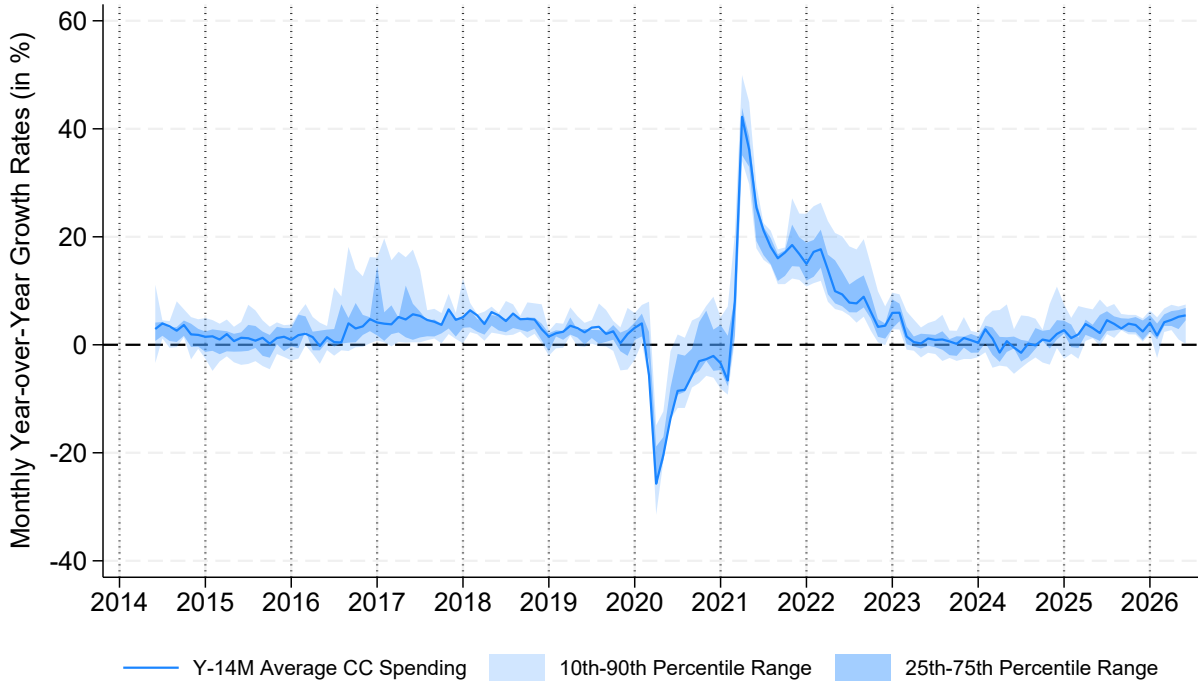
### 7.3 Bank-Level Heterogeneity and Sample Representativeness

Many credit card datasets available to researchers are drawn from a single bank, fintech platform, or payment processor. Such datasets can offer rich transaction-level detail, but their customer bases may not be representative of the broader population. Differences in customer composition, geographic footprint, product mix, credit quality, and cardholder behavior can all affect measured spending dynamics. The multi-bank structure of the Y-14M data allows us to quantify this concern directly by comparing spending measures constructed from individual banks to the aggregate measure constructed from the full set of reporting banks.

Figure 19 plots monthly year-over-year growth in average credit card spending for the full Y-14M sample from Figure 1, alongside the 25<sup>th</sup> – 75<sup>th</sup> and 10<sup>th</sup> – 90<sup>th</sup> percentile ranges of bank-level spending growth in our sample. In most periods, bank-level spending growth

Figure 19: Bank-Level Heterogeneity in Credit Card Spending Growth

This figure plots monthly year-over-year growth rates in aggregate average credit card (CC) spending (solid blue line), alongside the 25th–75th and 10th–90th percentile ranges of bank-level spending growth across banks in our sample, from June 2014 to June 2026.



is distributed tightly around the aggregate Y-14M series, suggesting that the aggregate measure is not driven by a small number of banks and that individual banks often capture similar broad consumption dynamics. At the same time, the dispersion across banks is not negligible. The 10th–90th percentile range widens notably in 2016–2017 and again around 2022, indicating that, in some periods, spending measures constructed from different banks can imply meaningfully different consumption dynamics.

Researchers using data from individual banks, fintech platforms, or payment processors should therefore validate their spending measures against external benchmarks and, to the extent possible, assess whether their results are driven by particular customer segments or geographic markets.

## 7.4 Approximating Credit Card Spending from Credit Bureau Data

In the absence of access to regulatory or private-sector credit card data, researchers often infer credit card spending from credit bureau data (Gibbs et al., 2025). These data, however, are designed primarily to capture liabilities and repayment behavior rather than consumption. Researchers typically observe credit card balances and, for some furnishers, actual payments, but they do not directly observe the flow of new purchases. Following Ganong and Noel (2020), credit card spending on card  $i$  in period  $t$  can be approximated as

$$s_{i,t} = \begin{cases} b_{i,t} - b_{i,t-1} + p_{i,t} & \text{if } b_{i,t} - b_{i,t-1} + p_{i,t} \geq 0 \\ 0 & \text{otherwise} \end{cases} \quad (9)$$

where  $b_{i,t}$  and  $b_{i,t-1}$  denote current and lagged outstanding balances and  $p_{i,t}$  denotes actual payments. This approximation is subject to two important caveats. First, it is inclusive of finance charges and fees, which are generally not separately observed in credit bureau data. Second, it requires actual payment information, which is often unavailable as credit card issuers do not consistently furnish this variable to credit reporting agencies (Guttman-Kenney and Shahidinejad, 2025). The Y-14M data allow us to assess the importance of these limitations as they contain not only outstanding balances, actual payments, finance charges, and fees, but also observed purchase volumes, which we use as the benchmark measure of credit card spending.

We follow Guttman-Kenney and Shahidinejad (2025) and estimate three sets of regressions:

$$PV_{i,t} = \alpha + \beta_1 b_{i,t} + \beta_2 b_{i,t-1} + \beta_3 \widehat{\Delta b}_{i,t} + \beta_4 1\{b_{i,t} > 0\} + \beta_5 1\{b_{i,t-1} > 0\} + \varepsilon_{i,t} \quad (10)$$

$$PV_{i,t} = \alpha + \beta_1 s_{i,t} + \varepsilon_{i,t} \quad (11)$$

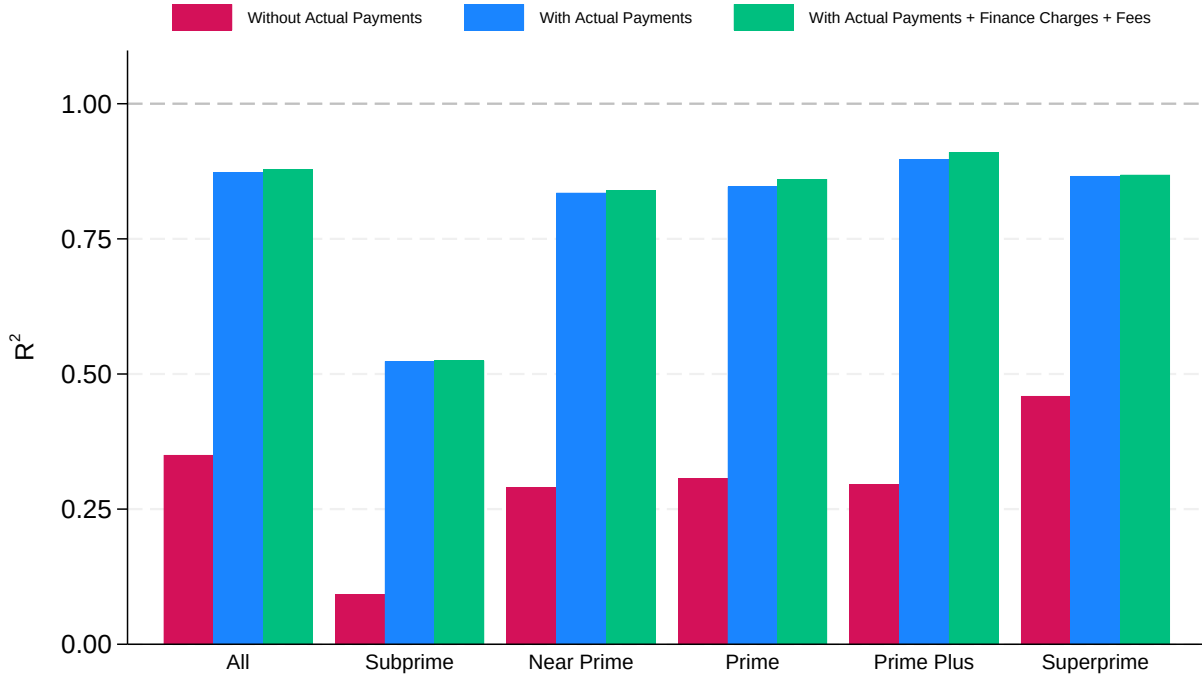
$$PV_{i,t} = \alpha + \beta_1 s_{i,t} + \beta_2 \text{Finance Charges}_{i,t} + \beta_3 \text{Fees}_{i,t} + \varepsilon_{i,t} \quad (12)$$

where  $PV_{i,t}$  is actual purchase volume,  $s_{i,t}$  is the bureau-style spending proxy from Equation (9), and  $\widehat{\Delta b}_{i,t} \equiv \max\{b_{i,t} - b_{i,t-1}, 0\}$  denotes the non-negative change in outstanding balances. Equation (10) evaluates how well spending can be inferred from balances alone, as would be necessary when actual payment data are unavailable. Equation (11) evaluates the approximation when actual payments are observed. Equation (12) augments the bureau-style spending proxy with finance charges and fees to assess how much of the remaining measurement error is attributable to these non-purchase components of credit card balances.

Figure 20 illustrates how well spending measures based on credit bureau data can ap-

Figure 20: Approximating Credit Card Spending from Credit Bureau Data

This figure plots  $R^2$  values from regressions that approximate observed credit card purchase volume using credit-bureau-style measures, based on Equations (10), (11), and (12) and the analysis in [Guttman-Kenney and Shahidinejad \(2025\)](#). Each bar reports results from a separate regression for the full sample and for each credit-score segment. The full sample includes 60.82 million credit card accounts. The credit-score segments are subprime, with scores between 300 and 600 ( $N = 4.06$  million); near prime, with scores between 601 and 660 ( $N = 5.53$  million); prime, with scores between 661 and 720 ( $N = 10.63$  million); prime plus, with scores between 721 and 780 ( $N = 13.77$  million); and superprime, with scores of at least 781 ( $N = 26.84$  million).



proximate actual credit card purchase volumes. The first specification (red bars) uses only balance-based information and mimics the case in which actual payment data are not available. The fit is weak, with an  $R^2$  of 0.35 in the full sample, and especially poor for subprime borrowers, where the  $R^2$  falls to 0.09. Adding actual payment information substantially improves the approximation. The  $R^2$  rises to 0.87 in the full sample and remains reasonably high across most FICO buckets, although the fit continues to be noticeably weaker for subprime borrowers ( $R^2 = 0.52$ ). Finally, adding finance charges and fees to the specification yields almost no additional explanatory power. This suggests that the residual discrepancy between spending inferred from balances and payments and actual purchase volumes is not primarily explained by these components, but instead reflects other non-purchase balance

flows, timing differences, or account-level noise.

Taken together, these results show that credit bureau data can provide a reasonable but imperfect proxy for observed credit card purchase volumes, provided that payment information is available.

## 8 Conclusion

We show that credit card spending data from the Federal Reserve’s Y-14M reports provide a reliable measure of aggregate consumption. Monthly credit card spending growth explains 92 percent of the variation in adjusted PCE growth at the national level, and annual credit card spending growth captures meaningful state-level variation in adjusted PCE growth, although the within-year cross-sectional relationship is more mixed. These results hold across a range of economic conditions, including the extraordinary circumstances of the COVID-19 pandemic, thus supporting the use of credit card spending as a credible consumption measure for applied research.

We then introduce a novel monthly county-level credit-card-based consumption dataset, covering more than 3,000 U.S. counties since 2014, which allows us to measure consumption at a frequency and geographic granularity unavailable in traditional data. The dataset reveals granular consumption dynamics that align closely with well-documented economic developments, such as the geographic incidence of the COVID-19 pandemic, and opens the door to research designs that require both high-frequency and granular geographic variation in consumption.

We demonstrate the research value of this dataset by applying it to monetary policy transmission. We first show that credit card spending exhibits impulse responses that are qualitatively similar and quantitatively comparable to those obtained with traditional consumption data. We then exploit the county-level granularity of the data and find that low-income counties experience substantially larger consumption declines following contractionary monetary policy than high-income counties. This heterogeneity is consistent with the predictions of HANK models and, to our knowledge, provides the first estimate of such differential responses using county-month consumption data.

Finally, we provide a researcher’s guide to the main caveats involved in using credit card data to measure consumption. We show that aggregate card spending is most informative about out-of-pocket, card-payable expenditures; that measured spending growth can reflect changes in the number and composition of cards; that data from different institutions may imply meaningfully different spending dynamics; and that credit bureau data can provide a reasonable but imperfect proxy for observed credit card purchase volume when payment

information is available.

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Online Appendix for:  
Measuring Consumption with Credit Card Data:  
Benchmarking and Beyond

Aditya Aladangady, Ricardo Duque Gabriel, Carlo Wix

## A1 Additional Figures

Figure A1: Monthly National Consumption Growth: Adjusted and Total PCE

This figure plots monthly year-over-year growth rates in average credit card (CC) spending (solid blue line), adjusted personal consumption expenditures (adjusted PCE; dashed red line), and total personal consumption expenditures (total PCE; dashed gray line) from June 2014 to June 2026.

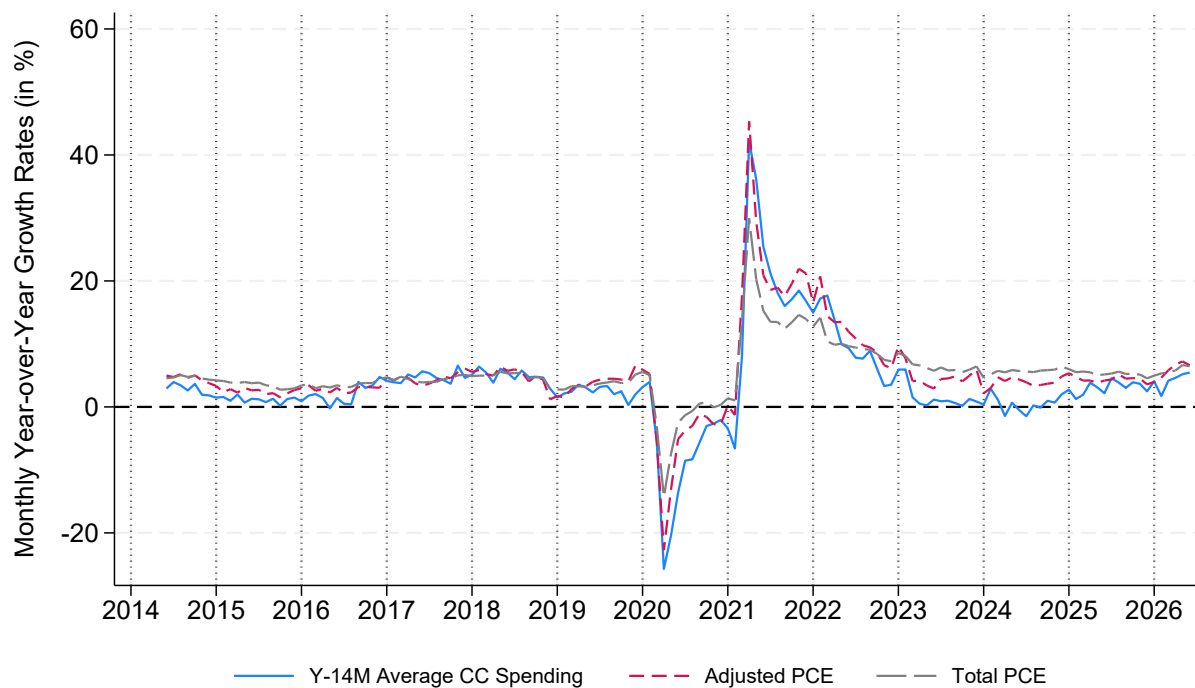


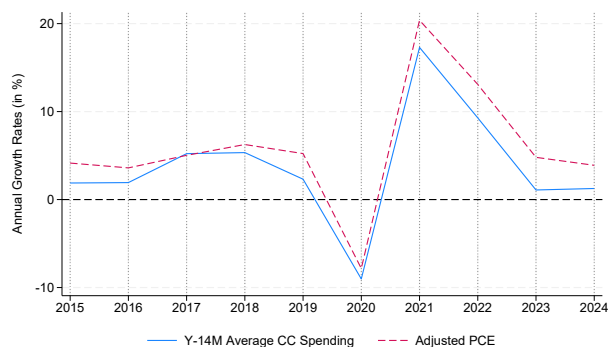
Figure A2: Monthly National Consumption Growth: Population Adjustment

This figure plots monthly year-over-year growth rates in average credit card (CC) spending (solid blue line), adjusted personal consumption expenditures (adjusted PCE; dashed red line), and adjusted PCE per capita (dashed green line) from June 2014 to June 2026. U.S. population data are available at an annual frequency and are linearly interpolated to obtain monthly population estimates.

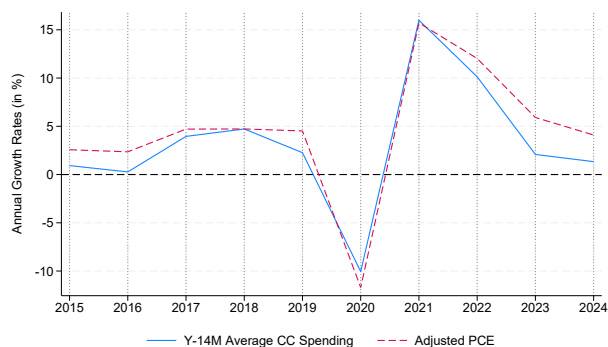


Figure A3: Annual State-Level Consumption Growth: Time-Series Evidence

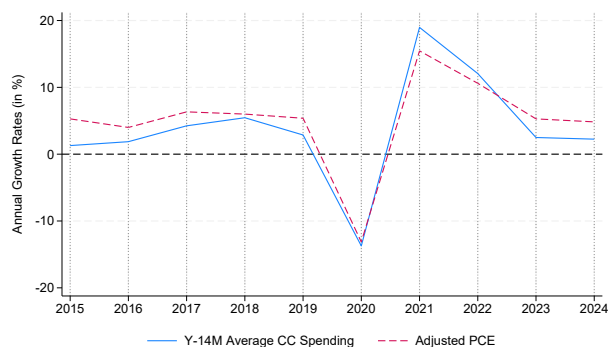
This figure plots annual year-over-year growth rates in average credit card (CC) spending (solid blue lines) and adjusted PCE (dashed red lines) for selected states from 2015 to 2024. Panel (a) shows California, Panel (b) New York, Panel (c) Washington, DC, and Panel (d) Maryland.



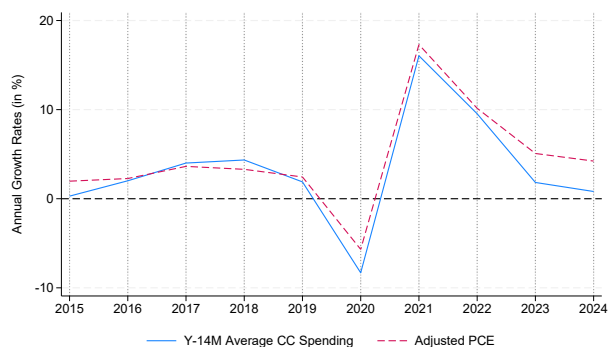
(a) California



(b) New York



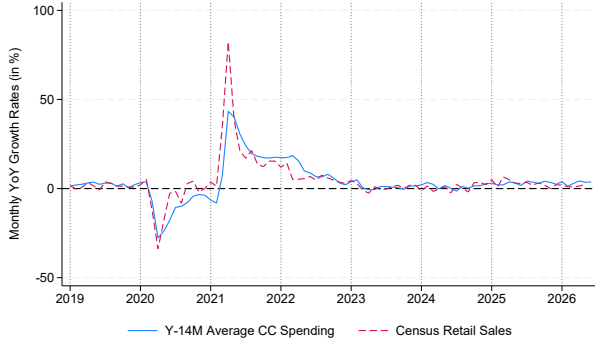
(c) Washington, DC



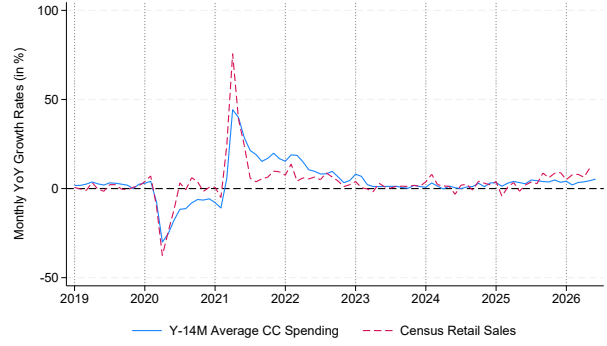
(d) Maryland

Figure A4: Monthly State-Level Retail Spending Growth: Time-Series Evidence

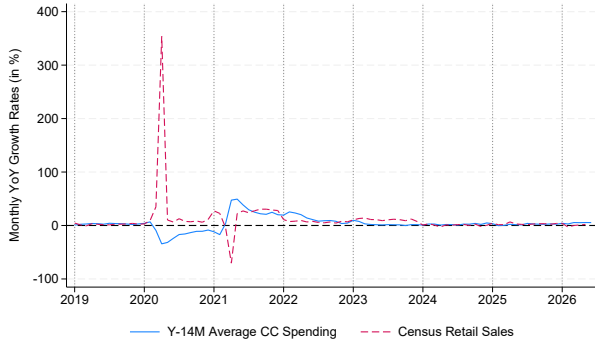
This figure plots monthly year-over-year (YoY) growth rates in average credit card (CC) spending (solid blue lines) and Census retail sales (dashed red lines) for selected states from January 2019 to June 2026. Panel (a) shows California, Panel (b) New York, Panel (c) Washington, DC, and Panel (d) Maryland.



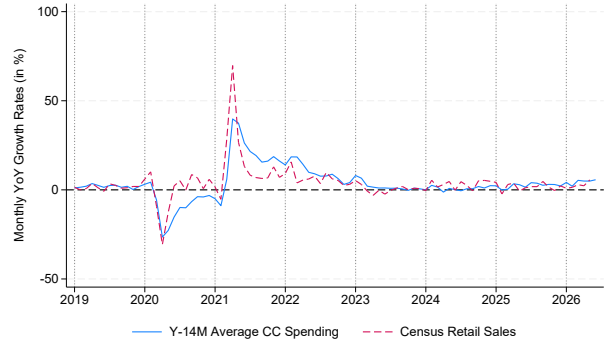
(a) California



(b) New York



(c) Washington, DC



(d) Maryland

Figure A5: Monthly Spending Relative to January 2020: Affinity Solutions Benchmark

This figure plots monthly credit card (CC) spending in the Y-14M data (solid blue line) and Affinity Solutions data from Opportunity Insights (dashed red line) from January 2020 to June 2026, expressed as seasonally adjusted changes relative to January 2020. The Y-14M series indexes average monthly credit card purchase volume to its January 2020 value and applies an analogous seasonal adjustment based on the 2019 monthly pattern. The Affinity Solutions series is the publicly available Opportunity Insights spending series.

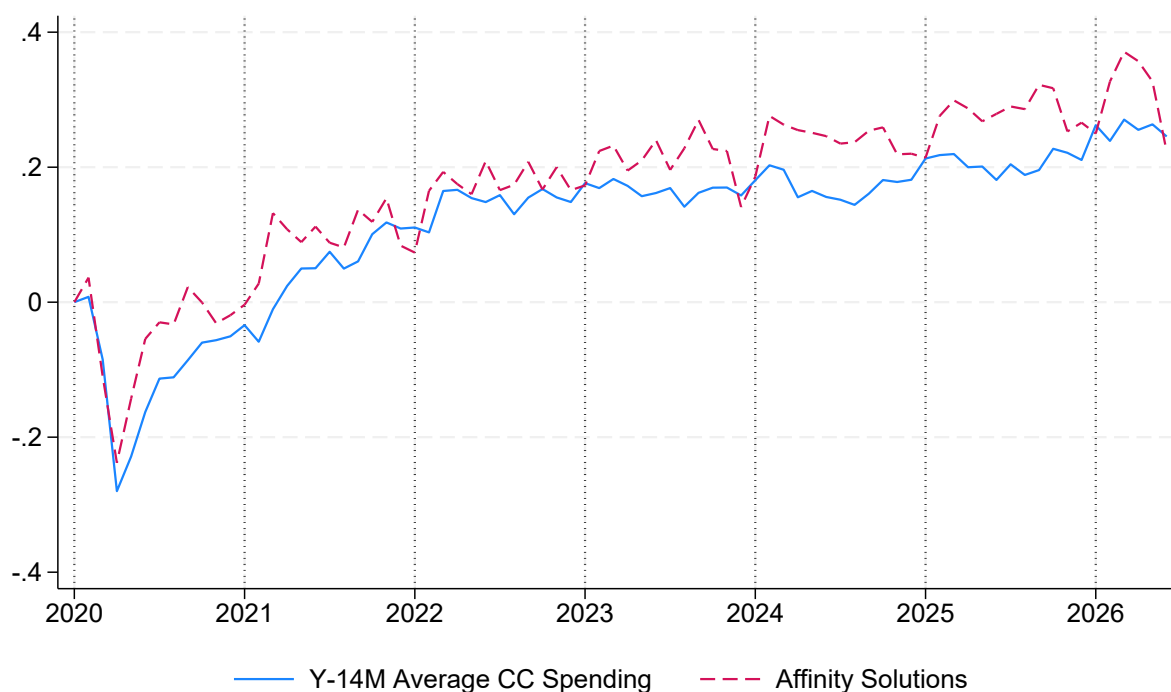
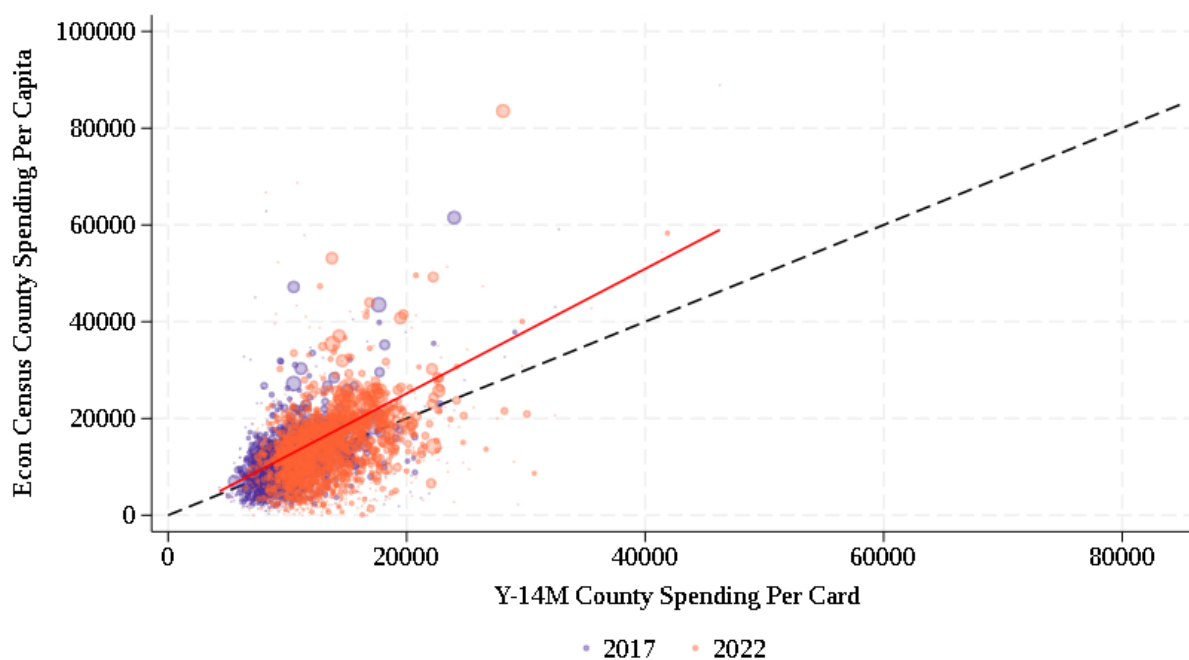


Figure A6: County-Level Spending Levels: Credit Card Spending per Card and Economic Census Spending per Capita

This figure plots county-level Economic Census spending per capita against average annual Y-14M credit card spending per card for the years 2017 and 2022. Each dot represents a county-year observation. The solid red line indicates the fitted regression line, and the dashed black line indicates the 45-degree line.



Note: Size represents county population. Counties with fewer than 3,000 residents or 30 establishments are not plotted.

Figure A7: County-Level Credit Card Spending: Y-14M and Affinity Solutions

This figure presents a binned scatterplot relating seasonally adjusted changes in average credit card spending in the Y-14M data to county-level spending changes reported by Affinity Solutions, with both measures expressed relative to January 2020. The sample covers 1,978 counties from January 2020 through June 2026. Each dot represents a bin of county-month observations, and the solid red line reports the quadratic fit estimated using the underlying unbinned observations. Affinity Solutions caps its spending-change measure at 1.12, whereas the Y-14M measure is not truncated.

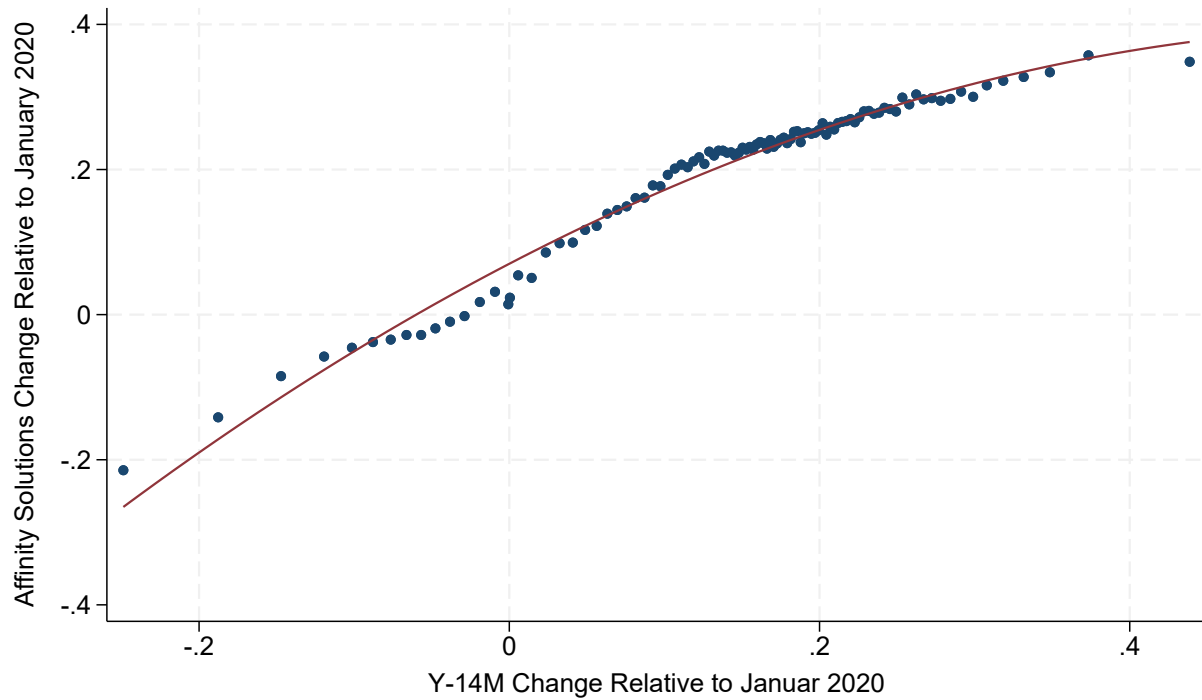


Figure A8: County-Level Consumption Growth and Local Economic Conditions: Excluding the COVID-19 Period

This figure presents binned scatterplots relating county-level credit card spending growth to local economic conditions after excluding the COVID-19 period. Panel (a) plots annual growth rates in average credit card spending against annual income growth, excluding observations from 2020 through 2022. Panel (b) plots monthly year-over-year growth rates in average credit card spending against monthly year-over-year changes in the unemployment rate, excluding observations from March 2020 through March 2022. Each dot represents a bin of county-level observations.

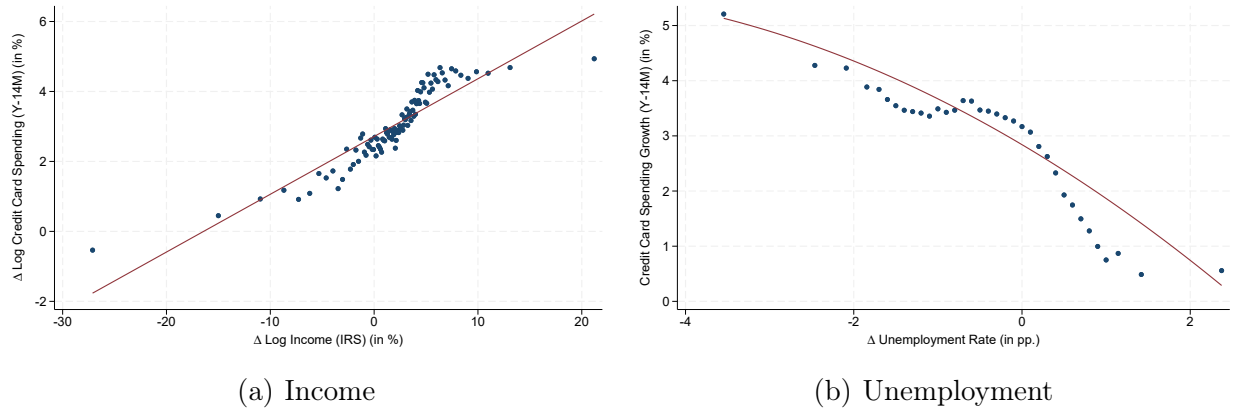


Figure A9: Monthly County-Level Consumption Growth by County-Level Income Decile

This figure plots monthly year-over-year growth rates in average credit card spending for high-income counties (top decile of average income; blue line) and low-income counties (bottom decile of average income; red line) from June 2014 to June 2026.

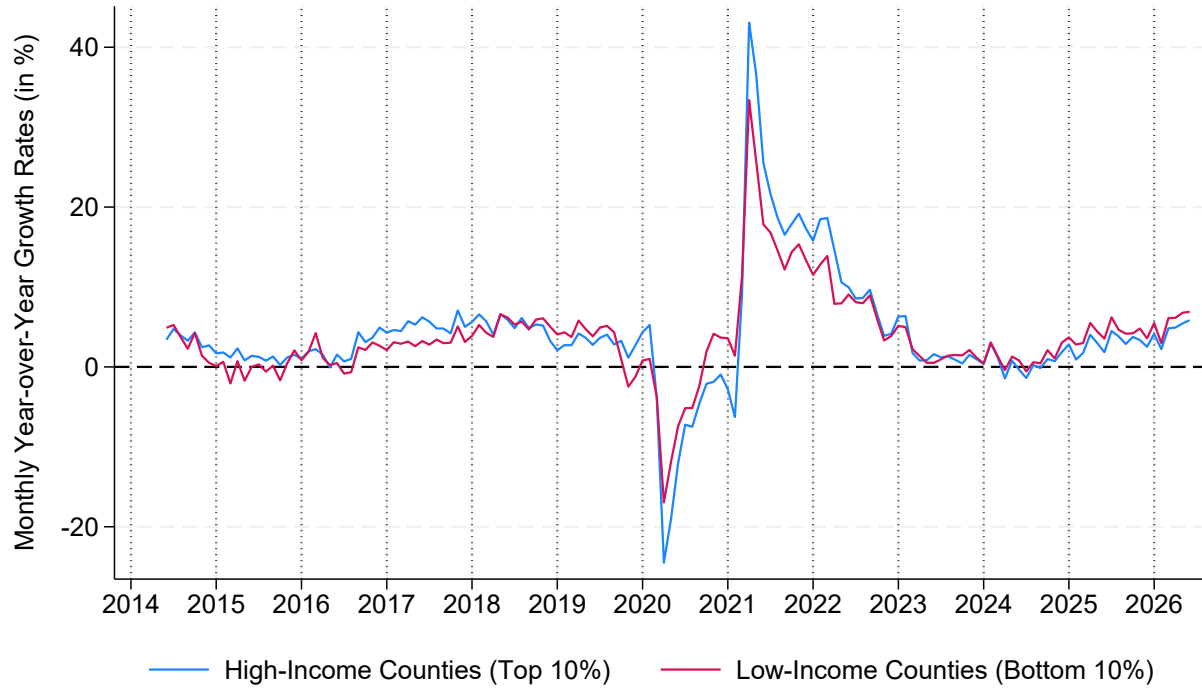


Figure A10: Share of Credit Card Transactions by Merchant Category

This figure plots the weighted share of credit card transactions by merchant category using transaction-level data from the 2024 Diary of Consumer Payment Choice.

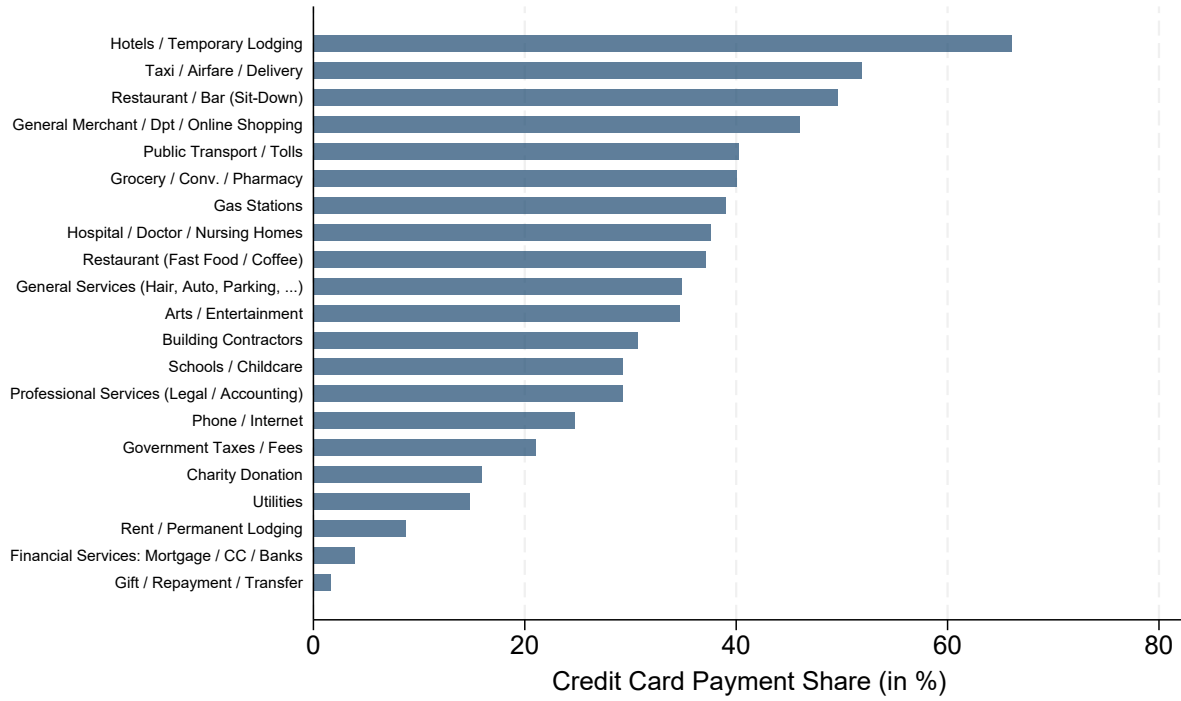
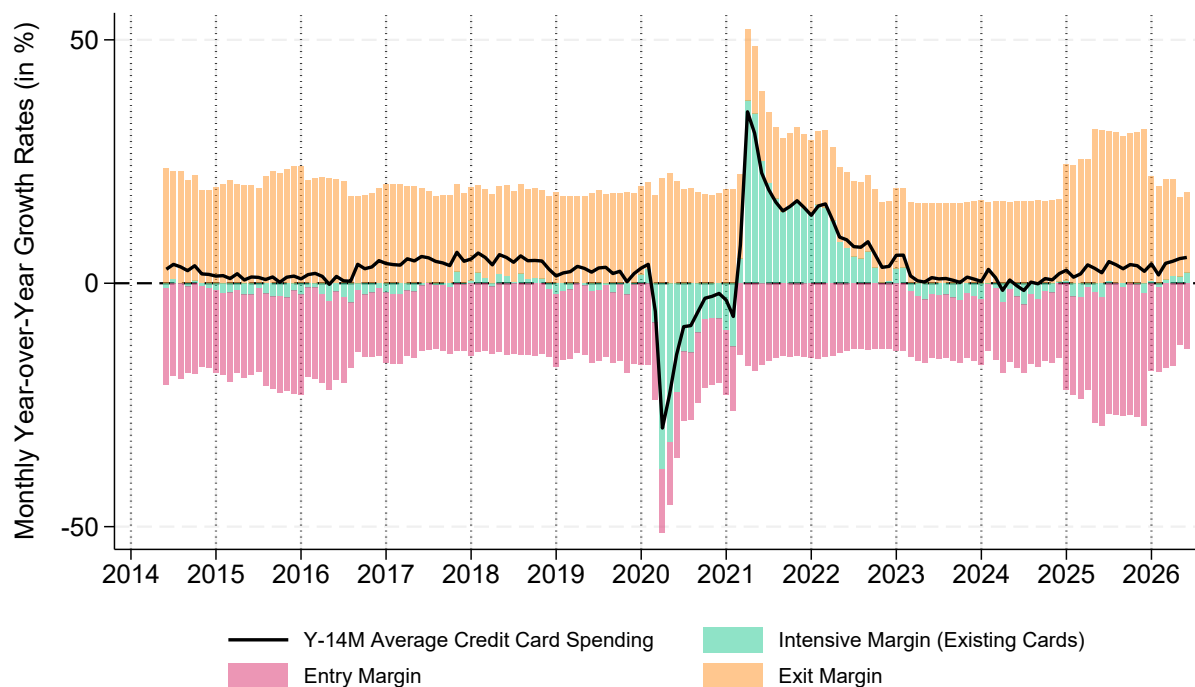


Figure A11: Decomposing Average Credit Card Spending Growth: Entry and Exit Margins

This figure plots monthly year-over-year growth in average credit card spending (solid black line) and its decomposition into an intensive margin among continuing cards (green bars), an entry margin due to cards entering the active set (red bars), and an exit margin due to cards exiting the active set (orange bars) from June 2014 to June 2026. Continuing cards have positive purchase volume in both the current month and the same month one year earlier. Entering cards have positive purchase volume in the current month but not one year earlier, while exiting cards have positive purchase volume one year earlier but not in the current month.



## A2 Additional Tables

Table A1: Benchmarking Monthly National Consumption: Total PCE

This table reports monthly national time-series regressions from June 2014 to June 2026. All variables are measured as monthly year-over-year growth rates. The dependent variable in all columns is total PCE growth, and the explanatory variable is average credit card (CC) spending growth. Column (1) uses the full sample. Column (2) excludes observations from March 2020 through March 2021, while Column (3) excludes observations from March 2020 through March 2022. Standard errors are reported in parentheses. \*\*\*, \*\*, and \* denote statistical significance at the 1, 5, and 10 percent levels, respectively.

|                      | $\Delta$ Total PCE |                                |                               |
|----------------------|--------------------|--------------------------------|-------------------------------|
|                      | Full Sample<br>(1) | Excl. COVID<br>(Narrow)<br>(2) | Excl. COVID<br>(Broad)<br>(3) |
| $\Delta$ CC Spending | 0.55***<br>(0.02)  | 0.52***<br>(0.02)              | 0.35***<br>(0.05)             |
| Adjusted $R^2$       | 0.87               | 0.84                           | 0.27                          |
| Observations         | 145                | 132                            | 120                           |

Table A2: Benchmarking Monthly National Consumption: Y-14M and HFIs

This table reports monthly national time-series regressions relating private-sector high-frequency indicators (HFIs) to Y-14M credit card (CC) spending. The dependent variables are spending measures from Fiserv, Numerator, Verisk Analytics, and Affinity Solutions. For Fiserv, Numerator, and Verisk Analytics, variables are measured as monthly year-over-year growth rates. For Affinity Solutions, both the HFI series and the Y-14M series are expressed as seasonally adjusted changes relative to January 2020. Standard errors are reported in parentheses. \*\*\*, \*\*, and \* denote statistical significance at the 1, 5, and 10 percent levels, respectively.

|                      | Fiserv            | Numerator         | Verisk            | Affinity          |
|----------------------|-------------------|-------------------|-------------------|-------------------|
| $\Delta$ CC Spending | 0.38***<br>(0.04) | 0.40***<br>(0.04) | 0.77***<br>(0.05) | 0.99***<br>(0.04) |
| Adjusted $R^2$       | 0.38              | 0.51              | 0.79              | 0.89              |
| Sample               | 2014m6–2025m1     | 2019m1–2025m12    | 2019m2–2024m1     | 2020m1–2026m6     |
| Observations         | 128               | 84                | 60                | 78                |