The heterogeneous reactions of household debt to income shocks

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Abstract

We study how household debt portfolios—aggregated at the ZIP code level—respond to local income shocks in the United States. We implement two separate identification strategies: (i) a Bartik-style instrument that shifts local earnings via national industry trends, and (ii) a novel instrument utilizing the timing and location of shale oil and gas well discoveries. Across both designs, positive income shocks are, on average, associated with deleveraging. This average, however, masks a sharp bifurcation in financial behavior. Deleveraging in total credit is driven by financially healthier households—those with higher credit scores, higher incomes, or lower leverage—who restrain the growth of credit-card and auto debt. In contrast, financially vulnerable households often treat the windfall as a gateway to new auto credit while still deleveraging credit-card and typically mortgage debt. Looking at mixed-profile households, we find strong mortgage leveraging among households with high income and high debt or low credit scores. These results show that the same income shock can trigger balance-sheet repair for some households and additional leverage for others—varying by both borrower type and debt category—underscoring substantial underlying heterogeneity and highlighting barriers to broad-based financial stability.

Keywords: consumer credit, household debt, heterogeneity, income shocks, local labor demand
JEL Codes: D14, D15, G51, H31

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1 Introduction

The period following the COVID-19 pandemic has been marked by a substantial reversal in household financial behavior. After an initial phase of unusually high savings and sharp paydowns of credit card debt, overall household debt has been rising steadily since 2021. This growth has been particularly pronounced in consumer credit, with both auto loan and credit card balances surging past pre-pandemic levels to new highs (Federal Reserve Bank of New York, 2025).[1] This escalating leverage coincides with a high-interest-rate environment that has significantly increased the cost of servicing this debt (Consumer Financial Protection Bureau, 2023). As a result, a visible rise in financial distress is occurring, evidenced by increasing delinquency rates, especially among younger and lower-income households (Federal Reserve Bank of New York, 2025). As pandemic-era excess savings dwindle (Abdelrahman et al., 2024), understanding how households manage their liabilities in response to income shocks is no longer just a timeless academic question—it is a critical issue for macroeconomic stability. Does a household that experiences a positive income shock increase leverage, or does it slow the accumulation of existing debts?

In this paper, we exploit detailed microdata on household balance sheets to document how different types of debt – mortgage, credit card, and auto loans – respond to income shocks, and we document how these responses depend on heterogeneity along multiple dimensions, including income, leverage, and credit scores. We examine responses to local Bartik income shocks that are commonly exploited as an exogenous source of household income —and, separately, to income shocks arising from discovery of oil in nearby counties.

Direct observation of this behavior has been limited by the lack of data with information on household balance sheets and income shocks. Recent work has explored hypothetical debt responses to income transfers based on survey evidence (e.g., Colarieti et al., 2024; Koşar et al., 2025; Shapiro & Slemrod, 2003), but evidence on actual debt responses to income shocks is sparse.[2] We overcome these limitations by combining detailed household balance-sheet data from Experian with county-level earnings information from the Bureau of Labor Statistics (BLS). We construct synthetic households at the ZIP code level, merging debt balances and other financial-health indicators with local earnings measures. To identify exogenous shifts in income, we use a Bartik (shift-share) design, exploiting pre-period county-industry employment shares that differentially expose local economies to national industry shocks.[3] Our empirical framework then links these exogenous income changes to household debt growth in total, as well as disaggregated into mortgage, auto, and credit card categories.

We find that, on average, household debt growth declines following positive income shocks—a pattern consistent with deleveraging behavior. However, this average effect masks substantial heterogeneity across households. Financially healthier households (those with higher credit scores, higher incomes, or lower leverage) use additional income primarily to deleverage high-cost liabilities, particularly credit card and auto debt. In contrast, financially insecure households tend to use income gains to expand access to new credit—most notably through auto borrowing—while simultaneously deleveraging secured debt such as mortgages. The sharp divergence in these responses underscores the importance of financial health as a determinant of whether income shocks translate into deleveraging or renewed borrowing.

We augment our analysis of Bartik shocks with an analogous investigation of the debt response to an alternative income shock —based on changes in labor demand associated with the shale oil and gas boom. Local

[1] Throughout this paper, we use the terms "debt" and "credit" interchangeably to denote total outstanding household liabilities.

[2] Agarwal et al. (2007) is a notable exception that focuses on credit card debt.

[3] See Adão et al. (2019), Borusyak et al. (2022), and Goldsmith-Pinkham et al. (2020) for inference based on Bartik instruments. (Bartik, 1991)

Bartik income shocks have the advantage of being a well-known and easy-to-replicate source of exogenous changes in local income. They are based on variation at the national level across industries, and hence they are representative of typical income fluctuations. However, households may perceive them as persistent, and such persistence could lead to stronger debt accumulation than the debt response to more transitory shocks. Therefore, to understand whether our Bartik-driven debt responses are robust and how debt reacts to a different shock profile, we examine the responses to a transitory income shock from the shale oil and gas boom. To isolate a pure income shock purged of confounding local wealth effects, we develop a novel instrument: we focus on non-shale-producing counties and instrument their earnings growth with the intensity of new well drilling in adjacent counties, interacted with global oil price changes. This strategy captures income spillovers (e.g., demand for labor and services) while excluding the direct wealth effects from mineral rights that accrue to landowners in drilling counties.

We find that in response to transitory oil-driven income shocks, households cut back on total credit, with an even larger deleveraging response than for the persistent Bartik shock. This effect is driven entirely by strong mortgage deleveraging. In contrast to the Bartik shock, the response of credit card debt is negative but not statistically significant, and the average response of auto loans turns positive.[4] Despite these differences in average debt responses by type of debt, the heterogeneity patterns are remarkably similar. For instance, less-levered (low DTI) households increase auto debt, while highly-levered households use the shock to deleverage their auto loans, reinforcing our core finding of a behavioral divide based on financial health.

Our analysis of the heterogeneous effect of income on household liabilities provides a comprehensive assessment of household behavior based on a unified empirical setting. Whereas prior studies have focused on subsets of household liabilities (e.g., credit card or mortgage debt) and/or particular dimensions of household heterogeneity, our empirical setting enables us to jointly evaluate multiple dimensions of heterogeneity in response to observable income shocks. Several results reinforce findings from the prior literature, while others bring new evidence on how types of households and types of debt respond to income shocks.

It is possible to rationalize particular results in isolation. For example, the positive auto debt response by financially insecure households is consistent with the evidence in Di Maggio et al. (2017) and can be rationalized by high propensities to spend among households facing credit constraints (e.g., Carroll, 1997).

Taken as a whole, however, our results highlight that multiple (and potentially interacting) mechanisms are likely responsible for our complex patterns of heterogeneity. Table 1 summarizes our main results and their relationship to prior theoretical and empirical literature. The table focuses on theoretical and empirical papers that explicitly examine consumer debt responses to an income shock along at least one of our dimensions of heterogeneity. We indicate instances in which our main results are consistent with the literature with a ✓and contradictory evidence with a X.

Several patterns that are apparent in the table can guide the development of theoretical models of consumer behavior (Panel A). First, the deleveraging of total credit is primarily driven by financially healthier households (those with high credit scores, low DTI, and high incomes). This evidence is difficult to reconcile with theories in which debt repayment is strongest among households facing the highest borrowing costs. However, the heterogeneous response by credit type is consistent with an important role of borrowing costs (e.g., Koşar et al., 2025): our second set of results reveals a clear hierarchy of debt management. Credit card debt, with its high interest rates, is a primary target for deleveraging across all household types. Third, the responses of mortgage

[4]The positive average auto loan response may reflect increased demand for commuting to work in the adjacent shale-producing counties, thus highlighting a key difference in the nature of the oil shock relative to the Bartik shock.

debt and auto debt move in opposite directions, with financially insecure households accumulating auto debt while reducing mortgage debt growth. Financially healthy households exhibit the opposite behavior.

Our evidence expands the set of categories of heterogeneity for which there is an observed debt response to income shocks. Panel B lists papers that examine debt responses along similar categories of heterogeneity. Although only a subset of our dimensions of heterogeneity are covered by the prior literature, in instances of overlap our evidence echoes findings of the literature. In particular, Agarwal et al. (2007) find that financially unconstrained households were the most likely to use the 2001 tax rebates to pay down credit card debt. Likewise, Agarwal and Qian (2014) find that high-credit-score households in Singapore deleveraged the most (consumed the least) in response to income shocks. Finally, Di Maggio et al. (2017) document that shocks to disposable income (due to reduced mortgage payments) induce the strongest deleveraging response among financially secure households.[5] Our study confirms these patterns while providing new evidence for the heterogeneity categories not covered by these studies (denoted by a dash in the table).

Although our evidence broadly agrees with the literature based on observed income shocks, there are important discrepancies compared to the literature based on surveys of how households would respond to a hypothetical income shock (bottom rows of Panel B). For example, Armantier et al. (2020, 2021) and Shapiro and Slemrod (2003) document that low-income households have the highest propensity to deleverage out of an income transfer. This is inconsistent with the heterogeneity in the total debt response from our study, but it is consistent with the pattern in the mortgage debt response. These nuances underscore the importance of examining a comprehensive set of household characteristics and credit types when evaluating consumer debt responses to income shocks.

The remainder of the paper is organized as follows: section 2 describes our data sources and the empirical strategy, section 3 presents our main findings, section 4 executes the robustness check using the shale oil-based instrument, and section 5 discusses policy implications and concludes.

2 Data and Methodology

Our study relies on balance sheet micro data, aggregated at the ZIP code level, and income shocks identified through two distinct approaches. The first approach identifies local income shocks following the approach in Bartik (1991) and used extensively elsewhere in the literature. These shocks account for a substantial share of the variation in local earnings and can be considered representative of typical local income shocks. And although they are transitory, they are more persistent than windfall transfers that are the focus of much of the empirical literature. Specifically, the autoregressive coefficient of the Bartik shock is 0.49. We augment our analysis of Bartik-based income shocks with an analysis of transitory income shocks driven by by oil fracking in adjacent counties. These oil fracking shocks are less persistent (autoregressive coefficient is -0.03 and not statistically significant) than the Bartik shock and are concentrated in a specific industry. We describe identification of these shocks in detail below.

[5]These findings also connect to the literature on heterogeneity in marginal propensities to consume (e.g., Kueng, 2018; Lewis et al., 2024) by highlighting that consumption responses are only part of the picture. When households actively adjust their liabilities, the effect of policy-driven income boosts on aggregate demand can be delayed (Auclert et al., 2024; Miranda-Pinto et al., 2025). Indeed, households that use income gains to pay down high-interest obligations may raise their net worth over time, ultimately supporting future consumption once their balance sheets improve.

2.1 Data

In our study, we employ semi-annual household balance sheet micro data obtained from Experian credit bureau. We analyze data encompassing the total outstanding credit balance across all open trade lines reported within the last three months. To gain deeper insights, we further categorize this total credit amount into specific types of credit: mortgage-related trades, credit card and auto loans.

To complement our analysis of credit behavior, we incorporate three demographic variables that serve as indicators of a debtor's financial health. The first and probably best-known one is Vantage Score (thereafter VS), a credit assessment metric collaboratively developed by the three major credit reporting agencies, designed to forecast one's likelihood of repaying borrowed funds. It is utilized by lenders, landlords, and financial entities to assess creditworthiness. Created in 2006 by Experian, TransUnion, and Equifax, the VS algorithm initially differed in scale from the more renowned FICO scores. However, recent updates have aligned it with FICO's 300 to 850 scale.[6]

Our second variable is Income Insight Score (thereafter IIS), which encompasses Experian's proprietary models. This metric utilizes credit data to approximate consumer income. This score aids in identifying consumers' repayment capacity by assessing overall income, including wages, rent, investments, and alimony, drawing from Forms 1040 and W-2 information. Finally, the Debt-to-Income (thereafter DTI) ratio represents the individual's total monthly debt payments on open trades as a share of their IIS. This metric provides valuable insight into an individual's leverage by assessing their debt obligations in relation to their income.[7] Table 2 demonstrates summary statistics at the individual level.

Figure 1 presents the distribution of our control variables. The histograms highlight distinct distributions, with VS following a near-normal shape, IIS being right-skewed, and DTI showing a peak around 10-15% of DTI ratio. Figure 2 explores the evolution of total credit across different quartiles of household financial health indicators. We use a dynamic approach for quartiles calculation. As a result, if a household moves from one quartile to another from year to year, it is automatically reassigned to its new quartile. In the right-most panel, diverging trends emerge. Households in the lower DTI quartiles (Q1 and Q2) have shown a steady increase in credit levels, whereas Q3 has remained relatively stable around $30 million. In contrast, Q4—households with the highest DTI—has experienced a continuous decline. Interestingly, by the end of 2019, households in the second DTI quartile (Q2) held more total credit on average than their Q3 counterparts, suggesting a shift in credit distribution dynamics.

Although the Experian dataset provides comprehensive coverage of household debt, it lacks a direct measure of household income. To address this limitation, we construct synthetic households by aggregating individual debt balances at the ZIP code level.[8] We retain only active ZIP codes which can be observed for every year of our time frame and also that have more than 10 residents. Then, to incorporate household income dynamics, we merge the ZIP code level Experian data with county-level income data from the Bureau of Labor Statistics' (BLS) Quarterly Census of Employment and Wages (QCEW), which provides detailed earnings and employment information. Since our data sources operate at different frequencies, we aggregate both datasets to an annual frequency. This combined dataset enables us to analyze how debt at the ZIP code level responds to county-level income shocks across the United States from 2005 to 2019.

Table 3 presents summary statistics for the main variables. The data on credit and its growth (panel A), and consumer characteristics (panel B) originate from the Experian dataset, while local economic variables

[6]More information on the VS can be found here.

[7]More information on the IIS and DTI can be found here.

[8]Specifically, for credit variables, we sum all outstanding debt for residents within each ZIP code, while for VS, IIS, and DTI, we compute the average to preserve meaningful values across the synthetic households.

(panel C) are sourced from BLS. Average total credit at the ZIP code level stands at \$26.14 million with a standard deviation of \$44.31 million, indicating substantial dispersion in overall credit balances across ZIP codes. Mortgage credit accounts for the largest share of total credit, with credit card and auto loans being significantly smaller. Turning to credit growth (relative to total outstanding credit), the average annual change in total credit is about 2.76%, with mortgage credit expanding at a lower rate of 1.62% and credit card and auto credit growing more modestly. With regard to local economic fundamentals, county-level earnings growth averages 3.26% per year and the Bartik earnings shock stands at 3.50%.

2.2 Methodology

Our analysis examines the dynamic effects of income on debt. To ensure credit values are comparable across ZIP codes with varying population sizes and credit market participation, we first normalize the raw credit data. We define the per-borrower credit for any credit type j in ZIP code z at time t as:

$$\text{Credit}^j_{z,t} = \frac{\text{RawCredit}^j_{z,t}}{N_{z,t}} \tag{1}$$

where $\text{RawCredit}^j_{z,t}$ is the total dollar amount of credit type j outstanding and $N_{z,t}$ is the number of residents in that ZIP code with a positive credit balance. This per-borrower measure, $\text{Credit}^j_{z,t}$, is used throughout our analysis to prevent distortions from population differences.

Using this normalized variable, we specify a panel local projections model to estimate the impulse response of credit to an income shock:

$$\frac{\Delta \text{Credit}^j_{z,t+h}}{\text{Credit}^{\text{TOTAL}}_{z,t-1}} = \alpha^j_z + \beta^j_t + \gamma^j_h \cdot \Delta \ln(\text{Earnings}_{c,t}) + \text{Controls}_{z,t-1} + \varepsilon_{z,t+h} \tag{2}$$

where the dependent variable measures the change in per-borrower credit of type j from year $t-1$ to $t+h$ (for horizon $h = 0, 1, ..., 5$), scaled by the total per-borrower credit in the ZIP code at $t-1$. The credit types j include total credit, mortgages, credit cards, and auto loans.

The independent variable $\Delta \ln(\text{Earnings}_{c,t})$ stands for earnings growth for county c at year t. The term $\text{Controls}_{z,t-1}$ includes the first lags of the three consumer credit characteristics variables (averaged at the ZIP code level): Vantage (or credit) Score (VS), Income Insight Score (IIS), and Debt-to-Income ratio (DTI). $\varepsilon_{z,t+h}$ is the structural error term. The coefficient of interest, γ^j_h, indicates the sensitivity of debt type j to a change in local earnings at each horizon $h = 0, 1, ..., 5$.

To mitigate concerns about the endogeneity of local earnings ($\mathbb{E}[\Delta \ln(\text{Earnings}_{c,t}) \cdot \varepsilon_{z,t+h}] \neq 0$), we employ a Bartik-type instrumental variable (IV) strategy. Following Auerbach et al. (2025), we construct our instrument from two-digit private NAICS industries by interacting county-level pre-sample (2000–2004) employment shares $w_{c,i}$ with the corresponding national growth in BLS earnings for each industry i at year t. Formally, for county c in year t, the instrument is the inner product:

$$\text{Earnings shock}_{c,t} = \sum_{i=1}^{20} w_{c,i} \cdot \Delta \ln(\text{Earnings}_{i,t}) \tag{3}$$

Using the terminology of Goldsmith-Pinkham et al. (2020), our Bartik instrument isolates shifts in local labor demand that are due to differential local exposure to common (national) shocks. As discussed in Auerbach et al. (2025), the Bartik shock is plausibly exogenous to the local economy unless there are county-level supply-side factors that are correlated with local industry shares and coincidentally fluctuate with national industry growth rates, conditional on local fixed effects. Goldsmith-Pinkham et al. (2020) recommend assessing the exogeneity assumption by highlighting the industries driving the Bartik shock. Appendix B documents that the dominant industries are mining (which includes oil and gas extraction) and manufacturing, consistent with the dominant industries typically found in applications of a Bartik shock.

In all regressions, we employ clustered standard errors at the county level to account for potential correlations of residuals within ZIP codes that share the same county-level income shocks. This approach follows the recommendations of Petersen (2009), who emphasizes the importance of clustering standard errors to capture within-cluster correlation structures, thereby ensuring more reliable and unbiased standard error estimates in panel data analyses.

Heterogeneity. We assess the heterogeneous response of credit based on different synthetic household characteristics by interacting the earnings shock with consumer credit characteristics. Specifically, we estimate the following OLS specification:

$$\frac{\Delta \text{Credit}^{j}_{z,t}}{\text{Credit}^{\text{TOTAL}}_{z,t-1}} = \alpha_z + \beta_t + \gamma \cdot \text{Earnings shock}_{c,t} + \delta \cdot \text{Earnings shock}_{c,t} \cdot \text{Controls}_{z,t-1} + \text{Controls}_{z,t-1} + \varepsilon_{z,t}, \quad (4)$$

where controls for consumer credit characteristics are in quartile dummy form. By interacting the instrument with the dummy controls, we gauge the differential impact of the earnings shock on household credit for different VS, IIS, and DTI quartiles.

In these heterogeneity specifications, we directly estimate the effect of the earnings shock (and its interactions) in a single-stage OLS regression. A 2SLS approach is infeasible, as it would require instrumenting for multiple independent variables (earnings and its interactions with consumer characteristics) in a single regression.

3 Empirical Results: Bartik Instrument

3.1 Average Effects

Tables 4 and 5 present the core results from our instrumental variable (IV) estimation. We identify the causal effect of exogenous earnings growth on household credit by instrumenting county-level earnings growth with a Bartik shock. The tables demonstrate the contemporaneous effects of the shock at horizon $h = 0$. Our baseline specification includes controls for lagged ZIP code level financial indicators (i.e., the consumer credit characteristics of VS, IIS, and DTI), as well as ZIP code and year fixed effects, with standard errors clustered at the county level.

Table 4 displays the results for total credit growth. Our preferred specification in Column (1), which uses ZIP code fixed effects, reveals a statistically and economically significant deleveraging response. The estimated elasticity of total credit growth to an earnings shock is -0.172, significant at the 1% level. This implies that a 1 percentage point increase in local earnings growth leads to a 0.172 percentage point reduction in the rate of credit growth, signaling that households use positive income shocks to reduce their leverage.[9] This reaction aligns with survey findings by Sahm et al. (2009) and Koşar et al. (2025), which show that households often channel windfall income toward debt reduction rather than increased consumption. The first-stage regression results underscore the strength and validity of our instrument. The Kleibergen-Paap F-statistic of 571.04 far exceeds conventional thresholds for instrument relevance, mitigating concerns about weak instrument bias.

[9] In our specification, a negative coefficient does not necessarily imply that debt is completely repaid; rather, it indicates that the growth of outstanding credit either slows down or reverses, which is consistent with a deleveraging response.

As a robustness check, Column (2) replaces ZIP code fixed effects with county fixed effects. In this specification, the estimated coefficient on earnings growth attenuates substantially to -0.044 and is only significant at the 10% level. This attenuation is expected, as the county-level fixed effects absorbs a significant portion of the identifying variation from our county-level Bartik instrument. Therefore, we proceed with the ZIP code fixed effects model as our baseline for the remainder of the analysis.

To understand the drivers of this average response, Table 5 decomposes the effect across the main components of household debt. Panel A presents the second-stage IV estimates. The primary driver of the total credit deleveraging is mortgage credit, which shows an elasticity of -0.130 (significant at the 1% level). This pronounced response supports the countercyclical home equity extraction channel identified by Chen et al. (2020).

Beyond mortgages, we find that households also deleverage other forms of debt. The growth of credit card debt exhibits a highly significant negative elasticity of -0.025. This suggests households use additional income to deleverage high-interest, revolving debt, a behavior consistent with standard household finance models and empirical evidence by Agarwal and Qian (2014).

Notably, we also find a statistically significant deleveraging in auto loans, with an estimated elasticity of -0.018 (significant at the 5% level). This finding is consistent with recent survey evidence from Colarieti et al. (2024), who show that households explicitly plan to pay down auto loans in response to positive financial shocks. In their study, when asked how they would use an unexpected positive income payment, one of the primary options selected by households was to "Make more repayments on our other loans (e.g., mortgages, auto loans, etc.)". This indicates that the deleveraging response is broad-based and extends even to forms of installment credit that are often considered less sensitive to temporary income fluctuations.

Dynamic Effects To dynamically evaluate the reaction of household borrowing to our exogenous income shock, we estimate the impulse response functions (IRFs) over a five-year horizon. This panel local projections model, building upon the foundational work of Jordà (2005), facilitates an exploration of the shock's dynamic effects across various types of credit.

Figure 3 depicts the dynamic responses of different household credit types to a positive income shock. This shock is estimated using an IV regression based on a 1% increase in earnings growth - instrumented by the Bartik - over five years.[10]

Total credit growth initially shows a statistically significant negative response for the first two years, bottoming out in year two. In year three, the response recovers towards zero and becomes statistically insignificant, with the point estimate turning positive in years four and five while remaining insignificant. Mortgage credit follows a similar initial path with a significant negative response that becomes statistically insignificant by year two. However, it then transitions into a strong, positive response that becomes statistically significant in years four and five.

In contrast, credit card debt shows a consistently negative and statistically significant response across all five years. Similarly, auto loans exhibit a negative response that is marginally significant. Remember that the growth of each credit type is calculated as the change over the lagged total credit. Since card and auto loans are not a big part of total credit, the impulse responses are close to zero.

[10]See Appendix C for details on the effect and persistence of the Bartik instrument on earnings growth.

3.2 Heterogeneity

To understand how the response to earnings shocks varies across households, we examine the heterogeneity of the effects based on key ZIP code level financial characteristics. Table 6 presents the results of interacting the county-level earnings shock with quartiles of the local distributions of consumer credit/vantage scores (Panel A), debt-to-income (DTI) ratios (Panel B), and income (score) levels (Panel C). Figure 4 provides visual aid in the interpretation of the results. The findings reveal substantial and complex heterogeneity, showing that the aggregate tendency to deleverage following a positive earnings shock masks offsetting behaviors across both household types and credit categories.

Panel A documents that the deleveraging response for total credit is driven by households in areas with higher credit scores. For total credit, the baseline (Q1) coefficient is statistically insignificant, but the interaction terms for higher quartiles are negative and highly significant. The total effect for the highest-credit-score quartile (Q4) is a statistically significant reduction of -0.215 (calculated as $-0.035-0.180$), indicating a strong deleveraging propensity. This aggregate result, however, masks sharply contrasting behaviors across different types of debt.

Diving deeper into the components reveals that high-credit-score households aggressively deleverage their consumer debts, particularly auto loans. A positive earnings shock leads lower-credit-score (Q1) households to significantly increase their auto debt (coefficient of 0.067), suggesting they use the additional income to finance vehicle purchases. In stark contrast, higher-score (Q4) households use the income shock to substantially deleverage their auto loans, with a total effect of -0.096 ($0.067-0.163$).

This deleveraging of consumer debt is so strong that it drives the contraction in total credit among high-credit-score households, despite a completely opposite behavior in the mortgage market. For mortgage debt, low-score households deleverage significantly (-0.140), whereas high-score (Q4) households actively move in the opposite direction. Their total effect of -0.075 ($-0.140+0.065$) shows that they significantly mute their mortgage deleveraging to roughly half the pace of their low-score counterparts. This suggests that financially secure households are making a strategic choice: they use income windfalls to tackle high-interest consumer debt while deleveraging their lower-interest mortgage liability much less aggressively.

Panel B explores heterogeneity based on household leverage, measured by the debt-to-income (DTI) ratio. Here, the first quartile (Q1) represents the most financially healthy households with the lowest debt levels relative to income. The results reveal a now-familiar distinction in how households treat consumer debt versus long-term housing debt. The deleveraging response for total credit and mortgage debt is overwhelmingly driven by these low-DTI households. The lowest DTI quartile (Q1) exhibits significantly slower growth in both total credit (-0.206) and mortgage credit (-0.276). Conversely, for the most levered (Q4) households, this deleveraging effect is almost completely offset, with total effects close to zero. This suggests that highly levered households are either constrained in their ability to deleverage their largest liability—the mortgage—or prioritize other uses for their additional income.

This interpretation is strongly supported by their behavior regarding consumer debt, which shows a clear prioritization based on financial constraint. For credit card debt, all households regardless of DTI use a positive earnings shock to slow their credit card debt growth, with the most levered (Q4) households doing so most aggressively. The pattern for auto loans is more nuanced and reveals divergent behavior: the most financially stable households (Q1) slightly increase their auto debt, while the most levered households (Q4) exhibit significantly slower auto debt growth. This finding aligns with the work of Koşar et al. (2025), who show that financially constrained households—those with low net wealth-to-income ratios—have a high propensity to repay debt. Critically, their measure of debt explicitly excludes mortgages. Our results therefore provide a sharp clarification of this dynamic: while high-DTI households do not deleverage their large mortgage balances, their aggressive deleveraging of both credit card and auto loans reveals a clear priority to deleverage their most expensive liabilities.

Panel C, which examines heterogeneity by income, completes the narrative. A clear pattern emerges for consumer debt: the propensity to deleverage increases with income. For both credit card and auto loans, the deleveraging response is monotonically increasing with income. The divergence is particularly stark for auto loans: the lowest-income (Q1) households significantly increase their auto debt (coefficient of 0.095), while the highest-income (Q4) households substantially deleverage (total effect of -0.104).

However, a contrasting pattern emerges for mortgage debt, mirroring the behavior of both high-credit-score and high-DTI households. While low-income households use the income windfall to significantly deleverage their mortgage debt (-0.210), this effect is almost entirely offset for the highest-income households, with a total effect close to zero. This suggests that wealthier households may view their mortgage as a strategic liability or have other investment priorities, choosing instead to focus their deleveraging efforts on more expensive consumer credit.

Taken together, these findings underscore that the transmission of income shocks to household balance sheets is far from uniform. The response varies systematically across two key dimensions: household financial condition and the type of credit. Aggregating all households or all debt categories obscures critical behavioral patterns.

Specifically, we document three key results. First, the deleveraging of total credit is primarily driven by financially healthier households (those with high credit scores, low DTI, and high incomes). Second, our results reveal a clear hierarchy of debt management. Credit card debt, with its high interest rates, is a primary target for deleveraging across nearly all household types. The key divergence appears in the treatment of mortgage debt: less financially secure households (e.g., low income, low credit score) also use income windfalls to deleverage their mortgages, whereas their more financially secure counterparts strategically avoid accelerated mortgage payments. Third, the auto loan market consistently acts as a barometer for financial health, revealing starkly divergent behaviors: the same positive shock induces borrowing from less financially secure households while promoting repayment among more secure ones. These multi-dimensional responses, summarized in Table 1, are essential for macroeconomic models aiming to accurately capture the real effects of income fluctuations on the economy.

3.3 Two-way Heterogeneity

Moving beyond one-dimensional heterogeneity, we extend our analysis to account for two-way heterogeneity regressions by implementing the model specified in equation (4), incorporating dual sets of dummy variables as controls. This approach allows for a more in-depth exploration of household heterogeneity, recognizing that households classified in a given quartile based on one score of financial health (e.g., credit score) may not necessarily fall into the same quartile when assessed against another score (e.g., income).

Rather than presenting the detailed regression outputs, we use heatmaps (see figures 5 to 8) which offer a more intuitive visual representation of these heterogeneity outcomes.[11] The heatmaps illustrate the interaction effects between the income shock and two of the three score quartiles, with color gradients representing the magnitude and direction of the coefficients. Shades of red indicate negative coefficients, while shades of green denote positive coefficients, with darker hues corresponding to larger absolute values. For each type of credit we have three heatmaps, one for each pair of control dummy variables.

[11] Regression outputs can be made available upon request.

Joint Distributions The interpretation of our two-way heterogeneity analysis requires understanding the distribution of observations across these joint categories. As shown in Table A1 in the Appendix, these joint distributions are not uniform, and some household profiles are much rarer than others. This is most prominent in Panel A, which shows that the observation counts are heavily concentrated along the main diagonal. This pattern indicates a strong positive association between Vantage Score (VS) and Income Score (IIS). Combinations along the "main diagonal", e.g., low credit score (VS Q1) and low income (IIS Q1) are very common, but "off-diagonal" profiles like low credit score and high income (VS Q1, IIS Q4) or high credit score and low income (VS Q4, IIS Q1) represent a tiny fraction of the sample (375 and 167 observations, respectively). Accordingly, the regression estimates for these sparsely populated cells in our heatmaps are less precise and should be interpreted with caution. In contrast, Panels B and C show that the DTI ratio is more evenly distributed across both income (IIS) and credit score (VS) quartiles, resulting in a more balanced and robust set of estimates for those interactions.

Total Credit Figure 5 presents the two-way interaction effects for total credit, revealing a deeply heterogeneous response to income shocks that depends on the combination of household financial characteristics. Far from a uniform deleveraging, the results show a clear split where some groups expand credit while others contract it.

The VS $\times$ IIS panel illustrates this divergence most starkly. A strong positive credit response is concentrated among households with low credit scores but high incomes. This effect peaks for the VS Q1, IIS Q4 group, which exhibits a large and significant increase in total credit (coefficient of 0.43). This suggests that for households with poor credit histories but strong income prospects, a positive shock primarily serves to relax borrowing constraints. Conversely, households with high credit scores and low incomes (e.g., VS Q4, IIS Q1) actively deleverage, with a coefficient of -0.24, using the additional income for balance-sheet repair. However, as mentioned above, these extreme off-diagonal groups represent a very small fraction of the sample, comprising only 375 and 167 ZIP code-year observations, respectively (see Table A1, Panel A). The bulk of the data lies closer to the main diagonal, where the responses are more moderate. The overall pattern shows a clear gradient from leveraging to deleveraging as credit scores improve and income levels fall.

The panels incorporating the DTI ratio confirm that financial vulnerability is a key driver of this behavior. While deleveraging (red cells) is the more frequent response, the exceptions are telling. Notably, the most financially constrained households—those with high leverage combined with either low credit scores (VS Q1, DTI Q4) or low incomes (DTI Q4, IIS Q1)—are the only groups that modestly increase their borrowing (coefficients of 0.09 and 0.06, respectively). In sharp contrast, the most aggressive deleveraging is undertaken by financially healthier households, such as those with high credit scores and moderate leverage (VS Q4, DTI Q2), who show a strong negative response of -0.32. In sum, the two-way analysis demonstrates that an income shock acts as an opportunity for balance-sheet repair for financially sound households, but as a gateway to new credit for those who are more constrained.

Mortgage Credit Figure 6 displays the two-way interaction effects for mortgage credit. The results reveal a highly segmented response to income shocks, where the decision to expand mortgage borrowing versus deleverage existing balances depends critically on the interplay between creditworthiness, income, and existing leverage.

The VS $\times$ IIS panel shows a stark divide in behavior. Similarly to the total credit heatmap in figure 5, in the off-diagonal corners, households with low credit scores and high income (VS Q1, IIS Q4) substantially increase their mortgage debt (coefficient of 0.44), while those with high credit scores and low income (VS Q4, IIS Q1) deleverage (coefficient of -0.19). The bulk of the data lies closer to the main diagonal, where the responses are more moderate. For instance, households with higher credit scores and mid-range incomes (e.g., VS Q3, IIS Q3) show a modest deleveraging of -0.04.

The panels that incorporate the DTI ratio highlight the crucial role of existing leverage. A striking pattern emerges in the VS $\times$ DTI panel: households in the highest leverage quartile (DTI Q4) consistently show a slight increase in mortgage debt, regardless of their credit score (the entire rightmost column is shaded green). This indicates that the most heavily indebted households do not use income gains to deleverage their largest liability. Instead, among lower-leverage households (DTI Q1-Q3), deleveraging is the norm. Intriguingly, the most aggressive mortgage deleveraging is observed among those with low credit scores and low leverage (VS Q1, DTI Q1, coefficient of -0.30), suggesting a strong drive to improve their financial standing. This nuanced behavior underscores that mortgage debt management is a strategic decision shaped by a household's complete financial profile, rather than a uniform response to income changes.

Credit Card Debt Figure 7 displays the heatmaps for household credit card debt. Contrary to other credit types, the response here is remarkably homogeneous and consistently negative. Across all panels and for every combination of household characteristics, the coefficients are negative, indicating that all groups use a positive income shock to deleverage high-interest credit card debt. This universal deleveraging underscores the high priority households place on reducing costly revolving credit.

While the overall effect is modest, with coefficients ranging from -0.01 to -0.07, the panels reveal a subtle and intuitive pattern. The propensity to deleverage becomes slightly more pronounced for households that are either financially healthier or more leveraged. For instance, in the VS $\times$ IIS panel, the deleveraging effect is strongest for households with the highest credit scores and incomes (VS Q4, IIS Q4, with a coefficient of -0.06). Similarly, in the VS $\times$ DTI panel, the deleveraging is most pronounced for households with high credit scores and high leverage (VS Q4, DTI Q4, at -0.07). Overall, the findings for credit card debt point to a common financial imperative: when given extra resources, households of all types prioritize deleveraging their most expensive liabilities.

Auto Loans Figure 8 provides a compelling look into the behavior of auto loan credit, which acts as a clear barometer for households' financial priorities following an income shock. The panels reveal a sharp bifurcation driven primarily by income and creditworthiness.

A powerful and consistent pattern emerges across the panels featuring the Income Insight Score (IIS). Households in the lower half of the income distribution (IIS Q1 and Q2) uniformly increase their auto debt in response to a positive shock. This behavior holds regardless of their credit score or existing leverage, suggesting that the income gain unlocks pent-up demand for vehicle financing. The tendency to borrow is strongest among low-income, low-leverage households (DTI Q1, IIS Q1), who show a coefficient of 0.13. Conversely, households in the upper half of the income distribution (IIS Q3 and Q4) consistently use the shock to deleverage their auto loans.

The VS $\times$ DTI panel adds further nuance, showing that even absent a direct income sort, credit history and leverage create a similar divide. Households with the lowest credit scores (VS Q1) increase their auto borrowing across all DTI quartiles, pointing to relaxed credit constraints. At the opposite extreme, the most pronounced deleveraging is observed among households with high credit scores and high leverage (VS Q4, DTI Q4, coefficient of -0.11). Taken together, the results suggest that for financially constrained households, an income shock is an opportunity to acquire a key asset, whereas for more established households, it is an opportunity to deleverage existing installment debt.

Outtakes Taken together, these two-way heterogeneity results move decisively beyond a simple narrative of deleveraging. Instead, they reveal a stark bifurcation in household financial strategy following an income shock. The direction of the credit response—not just its intensity—is critically dependent on a household's joint position in credit score, income, and existing leverage. For financially stable households (e.g., those with high credit scores and low leverage), a positive income shock presents an opportunity for balance-sheet repair. In contrast, for financially constrained households (e.g., those with low credit scores or high leverage), the same shock acts as a gateway to new credit, relaxing borrowing constraints and enabling the financing of key assets like vehicles.

This heterogeneity, however, is not uniform across all types of debt. We uncover a clear hierarchy in financial priorities. The response to credit card debt is remarkably homogeneous: households of all types use additional income to reduce their credit card leverage, signaling a universal imperative. This stands in sharp contrast to the often opposing choices made for mortgages and auto loans. In policy contexts, these findings caution against a one-size-fits-all approach. Interventions like stimulus payments or targeted income support will not have a monolithic effect; the same dollar may be used to deleverage, take on new debt, or consume, depending entirely on the recipient's multidimensional financial profile.

4 Empirical Results: Shale Wells Instrument

4.1 Instrument description

To strengthen the robustness of our findings and deepen the understanding of our income shock, we examine whether our results hold when employing an alternative, industry-specific demand shock—the shale oil revolution shock. We select this shock for two reasons. First, as detailed in appendix B, the mining industry is the main driving force behind the Bartik instrument, making a focused analysis on this sector particularly relevant. Second, discovery and utilization of shale oil and gas wells is well-documented as temporary, demand-inducing, unanticipated, and exogenous to local economies (Feyrer et al., 2017). Incorporating this narrower shock alongside the general demand Bartik shock enhances our comprehension of how earnings variations influence household credit, ensuring that our results reflect underlying economic mechanisms rather than being driven by the specific design of the Bartik instrument.

For this exercise, we exploit drilling activity related to shale discoveries as a source of exogenous variation in local income. While oil discoveries and subsequent production increases are often categorized as supply-side shocks due to their impact on energy supply, the drilling phase—which generates substantial economic activity by boosting demand for workers and related services in the region—operates primarily through a localized labor demand channel.

The earnings surge from the discovery of wells presents a unique exogenous positive shock to the income and wealth of affected communities for several reasons. First, the economic viability of shale wells depends on broader macroeconomic forces—such as global energy demand and prevailing prices (Lake et al., 2013)—and is therefore unrelated to the local economic landscape. Figure 14 provides strong visual support for this link, showing that the aggregate number of new wells drilled co-moves closely with global WTI oil prices. The volatile nature of the drilling series also supports the characterization of these shocks as transitory rather than long-lived. Second, the technological breakthroughs that enabled the shale boom—horizontal drilling and hydraulic fracturing—were unforeseen, and their viability varies across different geographical regions. Even oil and gas companies find it exceedingly difficult to predict how many wells a particular area might require to develop recoverable resources (Gilje et al., 2016). These characteristics collectively suggest that it is unlikely for households to strategically relocate to shale-producing counties to capitalize on shale-related earnings.

This same unpredictability is crucial for ruling out a second key threat to identification: anticipation effects. If households already in the county could foresee the income boom, they might alter their credit behavior before the shock materializes—for instance, by borrowing against future income. Such ex ante behavioral changes would violate our exogeneity assumption. While the unpredictable nature of shale discoveries and oil prices makes anticipation unlikely on theoretical grounds, we can formally test for it by regressing current credit growth on the $t+1$ lead of our shale instrument.

The results, detailed in Appendix D (see Table A4 and Figure A3), provide strong empirical support for our exogeneity assumption. When we regress current credit growth on the lead of the instrument, the coefficients are statistically indistinguishable from zero for total credit, mortgage credit, and auto loans. We find only a small, marginally significant coefficient for credit card debt, but the overall lack of a systematic pre-trend confirms that households do not, on average, alter their borrowing behavior in anticipation of the income shock.

We obtain well-level data from Enverus covering horizontally and directionally drilled oil and gas wells. To align with our main panel, we aggregate wells to the county–year level. A well's lifetime involves several key stages, but the most significant income shock is triggered on the spud date, which marks the beginning of drilling operations. This phase generates an increase in local labor demand as operators hire drilling crews and procure related services. While other stages like well completion can also generate local earnings, the initial drilling phase represents the largest wave of new labor income. Therefore, we focus our analysis on this drilling-induced shock as our primary source of variation.

A crucial feature of the drilling shock is its transitory nature. While a shale well may produce for many years, it is economically "short-lived," with output heavily front-loaded: shale/tight oil wells typically exhibit first-year declines of roughly 50–90% as early-time flow is dominated by pressure depletion and transient linear flow near hydraulic fractures (Guan et al., 2024; Wachtmeister et al., 2017). By around two to three years, many wells have already delivered more than half of their estimated ultimate recovery, with subsequent production occurring at substantially lower rates (Tang et al., 2024). This physical characteristic implies that the resulting income shock should be inherently temporary, in contrast to the more persistent Bartik shock.

We formally validate this transitory property in our empirical analysis. First, we find that the autoregressive coefficient—AR(1) of our shale instrument is -0.03 and not statistically significant. Second, as detailed in Appendix D (Table A4 - Panel C, and figure A3) the lagged value of the wells instrument has no statistically significant effect on total, mortgage, or credit card debt growth. This empirical evidence supports the characterization of the shock as temporary, allowing us to identify debt responses to an income shock that is demonstrably less persistent than the one captured by the Bartik instrument.

The development of a new shale well generates a composite local economic shock. This includes both a labor demand shock (boosting employment and wages) and a separate wealth shock (raising the value of mineral rights and local property). For our analysis, it is essential to isolate the pure labor demand component. This ensures our estimates are comparable to the Bartik instrument—which is also a labor demand shock—and are not confounded by this distinct, wealth-transfer effect.

A key empirical challenge is that this confounding wealth shock can also affect household balance sheets, both directly and indirectly. Gilje et al. (2016) document that these same wealth transfers (from mineral royalties) create a localized liquidity boom for banks within the drilling counties. This, in turn, generates a positive credit supply shock as banks "export" this new liquidity. Simply instrumenting with drilling activity in a given county would thus conflate the labor demand shock with this wealth-driven financial channel, violating the exclusion restriction.

This paper's central methodological contribution is a novel identification strategy designed to disentangle these channels and isolate the pure income shock. Our strategy focuses on counties that have no shale oil or gas deposits but are adjacent to counties with active drilling. We use county adjacency data from the U.S. Census Bureau to construct this sample.

The logic of this approach is twofold, allowing us to satisfy the exclusion restriction by construction. First, by focusing on non-shale counties, our sample excludes landowners who receive direct wealth transfers from mineral royalties and lease payments. This mechanically purges the direct wealth effect. Second, this design also isolates our instrument from the credit supply channel documented by Gilje et al. (2016). That channel originates from the deposit booms in drilling counties and propagates through a bank's entire branch network. Our instrument, in contrast, is built on geographic adjacency to capture labor market spillovers (e.g., from commuting and demand for local services). Because geographic adjacency and bank branch network overlaps are not systematically correlated, any exported credit supply effect is orthogonal to our instrument.

In sum, our sample construction is critical: by focusing on adjacent non-shale counties, we eliminate the direct wealth transfers and the associated local deposit booms, thereby isolating the labor demand channel. Summary statistics for this sample appear in Table 7.

Our instrument for local earnings in a non-shale county c at time t is constructed as the interaction between a measure of drilling intensity in adjacent counties and exogenous shifts in global oil prices. Formally, we define the instrument $Z_{c,t}$ as:

$$Z_{c,t} = \left(\frac{\text{NewWells}_{N(c),t}}{\sum_{s<t} \text{NewWells}_{N(c),s}} \right) \times \Delta \ln(\text{WTI})_t \tag{5}$$

The first term in the interaction captures the relative intensity and maturity of the drilling activity in the adjacent counties. It is the ratio of the flow of new wells drilled in neighboring counties $N(c)$ during period t to the stock of all wells that existed in those same counties prior to period t. The economic intuition is that the local response to a global oil price shock is non-linear and depends on the existing saturation of wells. A positive oil price shock will induce a large wave of new drilling in an area that is newly developing (where the stock of wells is small, making this ratio high). In contrast, the same price shock will trigger a much smaller response in a 'mature' area that is already heavily developed (where the stock of wells is large and the ratio is low). This term, therefore, measures how much "room" (or potential) exists for an oil price shock to translate into new local drilling activity.

As in section 2.2 we estimate equation (2), but this time using the wells instrument described in equation (5) and focus only on horizon $h = 0$. Our IV model therefore become:

$$\frac{\Delta \text{Credit}^j_{z,t}}{\text{Credit}^{\text{TOTAL}}_{z,t-1}} = \alpha^j_z + \beta^j_t + \gamma^j_h \cdot Z_{c,t} + \text{Controls}_{z,t-1} + \varepsilon_{z,t} \tag{6}$$

4.2 Average Effects

We now present the results from our instrumental variable estimation using the shale wells instrument. Table 8 shows the impact on total credit growth, while Table 9 decomposes this effect across different debt categories.

The first-stage results, reported in the lower panel of Table 8, confirm the relevance of our instrument. The coefficient on the interaction term—our measure of oil price-driven drilling potential in neighboring counties—is positive and statistically significant at the 1% level. This indicates that an increase in drilling activity, spurred by higher global oil prices in areas with growth potential, is strongly and positively correlated with earnings growth in adjacent non-shale counties.

To assess instrument strength, we report the Kleibergen–Paap Wald F-statistic, which is robust to heteroskedasticity and clustering. In our preferred specification with ZIP code fixed effects (Column 2), the F-statistic is 13.55. This value is comfortably above the conventional rule-of-thumb threshold of 10 (Staiger & Stock, 1997), mitigating concerns that our second-stage estimates are biased by a weak instrument.

The second-stage results in Table 8 reveal a powerful deleveraging response to the income shock. Our preferred specification (Column 2) shows an estimated elasticity of total credit growth to earnings of –0.615, statistically significant at the 5% level. This implies that a one percentage point increase in local earnings growth, driven by the shale boom, leads to a 0.615 percentage point reduction in the rate of total credit growth.

Notably, this deleveraging effect is substantially larger—more than three times—than the elasticity of –0.172 estimated using the broader Bartik instrument. This suggests that the nature of the income shock matters: the more temporary income gains associated with a localized resource boom appear to trigger a more aggressive debt reduction response from households compared to a more general, industry-mix-driven shock.

To understand the drivers of this pronounced response, we decompose the effect across the main components of household debt in Table 9. Panel A presents the IV estimates. Consistent with our previous findings, the aggregate deleveraging in credit is overwhelmingly driven by mortgage credit. The estimated elasticity is –0.669 and is significant at the 5% level, reinforcing the importance of the mortgage deleveraging channel. However, we find no statistically significant effect on credit card debt, with a point estimate close to zero. This suggests that households prioritize deleveraging large-scale mortgage debt over high-interest revolving credit when faced with a shale-related income windfall.

Further, we find a positive, albeit less precisely estimated, effect on auto loans. The estimated elasticity is 0.138, significant at the 10% level. This result presents a more nuanced picture than the broad-based deleveraging documented earlier, suggesting households may increase their auto debt in response to the shale shock. A plausible explanation is that this specific type of income shock is intrinsically linked to industrial activity in often rural areas, where reliable transportation (e.g., trucks) can be a prerequisite for employment or a complementary productive asset. Households may therefore use the income opportunity to finance vehicle purchases that are perceived as investments to further capitalize on the local economic boom.

Finally, Panel B reports the reduced-form estimates, which directly regress credit growth on our instrument. The signs and significance of the coefficients are consistent with our IV results, confirming that the shale shock is associated with a contraction in mortgage credit and an expansion in auto loans.

4.3 Heterogeneity

To investigate how the response to the shale income shock varies across different household types, we extend our reduced-form model to include interactions between our instrument and quartiles of ZIP code level financial characteristics, as specified in equation (7):

$$\frac{\Delta \mathrm{Credit}^{j}_{z,t}}{\mathrm{Credit}^{\mathrm{TOTAL}}_{z,t-1}} = \alpha_z + \beta_t + \gamma \cdot Z_{c,t} + \delta \cdot Z_{c,t} \cdot \mathrm{Controls}_{z,t-1} + \mathrm{Controls}_{z,t-1} + \varepsilon_{z,t} \tag{7}$$

Table 10 presents these results, examining heterogeneity based on consumer credit scores (Panel A), debt-to-income (DTI) ratios (Panel B), and income levels (Panel C). The findings reveal nuanced patterns, showing that the aggregate response is driven by specific segments of the population and varies considerably across debt categories.

Panel A examines heterogeneity by credit score and shows a consistent mortgage deleveraging response across all quartiles. The baseline effect for the lowest-score quartile (Q1) is -0.063 and is marginally significant. The interaction terms for the higher quartiles (Q2–Q4) are small and statistically insignificant, indicating that there is no evidence of different behavior between credit score groups. For the other debt categories—total credit, credit card, and auto loans—we likewise find no significant heterogeneous patterns.

Panel B, which sorts households by their level of indebtedness, uncovers statistically significant heterogeneity patterns. In the auto loan market, we observe a clear behavioral divide. The baseline estimate shows that the most financially secure households (lowest DTI, Q1) significantly increase their auto debt (coefficient of 0.032). In contrast, the interaction terms for higher DTI quartiles are negative and highly significant, indicating a reversal in behavior. This finding is consistent with the pattern identified using the Bartik instrument, reinforcing the robustness of this channel. For the most indebted households (Q4), the total effect is a statistically significant deleveraging (calculated as $0.032-0.043=-0.011$). This suggests a clear behavioral divide: financially stable households use the opportunity to finance vehicle purchases, while financially constrained households prioritize reducing their leverage.

A different pattern emerges for other debt types. For mortgage debt, we find a consistent deleveraging effect across all DTI groups, with a significant baseline effect of -0.077 for the least-levered households and no statistically significant differences for other groups. For credit card debt, the deleveraging is driven by the most-levered households (Q4), whose interaction term is negative and highly significant.

Finally, Panel C reveals that some, but not all, behaviors vary by income. For mortgage debt, we again find a consistent deleveraging response across all income quartiles. The baseline effect for the lowest-income households (Q1) is -0.076 and statistically significant, while the interaction terms for higher-income groups are not significant. However, the auto loan market does show heterogeneity. The lowest-income quartile significantly increases its auto debt (coefficient of 0.022). This effect is attenuated for the second income quartile, whose interaction term is negative and significant. This suggests a different mechanism than the balance-sheet repair seen among high-DTI households in Panel B. Here, the lowest-income households may be using the income shock to overcome previous borrowing constraints to finance a necessary capital investment—a vehicle—which allows them to better access the economic opportunities created by the shale boom.

Comparison with Bartik Heterogeneity How do these heterogeneity patterns compare to those identified using the Bartik instrument? While the signs of the coefficients are broadly similar across both identification strategies, the shale results are considerably less precise, constraining the conclusions we can draw. The one area where the evidence is unambiguous is the DTI heterogeneity in auto loans. Here, both instruments tell the same story with statistical confidence: low-leverage households increase auto borrowing while high-leverage households deleverage, with all interaction terms significant and in the same direction. Income-based heterogeneity in auto loans also finds some support, with significant differences between the lowest and second-lowest income quartiles, though the pattern is less complete than under the Bartik shock.

For other debt categories, the picture is less clear. For mortgage debt, the baseline deleveraging effect (Q1) is consistently significant across all three household characteristics, but the interaction terms are uniformly insignificant—meaning we cannot reject the hypothesis that all household types respond similarly to the shale shock. This contrasts with the Bartik results, where financially secure households significantly muted their mortgage deleveraging relative to vulnerable households. For total credit, the shale coefficients share broadly similar signs with the Bartik results but lack statistical significance. For credit cards, while most interactions are insignificant, we observe the same deleveraging among high-DTI households seen in the Bartik specification, though the pattern is not replicated across income or credit score sorts. The reduced precision likely reflects both the smaller sample and the more localized nature of the shale shock. Nevertheless, the robust confirmation of the DTI-based behavioral divide in auto lending—the same pattern observed under both the more persistent Bartik and transitory shale income shocks—strengthens the conclusion that leverage is a key determinant of how households allocate income windfalls between debt reduction and asset acquisition.[12]

5 Conclusion

The heterogeneous response of household liabilities to income shocks has important implications for household financial fragility and for macroeconomic stabilization policy. We provide a comprehensive assessment of how consumer debt liabilities respond to income shocks across multiple credit categories and multiple dimensions of household heterogeneity. We examine representative (Bartik) income shocks as well a transitory shock to labor demand associated with new shale discoveries.

The results point to clear and economically meaningful patterns. Deleveraging is concentrated among households in stronger financial positions—those with high credit scores, low debt-to-income ratios, and higher earnings. Households facing higher borrowing costs are less likely to reduce leverage and, in some cases, expand it. Across all groups, credit card debt receives top priority for deleveraging, consistent with its high carrying costs. Beyond that, households follow distinct strategies: financially healthy households deleverage auto and mortgage debt, while financially constrained households increase auto borrowing even as they slow mortgage growth. These patterns suggest that financial health shapes not only the magnitude but also the composition of household balance-sheet adjustment. Theories of consumption and credit that abstract from this heterogeneity risk missing an important channel through which income shocks feed into aggregate demand and financial stability.

[12]Similar to section 3.3, we have conducted a two-way heterogeneity analysis. The relevant heatmaps can be found in figures 10 - 13. Full estimation output tables can be made available upon request.

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Table 1: **Literature Comparison: Heterogeneous Debt Responses to Income Shocks.**
This table compares findings from theoretical and empirical literature on household debt responses to income shocks. Agreement is assessed by matching household characteristics and the direction of debt response. *Symbols:* ✓= finding aligns with our results for comparable household types; X = finding differs from our results; — = not examined or not directly comparable.

			Our Results:						
			Strong Deleveraging Response to Income Shock				**Strong Leveraging Response to Income Shock**		
			Total Credit			Credit Cards	Auto	Mortgage	
Reference	**Most Deleveraging**	**Mechanism**	High-income	Low-leverage	High-credit-score	All types	Financially vulnerable	High-income, high-debt	High-income, low-credit-score
Panel A: Theoretical Predictions									
Koşar et al. (2025)	Low-net-worth / fin. constr.	High borrowing costs	X	X[a]	X	✓	—	—	—
Carroll (1997)	Non-poor	Borrowing Constraints	✓[b]	✓[b]	—	—	—	—	—
Miranda-Pinto et al. (2025)	Non- poor	Debt decrease due to stochastic min. cons. thresholds	✓	✓	—	—	—	—	—
Panel B: Empirical Evidence									
Administrative Data:									
Agarwal et al. (2007)	Financially Unconstrained	Repayment of high-interest credit card debt	✓[c]	✓[c]	—	✓	—	—	—
Agarwal and Qian (2014)	Credit card borrowers (High Credit Limit)	Repayment of high-interest credit card debt	—	—	✓[c]	✓	—	—	—
Di Maggio et al. (2017)	High Credit Score, High Income	Cash flow channel of mon. policy; lower rates increase disp. income, then used for voluntary deleveraging.	✓[d]	—	✓[d]	✓	✓	—	—
Survey Data:									
Colarieti et al. (2024)	"Strongly constrained", including low income, low assets, high debt	Precautionary debt repayment to ensure future credit access.	X[e]	X[e]	—	✓[f]	—	—	—
Armantier et al. (2020, 2021)	Lower-income stimulus recipients	Stimulus used for balance sheet repair	X[g]	—	—	—	—	—	—
Shapiro and Slemrod (2003)	Low-income, Low-wealth	Pre-existing budgets targeting debt repayment rather than liquidity constraints.	X[g]	—	—	—	—	—	—

[a] Koşar et al. (2025) exclude mortgages from their analysis. If we compare their predictions with our credit card and auto debt results, we agree that high-leverage households deleverage the most.
[b] We classify non-poor households as comparable to our high credit score, high income, and low DTI households, treating saving as equivalent to debt repayment.
[c] Agarwal et al. (2007) and Agarwal and Qian (2014) define unconstrained households using high credit limits and low utilization rather than income or credit scores. These characteristics are highly correlated and describe financially stable households that deleverage when receiving a windfall.
[d] However, our results disagree if we focus on mortgage debt reaction in our paper: Contrary to our findings, Di Maggio et al. (2017) find that higher-income and higher-credit-score (High FICO) households deleverage the most (their mortgage debt).
[e] In Colarieti et al. (2024) households are characterized not only by credit characteristics (e.g., high debt) but also by behavioral tendencies (e.g., spenders and strongly constrained). This make the disagreement between our results more nuanced and possibly our results less comparable.
[f] The apparent disagreement on total deleveraging for constrained households likely stems from methodological differences: we classify new auto loans as leveraging (increasing debt), while Colarieti et al. (2024) categorize auto purchases as consumption. Excluding auto debt, our results align.
[g] Armantier et al. (2020, 2021) and Shapiro and Slemrod (2003) find that low-income households exhibit the highest propensity to deleverage, which is inconsistent with our results for total credit but is consistent with the heterogeneity in the mortgage debt response.

Table 2: **Summary Statistics: Individual level.**
The panels below present summary statistics for the underlying individual-level data, which are aggregated at the ZIP code level for our regression analysis. Panel A reports statistics on consumer credit balances, in thousands of dollars, and their growth. The growth variables are calculated as the annual change in a specific credit category divided by the individual's lagged total credit balance. Panel B summarizes key consumer financial health indicators: Credit (or Vantage) Score, Debt-to-Income Ratio, and Experian's proprietary Income Score. The number of observations is reported in thousands. P25, P50, and P75 denote the 25th, 50th, and 75th percentiles, respectively.

	# Observ. (thousands)	Mean	Std. Dev	P25	P50	P75
Panel A: Consumer Credit (Individual–half-year level, 2005–2019)						
Total consumer credit ($ thousands)	325,713	85.73	175.88	1.53	17.21	109.58
Mortgages ($ thousands)	121,215	185.80	227.82	68.30	132.61	232.13
Credit card debt ($ thousands)	289,034	5.44	10.37	0.31	1.75	6.02
Auto loans ($ thousands)	114,429	17.19	19.32	7.56	13.70	22.31
$\Delta \ln$(Total consumer credit) (%)	249,857	75.42	2,564.60	-0.60	0.01	2.07
$\Delta \ln$(Mortgages) (%)	79,994	2.18	350.00	-0.21	-0.02	0.30
$\Delta \ln$(Credit card debt) (%)	216,687	4.70	123.12	-0.08	0.00	0.18
$\Delta \ln$(Auto loans) (%)	51,407	0.36	26.99	-0.11	-0.01	0.14
Panel B: Consumer Credit Characteristics (Individual–half-year level, 2005–2019)						
Credit Score	468,718	670.65	103.90	576.00	667.00	770.00
Debt-to-Income Ratio	324,712	12.26	13.07	1.00	9.00	19.00
Income Score	464,410	76.23	60.61	40.00	64.00	88.00

Table 3: **Summary Statistics: ZIP code level.**

The panels below present summary statistics for the main variables used in our regression analysis, aggregated at the ZIP code-year or county-year level for 2005–2019. Panel A reports statistics on consumer credit balances, in millions of dollars, and their growth. The growth variables represent the annual change in each credit type divided by lagged total credit balance. Panel B summarizes ZIP code averages of key consumer financial health indicators: Credit (or Vantage) Score, Debt-to-Income Ratio, and Experian's proprietary Income Score. Panel C reports county-level local economic fundamentals from the BLS QCEW, including our Bartik earnings shock instrument (see Eq. 3). All variables are winsorized at the 1% and 99% levels. P25, P50, and P75 denote the 25th, 50th, and 75th percentiles, respectively.

	# Observ.	Mean	Std. Dev	P25	P50	P75
Panel A: Consumer Credit (ZIP code–year level, 2005–2019)						
Total consumer credit ($ mn)	440,460	26.14	44.31	1.86	5.90	29.43
Mortgages ($ mn)	440,460	21.12	38.11	1.16	4.06	22.21
Credit card debt ($ mn)	440,460	1.49	2.20	0.15	0.43	1.90
Auto loans ($ mn)	440,460	1.79	2.51	0.22	0.63	2.37
$\Delta\ln$(Total consumer credit) (%)	411,096	2.76	14.71	-4.30	1.15	7.82
$\Delta\ln$(Mortgages) (%)	411,096	1.62	12.51	-4.42	0.32	6.02
$\Delta\ln$(Credit card debt) (%)	411,096	0.06	1.44	-0.46	0.07	0.56
$\Delta\ln$(Auto loans) (%)	411,096	0.49	2.65	-0.48	0.22	1.20
Panel B: Consumer Credit Characteristics (ZIP code–year level, 2005–2019)						
Avg. Credit Score	440,460	671.40	34.80	647.00	673.00	696.50
Avg. Debt-to-Income Ratio	440,460	11.13	2.59	9.50	11.00	13.00
Avg. Income Score	440,460	73.14	19.14	60.50	69.50	81.50
Panel C: Local Economic Fundamentals (county–year, 2005–2019)						
ln(Earnings)	440,331	20.98	2.37	19.19	20.90	22.84
$\Delta\ln$(Earnings) (%)	440,331	3.26	6.12	0.52	3.58	6.14
Bartik earnings shock	440,340	3.50	2.50	3.03	4.27	5.05

Table 4: **Core IV Test.**

This table presents the core instrumental variable (IV) estimation of the effect of local earnings growth on total household credit. The dependent variable is the annual change in total credit for a ZIP code, scaled by its lagged total credit balance. County-level earnings growth is instrumented with a Bartik-style earnings shock. The lower panel displays the first-stage results and the Kleibergen-Paap F-statistic. All specifications control for lagged borrower financial characteristics and include time fixed effects. Column (1) includes ZIP code fixed effects, while Column (2) uses county fixed effects. Standard errors, in parentheses, are clustered at the county level. * denotes significance at the 10% level, ** the 5% level, and *** the 1% level.

Dependent Variable: ΔTotal Credit$_{\text{ZIP},t}$		
	(1)	(2)
$\Delta\ln(\text{Earnings})_{\text{county},t}$	-0.172^{***}	-0.044^{*}
	(0.03)	(0.03)
First stage regression		
Earnings shock$_{\text{county},t}$	2.116^{***}	2.137^{***}
	(0.09)	(0.09)
Kleibergen–Paap F-statistic	571.04	574.85
Other borrower financials$_{\text{ZIP},t-1}$	✓	✓
County FEs	–	✓
ZIP code FEs	✓	–
Time FEs	✓	✓
Observations	410,975	410,975
R-squared	0.23	0.23

Table 5: **Decomposition of Debt Response by Category.**

This table decomposes the household debt response to a local earnings shock across different credit categories. Panel A presents the second-stage results from our IV estimation. The dependent variable in each column is the annual change in the specified credit category, scaled by lagged total credit. County-level earnings growth is instrumented with the Bartik earnings shock. Panel B presents the corresponding reduced-form regressions, showing the direct effect of the Bartik earnings shock on each debt category. All specifications control for lagged borrower financial characteristics and include ZIP code and time fixed effects. Standard errors, in parentheses, are clustered at the county level. * denotes significance at the 10% level, ** the 5% level, and *** the 1% level.

	ΔTotal Credit	ΔMortgage Credit	ΔCredit Card Debt	ΔAuto Loans
Panel A: IV Regressions				
$\Delta \ln(\text{Earnings})_{\text{county},t}$	-0.172^{***}	-0.130^{***}	-0.025^{***}	-0.018^{**}
	(0.03)	(0.02)	(0.00)	(0.01)
Other borrower financials$_{\text{ZIP},t-1}$	✓	✓	✓	✓
ZIP code FEs	✓	✓	✓	✓
Time FEs	✓	✓	✓	✓
Observations	410,975	410,975	410,975	410,975
R-squared	0.12	0.10	0.05	0.05
Panel B: Reduced Form Regressions				
Earnings shock$_{\text{county},t}$	-0.365^{***}	-0.276^{***}	-0.053^{***}	-0.038^{**}
	(0.06)	(0.05)	(0.01)	(0.02)
Other borrower financials$_{\text{ZIP},t-1}$	✓	✓	✓	✓
ZIP code FEs	✓	✓	✓	✓
Time FEs	✓	✓	✓	✓
Observations	410,984	410,984	410,984	410,984
R-squared	0.16	0.14	0.09	0.10

Table 6: **Heterogeneity in Reduced-Form Effects by ZIP Characteristics.**
This table reports results from reduced-form regressions in equation (4) exploring the heterogeneous effects of the Bartik earnings shock on different debt categories. The dependent variable in each column is the annual change in the specified credit category, scaled by lagged total credit. Each panel interacts the earnings shock with quartile dummies for a specific ZIP code level financial characteristic, where Q1 is the lowest quartile. The baseline coefficient shows the effect for the Q1 group. Panel A examines heterogeneity by Credit Score, Panel B by Debt-to-Income (DTI) ratio, and Panel C by Income Score. All specifications control for lagged borrower financial characteristics and include ZIP code and time fixed effects. Standard errors, in parentheses, are clustered at the county level. * denotes significance at the 10% level, ** the 5% level, and *** the 1% level.

	ΔTotal Credit	ΔMortgage Credit	ΔCredit Card Debt	ΔAuto Loans
Panel A: Credit Score Heterogeneity				
Earnings shock$_{\text{county},t}$	-0.035	-0.140^{***}	-0.035^{***}	0.067^{***}
	(0.06)	(0.05)	(0.01)	(0.02)
Earnings shock$_{\text{county},t} \times Q2$	-0.087^{***}	0.030	-0.003	-0.078^{***}
	(0.01)	(0.02)	(0.00)	(0.01)
Earnings shock$_{\text{county},t} \times Q3$	-0.150^{***}	0.017	-0.008^{***}	-0.116^{***}
	(0.03)	(0.03)	(0.00)	(0.02)
Earnings shock$_{\text{county},t} \times Q4$	-0.180^{***}	0.065^{***}	-0.025^{***}	-0.163^{***}
	(0.03)	(0.03)	(0.00)	(0.02)
Other borrower financials$_{\text{ZIP},t-1}$	✓	✓	✓	✓
ZIP code FEs	✓	✓	✓	✓
Time FEs	✓	✓	✓	✓
Observations	410,984	410,984	410,984	410,984
R-squared	0.12	0.11	0.08	0.09
F-statistics	1090	689	188	526
Panel B: Debt-to-Income Ratio Heterogeneity				
Earnings shock$_{\text{county},t}$	-0.206^{***}	-0.276^{***}	-0.023^{***}	0.039^{*}
	(0.06)	(0.05)	(0.01)	(0.02)
Earnings shock$_{\text{county},t} \times Q2$	-0.025	0.058^{**}	-0.016^{***}	-0.040^{***}
	(0.03)	(0.03)	(0.00)	(0.01)
Earnings shock$_{\text{county},t} \times Q3$	0.008	0.096^{***}	-0.019^{***}	-0.055^{***}
	(0.03)	(0.03)	(0.01)	(0.01)
Earnings shock$_{\text{county},t} \times Q4$	0.186^{***}	0.298^{***}	-0.030^{***}	-0.074^{***}
	(0.03)	(0.03)	(0.00)	(0.01)
Other borrower financials$_{\text{ZIP},t-1}$	✓	✓	✓	✓
ZIP code FEs	✓	✓	✓	✓
Time FEs	✓	✓	✓	✓
Observations	410,984	410,984	410,984	410,984
R-squared	0.12	0.12	0.08	0.09
F-statistics	1093	707	192	448
Panel C: Income Heterogeneity				
Earnings shock$_{\text{county},t}$	-0.070	-0.210^{***}	-0.029^{***}	0.095^{***}
	(0.06)	(0.05)	(0.01)	(0.02)
Earnings shock$_{\text{county},t} \times Q2$	-0.054^{**}	0.055^{***}	-0.001	-0.080^{***}
	(0.03)	(0.02)	(0.00)	(0.01)
Earnings shock$_{\text{county},t} \times Q3$	-0.093^{***}	0.090^{***}	-0.014^{***}	-0.135^{***}
	(0.03)	(0.02)	(0.01)	(0.01)
Earnings shock$_{\text{county},t} \times Q4$	-0.081^{***}	0.208^{***}	-0.036^{***}	-0.199^{***}
	(0.03)	(0.02)	(0.00)	(0.01)
Other borrower financials$_{\text{ZIP},t-1}$	✓	✓	✓	✓
ZIP code FEs	✓	✓	✓	✓
Time FEs	✓	✓	✓	✓
Observations	410,984	410,984	410,984	410,984
R-squared	0.12	0.11	0.08	0.09
F-statistics	1087	695	198	575

Table 7: **Summary Statistics for Shale Analysis Sample.**
This table presents summary statistics for the variables used in the shale oil shock analysis for 2005–2019. Panels A, B, and C describe the county samples and well-drilling activity. Panel A covers shale-producing counties, Panel B covers adjacent non-shale counties, and Panel C covers both. Panels D, E, and F summarize consumer credit data, financial characteristics, and local economic fundamentals for the ZIP codes and counties within this specific sample. The growth variables in Panel D represent the annual change in each credit type divided by lagged total credit. Panel E summarizes ZIP code averages of key consumer financial health indicators: Credit (or Vantage) Score, Debt-to-Income Ratio, and Experian's proprietary Income Score. All variables are winsorized at the 1% and 99% levels. P25, P50, and P75 denote the 25th, 50th, and 75th percentiles, respectively.

	# Observ.	Mean	Std. Dev	P25	P50	P75
Panel A: Shale counties						
Number of counties per year	15	369	62.07	322	365	426
Number of new wells drilled (county–year)	5,535	35	72.17	2	7	26
Panel B: Non-shale neighbouring counties						
Number of counties per year	15	318	23.83	298	317	344
Number of new wells drilled (county–year)	4,772	53.52	144.68	3	9	38
Ratio of new wells drilled	4,281	0.19	0.44	0.02	0.05	0.16
Ratio of new wells drilled $\times \Delta \ln(\text{WTI})$	4,281	0.011	0.090	−0.004	0.001	0.013
Panel C: All counties						
Number of counties per year	15	687	47.07	661	676	733
Number of new wells drilled (county–year)	10,307	122.45	240.65	5	25	111
Ratio of new wells drilled	9,422	0.21	0.45	0.02	0.07	0.20
Ratio of new wells drilled $\times \Delta \ln(\text{WTI})$	9,422	0.015	0.095	−0.004	0.002	0.017
Panel D: Consumer Credit Characteristics (ZIP–year level, 2005–2019)						
Total consumer credit ($ mn)	229,806	24.12	44.18	1.67	5.03	23.76
Mortgages ($ mn)	229,806	19.80	38.16	1.01	3.39	17.34
Credit card debt ($ mn)	229,806	1.40	2.18	0.14	0.38	1.63
Auto loans ($ mn)	229,806	1.68	2.41	0.21	0.58	2.13
$\Delta \ln$(Total consumer credit) (%)	213,987	2.76	14.46	−4.23	1.18	7.78
$\Delta \ln$(Mortgages) (%)	213,987	1.55	12.10	−4.35	0.30	5.87
$\Delta \ln$(Credit card debt) (%)	213,987	0.06	1.51	−0.49	0.07	0.56
$\Delta \ln$(Auto loans) (%)	213,987	0.51	2.78	−0.53	0.23	1.30
Panel E: Consumer Financial Characteristics (ZIP–year level, 2005–2019)						
Avg. Credit Score	229,806	670.55	33.51	648.50	671.50	694.00
Avg. Debt-to-Income Ratio	229,806	10.98	2.55	9.50	11.00	12.50
Avg. Income Score	229,806	72.00	18.42	60.00	68.33	79.67
Panel F: Local Economic Fundamentals (county–year level, 2005–2019)						
ln(Earnings)	229,686	20.69	2.40	18.89	20.53	22.59

Table 8: **IV Results using Shale Instrument.**
This table presents the IV estimation of the effect of local earnings growth on total household credit, using the shale oil instrument. The dependent variable is the annual change in total credit for a ZIP code, scaled by its lagged total credit balance. County-level earnings growth is instrumented by the interaction of drilling intensity in neighboring counties and global oil price changes - see equation (5). The lower panel displays the first-stage results and the Kleibergen-Paap F-statistic. All specifications control for lagged borrower financial characteristics and include time fixed effects. Column (1) includes county fixed effects, while Column (2) uses ZIP code fixed effects. Standard errors, in parentheses, are clustered at the county level. * denotes significance at the 10% level, ** the 5% level, and *** the 1% level.

Dependent Variable: ΔTotal Credit$_{\text{ZIP},t}$		
	(1)	(2)
$\Delta\ln(\text{Earnings})_{\text{county},t}$	-0.484^{*}	-0.615^{**}
	(0.270)	(0.292)
First stage regression		
Neighbor drilled wells ratio$_{\text{county},t} \times \Delta\ln(\text{WTI})_t$	0.096^{***}	0.094^{***}
	(0.026)	(0.026)
Kleibergen–Paap F-statistic	13.95	13.55
Other borrower financials$_{\text{ZIP},t-1}$	✓	✓
County FEs	✓	–
ZIP code FEs	–	✓
Time FEs	✓	✓
Observations	213,870	213,177
R-squared	0.19	0.19

Table 9: **Decomposition of Debt Response using Shale Instrument.**
This table decomposes the household debt response to the shale oil income shock across different credit categories. Panel A presents the second-stage results from our IV estimation. The dependent variable in each column is the annual change in the specified credit category, scaled by lagged total credit. County-level earnings growth is instrumented with the shale instrument - see equation (5). Panel B presents the corresponding reduced-form regressions, showing the direct effect of the shale instrument on each debt category. All specifications control for lagged borrower financial characteristics and include ZIP code and time fixed effects. Standard errors, in parentheses, are clustered at the county level. * denotes significance at the 10% level, ** the 5% level, and *** the 1% level.

	ΔTotal Credit	ΔMortgage Credit	ΔCredit Card Debt	ΔAuto Loans
Panel A: IV Regressions				
$\Delta \ln(\text{Earnings})_{\text{county},t}$	-0.615^{**}	-0.669^{**}	-0.009	0.138^{*}
	(0.29)	(0.27)	(0.03)	(0.07)
First stage regression				
Neighbor drilled wells ratio$_{\text{county},t} \times \Delta \ln(\text{WTI})_t$	0.094^{***}	0.094^{***}	0.094^{***}	0.094^{***}
	(0.00)	(0.00)	(0.00)	(0.00)
Kleibergen–Paap F-statistic	13.55	13.55	13.55	13.55
Other borrower financials$_{\text{ZIP},t-1}$	✓	✓	✓	✓
ZIP code FEs	✓	✓	✓	✓
Time FEs	✓	✓	✓	✓
Observations	213,177	213,177	213,177	213,177
R-squared	0.19	0.19	0.19	0.19
Panel B: Reduced Form Regressions				
Neighbor drilled wells ratio$_{\text{county},t} \times \Delta \ln(\text{WTI})_t$	-0.058^{**}	-0.063^{***}	-0.001	0.013^{**}
	(0.02)	(0.02)	(0.00)	(0.01)
Other borrower financials$_{\text{ZIP},t-1}$	✓	✓	✓	✓
ZIP code FEs	✓	✓	✓	✓
Time FEs	✓	✓	✓	✓
Observations	213,177	213,177	213,177	213,177
R-squared	0.16	0.14	0.10	0.11

Table 10: **Heterogeneity using Shale Instrument.**
This table reports results from reduced-form regressions exploring the heterogeneous effects of the shale oil income shock on different debt categories. The dependent variable in each column is the annual change in the specified credit category, scaled by lagged total credit. The main independent variable is our shale instrument, which interacts drilling intensity in neighboring counties with global oil price changes - see equation (5). Each panel interacts this instrument with quartile dummies for a specific ZIP code level financial characteristic, where Q1 is the lowest quartile. Panel A examines heterogeneity by Credit Score, Panel B by Debt-to-Income (DTI) ratio, and Panel C by Income Score. All specifications control for lagged borrower financial characteristics and include ZIP code and time fixed effects. All variables are winsorized at the 1% and 99% levels. Standard errors, in parentheses, are clustered at the county level. * denotes significance at the 10% level, ** the 5% level, and *** the 1% level.

	ΔTotal Credit	ΔMortgage Credit	ΔCredit Card Debt	ΔAuto Loans
Panel A: Credit Score Heterogeneity				
Neighbor drilled wells ratio$_{\text{county},t}$ $\times \Delta \ln(\text{WTI})_t$	-0.044	-0.063^{*}	0.002	0.017
	(0.05)	(0.04)	(0.01)	(0.02)
Neighbor drilled wells ratio$_{\text{county},t}$ $\times \Delta \ln(\text{WTI})_t \times Q2$	-0.051	0.024	-0.004	-0.003
	(0.01)	(0.05)	(0.01)	(0.01)
Neighbor drilled wells ratio$_{\text{county},t}$ $\times \Delta \ln(\text{WTI})_t \times Q3$	-0.059	0.011	-0.005	-0.010
	(0.03)	(0.05)	(0.01)	(0.02)
Neighbor drilled wells ratio$_{\text{county},t}$ $\times \Delta \ln(\text{WTI})_t \times Q4$	-0.019	-0.005	0.007	-0.010
	(0.07)	(0.05)	(0.01)	(0.02)
Other borrower financials$_{\text{ZIP},t-1}$	✓	✓	✓	✓
ZIP code FEs	✓	✓	✓	✓
Time FEs	✓	✓	✓	✓
Observations	213,177	213,177	213,177	213,177
R-squared	0.13	0.12	0.09	0.10
F-statistics	229	142	57	74
Panel B: Debt-to-Income Ratio Heterogeneity				
Neighbor drilled wells ratio$_{\text{county},t}$ $\times \Delta \ln(\text{WTI})_t$	-0.045	-0.077^{**}	0.006	0.032^{***}
	(0.04)	(0.04)	(0.01)	(0.01)
Neighbor drilled wells ratio$_{\text{county},t}$ $\times \Delta \ln(\text{WTI})_t \times Q2$	-0.049	0.009	0.009	-0.022^{*}
	(0.05)	(0.04)	(0.01)	(0.01)
Neighbor drilled wells ratio$_{\text{county},t}$ $\times \Delta \ln(\text{WTI})_t \times Q3$	0.040	0.029	0.003	-0.028^{**}
	(0.05)	(0.05)	(0.01)	(0.01)
Neighbor drilled wells ratio$_{\text{county},t}$ $\times \Delta \ln(\text{WTI})_t \times Q4$	-0.041	-0.026	-0.018^{***}	-0.043^{***}
	(0.06)	(0.05)	(0.01)	(0.01)
Other borrower financials$_{\text{ZIP},t-1}$	✓	✓	✓	✓
ZIP code FEs	✓	✓	✓	✓
Time FEs	✓	✓	✓	✓
Observations	213,177	213,177	213,177	213,177
R-squared	0.13	0.12	0.09	0.10
F-statistics	232	143	58	74
Panel C: Income Heterogeneity				
Neighbor drilled wells ratio$_{\text{county},t}$ $\times \Delta \ln(\text{WTI})_t$	-0.056	-0.076^{**}	0.002	0.022^{*}
	(0.04)	(0.03)	(0.00)	(0.01)
Neighbor drilled wells ratio$_{\text{county},t}$ $\times \Delta \ln(\text{WTI})_t \times Q2$	-0.052	0.033	-0.003	-0.019^{*}
	(0.05)	(0.03)	(0.00)	(0.01)
Neighbor drilled wells ratio$_{\text{county},t}$ $\times \Delta \ln(\text{WTI})_t \times Q3$	0.036	0.051	0.008	-0.009
	(0.05)	(0.03)	(0.01)	(0.01)
Neighbor drilled wells ratio$_{\text{county},t}$ $\times \Delta \ln(\text{WTI})_t \times Q4$	0.068	0.052	0.005	0.012
	(0.07)	(0.05)	(0.01)	(0.02)
Other borrower financials$_{\text{ZIP},t-1}$	✓	✓	✓	✓
ZIP code FEs	✓	✓	✓	✓
Time FEs	✓	✓	✓	✓
Observations	213,177	213,177	213,177	213,177
R-squared	0.13	0.12	0.09	0.10
F-statistics	229	142	58	76

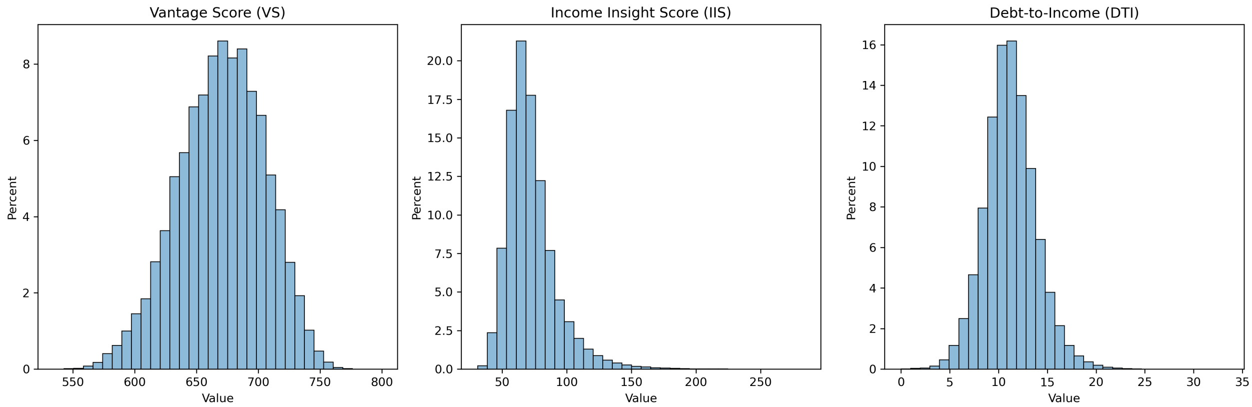

Figure 1: **Distribution of Key Financial Characteristics.** This figure presents histograms for the three main ZIP code level financial characteristics used as controls in our analysis: Vantage Score (VS), Income Insight Score (IIS), and the Debt-to-Income (DTI) ratio.

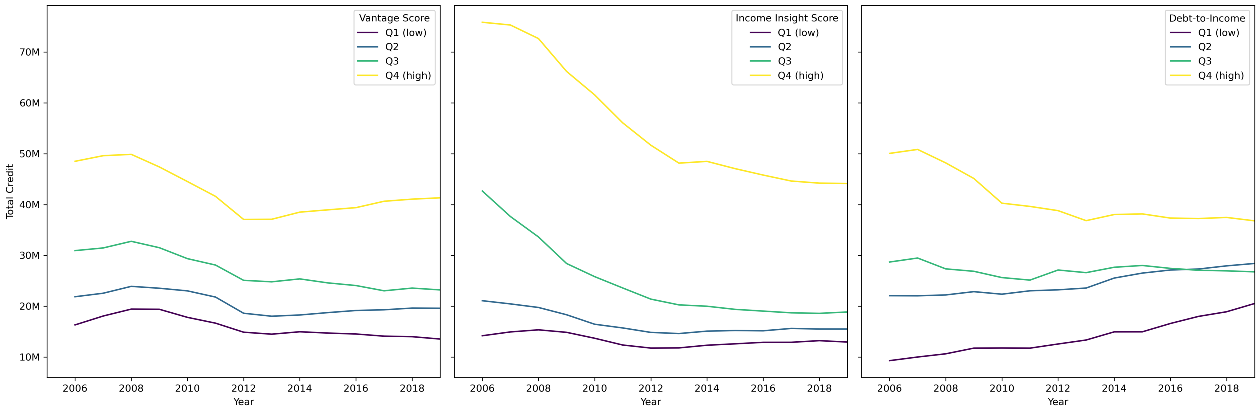

Figure 2: **Evolution of Total Credit by Financial Health Quartile.** This figure displays the time series of average total credit at the ZIP code level from 2005 to 2019, broken down by quartiles of key financial health indicators. Each panel sorts ZIP codes into quartiles based on their average Vantage Score (VS, left), Income Insight Score (IIS, middle), and Debt-to-Income ratio (DTI, right). Quartiles are dynamically recalculated annually, with Q1 representing the lowest 25% and Q4 the highest 25% of the respective indicator.

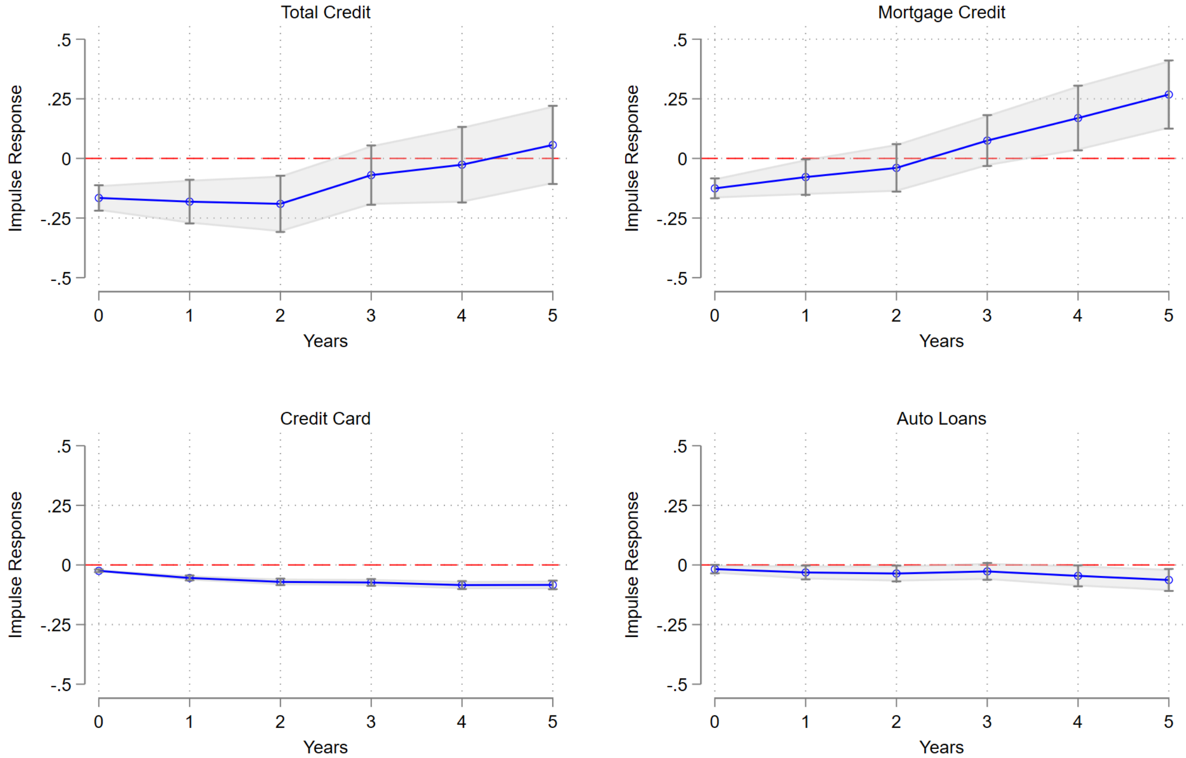

Figure 3: **Impulse Response of Household Debt to a Bartik Income Shock.** This figure shows the impulse response of different credit categories to a one-percentage-point positive shock to local earnings, estimated via instrumental variables with local projections - see equation (2). The dependent variable is the change in credit scaled by lagged total credit. The solid line represents the point estimate of the response over five years, and the shaded area indicates the 95% confidence interval.

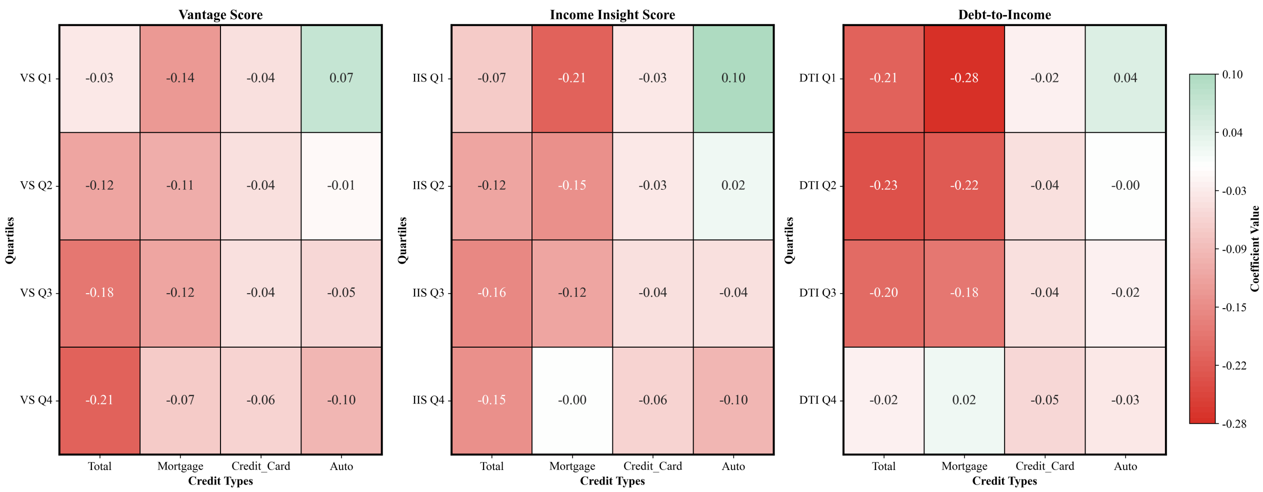

Figure 4: **Heterogeneous Debt Response to Bartik Shocks.** This figure presents heatmaps of the estimated coefficients from the reduced-form heterogeneity analysis - see equation (4). Each panel shows the interaction between the Bartik earnings shock and quartiles of a specific financial characteristic: Vantage Score (VS, left), Income Insight Score (IIS, middle), and Debt-to-Income ratio (DTI, right). The columns correspond to the response of total credit, mortgage, credit card, and auto loans. Red cells indicate a negative (deleveraging) response, while green cells indicate a positive (leveraging) response.

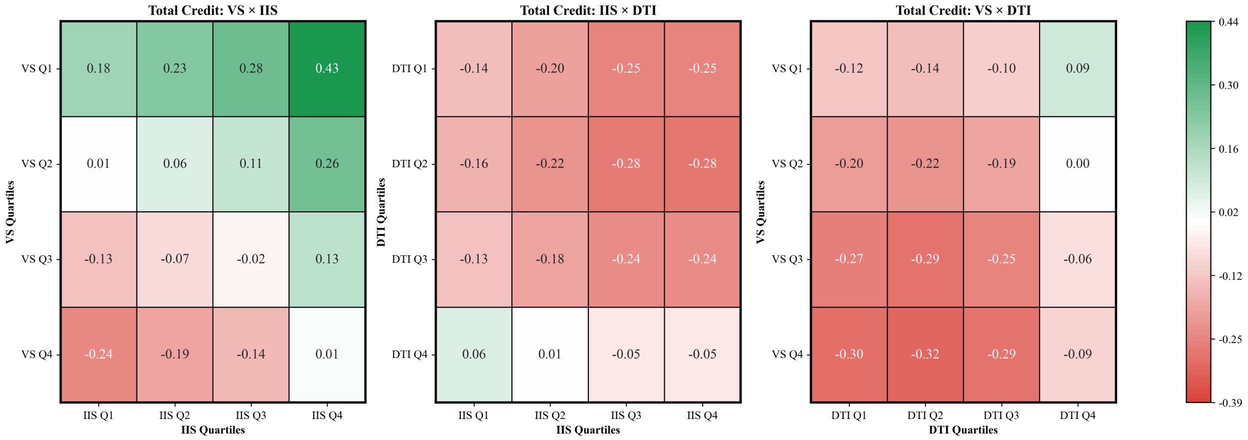

Figure 5: **Two-Way Heterogeneity: Total Credit Response to Bartik Shock.** This figure presents heatmaps of the estimated coefficients for total credit from regressions with two-way interactions. The panels show the interaction of the Bartik earnings shock with joint quartiles of Vantage Score (VS) and Income Insight Score (IIS); IIS and Debt-to-Income (DTI); and VS and DTI. The color gradient from red (negative) to green (positive) represents the magnitude and direction of the credit response.

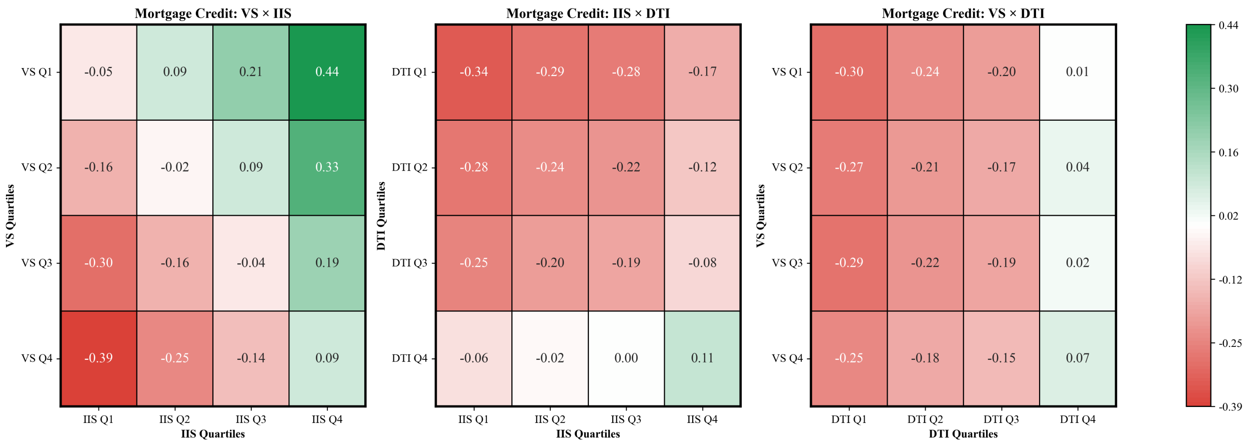

Figure 6: **Two-Way Heterogeneity: Mortgage Credit Response to Bartik Shock.** This figure presents heatmaps of the estimated coefficients for mortgage credit from regressions with two-way interactions. The panels show the interaction of the Bartik earnings shock with joint quartiles of Vantage Score (VS) and Income Insight Score (IIS); IIS and Debt-to-Income (DTI); and VS and DTI. The color gradient from red (negative) to green (positive) represents the magnitude and direction of the credit response.

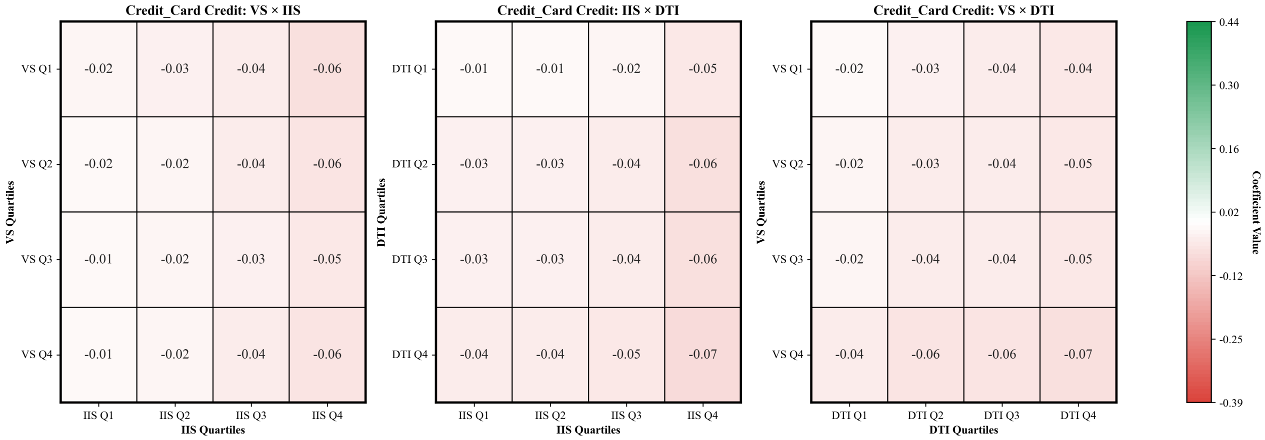

Figure 7: **Two-Way Heterogeneity: Credit Card Debt Response to Bartik Shock.** This figure presents heatmaps of the estimated coefficients for credit card debt from regressions with two-way interactions. The panels show the interaction of the Bartik earnings shock with joint quartiles of Vantage Score (VS) and Income Insight Score (IIS); IIS and Debt-to-Income (DTI); and VS and DTI. The color gradient from red (negative) to green (positive) represents the magnitude and direction of the credit response.

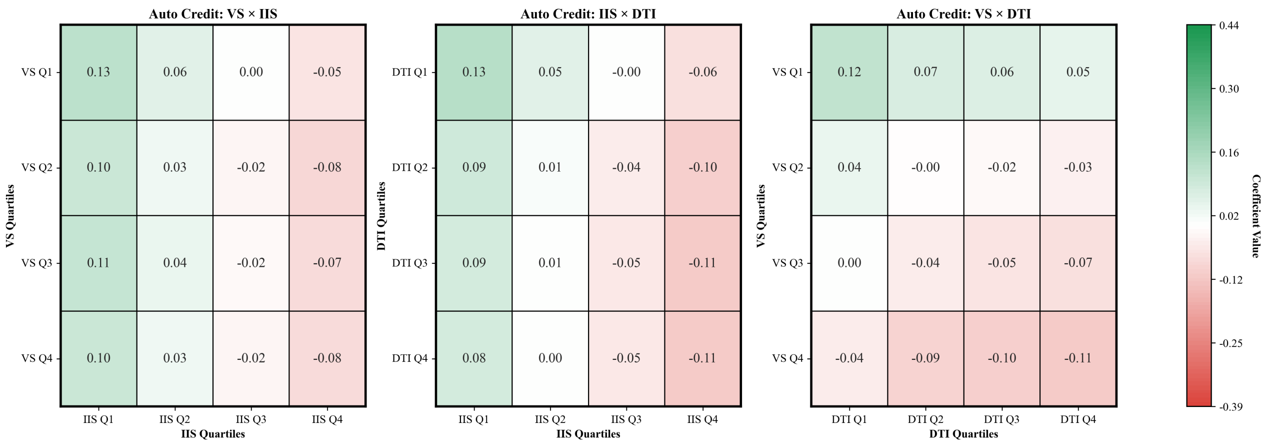

Figure 8: **Two-Way Heterogeneity: Auto Loan Response to Bartik Shock.** This figure presents heatmaps of the estimated coefficients for auto loans from regressions with two-way interactions. The panels show the interaction of the Bartik earnings shock with joint quartiles of Vantage Score (VS) and Income Insight Score (IIS); IIS and Debt-to-Income (DTI); and VS and DTI. The color gradient from red (negative) to green (positive) represents the magnitude and direction of the credit response.

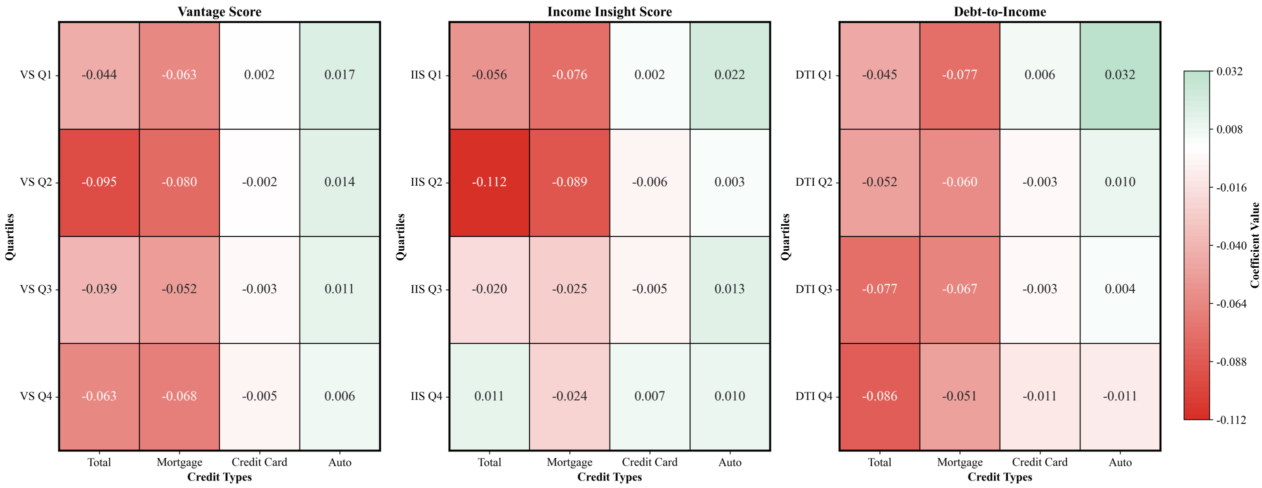

Figure 9: **Heterogeneous Debt Response to Shale Shock.** This figure presents heatmaps of the estimated coefficients from the reduced-form heterogeneity analysis using the shale instrument - see equation (7). Each panel shows the interaction between the shale shock and quartiles of a specific financial characteristic: Vantage Score (VS, left), Income Insight Score (IIS, middle), and Debt-to-Income ratio (DTI, right). The columns correspond to the response of total credit, mortgage, credit card, and auto loans. Red cells indicate a negative (deleveraging) response, while green cells indicate a positive (leveraging) response.

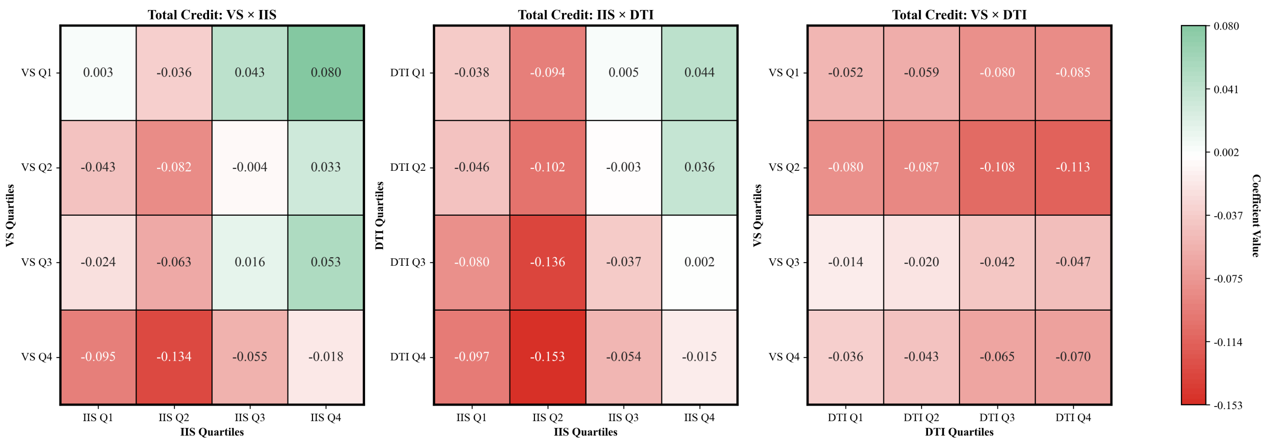

Figure 10: **Two-Way Heterogeneity: Total Credit Response to Shale Shock.** This figure presents heatmaps of the estimated coefficients for total credit from regressions with two-way interactions. The panels show the interaction of the Shale Oil & Gas Shock with joint quartiles of Vantage Score (VS) and Income Insight Score (IIS); IIS and Debt-to-Income (DTI); and VS and DTI. The color gradient from red (negative) to green (positive) represents the magnitude and direction of the credit response.

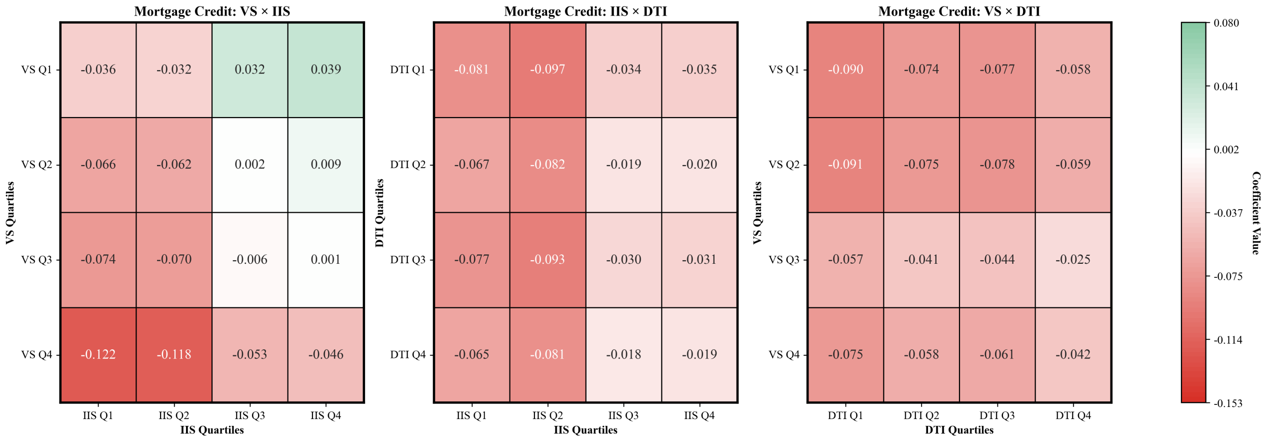

Figure 11: **Two-Way Heterogeneity: Mortgage Credit Response to Shale Shock.** This figure presents heatmaps of the estimated coefficients for mortgage credit from regressions with two-way interactions. The panels show the interaction of the Shale Oil & Gas Shock with joint quartiles of Vantage Score (VS) and Income Insight Score (IIS); IIS and Debt-to-Income (DTI); and VS and DTI. The color gradient from red (negative) to green (positive) represents the magnitude and direction of the credit response.

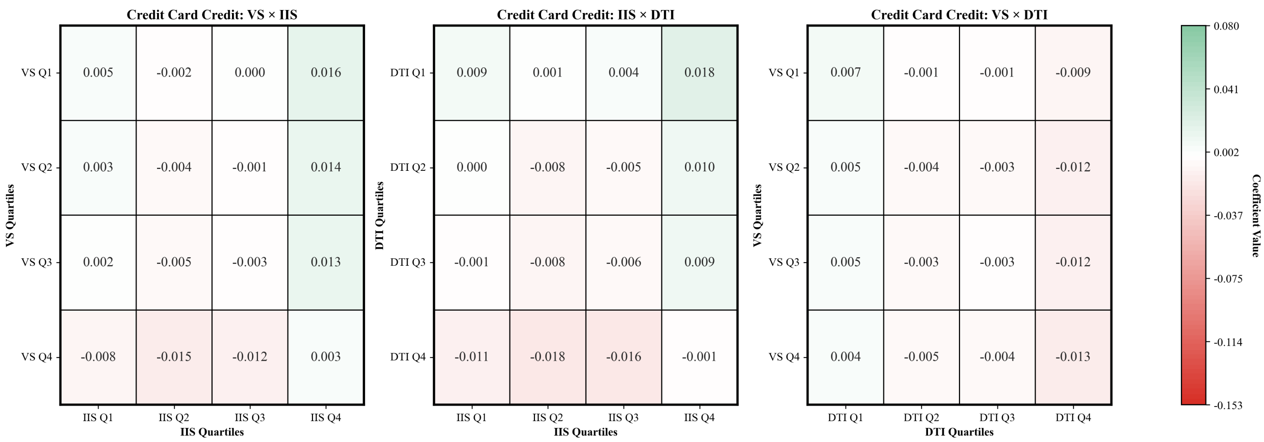

Figure 12: **Two-Way Heterogeneity: Credit Card Debt Response to Shale Shock.** This figure presents heatmaps of the estimated coefficients for credit card debt from regressions with two-way interactions. The panels show the interaction of the Shale Oil & Gas Shock with joint quartiles of Vantage Score (VS) and Income Insight Score (IIS); IIS and Debt-to-Income (DTI); and VS and DTI. The color gradient from red (negative) to green (positive) represents the magnitude and direction of the credit response.

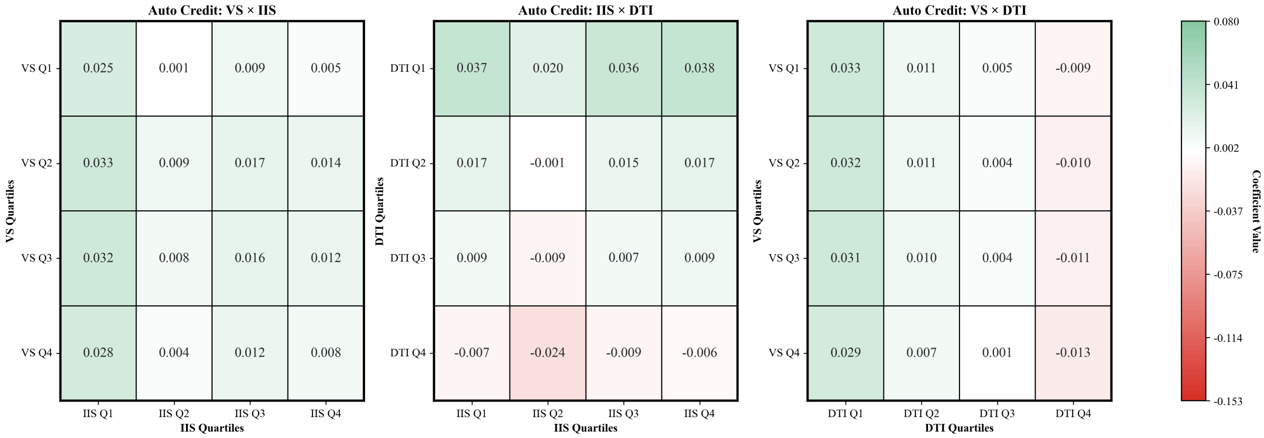

Figure 13: **Two-Way Heterogeneity: Auto Loan Response to Shale Shock.** This figure presents heatmaps of the estimated coefficients for auto loans from regressions with two-way interactions. The panels show the interaction of the Shale Oil & Gas Shock with joint quartiles of Vantage Score (VS) and Income Insight Score (IIS); IIS and Debt-to-Income (DTI); and VS and DTI. The color gradient from red (negative) to green (positive) represents the magnitude and direction of the credit response.

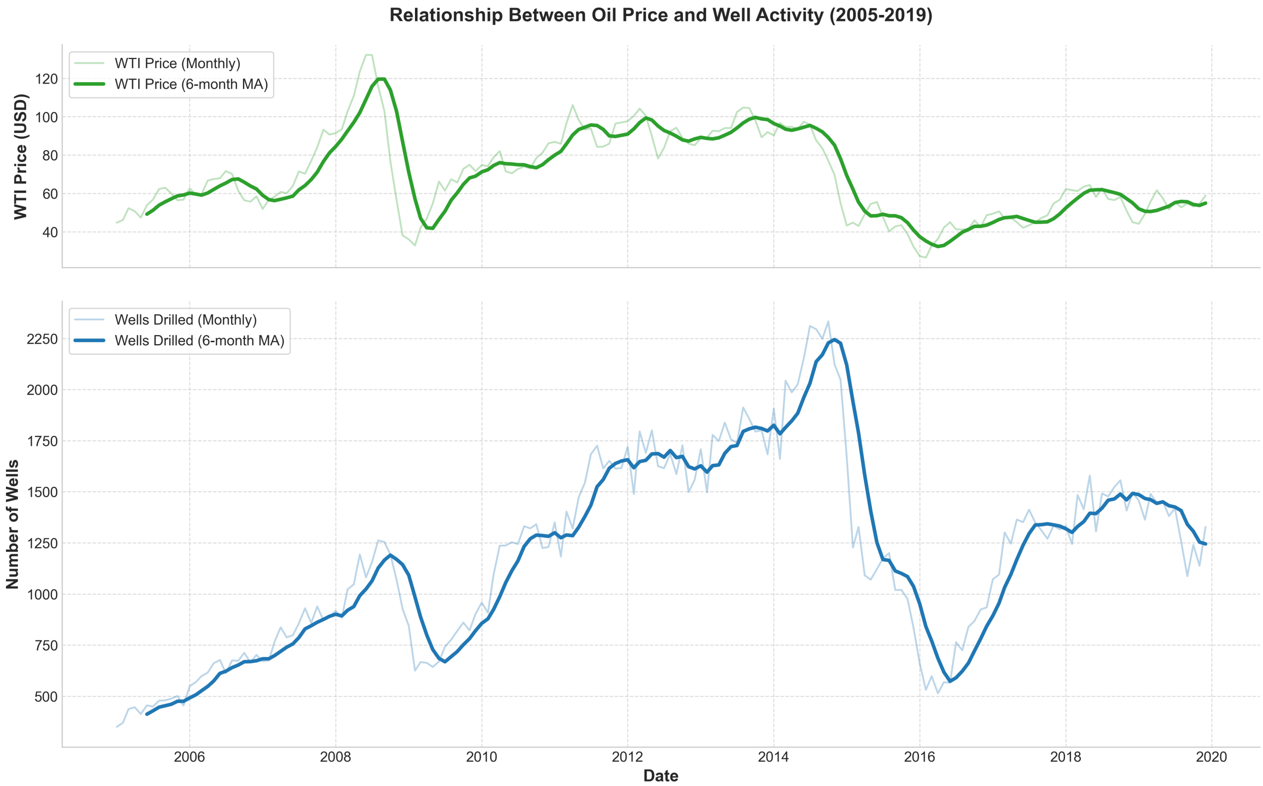

Figure 14: **Time Series of Oil Prices and Well Activity.** This figure plots the monthly time series of the WTI oil price (top panel) and the number of newly drilled wells (bottom panel) from 2005 to 2019. The figure includes both the raw monthly series and a 6-month moving average for each variable.

A Appendix: Two-way heterogeneity - Distribution of Observations

This appendix provides the underlying data distribution for the two-way heterogeneity analysis presented in Section 3.3 and Figures 5–8. Table A1 details the number of ZIP code-year observations for each joint-quartile combination of our financial health indicators. The primary purpose of this table is to provide context on the statistical precision within each cell of our interaction analysis. As the panels show, the distribution of observations is not uniform; some household profiles are far more common than others. For instance, Panel A (VS vs. IIS) shows that the observation counts are heavily concentrated along the main diagonal. The combination of low credit score and low income (VS Q1, IIS Q1) is highly populated (81,704 observations). In contrast, the "off-diagonal" cells, such as high credit score and low income (VS Q4, IIS Q1), are extremely sparse (167 observations). Consequently, the regression estimates for these rare profiles, as seen in the heatmaps, are less precise and should be interpreted with caution. In contrast, Panels B and C show that the joint distributions involving the DTI ratio are more balanced, with a more even spread of observations across the quartiles.

Table A1: **Pair-wise Observation Counts by Quartile.**
This table shows the number of ZIP code-year observations in the joint distribution of financial health indicators, supporting the two-way heterogeneity analysis. Each panel cross-tabulates observations across quartiles for a pair of indicators. Panel A compares Vantage Score (VS) and Income Insight Score (IIS), Panel B compares Debt-to-Income (DTI) ratio and IIS, and Panel C compares VS and DTI. For each variable, Q1 represents the lowest quartile (bottom 25%) and Q4 represents the highest quartile (top 25%).

Panel A: VS Quartiles vs IIS Quartiles				
	IIS Q1	**IIS Q2**	**IIS Q3**	**IIS Q4**
VS Q1	81,704	18,919	3,144	375
VS Q2	21,640	53,739	23,311	4,698
VS Q3	2,752	27,438	48,447	23,136
VS Q4	167	4,083	23,223	74,320
Panel B: DTI Quartiles vs IIS Quartiles				
	IIS Q1	**IIS Q2**	**IIS Q3**	**IIS Q4**
DTI Q1	35,055	30,822	26,822	27,282
DTI Q2	29,168	27,796	24,329	24,000
DTI Q3	20,908	21,660	20,202	20,783
DTI Q4	21,118	23,901	26,772	30,464
Panel C: VS Quartiles vs DTI Quartiles				
	DTI Q1	**DTI Q2**	**DTI Q3**	**DTI Q4**
VS Q1	30,442	28,266	21,154	24,278
VS Q2	29,198	27,015	21,501	25,668
VS Q3	29,738	25,451	20,352	26,226
VS Q4	30,603	24,561	20,546	26,083

B Appendix: Bartik Instrument Drivers

Our empirical strategy uses a Bartik instrument to identify exogenous shifts in local labor demand. As established by Goldsmith-Pinkham et al. (2020), the Bartik estimator is numerically equivalent to an instrumental variable regression using local industry shares as instruments, weighted by national industry growth rates. This equivalence implies that identification hinges on the exogeneity of the local industry shares, which are interpreted as measuring differential exposure to common shocks. The central identification concern, therefore, is that "the industry shares predict outcomes through channels other than those posited by the researcher" (Goldsmith-Pinkham et al., 2020).

Our specific implementation of the instrument characterizes these shifts as a generalized demand shock, drawing on work by Autor et al. (2013) and Auerbach et al. (2025). Two key threats challenge this approach. The first is a potential correlation between pre-period industry shares and persistent local trends (e.g., demographic or policy-related) that could independently affect consumer credit. In equation (2) we mitigate this risk by incorporating location fixed effects in our multi-period panel analysis, thereby controlling for time-invariant county characteristics.

The second, more subtle threat involves county-level supply-side factors that may be correlated with both local industry shares and national industry growth, even conditional on fixed effects. To address this, Goldsmith-Pinkham et al. (2020) propose using Rotemberg weights to decompose the Bartik estimator and reveal which specific industries are the primary drivers of the results. These weights quantify how sensitive the overall estimate is to the potential endogeneity of each underlying industry share, thus highlighting where the identifying assumptions are most critical.

Following the related methodology of Auerbach et al. (2025), we assess our instrument's drivers by estimating the response of earnings in each industry to the overall Bartik-instrumented demand shock. This approach offers a clear interpretation of how a general demand shock affects specific industries and is particularly well-suited to a panel setting, as it conveniently summarizes the average industry-level relevance across years and captures general equilibrium effects like input-output linkages.

Table A2 reports our findings. The results show that the Bartik instrument is predominantly driven by a few key sectors. Mining (NAICS 21), Construction (NAICS 23), and Manufacturing (NAICS 31-33) exhibit the largest and most significant earnings responses to a general demand shock. This outcome aligns with the findings from other applications of traditional Bartik shocks, including those analyzed in Auerbach et al. (2025) and the canonical example in Goldsmith-Pinkham et al. (2020).

Table A2: **Bartik Instrument Drivers by Industry.**
This table identifies the NAICS 2-digit industries that are the primary drivers of the Bartik instrument. Each column reports the coefficient from a regression of that industry's earnings on the Bartik-instrumented total local earnings. All regressions include county and year fixed effects. Variables are winsorized at the 1% and 99% levels. Standard errors are in parentheses. * denotes significance at the 10% level, ** the 5% level, and *** the 1% level.

	Industry				
	Mining	Construction	Manufacturing	Accom. & Food	Public Admin.
Bartik	0.366***	0.250***	0.203***	0.090***	0.086***
	(0.010)	(0.014)	(0.014)	(0.006)	(0.009)
N	52,272	52,272	52,272	52,272	52,272
F statistic (robust)	1,423.147	337.998	215.291	249.544	220.412

C Appendix: Dynamic First Stage and Shock Persistence

To validate our instrumental variable strategy over a multi-year horizon, we examine the persistence of the Bartik shock's impact on local earnings growth. This analysis is equivalent to estimating a dynamic first stage for our local projections model in equation (2). While a standard first stage establishes the contemporaneous relevance of the instrument, this dynamic version demonstrates that a Bartik shock at time t has a strong and lasting effect on earnings growth in subsequent years, justifying its use across the full five-year window of our main analysis.

We estimate the following series of reduced-form regressions for each horizon $h = 0, 1, \ldots, 5$:

$$\Delta \ln(\text{Earnings}_{c,t+h}) = \alpha_z + \beta_t + \gamma_h \cdot \text{Earnings shock}_{c,t} + \text{Controls}_{z,t-1} + \varepsilon_{z,t+h} \tag{8}$$

Here, the dependent variable, $\Delta \ln(\text{Earnings}_{c,t+h})$, is the growth in county-level log earnings from year $t-1$ to year $t+h$. The key independent variable is the Earnings $\text{shock}_{c,t}$, our Bartik instrument as defined in equation (3). The specification includes ZIP code (α_z) and year (β_t) fixed effects, and the vector $\text{Controls}_{z,t-1}$ contains lagged ZIP code level financial characteristics. The coefficient of interest, γ_h, traces the impulse response of future earnings growth to the initial Bartik shock.

Figure A1 plots the estimated coefficients γ_h. The results confirm that the Bartik shock is a strong predictor of earnings growth over a prolonged period. The coefficient at horizon $h = 0$ is approximately 2.1 and highly statistically significant, confirming the instrument's strong contemporaneous relevance. The impact of the shock is amplified substantially in the following year ($h = 1$), where the coefficient jumps to roughly 3.25. This effect remains highly significant and positive for the entire five-year horizon, peaking around year 4 before showing signs of a slow decay. This sustained predictive power validates the Bartik instrument for capturing persistent economic shifts and their effects on household balance sheets.

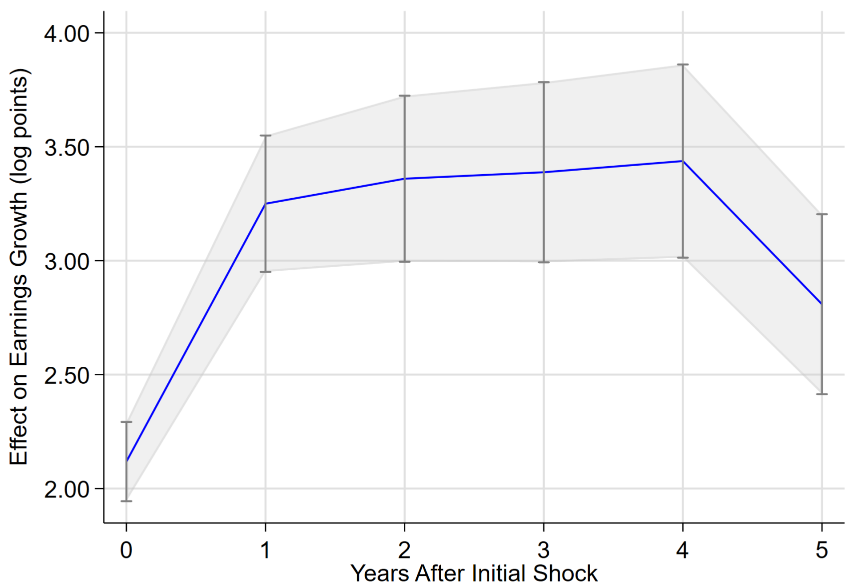

Figure A1: **Impulse Response of Earnings Growth to a Bartik Income Shock.** This figure shows the dynamic first-stage response of earnings growth to a one-unit positive shock in the Bartik instrument, as specified in equation (8). The dependent variable is the change in the natural logarithm of earnings from year $t-1$ to $t+h$ (for horizon $h = 0, 1, \ldots, 5$). The solid line represents the point estimate of the response at each horizon, and the shaded area indicates the 95% confidence interval based on standard errors clustered at the county level.

D Appendix: Testing for Anticipation Effects

A critical assumption for our identification strategy is that households do not anticipate the income shocks and adjust their borrowing behavior before the shocks materialize. If households could foresee the income gains, they might borrow against future income in advance, violating the exogeneity of our instruments. To formally test for such anticipation effects, we regress current credit growth on the lead (t+1) of each instrument—the Bartik earnings shock and the shale oil shock. If anticipation effects are present, we would expect to observe statistically significant coefficients on these forward-looking instruments.

Table A3 presents the results for the Bartik instrument. The lead coefficients are statistically significant for total credit, mortgage, and credit card debt, suggesting some degree of anticipation or pre-trending in these categories. This pattern is consistent with the relatively persistent nature of the Bartik shock. Because Bartik shocks reflect broader industry-mix driven changes that may be partially foreseeable, households with access to credit markets may begin adjusting their balance sheets in advance. This motivates our use of the shale oil instrument as a complementary identification strategy.

Figure A2 visualizes these results by plotting the coefficients for the lead, current, and lagged Bartik shock across all debt categories. The significant lead coefficients for total, mortgage, and credit card debt highlight the forward-looking behavior embedded in responses to more persistent local economic shifts. The lagged shock exhibits continued effects, particularly for total and mortgage credit, reflecting the gradual nature of debt adjustment.

Table A4 presents analogous tests for the shale oil instrument. Here, we regress current credit growth on the lead of our shale instrument: the interaction of the neighbor-county drilling intensity ratio with oil price changes. The results are highly reassuring. For total credit, mortgage debt, and auto loans, the lead coefficients are statistically insignificant and economically negligible. We observe a small, marginally significant coefficient for credit card debt in one specification (-0.010), but the magnitude remains economically trivial compared to the current effect. Overall, these results confirm that households do not anticipate the transitory income gains from nearby shale drilling activity, validating the shale instrument as free from anticipation effects.

Figure A3 provides a visual summary of the shale anticipation tests. The lead coefficients are centered near zero across all debt types, with confidence intervals that comfortably span zero. The current shale shock generates significant deleveraging in mortgage debt and leveraging in auto loans, as documented in Section 4. Importantly, the absence of significant lead effects distinguishes the shale instrument from the Bartik shock and underscores its suitability for identifying responses to unanticipated, transitory income changes.

Taken together, these anticipation tests highlight an important distinction between our two identification strategies. While the Bartik instrument captures representative but partially persistent income shocks that may involve some forward-looking adjustment, the shale instrument isolates truly unanticipated transitory shocks. This complementarity strengthens our conclusions by demonstrating that the core patterns of heterogeneous debt responses are robust across different types of income variation.

Table A3: **Anticipation Test: Bartik Instrument.**

This table tests for anticipation effects by regressing current credit growth on the lead (t+1), current (t), and lagged (t-1) values of the Bartik earnings shock. The dependent variable in each column is the annual change in the specified credit category, scaled by lagged total credit. All specifications include ZIP code and time fixed effects and control for lagged borrower financial characteristics. Standard errors, in parentheses, are clustered at the county level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	ΔTotal Credit	ΔMortgage Credit	ΔCredit Card Debt	ΔAuto Loans
	Panel A: Lag			
	(1)	(2)	(3)	(4)
Earnings shock$_{\text{county},t-1}$	-0.017	0.092^{*}	-0.066^{***}	-0.034^{**}
	(0.060)	(0.053)	(0.007)	(0.016)
Observations	410,984	410,984	410,984	410,984
R-squared	0.155	0.137	0.086	0.098
	Panel B: Current			
	(5)	(6)	(7)	(8)
Earnings shock$_{\text{county},t}$	-0.365^{***}	-0.276^{***}	-0.053^{***}	-0.038^{**}
	(0.057)	(0.046)	(0.006)	(0.019)
Observations	410,984	410,984	410,984	410,984
R-squared	0.156	0.137	0.086	0.098
	Panel C: Lead			
	(9)	(10)	(11)	(12)
Earnings shock$_{\text{county},t+1}$	-0.635^{***}	-0.540^{***}	-0.015^{**}	0.013
	(0.074)	(0.056)	(0.006)	(0.020)
Observations	381,628	381,628	381,628	381,628
R-squared	0.163	0.145	0.091	0.104
Other borrower financials$_{\text{ZIP},t-1}$	✓	✓	✓	✓
ZIP code FEs	✓	✓	✓	✓
Time FEs	✓	✓	✓	✓

Table A4: **Anticipation Test: Shale Oil Instrument.**

This table tests for anticipation effects using the shale oil instrument by regressing current credit growth on the lead (t+1), current (t), and lagged (t-1) values of the neighbor-county drilling intensity interacted with oil price changes. The dependent variable in each column is the annual change in the specified credit category, scaled by lagged total credit. All specifications include ZIP code and time fixed effects and control for lagged borrower financial characteristics. The sample is restricted to non-shale counties adjacent to shale-producing counties. Standard errors, in parentheses, are clustered at the county level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	ΔTotal Credit	ΔMortgage Credit	ΔCredit Card Debt	ΔAuto Loans
	Panel A: Lag			
	(1)	(2)	(3)	(4)
Neighbor drilled wells ratio$_{\text{county},t-1}$ $\times\Delta\ln(\text{WTI})_{t-1}$	0.030	-0.000	-0.004	0.016^{***}
	(0.025)	(0.021)	(0.002)	(0.006)
Observations	188,622	188,622	188,622	188,622
R-squared	0.151	0.130	0.107	0.111
	Panel B: Current			
	(5)	(6)	(7)	(8)
Neighbor drilled wells ratio$_{\text{county},t}$ $\times\Delta\ln(\text{WTI})_{t}$	-0.058^{**}	-0.063^{***}	-0.001	0.013^{**}
	(0.023)	(0.019)	(0.003)	(0.006)
Observations	213,289	213,289	213,289	213,289
R-squared	0.161	0.139	0.097	0.108
	Panel C: Lead			
	(9)	(10)	(11)	(12)
Neighbor drilled wells ratio$_{\text{county},t+1}$ $\times\Delta\ln(\text{WTI})_{t+1}$	-0.040	-0.013	-0.010^{***}	-0.001
	(0.028)	(0.021)	(0.004)	(0.006)
Observations	188,622	188,622	188,622	188,622
R-squared	0.168	0.147	0.105	0.115
Other borrower financials$_{\text{ZIP},t-1}$	✓	✓	✓	✓
ZIP code FEs	✓	✓	✓	✓
Time FEs	✓	✓	✓	✓

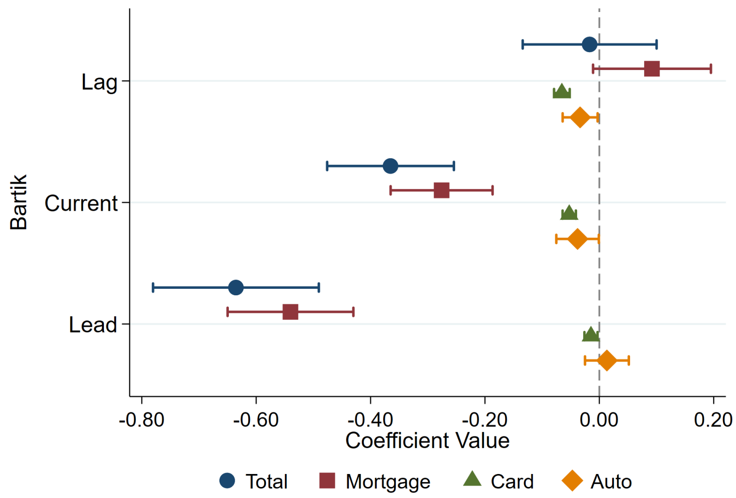

Figure A2: **Anticipation Test Coefficients: Bartik Instrument.** This figure plots the estimated coefficients for the lagged (t-1), current (t), and lead (t+1) Bartik earnings shock from the regressions in Table A3. Each shape corresponds to a different debt category: total credit, mortgage, credit card, and auto loans. The horizontal dashed line at zero provides a reference for statistical significance. Error bars represent 95% confidence intervals based on county-clustered standard errors.

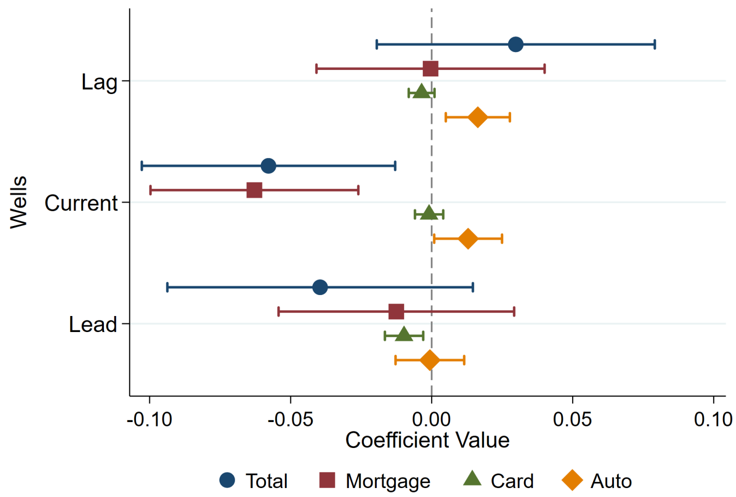

Figure A3: **Anticipation Test Coefficients: Shale Oil Instrument.** This figure plots the estimated coefficients for the lagged (t-1), current (t), and lead (t+1) shale oil shock from the regressions in Table A4. The shale shock is defined as the neighbor-county drilling intensity ratio interacted with oil price changes. Each shape corresponds to a different debt category: total credit, mortgage, credit card, and auto loans. The horizontal dashed line at zero provides a reference for statistical significance. Error bars represent 95% confidence intervals based on county-clustered standard errors.