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 more than 3,000 U.S. counties since 2014. We first show that the data closely approximate traditional consumption measures, explaining 92 percent of the variation in monthly adjusted personal consumption expenditures (PCE) growth at the national level and 88 percent at the annual state level. We then exploit the high frequency and geographic granularity of the data to estimate heterogeneous consumption responses to monetary policy shocks across the county-level income distribution, an analysis infeasible with traditional data sources. We find that low-income counties exhibit substantially larger spending declines than high-income counties, consistent with predictions of heterogeneous agent New Keynesian models.

Keywords: Measurement and Data, Consumption, Credit Card Spending
JEL Codes: D12, E01, E21

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1 Introduction

Over the past decade, and especially since the COVID-19 pandemic, credit card spending data have become an increasingly used resource for studying macroeconomic consumption (Vavra, 2021). Compared to traditional data, such as personal consumption expenditures (PCE) from the Bureau of Economic Analysis (BEA) or Census Retail Sales data, credit card data offer several advantages. They are available at a higher frequency, greater granularity, and for a large sample size, allowing researchers to analyze heterogeneous consumption dynamics with greater statistical precision. As a result, a growing body of literature has leveraged credit card data to study macroeconomic consumption patterns (Mian et al., 2013; Ganong and Noel, 2019a; Chetty et al., 2024).

The use of credit card data, however, also comes with important caveats. Depending on the data source, credit card data may be subject to selection bias, as the customer bases of individual banks and financial services firms are not fully representative of the broader population (Chetty et al., 2024). Even among credit card users, some purchases—particularly big-ticket items such as cars—are typically financed through loans or paid via bank transfers, resulting in incomplete coverage of total consumption. Growth in credit card spending may also partly reflect shifts in payment behavior rather than changes in underlying consumption (Bayeh et al., 2025).

Our paper makes two contributions. First, we use data from the Federal Reserve's Y-14M reports to systematically benchmark credit card spending against traditional consumption measures, establishing its reliability (and limitations) as a proxy for consumption both in the time series and in the cross-section. Second, we introduce a novel monthly county-level consumption dataset and demonstrate its research value through an application to the heterogeneous transmission of monetary policy across the income distribution, an analysis that is infeasible with traditional consumption data.

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 from 20 banks over the period from 2014 to 2025, 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.[1]

We start by benchmarking monthly year-over-year growth in credit card spending against 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 non-profit sector, healthcare expenditures paid by insurance, and imputed rental equivalent consumption by households who own their homes. We call our baseline measure *adjusted PCE* and we discuss these adjustments, alongside robustness checks, in detail in Section 7.

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 further show that there are important differences across large PCE sub-categories over time. We then study the cross-section and benchmark annual credit card spending growth against annual PCE growth at the state level. We find that credit card spending growth approximates PCE growth reasonably well, both within individual states over time, as well as within individual years across states. Across all years and states, variation in credit card spending growth explains 88 percent of the variation in annual adjusted PCE growth at the state level.

Having established the reliability of credit card spending as a measure for consumption, 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 breaks this trade-off and enables us to track consumption at the county level on a monthly basis, a level of granularity unavailable in traditional data sources. We document that the county-level spending patterns align closely with well-documented economic developments: counties hit hardest in the early stages of the COVID-19 pandemic, such as those in the Northeast and the Bay Area, exhibit markedly sharper consumption declines in April 2020, while geographically proximate counties within the same metropolitan area track each other closely throughout the sample period. 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.

[1]Compared to other credit card datasets, our data has the disadvantage that we do not observe individual transactions but only month-end snapshots of overall spending volumes. We can therefore not distinguish between different spending categories. We discuss this limitation in Section 7.

Finally, we present a research application that demonstrates the value of county-level monthly consumption data for studying the transmission of monetary policy. 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 exhibits responses that are qualitatively consistent with those of PCE and retail sales—a gradual decline, a trough at medium horizons, and partial mean reversion—validating its use as a consumption proxy in dynamic settings.

We then exploit the geographic granularity of our novel dataset to do what existing consumption data cannot: estimate the heterogeneous effects of monetary policy on consumption across the U.S. income distribution at the county level and at monthly frequency. A large theoretical literature, anchored in heterogeneous agent New Keynesian models, predicts that monetary policy transmits more strongly to lower-income, liquidity-constrained households, yet direct empirical evidence at fine geographic resolution has been limited by data availability. Using our county-month panel, we show that low-income counties exhibit a substantially larger consumption decline following a contractionary shock than high-income counties, consistent with these predictions.

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 DFAST/CCAR 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. 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 2025. Finally, in each month, we only consider cards with nonzero purchase volume. This restriction avoids confounding actual consumption changes with shifts in spending across cards held by the same consumer.[2] This leaves us with a dataset of 140 to 247 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 either monthly year-over-year growth rates (datasets A and C) or annual growth rates (dataset B) in average credit card spending as:

$$\Delta\text{CC Spending}_t = \left(\frac{\frac{1}{N_t}\sum_{i=1}^{N_t} \text{CC Spending}_{i,t} - \frac{1}{N_{t-\tau}}\sum_{i=1}^{N_{t-\tau}} \text{CC Spending}_{i,t-\tau}}{\frac{1}{N_{t-\tau}}\sum_{i=1}^{N_{t-\tau}} \text{CC Spending}_{i,t-\tau}} \right) \times 100 \quad (1)$$

where i indexes individual cards; N_t is the number of active cards in period t; $\tau = 12$ for the monthly datasets and $\tau = 1$ for the annual dataset.

2.2 Personal Consumption Expenditure (PCE) Data

In order to validate that Y-14M credit card spending approximates consumption, we benchmark it against several national and state-level measures. Our primary benchmarks are national and state-level Personal Consumption Expenditures (PCE) data from the National Income and Product Accounts (NIPA) 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 non-profit 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, initial national PCE estimates are typically released about four weeks after the end of the reference month and are subject to revision as additional data become available. BEA also publishes estimates of PCE at the state level, reflecting

[2]We discuss all our sample construction decisions in more detail in Section 7.

spending by households and non-profits residing in each U.S. state.[3]

Both national and state-level PCE include components that are not true out-of-pocket expenditures by households, such as spending by the non-profit 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. We therefore exclude these components from our baseline measure and refer to the resulting aggregate as *Adjusted PCE*.

2.3 Census Retail Sales Data

Another benchmark we utilize is Census Retail Sales Data, one of the many sources employed by 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 (MRTS). 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.

3 Descriptive Statistics

Table 1 reports summary statistics for our datasets at the monthly national level (Panel A), the annual state level (Panel B), and the monthly county level (Panel C). The 136 monthly observations in Panel A span roughly 11 years of data; the 510 state-year observations in Panel B correspond to about 10 years across 51 states (including the District of Columbia); and the 444,066 county-month observations in Panel C cover more than 3,000 counties over approximately the same period. The national-level data (Panel A) cover, on average, about 190 million credit cards from 13 banks per month; the state-level data (Panel B) about 3.5 million credit cards from 13 banks per state and year; and the county-level data (Panel C) about 59 thousand credit cards from 8 to 13 banks per county and month. While all 13 banks are represented in the national and state-level data, bank coverage at the county level varies, but the smallest counties are still covered by at least 8 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 PCE growth and monthly year-over-year retail sales growth, a pattern that also holds for annual credit card spending growth relative to annual PCE growth at the state level (Panel B). Credit card spending growth also exhibits

[3]Details on the construction of National PCE are available here and details on State PCE here.

Table 1: Descriptive Statistics

This table provides summary statistics for the sample using data at the monthly national level (Panel A), the annual state level (Panel B), and the monthly county level(Panel C).

	Obs.	Mean	Median	p(1)	p(99)
Panel A. Monthly National Level.					
Number of Cards (in m)	136	189.52	184.91	142.43	243.45
Number of Banks	136	13	13	13	13
Monthly YoY CC Spending Growth (in %)	136	3.65	2.81	-20.44	36.12
Monthly YoY PCE Growth (in %)	136	5.34	4.23	-13.15	29.39
Monthly YoY Retail Sales Growth (in %)	136	5.16	3.88	-6.20	28.88
Panel B. Annual State Level.					
Number of Cards (in m)	510	3.50	1.96	0.27	30.42
Number of Banks	510	13	13	13	13
Annual YoY CC Spending Growth (in %)	510	3.86	2.61	-8.62	18.26
PCE Growth (in %)	510	5.08	3.93	-7.46	23.05
Panel C. Monthly County Level.					
Number of Cards (in k)	444,066	59.13	9.35	0.364	891.75
Number of Banks	444,066	11.60	12	8	13
Monthly YoY CC Spending Growth (in %)	444,066	3.99	3.10	-15.94	31.49

greater volatility than PCE growth: the 1st percentile of monthly credit card spending growth is -20.4 percent compared to -13.2 percent for PCE, and the 99th percentile is 36.1 percent compared to 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 will show in the next section, credit card spending growth closely tracks the time-series movement of both PCE growth and retail sales growth.

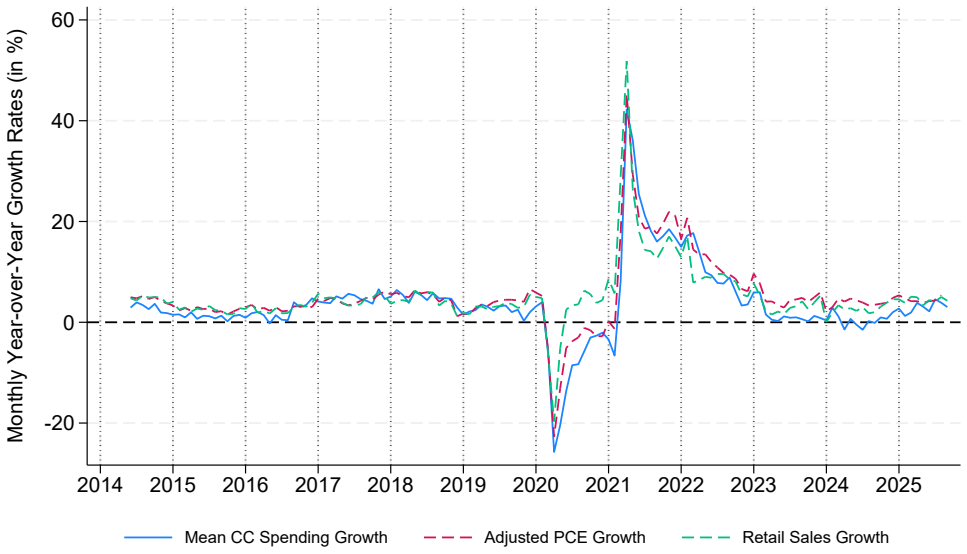
4 Benchmarking Against Traditional Consumption Data

4.1 Time Series Evidence: Monthly National Data

Figure 1 plots monthly year-over-year growth rates in credit card spending (solid blue line) alongside monthly year-over-year growth rates in PCE (dashed red line) and retail sales (dashed green line). Credit card spending closely tracks both traditional consumption measures over time, including during both relatively stable periods and the extraordinary circumstances of the COVID-19 pandemic. While average credit card spending growth was marginally lower than PCE and retail sales growth from 2014 to 2016, the three series exhibit very similar dynamics in the years leading up to the pandemic from 2016 to 2020.

Figure 1: Monthly Year-over-Year Consumption Growth

This figure plots monthly year-over-year growth rates in mean credit card spending (solid blue line), adjusted personal consumption expenditures (PCE; dashed red line), and retail sales (dashed green line) from 2014 to 2025.



Importantly, the sharp decline in credit card spending at the onset of the COVID-19 pandemic closely mirrors the declines in 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 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 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 PCE and retail sales growth, before the three series converge once more by 2025.

Table 2 reports results from simple time-series regressions of monthly year-over-year PCE growth and retail sales growth on credit card spending growth. As shown in Column (1), credit card spending growth is strongly correlated with PCE growth, yielding an R^2 of 0.92. The slope coefficient of 0.88 indicates that a one percentage point increase in credit card spending growth is associated with a 0.88 percentage point increase in PCE growth, consistent with credit card spending being a more volatile proxy for consumption. Notably, credit card spending growth explains more of the variation in PCE growth than retail sales growth does (Column 2, $R^2 = 0.84$). Column (3) shows that credit card spending growth

Table 2: Time-Series Regressions: Consumption Growth on Credit Card Spending Growth

This table reports results from simple time-series regressions estimated at the monthly national level. All variables are measured as monthly year-over-year growth rates. Column (1) reports a regression of PCE growth on growth in average credit card spending; Column (2) reports a regression of PCE growth on retail sales growth; and Column (3) reports a regression of retail sales growth on growth in average credit card spending.

	Δ PCE		Δ Retail Sales
	(1)	(2)	(3)
Δ CC Spending	0.88***		0.70***
	(0.02)		(0.04)
Δ Retail Sales		1.00***	
		(0.04)	
R^2	0.92	0.84	0.71
Observations	135	135	136

is also strongly correlated with retail sales growth, although less so than with PCE growth. Taken together, Figure 1 and Table 2 indicate that credit card spending provides a close approximation to traditional measures of consumption at the monthly national level.

4.2 Credit Card Spending versus PCE Subcategories

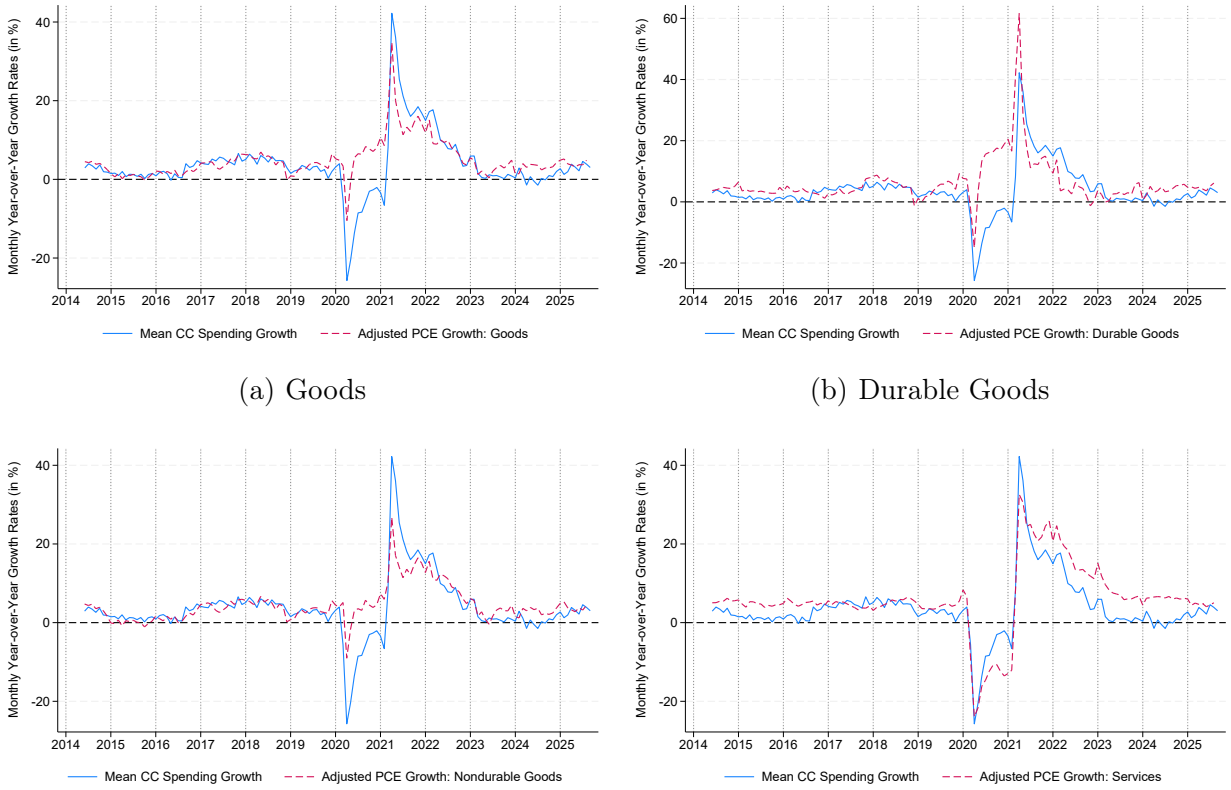
One limitation of the Y-14M data is that we do not observe the specific goods and services purchased with credit cards. To assess how this limitation affects our benchmarking, Figure 2 compares monthly year-over-year growth rates in credit card spending against growth rates of major PCE subcategories: total goods (Panel a), durable goods (Panel b), nondurable goods (Panel c), and services (Panel d).

During normal times, credit card spending growth tracks nondurable goods expenditure growth most closely (Panel c), consistent with the fact that everyday purchases such as groceries, gas, and dining are frequently paid for by credit card. The fit with total goods (Panel a) and durable goods (Panel b) is also strong during this period, while services expenditure growth (Panel d) tends to run above credit card spending growth in the pre-pandemic period.

The COVID-19 pandemic reveals important differences across categories. Credit card spending declined more sharply than goods expenditures and roughly in line with services expenditures, consistent with the well-documented shift from services to goods consumption during lockdowns (Chetty et al., 2024). The subsequent recovery further highlights these divergences: goods expenditures surged dramatically in 2021 — particularly durables, which

Figure 2: Credit Card Spending versus PCE Subcategories

This figure plots monthly year-over-year growth rates in mean credit card spending (solid blue line) and in PCE subcategories (dashed red line) from 2014 to 2025. Panel (A) shows total goods, Panel (B) durable goods, Panel (C) nondurable goods, and Panel (D) services.



(a) Goods

(b) Durable Goods

(c) Nondurable Goods

(d) Services

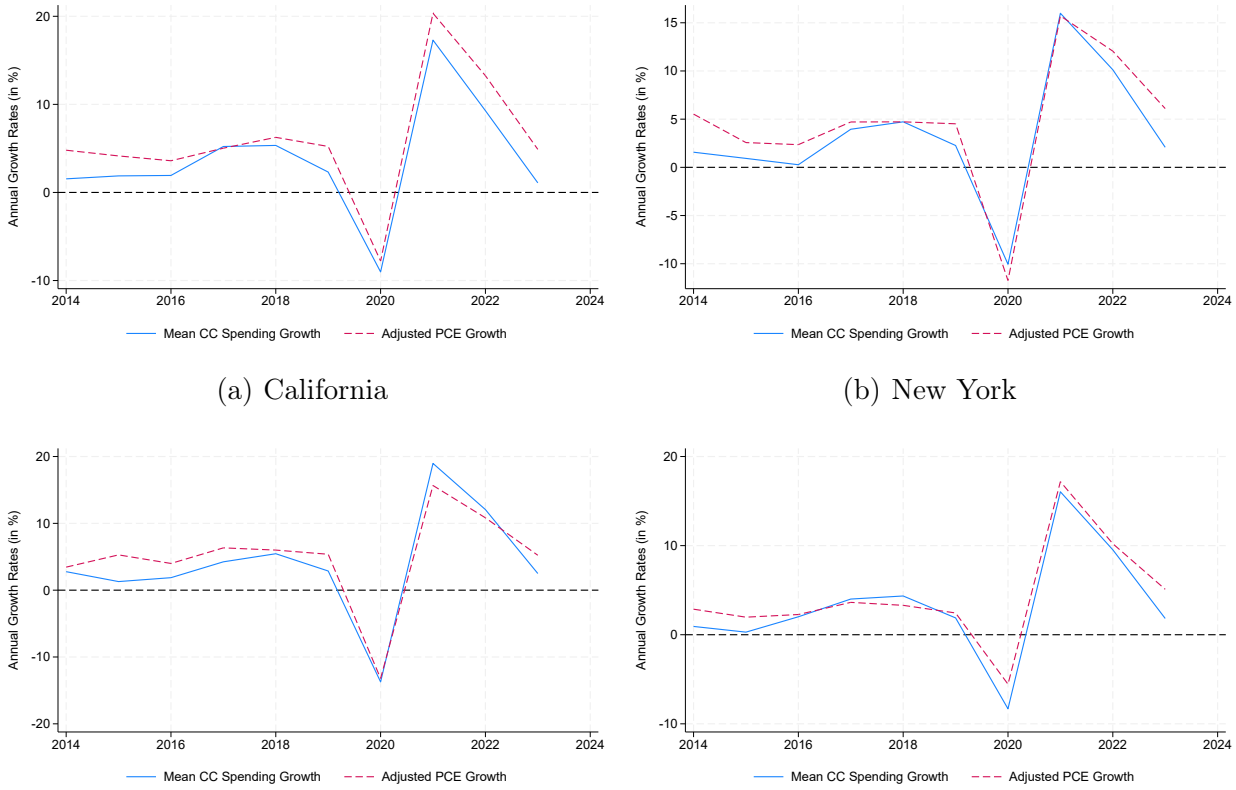
exceeded 100 percent year-over-year growth — while credit card spending growth, though elevated, remained closer to the nondurable goods and services trajectories. In more recent years, credit card spending growth provides a good approximation to goods expenditure growth, while services expenditure growth has been notably stronger. Because our credit card data are not observed at the transaction level, we cannot decompose these shifts in consumption patterns across goods and services categories directly.

4.3 Cross-Sectional Evidence: Annual State-Level Data

We next show that credit card spending closely tracks consumption not only at the national level, but also across states. Because state-level PCE data are available only at an annual frequency, we benchmark annual growth in credit card spending against annual state-level

Figure 3: Annual State-Level Consumption Growth

This figure plots annual year-over-year growth rates in average credit card spending (solid blue lines) and in adjusted personal consumption expenditures (PCE; dashed red lines) in California (Panel A), New York (Panel B), Washington, DC (Panel C), and Maryland (Panel D).



(a) California

(b) New York

(c) Washington, DC

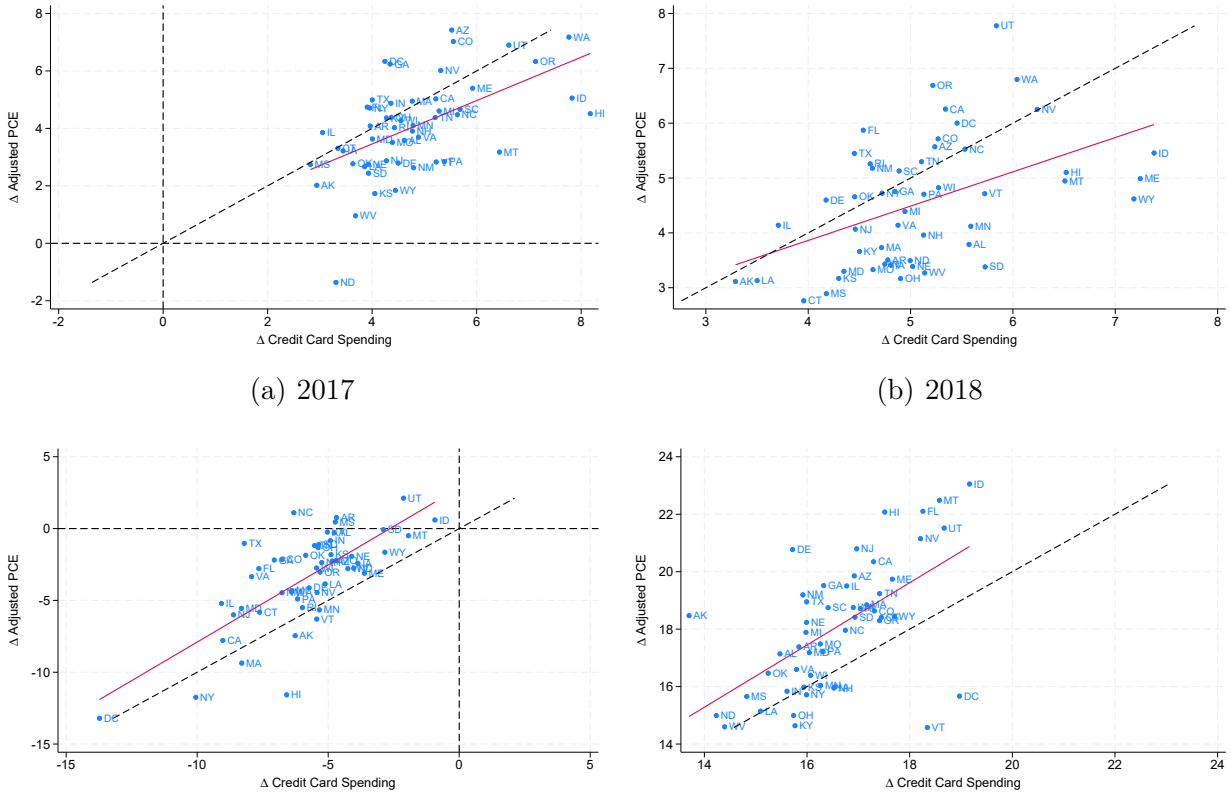
(d) Maryland

PCE growth. Figure 3 plots annual growth rates of credit card spending (solid blue lines) alongside annual adjusted PCE growth (dashed red lines) for four selected states: California, New York, Washington, DC, and Maryland. Although credit card spending growth is modestly lower than adjusted PCE growth early in the sample (2014-2016), the two series track each other closely from 2016 onward. Importantly, in each state, credit card spending closely mirrors both the sharp contraction in consumption in 2020 and the subsequent recovery. Washington, DC exhibits the sharpest decline among the four states, yet credit card spending continues to track adjusted PCE growth closely even in this extreme case.

Figure 4 presents scatter plots illustrating the cross-sectional relationship between annual credit card spending growth and annual adjusted PCE growth across states in four selected years: 2017, 2018, 2020, and 2021. The solid red line denotes the estimated regression line, while the dashed black line corresponds to the 45-degree line representing a one-to-

Figure 4: Annual CC Spending vs. PCE Growth: State-Level Cross-Section

This figure plots the annual rates in average credit card spending against the annual growth rates in adjusted personal consumption expenditures (PCE) at the state level for the years 2017 (Panel A), 2018 (Panel B), 2020 (Panel C), and 2021 (Panel D).



(a) 2017 (b) 2018

(c) 2020 (d) 2021

one relationship between the two measures. Although some dispersion remains, credit card spending growth and adjusted PCE growth exhibit a strong positive association across states in each year. Notably, in 2020 and 2021, the regression line closely parallels the 45-degree line, with estimated slope coefficients near unity. This indicates that the cross-sectional variation in credit card spending growth maps nearly one-to-one onto the cross-sectional variation in adjusted PCE growth during the extraordinary circumstances of the pandemic.

As shown in Table 3, this cross-sectional relationship is statistically significant both when pooling observations across years and when estimated separately within individual years. Pooling all years, the slope coefficient is 0.94 with an R^2 of 0.88, indicating that variation in credit card spending growth explains the vast majority of the cross-sectional variation in adjusted PCE growth at the state level. The relationship is weaker in 2019, 2022, and 2023, where the estimated coefficients are not statistically significant. Taken together, the

Table 3: Annual CC Spending vs. PCE Growth: State-Level Cross-Section

This table shows the results of a state-level regression of monthly year-over-year PCE growth on monthly year-over-year growth in average credit card spending for the full sample and within each year. Robust standard error are reported in parentheses.

	Δ PCE Index				
	All Years	2015	2016	2017	2018
Δ CC Spending	0.94***	0.53***	0.67**	0.75***	0.63***
	(0.02)	(0.18)	(0.27)	(0.18)	(0.15)
R^2	0.88	0.14	0.23	0.30	0.22
Observations	510	51	51	51	51
	2019	2020	2021	2022	2023
Δ CC Spending	-0.07	1.07***	1.08***	0.26*	0.19
	(0.17)	(0.13)	(0.31)	(0.15)	(0.13)
R^2	0.00	0.52	0.34	0.04	0.04
Observations	51	51	51	51	51

combined results in Figures 3 and 4 and Tables 3 indicates that credit card spending provides a close approximation to traditional measures of consumption not only in the time series, but also in the state-level cross section.

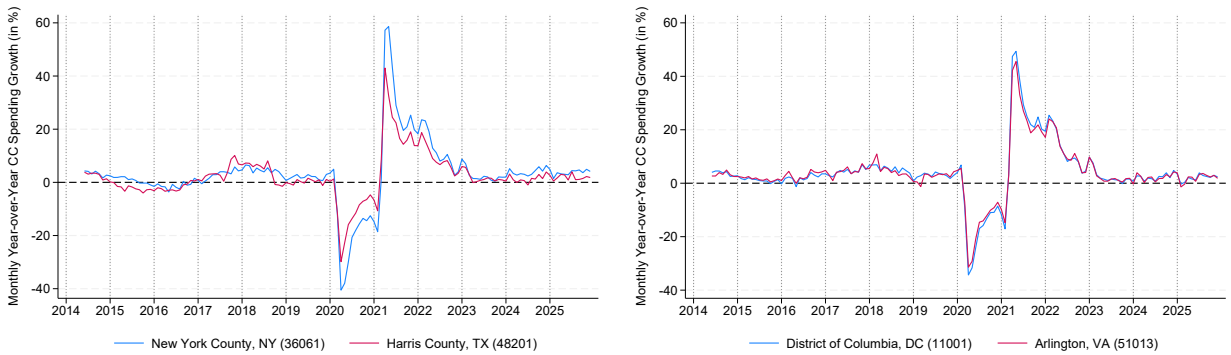
5 Beyond Benchmarking: A New Monthly County-Level Consumption Dataset

Traditional consumption measures, such as PCE, are available either at high frequency but with limited geographic detail (monthly national PCE) or at finer geographic disaggregation but at lower frequency (annual state-level PCE). In this section, we move beyond these limitations by introducing a newly constructed, high-frequency, geographically granular credit card spending dataset that allows us to track consumption at the county level on a monthly basis.

Figure 5 plots monthly growth rates of credit card spending for four selected counties. Panel (a) compares spending growth in New York County, NY (blue line) and Harris County, TX (red line). 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 (blue line) and Arlington County, VA (red line), two neighboring

Figure 5: Monthly County-Level Credit Card Spending Growth

This figure plots monthly year-over-year growth rates in average credit card spending for four selected counties. 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

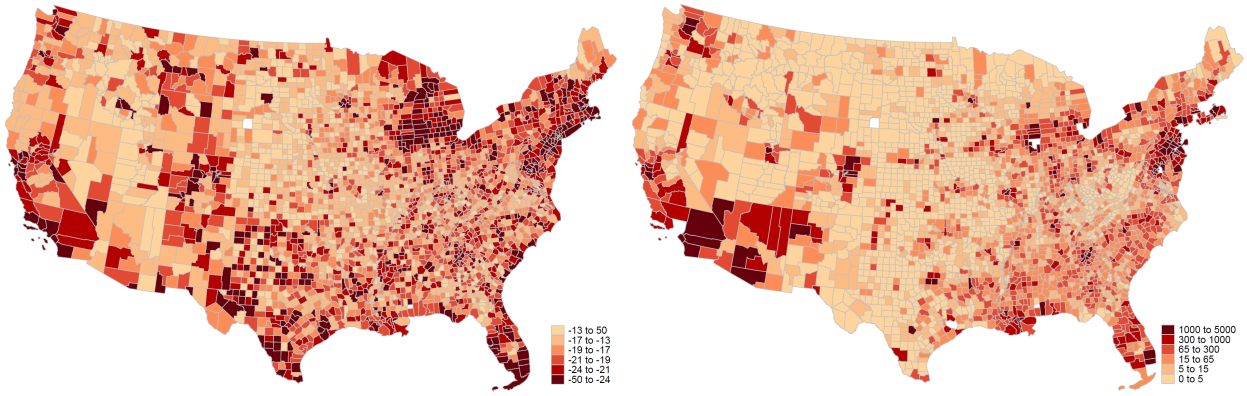
counties within the Washington metropolitan area. Reflecting their shared economic environment, the two counties exhibit nearly identical spending growth rates throughout the sample period. Overall, the county-level credit card spending data reveal granular consumption dynamics that align closely with well-documented economic developments.

To illustrate the geographic breadth of the dataset, Figure 6 presents county-level maps of credit card spending growth (Panel a) and new COVID-19 cases per 100,000 residents (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 the highest concentration of early COVID-19 cases—particularly in the Northeast, the Bay Area, and South Florida—also 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 as of 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 between pandemic intensity and consumption is consistent with evidence that local COVID-19 severity strongly influenced consumer spending during this period (Chetty et al., 2024).

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 the next section, we present one such application: studying the

Figure 6: Monthly Mean CC Spending Growth by County as of April 2020

This figure plots county-level average credit card spending growth in April 2020, the first full month of the COVID-19 pandemic. Lighter colors indicate more negative growth rates, while darker colors indicate less negative (or positive) growth rates.



(a) CC Spending Growth

(b) New COVID Cases per 100k

heterogeneous transmission of monetary policy to consumption across the income distribution.

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. 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. 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 Personal Consumption Expenditures (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:

$$y_{i,t} = \ln\left(\frac{C_{i,t}}{\text{PCEPI}_t/100}\right) \tag{2}$$

where $C_{i,t}$ denotes nominal consumption in geographical unit i in period t. We use PCEPI rather than CPI because it is purpose-built for deflating personal consumption expenditures, employs chain-weighting to better account for substitution across consumption categories, and exhibits less volatility than CPI.

Monetary policy shock We use high-frequency identification (HFI) to measure monetary policy shocks, following the approach of Jarociński and Karadi (2020). Specifically, we use the median monetary policy surprise across Fed Funds futures contracts in a narrow window around FOMC announcements. 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. This normalization is achieved by regressing changes in the Federal Funds Rate on the raw shock and rescaling accordingly.

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

$$y_{i,t+h} - y_{i,t} = \beta_h \cdot \text{shock}_t + \Gamma'(L)X_{i,t} + \alpha_i + \varepsilon_{i,t+h} \tag{3}$$

where $y_{i,t+h} - y_{i,t}$ denotes the cumulative log change in real consumption from period t to horizon h, 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, the dependent variable, and macroeconomic indicators), and α_i captures fixed effects. The coefficient of interest, β_h, traces out the impulse response function at each horizon h. We implement equation (3) at three levels of aggregation. At the monthly national level, we estimate:

$$y_{t+h} - y_t = \beta_h \cdot \text{shock}_t + \sum_{j=0}^{p} \gamma_j \cdot \text{shock}_{t-j} + \sum_{j=1}^{p} \delta_j \cdot y_{t-j} + \phi \cdot \mathbf{1}_{\text{COVID}} + \alpha_m + \varepsilon_{t+h} \tag{4}$$

with $p = 2$ lags, month-of-year fixed effects α_m to control for seasonality, and standard errors clustered by date. At the state-year level, we estimate:

$$y_{s,t+h} - y_{s,t} = \beta_h \cdot \text{shock}_t + \sum_{j=0}^{p} \gamma_j \cdot \text{shock}_{t-j} + \sum_{j=1}^{p} \delta_j \cdot y_{s,t-j} + \theta' W_{s,t} + \alpha_s + \varepsilon_{s,t+h} \tag{5}$$

with $p = 1$ lag, state fixed effects α_s, controls $W_{s,t}$ for unemployment and inflation, 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 through cross-sectional variation in consumption levels.[4] Finally, at the county-month level, we estimate:

$$y_{c,t+h} - y_{c,t} = \beta_h \cdot \text{shock}_t + \sum_{j=0}^{p} \gamma_j \cdot \text{shock}_{t-j} + \sum_{j=1}^{p} \delta_j \cdot y_{c,t-j} + \theta' W_{c,t} + \alpha_c + \alpha_m + \varepsilon_{c,t+h} \quad (6)$$

with county fixed effects α_c, month-of-year fixed effects α_m, and controls $W_{c,t}$ includes national unemployment, inflation, county-level log house prices, and county-level log income. Because the monetary policy shock varies only at the national level, identification exploits time-series variation in 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. Following Schorfheide and Song (2024), we 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. For the monthly specifications, we additionally include a COVID indicator variable spanning March 2020 through June 2022 to absorb residual level shifts associated with fiscal stimulus and the subsequent normalization period.

6.2 Benchmarking: Monthly National and Annual State-Level

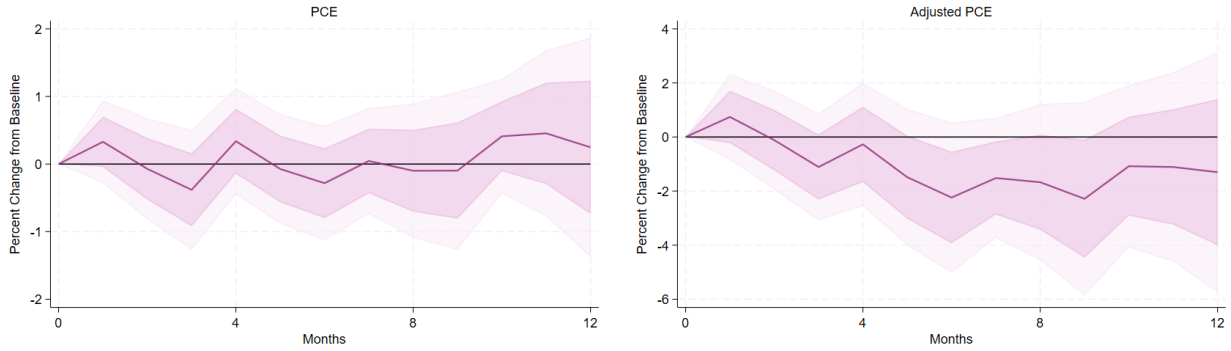
We begin by benchmarking the impulse response of credit card spending against those of traditional consumption measures at the national and state level, assessing whether credit card spending tracks not only the levels and growth rates documented in Section 4, but also the dynamic response of consumption to economic shocks.

Monthly National Results: Figure 7 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 fixed effects, two lags of the shock and the dependent variable, and a COVID indicator spanning

[4] 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.

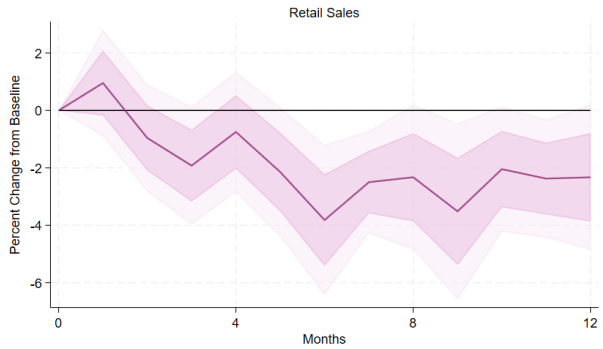
Figure 7: Monthly National Response to Monetary Policy Shocks

This figure displays impulse responses of consumption measures to a 25 basis point contractionary monetary policy shock, estimated using monthly national data (2014-2025) with local projections. The upper panels show real PCE (deflated by PCE price index) and real adjusted PCE, and the lower panels show real retail sales and real credit card spending. The dependent variable is the cumulative log change from the shock month. All specifications include month fixed effects, two lags of the shock and dependent variable, and a COVID indicator (March 2020–June 2022), with standard errors clustered by date. The shaded regions represent 68% (darker) and 90% (lighter) confidence intervals.

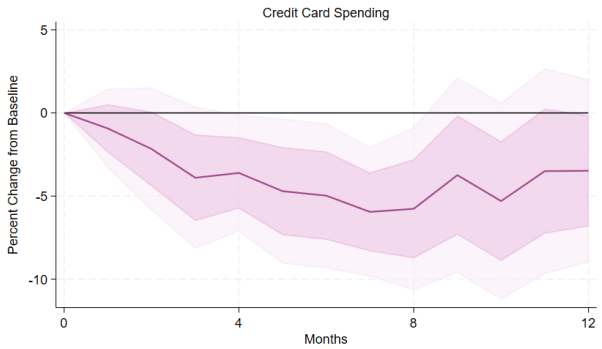


(a) PCE

(b) Adjusted PCE



(c) Retail Sales



(d) Credit Card Spending

March 2020 to June 2022, with standard errors clustered by date.

Three of the four consumption measures exhibit a clear contractionary response, with credit card spending showing the largest and most precisely estimated decline. Credit card spending falls gradually over the first eight months, reaching a trough of approximately -5% to -6%, before partially recovering toward -3% by month 12. Retail sales display a similar pattern, declining roughly 3% to 4% by month 6 and stabilizing thereafter, though with somewhat greater volatility. Adjusted PCE shows a more moderate response, falling approximately 2% by month 6 before mean-reverting toward -1% by the end of the horizon.

In contrast, aggregate PCE exhibits a muted response that oscillates around zero throughout the 12-month horizon. This stark difference reflects the composition of total PCE. In particular, total PCE includes housing costs (primarily owners' equivalent rent) which comprise approximately 15-20% of aggregate consumption and adjust sluggishly to monetary policy due to long-term lease contracts and the mechanical smoothing inherent in imputed rent measures. When this sticky component is excluded (Adjusted PCE), the consumption response becomes visible and statistically significant.

The ordering of magnitudes is consistent with economic theory. Credit card purchases disproportionately capture discretionary, interest-sensitive expenditures such as dining, travel, and retail goods, which households can readily postpone or reduce in response to tighter financial conditions. This amplified sensitivity makes credit card spending a particularly useful measure for detecting monetary policy transmission to household consumption, even when aggregate measures appear unresponsive.

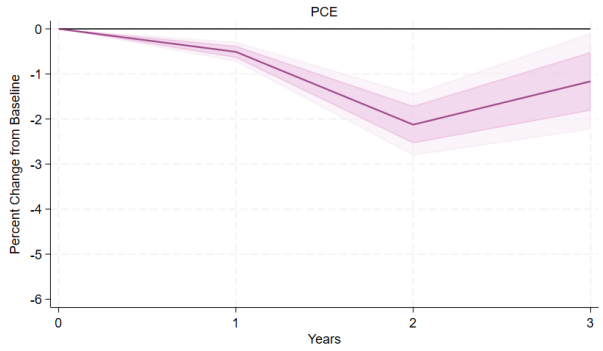
Annual State-Level Results: Figure 8 displays the impulse responses of three consumption measures to a 25 basis point contractionary monetary policy shock, estimated using state-year panel data from 2014 to 2025. The specification includes state fixed effects, one lag of the shock and the dependent variable, and controls for unemployment and inflation, with standard errors two-way clustered by state and year. The monetary policy shock is aggregated from monthly high-frequency surprises to annual frequency. The identification exploits time-series variation in the national monetary policy shock, with the state panel structure providing additional statistical power through cross-sectional variation in consumption levels. Because the specification includes state but not year fixed effects, the estimated coefficients reflect the average consumption response across all states to changes in monetary policy over time, controlling for time-invariant state characteristics such as industry composition, demographics, and baseline consumption levels.

All three measures exhibit a strikingly similar response pattern: an initial decline in year 1, a pronounced trough in year 2, followed by partial recovery in year 3. This consistent dynamic across different consumption measures provides strong evidence of a common monetary transmission mechanism operating at horizons beyond the immediate impact period. This consistent dynamic further validates credit card spending as a proxy for consumption in dynamic settings, confirming that it tracks not only the levels and growth rates documented earlier, but also the impulse response to economic shocks.

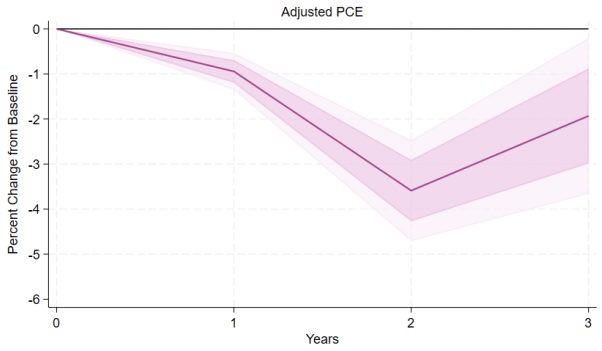
Notably, unlike at the national monthly level where total PCE was essentially unresponsive, all three measures, including total PCE, exhibit a clear contractionary response at the state-year level, likely reflecting the additional statistical power provided by the panel di-

Figure 8: State-Year Panel Response to Monetary Policy Shocks

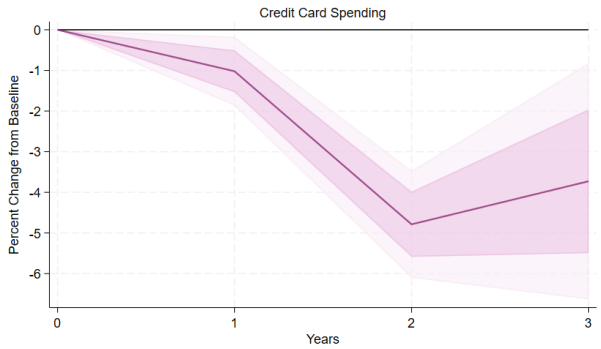
This figure displays impulse responses of consumption measures to a 25 basis point contractionary monetary policy shock, estimated using state-year panel data (2014-2025) with local projections. The upper panels show real PCE (deflated by PCE price index) and the real adjusted PCE measure, and the bottom panel shows real credit card spending. The dependent variable is the cumulative log change from the shock year. All specifications include state fixed effects, one lag of the shock and dependent variable, and controls for unemployment and inflation, with standard errors two-way clustered by state and year. The shaded regions represent 68% (darker) and 90% (lighter) confidence intervals.



(a) PCE



(b) Adjusted PCE



(c) Credit Card Spending

mension. The magnitudes, however, differ substantially. Credit card spending shows the largest sensitivity, declining approximately 1% in year 1 and reaching a peak contraction of 5% in year 2 before recovering to -4% by year 3. Adjusted PCE exhibits an intermediate response, falling 1% initially and bottoming at -3.5% in year 2. Total PCE displays the most muted reaction, with roughly half the magnitude of adjusted PCE throughout the response path (-0.5% in year 1, -2% at the trough, -1% by year 3).

The amplified response of credit card spending relative to aggregate consumption reflects that credit card purchases capture discretionary, interest-sensitive expenditures by liquidity-

constrained households, making them more responsive to monetary policy through both the interest rate and credit channels. The progressively wider confidence bands at longer horizons reflect increased uncertainty about the persistence of monetary policy effects and the relatively short sample period.

6.3 Beyond Benchmarking: Monthly County-Level

We now turn to the county-month level, where the Y-14M data offer a unique advantage: the ability to track consumption at a level of geographic and temporal granularity unavailable in traditional data sources. 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 9 displays the impulse response of county-level credit card spending to a 25 basis point contractionary monetary policy shock. The response closely mirrors the national estimate: spending declines monotonically over the first eight months, reaching a trough of approximately -7% to -8% before partially recovering by month 12. The precision of the county estimates is higher than the national counterpart, reflecting the large cross-sectional dimension of the panel.

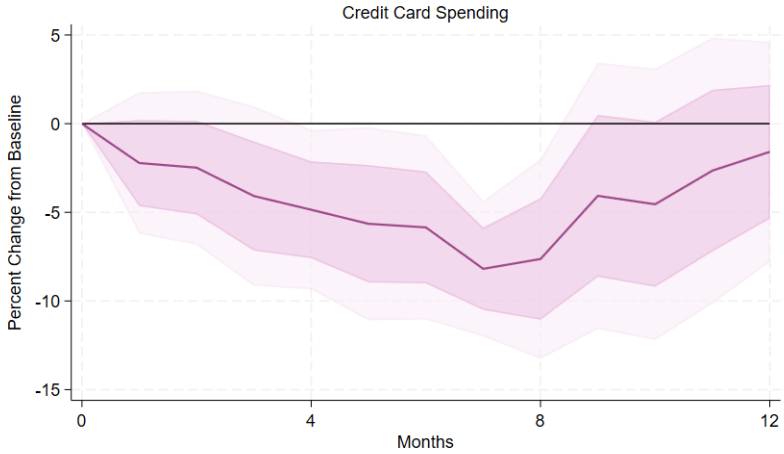
Heterogeneity by County Income. We next examine whether the transmission of monetary policy to consumption differs systematically across the income distribution. We split counties into above- and below-median groups based on their time-averaged IRS income, a classification that is highly stable over time: 91% of counties retain the same classification whether income is measured in 2013 or averaged over the full sample period. We estimate equation (6) augmented with a full interaction between the monetary policy shock and an indicator for above-median income counties:

$$\begin{aligned} y_{c,t+h} - y_{c,t} = \beta_h^{\text{low}} \cdot \text{shock}_t + \beta_h^{\Delta} \cdot \text{shock}_t \times \mathbf{1}[\text{High Income}_c] \\ + \mathbf{1}[\text{High Income}_c] + \Gamma'(L) X_{c,t} + \alpha_c + \alpha_m + \varepsilon_{c,t+h} \end{aligned} \tag{7}$$

where β_h^{low} captures the response of low-income counties and $\beta_h^{\Delta} = \beta_h^{\text{high}} - \beta_h^{\text{low}}$ identifies the differential response, with standard errors for β_h^{Δ} obtained directly from the interaction term rather than from separate regressions, thereby correctly accounting for the covariance

Figure 9: Monthly County-Level Response to Monetary Policy Shocks

This figure displays the impulse response of county-level credit card spending to a 25 basis point contractionary monetary policy shock, estimated using monthly county panel data (2014-2025) with local projections. The dependent variable is the cumulative log change in real credit card spending from the shock month. The specification includes county and month-of-year fixed effects, two lags of the shock and dependent variable, controls for unemployment, inflation, county-level house prices, and county-level income, 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% (darker) and 90% (lighter) confidence intervals.



(a) Credit Card Spending

between the two group estimators.[5]

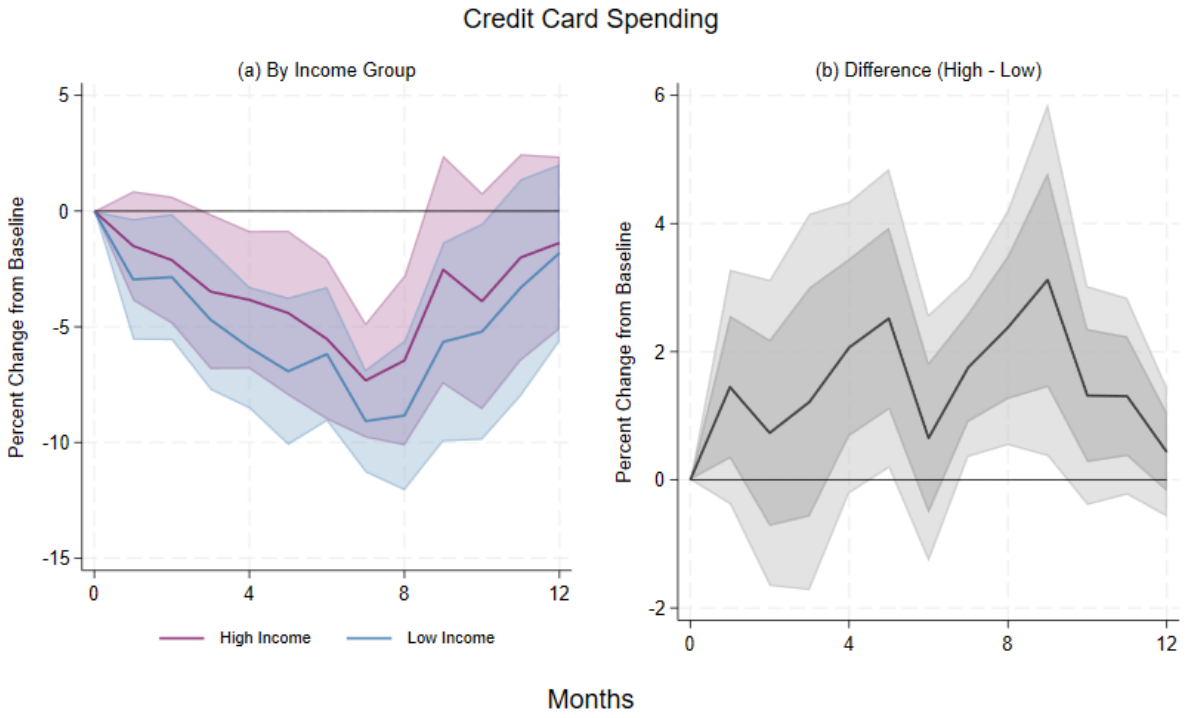
Figure 10 presents the results. Panel (a) shows that both groups exhibit a significant contractionary response, but the magnitude differs substantially: low-income counties decline by approximately -9% at the trough, compared to -7% for high-income counties. Panel (b) shows the difference $\hat{\beta}_h^{\Delta}$, which is positive throughout—high-income counties are less responsive—and statistically distinguishable from zero at the 68% level over most of the horizon, though the 90% confidence band includes zero at some months.

These findings are consistent with the predictions of heterogeneous agent New Keynesian (HANK) models (Kaplan et al., 2018). In these frameworks, monetary policy transmission operates disproportionately through households with low liquid wealth who are unable to

[5]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 10: Monthly County-Level Response to Monetary Policy Shocks, by Income Group

This figure displays impulse responses of county-level credit card spending to a 25 basis point contractionary monetary policy shock, estimated separately for above- and below-median income counties using monthly county panel data (2014-2025). Counties are classified by their time-averaged IRS income relative to the cross-sectional median. Panel (a) shows the impulse responses for high- and low-income counties estimated from a single regression with a full interaction between the shock and the income indicator. Panel (b) shows the difference (high minus low), with standard errors obtained directly from the interaction term. All specifications include county and month-of-year fixed effects, two lags of the shock and dependent variable, controls for unemployment, inflation, county-level house prices, and county-level income, 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% (darker) and 90% (lighter) confidence intervals.



smooth consumption in response to income or interest rate shocks. A key insight of Kaplan et al. (2014) is that a substantial share of households are "wealthy hand-to-mouth" as they hold illiquid wealth but have negligible liquid buffers, making their consumption highly sensitive to current income fluctuations. Low-income counties proxy for a higher concentration of both hand-to-mouth and wealthy hand-to-mouth households, and therefore exhibit amplified responses to contractionary monetary policy through both the direct interest rate channel and the indirect general equilibrium channel operating via labor income (Kaplan et al., 2018). We note that county-level income is an imperfect proxy for household-level

liquidity constraints: there is substantial within-county heterogeneity in wealth and income that our estimates average over, and the true degree of amplification among the most constrained households likely exceeds what we document at the county level. The persistence of the differential response through month 8 is further consistent with buffer-stock saving behavior (Carroll, 1997): lower-income households maintain smaller precautionary buffers relative to their income, and empirical evidence confirms that their consumption responds more sharply and persistently to adverse income shocks as these buffers are depleted (Ganong and Noel, 2019b). Higher-income households, by contrast, can draw down larger liquid reserves to smooth consumption, dampening the impact of tighter monetary conditions over the medium term.

Documenting these patterns requires the geographic and temporal granularity of the Y-14M data. Standard consumption measures are available only at the national or state level and at quarterly or annual 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.

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 gradual decline following contractionary monetary policy, a trough at medium horizons, and partial mean reversion thereafter. The key difference lies in magnitude—credit card spending responds approximately twice as strongly as adjusted PCE and three to four times as strongly as total PCE. Rather than undermining the validity of credit card data, this amplification reflects exactly what theory predicts: credit card transactions disproportionately capture discretionary, interest-sensitive, and postponable expenditures that represent the margin of adjustment for household consumption.

At the county level, the Y-14M data allow us to go further. Standard consumption measures are not available at both a sufficiently high frequency and sufficiently granular geographic disaggregation, 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. Our finding that low-income counties exhibit a substantially larger consumption decline following contractionary monetary policy is consistent with the predictions of HANK models and represents, to our knowledge, the first such estimate at the county level. To-

gether, these results suggest that credit card spending not only approximates consumption in levels, growth rates, and dynamic responses to shocks, but also opens the door to research designs that existing data cannot support.

7 A Researcher's Guide: Caveats and Best Practices

7.1 Caveat: Purchase Volume Data versus Transaction-Level Data

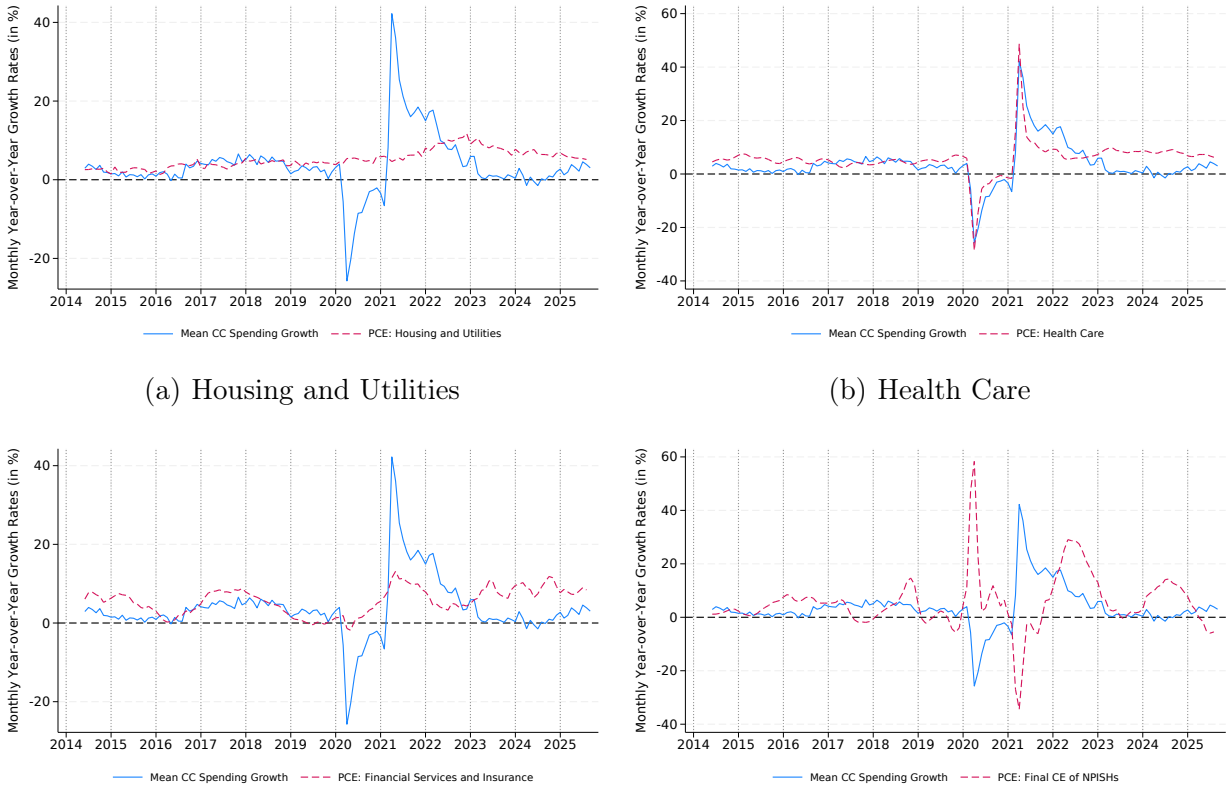
Our measure for credit card spending in the Y-14M data is the variable *Purchase Volume*, defined as the "net purchase dollar volume during the current month's cycle". While this measure allows us to observe the total dollar amount spent by a cardholder during a given month, it does not provide information on the types of goods and services purchased. This limitation represents an important drawback relative to bank account transaction-level data, which allow researchers to track spending patterns across different consumption categories. For example, Cox et al. (2020) use credit and debit account transaction data from Chase, Chetty et al. (2024) use credit and debit card spending data collected by Affinity Solutions, and Baker et al. (2020) use data from the fintech firm SaverLife to study spending dynamics across categories during the COVID-19 pandemic. Studying a related question to our analysis in Section 6, Buda et al. (2025) use customer-level bank transaction data from the Spanish bank BBVA to examine the transmission of monetary policy shocks to consumption at a daily frequency. Such transaction-level data can help uncover heterogeneous consumption responses across different categories of goods and services. By contrast, our data measure aggregate spending volumes and are therefore best suited for analyzing overall consumption dynamics rather than category-level consumption patterns. On the other hand, the Y-14M data offer the advantage of comprehensive coverage, capturing approximately 66 percent of outstanding consumer credit card balances. Many proprietary transaction-level datasets, by contrast, are drawn from a single bank or fintech platform and may therefore face more severe selection concerns

7.2 Construction of the *Adjusted PCE* Measure

In this section we elaborate in more detail on the construction of the *Adjusted PCE* measure. PCE includes a number of components that do not reflect true out-of-pocket expenditures by households, including spending by the non-profit sector, healthcare expenditures paid by insurance, and imputed rental equivalent consumption by homeowners. PCE also includes expenditures that are typically not paid for using credit cards, such as motor vehicle purchases and rents.

Figure 11: Monthly Credit Card Spending Growth vs. Excluded PCE Subcategories

This figure shows the monthly year-over-year growth rates in average credit card spending (solid blue line in each panel) and in various PCE subcategories (dashed red line in each panel) excluded from our Adjusted PCE measure.



(a) Housing and Utilities

(b) Health Care

(c) Financial Services and Insurance

(d) Final CE of NPISHs

Figure 11 plots monthly year-over-year growth rates for credit card spending alongside growth rates of the PCE subcategories excluded from the *Adjusted PCE* measure. The figure shows that most excluded subcategories exhibit consumption dynamics that differ markedly from those of credit card spending, as well as from aggregate PCE dynamics shown in Figures 1 and 2. In particular, housing and utilities expenditures (Panel a), which are nondiscretionary, display relatively stable growth before and after the pandemic; health care expenditure growth is substantially higher in the post-pandemic period (Panel b); financial services and insurance expenditures (Panel c) exhibit a similar but more volatile pattern; and consumption expenditures of non-profit institutions serving households (NPISHs) (Panel d) display an inverse pattern during and after the pandemic.

Taken together, Figure 11 illustrates how some subcategories included in broad consumption measures exhibit dynamics that are systematically different from credit card spending.

These categories are either smoother and less cyclical (e.g., housing and utilities) or do not capture true out-of-pocket expenditures of households (such as NPISH expenditures). Researchers using credit card data to study consumption should be aware of these discrepancies and adjust or caveat their analysis accordingly.

8 Conclusion

We show that credit card spending data from the Federal Reserve's Y-14M reports provide a reliable measure for macroeconomic 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 explains 88 percent of the variation in state-level adjusted PCE growth in the cross-section. These results hold across a range of economic conditions, including the extraordinary circumstances of the COVID-19 pandemic, establishing credit card spending as a credible consumption measure for applied research.

We then introduce a novel monthly county-level 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 through an application to monetary policy transmission. We show that credit card spending exhibits impulse responses that are qualitatively similar and quantitatively comparable to those obtained with traditional consumption data. Exploiting the county-level granularity, we find that low-income counties experience substantially larger consumption declines following contractionary monetary policy than high-income counties, consistent with the predictions of HANK models and, to our knowledge, the first such estimate at the county-month level.

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