

Social Transmission of Consumption^{*}

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Abstract

We find that consumption spreads through social networks via a “visibility bias” channel, consistent with the model of Han et al. (2023). Using county-level Facebook data and exogenous fracking-induced income shocks, we find that a 1% increase in a closely connected county’s consumption raises local spending by 0.35% in the following year. The effect is stronger for more socially connected households and for socially visible goods. Lacking a corresponding income boost, households respond by buying cheaper goods. This peer-induced spending strains household finances and increases local delinquency rates, underscoring how biased social observation can undermine financial stability.

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1 Introduction

Social networks can profoundly shape individual economic behavior. A burgeoning literature in economics and finance documents that personal connections influence decisions ranging from investment strategies to household consumption through multiple channels, including social learning, social perception, and social pressure (See the reviews by [Hirshleifer \(2020\)](#) and [Kuchler and Stroebel \(2021\)](#)). When individuals observe their peers' choices, they may update their beliefs to act similarly. In the context of consumption, upon observing friends' increased spending, observers may infer improved economic conditions, increasing their own spending. Alternatively, individuals may be subject to a visibility bias ([Han et al., 2023](#)): because consumption acts are more salient than non-consumption, people overestimate their friends' spending levels or infer overly optimistic economic signals, leading them to raise their own consumption, even without a personal income shock. In this paper, we examine whether consumption spreads through social networks and explore the underlying mechanism: Do the effects arise from rational learning from peers' spending, or from biased beliefs induced by this visibility bias that lead to overconsumption?

Empirically identifying social contagion in consumption is challenging because socially connected individuals typically share similar environments and economic conditions. When two communities show simultaneous consumption growth, this could simply reflect common economic shocks rather than a causal social influence. Our study addresses this identification challenge by exploiting a source of exogenous variation in one community's consumption and measuring its impact on the consumption of socially connected communities. In particular, we leverage the U.S. shale oil and gas boom as a natural experiment to iso-

late these effects. Between 2004 and 2014, oil and natural gas production surged unexpectedly in certain U.S. regions. This surge provides an ideal natural experiment for two reasons. First, it was plausibly exogenous—the boom resulted from unexpected technological breakthroughs in horizontal drilling and hydraulic fracturing (“fracking”) combined with pre-existing geological formations, not from local economic conditions. Second, these shocks had substantial economic impacts. As documented by [Feyrer et al. \(2017\)](#), counties with new oil and gas wells experienced significant income windfalls. Our analysis also shows that these income gains led to increased local consumption, providing a plausibly exogenous shock to spending in those counties.

We combine this shock with detailed data on social networks across counties. Specifically, we leverage the Facebook Social Connectedness Index (SCI) developed by [Bailey et al. \(2018b\)](#), which measures the intensity of friendship links between all U.S. county pairs. For each county i , we identify its most socially connected counterpart j (the county with which i has the strongest Facebook ties). We then examine whether a consumption surge in county j driven by a fracking boom spills over to an increase in county i ’s consumption the following year. We implement a two-stage least squares (2SLS) regression, using the value of county j ’s oil and gas production from new wells as an instrument for county j ’s consumption. We aim to isolate the social transmission effect of consumption from confounding economic spillovers or common shocks in the following ways. First, we focus on cases where county i itself had no new oil or gas wells and therefore experienced no direct income shock. Second, we control for county i ’s economic conditions (GDP, unemployment, etc.) as well as both county and time fixed effects. Therefore, if there is any economic spillover, this would be accounted for by county i ’s economic variables. Moreover,

time-invariant economic connections between two counties are controlled by county fixed effects.

Our analysis provides strong evidence of consumption contagion through social ties. We find that an exogenous 1% increase in consumption in the socially connected county j leads to approximately a 0.3–0.4% increase in county i 's consumption the next year, holding local conditions constant. This spillover effect is both statistically and economically significant, indicating that households increase their spending after observing friends' increased spending. To corroborate that this effect indeed reflects social influence, we examine heterogeneous responses across different household groups. Households that are more socially engaged or more likely to observe others—proxied by internet access at home and the presence of young children—exhibit substantially larger consumption responses. Specifically, consumption by internet-connected households rises significantly following friends' spending shocks, whereas households without internet show little to no response. Similarly, households with children under 18 (who tend to facilitate parental social interactions through schools and community activities) respond more strongly to peers' consumption than those without young children. These heterogeneous findings suggest that the transmission we document operates through social observation and interaction channels, rather than through fundamental economic linkages that would affect all households together.

We also examine which products most effectively transmit consumption norms through social networks. We classify products by their social visibility or “salience” using both a social-media sharing likelihood measure and price-based heuristics. The intuition is that certain purchases (for example, a celebratory bottle of wine or a new camera) are more likely to be noticed or shared among friends than others (e.g., a pesticide). Using an ex-

haustive list of product categories in our consumer panel dataset, we rank goods by their likelihood of being showcased on social media. Consistent with the visibility bias hypothesis, we find that consumption increases in highly socially salient categories have a stronger influence on peers' spending than increases in less visible categories. For instance, a spike in friend county spending on goods like cellular phones, cameras, or alcoholic products (which our measure rates as socially noticeable) leads to a larger response in focal county consumption than a spike in spending on relatively mundane items like bleach or pesticides. We obtain similar results when distinguishing expensive versus cheap products: increases in friends' purchases of higher-end goods induce a greater propagation of spending.

However, when we examine the response of follower households, we find that they increase their spending primarily on less salient and cheaper goods. Lacking the income windfall of their peers, these households cannot afford expensive or salient consumption goods. Instead, they reallocate their limited budgets towards more affordable and less salient items to align their consumption level with that observed in their peers. When we split households by income level, high-income households purchase expensive goods, while low-income households purchase cheap goods. This suggests that while visible and expensive consumption by peers serves as a powerful trigger, the consumption response of observers is largely shaped by their own budget constraints.

Finally, we examine the broader financial consequences of this social transmission of consumption. If households increase spending solely because they observe their friends doing so, they may do it by reallocating their budgets or taking on debt, given that their own income has not risen. In line with this hypothesis, we find that peer-induced consumption booms lead to higher delinquency rates on household mortgage debt in the follower

communities. In our context, when a county's close friend experiences a fracking-induced consumption surge, the focal county sees a subsequent uptick in mortgage delinquency and debt repayment problems. Moreover, the types of peer spending that most strongly drive consumption (socially salient goods) are also the ones that most strongly predict higher delinquency. This finding points towards a causal chain: visible peer consumption prompts financially constrained households to spend beyond their means, which can strain their finances and lead to an increased likelihood of loan delinquency. Our findings thereby highlight a collateral consequence of social consumption contagion — namely, its capacity to weaken households' financial stability.

In summary, our study provides one of the first empirical findings that consumption behavior spreads through social networks in a manner consistent with visibility-driven biases. We contribute to the literature on social economics and household finance along several key dimensions: First, our study establishes clean causal links demonstrating how consumption is transmitted socially, overcoming the reflection problem and economic spillover confounds (Manski, 1993).¹ Second, our study uncovers heterogeneity in the intensity of the effect across households and goods, offering empirical support for the visibility bias hypothesis. Third, our study links socially transmitted consumption to household financial fragility by showing how financially constrained households make specific consumption choices (e.g., cheap and non-salient goods) that culminate in negative financial outcomes, highlighting a novel channel through which social influence can propagate economic vulnerability.

¹The reflection problem, as introduced by Manski (1993), refers to the challenge researchers face when trying to determine whether the average behavior within a group causally influences the behavior of individual members in that group. The problem arises from observing correlations in behavior across a population or group, but it is challenging to disentangle whether these correlations stem from true endogenous social effects (where individuals are directly influenced by their peers' actions) or from other confounding factors.

Recognizing the social transmission mechanism of consumption has important implications: it suggests that purely observer-driven demand can amplify economic cycles and may need to be considered in models of consumption and saving. From a policy perspective, the evidence that visible peer consumption can induce financially unsustainable spending suggests a need for targeted financial literacy programs that address the cognitive pitfalls of visibility bias. Furthermore, socially amplified consumption booms may contribute to localized credit risk and systemic vulnerabilities, implying that regulators could incorporate social network exposure metrics into early-warning systems for household debt stress. Finally, given that digital connectivity magnifies peer effects, platform design choices—such as the prominence of conspicuous consumption cues—may have unintended macroeconomic consequences, warranting exploration of guidelines or nudges that mitigate harmful financial spillovers without stifling social interaction.

The rest of the paper is organized as follows. Section 2 describes the data sources and sample construction. Section 3 outlines our empirical design, including an instrumental variables approach. Section 4 presents the main empirical results and robustness analyses, including heterogeneity by household and product characteristics. Section 5 discusses the implications of our findings and concludes.

1.1 Related literature

This paper contributes to a burgeoning literature on social economics and finance (Hirshleifer, 2020; Kuchler and Stroebel, 2021), which investigates the influences of social interactions on economic outcomes. Theoretically, behavioral biases in social interactions may lead to overconsumption (Han et al., 2023), or the prevalence of active investment strate-

gies (Han et al., 2022). Among others, Han et al. (2023) is most related to our paper. Their key assumption is that consumption is more salient than non-consumption, which they term visibility bias. In their model, consumers do not adequately adjust for this bias and perceive that other consumers are consuming heavily. Therefore, observers believe that future consumption prospects are favorable and choose a high level of consumption themselves.² Our paper aims to empirically test this hypothesis and explore the heterogeneity of visibility bias in types of goods and household characteristics.

Our work also contributes to the literature on conspicuous consumption, which has extensively studied how households use visible spending for status signaling (e.g., dating back to Veblen’s theory of conspicuous consumption in 1899, and more recently, Charles et al. (2009) and Heffetz (2011)). We complement this literature by exploring a related mechanism rooted in cognitive bias. Specifically, we test the hypothesis that the salience of peer consumption can lead to biased beliefs about economic signals, as theorized by Han et al. (2023), which in turn leads to overconsumption. Consistent with this, we find that while the consumption of socially salient goods by friends acts as a trigger, the household’s response often manifests in increased spending on more affordable, non-salient items, particularly for those facing budget constraints. This suggests that the visibility of peer consumption may stimulate a general desire to consume—perhaps driven by a perceived shift in social norms or economic outlook—rather than a direct attempt to match the specific high-status goods of peers.

²In the model of Han et al. (2023), there is only one consumption good. The visibility bias assumption of consumption activity relative to non-consumption leads to overspending. The same logic applied in a broader setting with multiple consumption goods, where some consumption activity is more salient or visible, would imply higher consumption for the more visible goods.

A growing empirical literature has sought to causally identify peer effects in consumption, overcoming the reflection problem (Manski, 1993). A seminal study by Grinblatt et al. (2008) uses granular geographic data to show that automobile purchases are strongly influenced by the recent purchases of immediate neighbors, likely through an information-based channel. More recent studies leverage natural experiments. For instance, using lottery winnings in the Netherlands, Kuhn et al. (2011) find that neighbors of winners significantly increase their car consumption. De Giorgi et al. (2020) provide evidence that peers' consumption influences individual spending using rich Danish data and a workplace network design, highlighting a general social multiplier and its financing via lower savings. Our paper builds on this literature by using a novel exogenous shock (fracking-induced income) to identify consumption spillovers through a nationally-defined social network and yields a more nuanced understanding of the channel: we show that social consumption contagion is amplified by visible, salient expenditures and occurs even in the absence of any direct economic link, driven by biased observations. Furthermore, we explicitly connect these peer effects to negative financial outcomes – evidenced by subsequent increases in debt delinquency rates.

Our study builds on these identification strategies by leveraging large-scale social network data to move beyond geographic proximity. Bailey et al. (2018a) employ individual-level Facebook friendship data to measure social networks. They find that when people's friends experience larger recent house price increases, they are more likely to own a house rather than rent a house. If they buy a house, they also tend to buy a larger and more expensive one. Bailey et al. (2019) further document that friends' house price experiences affect individuals' mortgage leverage choices through expectations of future house price

change. These papers show that people’s interactions through social networks indeed affect their important economic decision making. Many studies also use regional level Social Connectedness Index, provided by [Bailey et al. \(2018b\)](#), to investigate the effects of social networks on various outcomes, including international trade ([Bailey et al., 2021](#)), flood insurance participation ([Hu, 2022](#)), investments ([Kuchler et al., 2022](#)), beliefs in public issues ([Bailey et al., 2024](#)) and in stock market ([Hirshleifer et al., 2025](#)), bank lending ([Rehbein and Rother, 2025](#)), and behavior of law enforcement officers ([Grosjean et al., 2023](#)). We advance this literature by demonstrating how people’s consumption is affected by the consumption of their friends.

Our work is also complementary to recent research that isolates specific channels of peer effects. In particular, [D’Acunto et al. \(2024\)](#) focus on the information channel in household spending. They study a financial-planning platform that provides subscribers with crowd-sourced data about the spending of anonymous peers who share similar demographics. Observing these peer benchmarks (without any personal social interaction) causes users to adjust their budgets toward the peer average. The finding that overspenders reduce their consumption once given accurate peer information suggests that many households had overestimated their peers’ spending, consistent with visibility bias. Our study highlights the flip side of this phenomenon, especially through social networks: in natural settings without corrective information, observing friends’ high consumption can induce people to spend beyond their means. We directly show that when peers experience a consumption surge (and presumably display it), others respond by boosting their own consumption even in the absence of an income shock, which may lead to subsequent financial vulnerability. Moreover, we find these peer effects are strongest for socially salient goods and among

households most socially connected or exposed to others' lives – exactly the scenarios where visibility bias would be most pronounced.

Finally, our paper makes a key contribution by linking socially-transmitted consumption directly to household financial fragility. Our finding that peer-induced spending leads to higher debt delinquency provides a causal micro-foundation for the macro-level patterns observed by [Bertrand and Morse \(2016\)](#), who document a "trickle-down consumption" effect where spending by the rich induces lower-income households to consume more and save less. We advance this literature by identifying the specific mechanism—visibility bias in observing peers' consumption—and by demonstrating the complete causal chain from exogenous consumption shocks to financial distress. By showing the full causal chain—from a friend's exogenous consumption shock to a household's own increased spending and subsequent financial distress—we document that an increase in friends' consumption can increase people's delinquency rate, highlighting a novel channel through which social networks can propagate economic vulnerability and potentially amplify financial instability.

2 Data and sample

2.1 Oil and natural gas data

To isolate an exogenous shock on consumption, we utilize the new oil and natural gas production data from [Feyrer et al. \(2017\)](#). They provide the annual real value of oil and natural gas from new wells that began production in the corresponding year from 2004 to 2014 at the county level. [Feyrer et al. \(2017\)](#) obtain these data from Enverus (formerly Drillinginfo). As [Feyrer et al. \(2017\)](#) argue, the sharpest increase in production occurred before 2012. Focusing on 2004–2014, therefore, captures most of the relevant variation in

fracking-induced income. Figure 1 displays each county’s cumulative value of new production per capita from 2004 to 2014.

2.2 Social connectedness data

To measure social ties between counties, we use Facebook Social Connectedness data introduced by Bailey et al. (2018b). They construct the Social Connectedness Index as follows.

$$Social\ Connectedness\ Index_{i,j} = \frac{FB_Connections_{i,j}}{FB_Users_i * FB_Users_j},$$

where $FB_Connections_{i,j}$ is the total number of Facebook friendship connections between Facebook users in county i and county j . And FB_Users_i and FB_Users_j are the number of Facebook users in county i and county j . The Social Connectedness Index is a cross-sectional measure calculated in 2021. Prior studies such as Bailey et al. (2021) and Kuchler et al. (2022) show that inter-county social connections are highly stable over time. Accordingly, using the 2021 snapshot of connections is unlikely to pose a major concern.

2.3 NielsenIQ Consumer Panel Data

To measure household consumption at the county level, we employ the NielsenIQ Consumer Panel Dataset (CPD). This dataset provides comprehensive information on daily consumption patterns and household characteristics for a broad panel of U.S. households. It covers approximately 30% of total household consumption across retail channels, including grocery stores, drug stores, and mass merchandisers. Participating households use in-home scanners or mobile apps to record their purchases by scanning product barcodes, providing granular and precise data on consumer spending. The dataset also offers rich household in-

formation, including income, education, age, race, marital status, household composition, and each household's county of residence.

Our sample period for the CPD dataset is from 2005 to 2014. This sample period is determined by the sample period of fracking data spanning 2004 to 2014, and our requirement that focal counties have no new oil or gas well shock for two consecutive years.³ To maintain a consistent sample and reduce measurement error, we restrict the panel to households that remained in the same county and consistently reported purchases in all 11 CPD panel years. This results in 90,010 household-year observations.

We calculate each household's annual expenditure on non-magnet goods.⁴ We winsorize the bottom 1% and top 1% of household consumption distribution each year to mitigate the influence of outliers. Using the provided sampling weights, we aggregate the household data to total county-year consumption values for non-magnet goods.

2.4 Delinquency data

To measure household financial distress, we construct county-level mortgage delinquency rates using data from Fannie Mae's Single-Family Loan Performance dataset and Freddie Mac's Single-Family Loan-Level dataset. These datasets cover millions of mortgages acquired by the Government-Sponsored Enterprises (GSEs) and provide monthly performance metrics. We define delinquency rates in two ways: the percentage of loans that are (1) one or more months past due, and (2) two or more months past due, each relative to

³The CPD records some 2014 consumption spending observations in the 2015 panel. Consequently, our analysis uses data from 11 panel years, spanning the 2005 through 2015 panels, while the sample period is from 2004 to 2015.

⁴Magnet goods are goods that do not use standard UPC (Universal Product Code), such as fruits and vegetables. Since only a subset of households report purchases of magnet goods after 2007, we focus on non-magnet goods.

the total number of GSE loans in that county-year.

Since the datasets provide only the first three digits of borrowers' zip codes, we map these to counties using HUD-USPS zip code crosswalk files and U.S. Census county population data. When a three-digit zip code corresponds to multiple counties, we assign the loans to the county with the largest population.

2.5 Control variables

To isolate the social transmission effect from potential economic spillovers or common shocks arising from the connected county's fracking-induced income shock, we include a comprehensive set of controls for the focal county's local economic conditions and other factors that could influence household consumption: log real GDP per capita, real GDP growth rate, and population growth rate from the U.S. Bureau of Economic Analysis (BEA), unemployment and unemployment growth rate from the U.S. Bureau of Labor Statistics (BLS), along with changes in log housing prices from the Federal Housing Finance Agency (FHFA). Consumption behaviors could be influenced by households' political alignment with the president's political party as households may become more optimistic about future economic conditions. To account for potential political influences on consumption, we include a political position variable measured as the Republican presidential candidate's vote share in each county during the most recent presidential elections. We also control for the interaction term of the vote share with whether the Republican candidate won. These controls account for any concurrent economic or social trends that could influence consumption.

3 Empirical Design

This section describes our empirical design and identification strategy. We detail our baseline specification in this section, while other specifications are discussed alongside the results in Section 4.

Identifying the social transmission of consumption through empirical methods poses significant challenges, primarily due to the reflection problem (Manski, 1993) and the potential confounding of social linkages with economic ones. Socially connected individuals or communities often share similar environments, demographic traits, and economic conditions, making it difficult to disentangle causal peer influence from correlated behaviors driven by common shocks. For instance, when two socially linked counties exhibit simultaneous consumption growth, this could merely reflect shared economic factors—such as regional business cycles, labor market trends, or supply chain interdependencies—rather than a genuine spillover through social observation.

To address these identification challenges, our study exploits exogenous income shocks induced by the recent U.S. shale oil and gas boom (e.g., Gilje et al., 2016; Feyrer et al., 2017; Bartik et al., 2019; Gilje, 2019; Cookson et al., 2022). The sharp increase in oil and natural gas production occurred from 2004 to 2014. This increase is plausibly exogenous because it stems from unexpected technological breakthroughs in hydraulic fracturing, horizontal drilling, and 3-D seismic imaging. These breakthroughs suddenly rendered vast, previously uneconomical shale deposits profitable to extract. The timing and location of these booms are determined by the interaction of this technological innovation with preexisting geological formations, rather than endogenous local economic fundamentals. Therefore, new

oil and natural gas production can be regarded as an exogenous shock that translates into income windfalls in certain counties (Feyrer et al., 2017).

We combine this shock with county-level Facebook Social Connectedness Index (SCI) data (Bailey et al., 2021) to capture social ties, focusing on pairs where the focal county experiences no direct fracking activity (and thus no income shock). We employ a two-stage least squares (2SLS) instrumental variables approach—instrumenting consumption of the connected county with the value of its new oil and gas production—to capture the effect of an exogenous increase in consumption of the connected county. Furthermore, we incorporate controls for the focal county’s local economic conditions (e.g., GDP, unemployment), along with county and time fixed effects, to account for any residual economic spillovers or time-invariant linkages between counties, thereby credibly attributing observed consumption changes in the focal county to social transmission rather than fundamental economic confounds.

To implement this identification strategy empirically, we estimate the following 2SLS regression for the focal county i and the county i ’s most socially connected county j .

$$\text{Log}(\text{Consumption}_{i,t}) = \alpha + \beta \widehat{\text{Log}(\text{Consumption}_{j,t-1})} + \Gamma C_{i,t} + \delta_i + \gamma_t + \epsilon_{i,t}, \quad (1)$$

where the dependent variable is the logarithm of average household consumption in county i ’ and year t . We calculate county-level consumption as the weighted average of households’ consumption, using the sampling weights in the CPD. The key independent variable is the logarithm of consumption in county j ’ in year $t - 1$, which is instrumented by the value of oil and gas production from new fracking wells in county j and year $t - 1$. Therefore, we study how an exogenous increase in consumption of the connected county j , driven by

the new oil and gas production, influences consumption of the focal county i next year. $C_{i,t}$ represents a set of control variables for county i , as described in the previous section. We include δ_i and γ_t as county fixed effects to absorb time-invariant differences across counties and year fixed effects to absorb any common shocks in year t . Standard errors are clustered at the county level.

To identify social spillover effects, we restrict the sample to cases where county i itself has no new oil or gas production in either year $t - 1$ or t . This ensures that county i experiences no direct fracking shock during the period we examine for spillovers. In this specification, our coefficient of interest β captures the social transmission effect: it indicates how much consumption in county i rises when consumption in its connected county j increases exogenously. Our hypothesis is that $\beta > 0$, indicating that a positive consumption shock in one county leads to higher spending in its peer county even in the absence of local income gains.

4 Empirical results

In this section, we present our empirical results. First, we investigate whether the focal county i 's consumption increases in response to an exogenous increase in its most socially connected county j 's consumption. We then examine heterogeneity of the social transmission of consumption in terms of household characteristics and product characteristics. To shed light on further consequences of the social transmission of consumption, we also examine whether the delinquency rate in the focal county rises when its connected county experiences an exogenous consumption shock.

4.1 Baseline results

We start our analysis by investigating whether the focal county's consumption increases when its most socially connected county's consumption increases due to an exogenous shock. Table 2 presents the coefficient estimation of the regression equation (1), where column (1) presents the first stage result and column (2) presents the second stage result. Column (2) result indicates that when annual consumption in the most socially connected county increases by 1% exogenously, the focal county's consumption in the following year increases by 0.348%. In other words, when a county's close social connection enjoys a consumption boom, households in the focal county significantly increase their own spending, even though the focal county itself experienced no income windfall. This result confirms our core hypothesis that consumption behavior spreads through social networks.

The first-stage regression results in column (1) of Table 2 indicate that a \$1,000 per capita increase in new oil and gas production in the socially connected county j is associated with approximately a 0.06% rise in j 's own consumption. This estimate corresponds to roughly a 1.6% increase in consumption for county j following a one-standard-deviation fracking shock (\$23,654 per capita, conditional on experiencing such a shock).

Table 3 presents the OLS regression and reduced form regression results. Column (1) shows that there is no correlation between county i 's consumption in t and county j 's consumption in $t - 1$ on average. This absence of correlation suggests that the focal county and socially connected county are not economically connected. If the focal county and socially connected county were economically linked, we would observe a significant relationship between their consumption patterns on average. Considering that a fracking shock rarely

occurs, we split the sample based on whether the connected county j has a positive or zero fracking shock, with results reported in columns (2) and (3). Column (2) shows that when county j experiences a positive fracking shock in year $t - 1$, a 1% increase in county j 's consumption in year $t - 1$ is associated with a 0.117% increase in county i 's consumption in year t . In contrast, column (3) indicates that there is no correlation with the two counties' consumption when county j has a zero shock. This contrast aligns with the visibility bias in the social transmission of consumption — it shows that when county j indeed experiences a positive income shock and increases its consumption visibly, county i responds. But if county j does not have a boom in its income and consumption, county i does not follow. Column (4) reports the reduced form result, where the statistically significant coefficient supports the validity of our IV research design.

Overall, our baseline findings demonstrate that consumption patterns spread through social networks. The OLS results reveal that consumption spillovers occur in focal counties only when their connected counties experience substantial consumption shocks. This pattern confirms the absence of economic connections between these counties and provides evidence that visibility bias is the primary mechanism underlying our findings, as spillover effects require significant observable changes in consumption behavior to transmit across county boundaries.

4.2 Household heterogeneity

In this subsection, we examine heterogeneous responses across different types of households in the focal county. This analysis not only sheds light on which households are most susceptible to peer influence, but also rules out an alternative explanation. If the observed

consumption comovement were driven by fundamental economic linkages between counties (e.g., trade or migration), we would expect it to affect all households in county i similarly. In contrast, if social transmission is the driver, households that are more exposed to observing others or are more sociable should respond more strongly.

Although we cannot directly observe sociability, we use two household characteristics as proxies. The first proxy is whether the household has an active internet connection at home. Since we use Facebook friendship to measure the social connectedness between counties, households with internet at home should be more likely to engage with friends on social media and thus more likely to observe peers' consumption online. The second proxy is whether the household has any children under 18. This is based on evidence that parents engage in broader social networks through their children's activities (Glass et al., 2016; Nomaguchi and Milkie, 2020; Pollmann-Schult, 2014). For example, they are likely to have social interactions with people through children's schooling, extracurricular activities, and parenting communities. Empirically, Gallagher and Gerstel (2001) document that the presence of children makes parents more connected in networks, measured by caregiving. Moreover, Nomaguchi and Milkie (2003) compare parents with their childless counterparts and find that parents have greater social integration.

To examine whether more sociable households in county i indeed respond more to consumption in county j , we replace $\text{Log}(\text{Consumption}_{i,t})$ in equation (1) with $\text{Log}(\text{Consumption}_{i,t,h})$, in which the subscript $h \in \{\text{with internet, without internet, with children under 18, without children under 18}\}$ represents household characteristics.

$$\text{Log}(\text{Consumption}_{i,t,h}) = \beta \text{Log}(\widehat{\text{Consumption}}_{j,t-1}) + \Gamma C_{i,t} + \delta_i + \gamma_t + \epsilon_{i,t} \quad (2)$$

For example, when $h = \textit{with internet}$, $Consumption_{i,t,h}$ measures the average consumption of households with internet in county i and year t . Therefore, we have four estimates of β from regression (2), for the four different characteristics of households. Our hypothesis is that more sociable households respond more to social transmission. Hence, we expect the estimated β for households with internet is greater than the estimated β for households without internet, and the estimated β for households with children under 18 is greater than the estimated β for households without children under 18. Finding such differences would support a social contagion interpretation and make it unlikely that unobserved common economic shocks (which should affect all households equally) are driving our results.

Table 4 presents the results of regression (2) to break down the peer effect by household subgroup in county i . The results show clear heterogeneity consistent with a social exposure mechanism. Households that are more socially connected (with internet access or with children) respond much more strongly to their peers' consumption than those that are less connected. Specifically, column (1) shows that when county j 's consumption increases by 1%, county i 's consumption of households with internet increases by 0.412%, which is statistically significant. In contrast, column (2) shows that when county j 's consumption increases by 1%, county i 's consumption of households without Internet decreases by 0.651%, which is statistically insignificant. Similarly, columns (3) and (4) illustrate that when county j 's consumption increases by 1%, county i 's consumption of households with young children increases by 1.04%, while county i 's consumption of households without young children increases by 0.286%. These differences are precisely what we would expect if social observation drives the spillover: those who are more likely to observe or discuss their friends' purchases (online or via school and community interactions) are the ones

adjusting their consumption the most.

Furthermore, this evidence suggests that latent economic commonalities or regional shocks are unlikely to explain our baseline effect. If counties i and j were fundamentally linked (for example, through trade or migration), we would expect all households in county i to be affected uniformly. Instead, we observe that spending increases are concentrated among the more socially active households in county i . This pattern strongly indicates social influence as the primary mechanism, rather than direct economic transmission.

One caveat is that when we split households into two types (with versus without internet, or with versus without young children), some counties only have one type of households. This leads to the different sample sizes in columns (1) to (4), which may make our comparisons unfair. To ensure the contrasts are not driven by sample composition, we redo this analysis by restricting to counties that contain both types of households for each split. We present this set of results in Online Appendix Table [A2](#). The results are very similar. For example, within the same set of counties, the internet-connected subgroup shows a significantly larger β than the unconnected subgroup, and likewise for households with versus without children. Thus, our conclusion holds: socially networked households (internet users and parents) exhibit a substantially higher propensity to increase spending in response to peer consumption shocks.

4.3 Product heterogeneity

4.3.1 Product heterogeneity for connected county

We now examine which product types are most effective at transmitting consumption norms through social networks. Intuitively, some purchases are more socially visible or

salient than others – for example, a fancy bottle of wine or a high-end camera is more likely to be noticed (or posted on social media) than mundane items like a detergent. We hypothesize that peer spending on more visible goods will have a larger influence on others. However, measuring product “visibility” is not straightforward. Therefore, to proxy for product visibility, we rate each product category in terms of the social-media sharing likelihood. Specifically, using the list of 1,380 product modules (categories) from the NielsenIQ CPD data, we measure how likely a person would post a purchase from each category on social media (1 = extremely unlikely, 10 = extremely likely). Appendix Table A3 reports the most and the least salient products. Our measure is intuitively reasonable: for instance, categories like alcoholic products, cameras, cellular phones, and baby products received high scores, whereas bleach, cigarettes, and pesticides received low scores. We classify any product category with a score above the median (score > 4) as “socially salient” and the rest as “socially non-salient.”

We test our hypothesis that socially salient goods have larger effects in the social transmission of consumption using regression equations (3) with $g \in \{\textit{socially salient}, \textit{socially nonsalient}\}$.

$$\text{Log}(\text{Consumption}_{i,t}) = \beta \text{Log}(\widehat{\text{Consumption}}_{j,t-1,g}) + \Gamma C_{i,t} + \delta_i + \gamma_t + \epsilon_{i,t}, \quad (3)$$

where the subscript g stands for goods characteristics. For instance, when $g = \textit{socially salient}$, $\text{Log}(\widehat{\text{Consumption}}_{j,t-1,g})$ represents the predicted log consumption of socially salient goods in county j and year $t - 1$. If visibility bias is at work, we expect that in regression (3), the β coefficient for socially salient goods is greater than its counterpart for socially nonsalient goods.

As an alternative way to capture visibility, we also categorize products by price, under the assumption that expensive purchases tend to be more conspicuous. In this process, we first compute the unit price for each UPC (universal product code). Then, we classify the UPCs whose price is equal to or greater than the median price of their product modules as expensive goods. The rest are cheap goods. We test our hypothesis that expensive goods are more influential using regression equations (3) with $g \in \{expensive, cheap\}$. We expect that in regression (3), the β coefficient for expensive goods exceeds its counterpart for cheap goods.

Table 5 reports the results of regression (3) with $g \in \{socially\ salient, socially\ nonsalient, expensive, cheap\}$. Columns (1) and (2) show that when county j 's consumption of socially salient goods increases by 1%, county i 's consumption increases by 0.443%. In contrast, when county j 's consumption of socially nonsalient goods increases by 1%, county i 's consumption increases by 0.295%. These differential peer effects support that products more likely to be observed, shared, or discussed within social networks have a disproportionately large influence on peers' spending behavior. Columns (3) and (4) in Table 5 show that when county j 's consumption of expensive goods increases by 1%, county i 's consumption increases by 0.531%. However, when county j 's consumption of cheap goods increases by 1%, county i 's consumption increases by merely 0.161%. This stark difference suggests that expensive goods are indeed more influential than cheap goods in the social transmission of consumption.

Taken together, these results provide compelling evidence that the social transmission of consumption operates through a visibility channel. Products that are inherently more noticeable—whether due to their social salience or higher prices—generate larger spillover

effects than mundane or inexpensive items, consistent with the model of Han et al. (2023).

4.3.2 Product heterogeneity for focal county

Next, we examine the types of products that focal county households purchase in response to their peers' consumption. This analysis allows us to distinguish between two potential mechanisms driving the social transmission of consumption. If households are motivated by status signaling—a desire to signal social standing relative to their peers—we would expect them to purchase similar types of products as their connected county, particularly salient and expensive goods that convey prestige. Alternatively, if the visibility bias mechanism is at work, households may interpret their peers' visible consumption as a signal of favorable economic conditions, leading them to increase consumption more broadly. Under this mechanism, households in the focal county do not necessarily match their peers' salient and expensive purchases. Instead, without their own income shock, households in the focal county would increase spending on more affordable alternatives. To test between these mechanisms, we run the following regression by aggregating the focal county's consumption separately for four product groups:

$$\text{Log}(\text{Consumption}_{i,t,g}) = \beta \text{Log}(\widehat{\text{Consumption}}_{j,t-1}) + \Gamma C_{i,t} + \delta_i + \gamma_t + \epsilon_{i,t}, \quad (4)$$

where with $g \in \{\textit{socially salient}, \textit{socially nonsalient}, \textit{expensive}, \textit{cheap}\}$.

Table 6 shows an important asymmetry in how households in the focal county adjust their consumption pattern in response to peer consumption. Columns (1) and (2) show that the increase in the focal county i 's consumption is concentrated in socially non-salient goods in response to county j 's consumption shock. Similarly, columns (3) and (4) show that the focal county's consumption response concentrates on cheap rather than expensive

goods. In line with this finding, Online Appendix Tables [A4](#) and [A5](#) show that in response to an increase in consumption of salient (expensive) goods in the connected county, the focal county significantly increases consumption of non-salient (cheap) goods rather than matching salient (expensive) goods.⁵ The finding that salient and expensive consumption triggers spending on nonsalient and cheap goods is inconsistent with status signaling, which would require households to purchase similar prestige items to maintain social standing. Instead, these results align precisely with the visibility bias hypothesis operating under budget constraints. The conspicuous consumption in county j captures attention and, through visibility bias, leads county i households to overestimate general prosperity and increase their own consumption. However, lacking the income shock, these households must express their consumption response within their existing budgets. They cannot afford luxury electronics or high-end goods, so they increase spending on everyday items—new clothing, routine groceries, or other affordable products. This pattern demonstrates how the social transmission of consumption operates through the visibility bias rather than status signaling, with financial constraints fundamentally shaping how peer influence manifests in actual purchasing decisions.

4.4 Interaction between income and price of goods

Inspired by our observations in the previous subsection, we further analyze how a household's financial flexibility influences its peer-induced spending, particularly in the types of goods purchased. In our setting, since the focal county does not experience an in-

⁵These tables also show that nonsalient and cheap goods from the connected county generate weaker spillover effects on the focal county than their salient and expensive counterparts, consistent with our earlier findings that conspicuous consumption drives stronger peer responses.

come boom, we expect households with less binding financial constraints to respond more strongly to peer consumption shocks. We use the income level of households measured by NielsenIQ to proxy households' financial constraint. Specifically, we classify households as high-income households in a given year if their income is above the median in their county in that year, and the rest are low-income households. We use the following regression to test our hypothesis.

$$\text{Log}(\text{Consumption}_{i,t,h,g}) = \beta_{h,g} \widehat{\text{Log}(\text{Consumption}_{j,t-1})} + \Gamma C_{i,t} + \delta_i + \gamma_t + \epsilon_{i,t}. \quad (5)$$

In the above regression, the dependent variable $\text{Log}(\text{Consumption}_{i,t,h,g})$ is the log of average consumption of type h households on type g products in county i and year t , where $h \in \{\text{high income}, \text{low income}\}$ and $g \in \{\text{expensive}, \text{cheap}\}$. This specification allows the peer effect $\beta_{h,g}$ to vary depending on the household's income group and the price category of goods. We expect to find that high-income households exhibit larger β coefficients than low-income households for a given type of good, reflecting their greater ability to increase spending. Moreover, this empirical setting will show how each group allocates any increased spending between cheap and expensive items. For example, low-income households might only increase consumption of cheap goods (if constrained), whereas high-income households might raise consumption of both cheap and expensive goods. We will interpret these patterns to further shed light into the role of budget constraints in mediating the visibility-driven consumption response.

Table 7 reports the results of regression (5) by splitting the consumption response in county i by both household income group and product price category. The findings show distinct patterns between low- and high-income households in their response to peer con-

sumption shocks. Column (1) shows that for low-income households, when observing a 1% increase in county j 's consumption, these households in county i decrease their consumption on expensive goods by 0.416%, which is statistically insignificant. Interestingly, column (2) shows that these households adjust their consumption on cheap goods in the opposite direction but with a similar magnitude – an increase in consumption by 0.426%, which is significant at 1% level. These similar magnitudes from columns (1) and (2) suggest that budget-constrained households reallocate their spending toward more affordable items when influenced by their peers' consumption. In contrast, columns (3) and (4) indicate that high-income households in county i increase their consumption on expensive goods by 1.787% and increase their consumption on cheap goods by 0.781%, which are both significant at the 1% level. The magnitude of their response is larger than that of low-income households for both product categories. This contrast between income groups illustrates how budget constraints mediate social influence. Low-income households appear to experience the same peer pressure to increase consumption after observing their friends' consumption, but must accommodate this impulse within their financial limitations. They achieve this by shifting their consumption from expensive to cheaper alternatives within their budgets. In contrast, high-income households with fewer constraints increase spending across all price categories but particularly expensive goods.

Overall, our findings highlight how financial constraints shape the way social influence translates into actual spending. While all households may be subject to the same visibility bias impulse, their reactions critically depend on financial constraints, resulting in fundamentally different spending patterns across income groups.

4.5 Delinquency rate

So far, our analysis has established that consumption spreads through social networks via visibility bias, with particularly strong effects among socially connected households and for highly visible goods. But does this peer-driven spending have consequences beyond consumption itself? We explore whether social transmission of consumption affects household financial stability in the focal county. When households increase spending simply because they observe their friends doing so, without experiencing their own income gains, they must find ways to finance this additional consumption. They may reallocate existing budgets or take on more debt, potentially straining their ability to meet financial obligations. We test this hypothesis by examining changes in county-level mortgage delinquency rates using the following regression:

$$Delinquency_{i,t} = \beta \text{Log}(\widehat{Consumption}_{j,t-1}) + \Gamma C_{i,t} + \delta_i + \gamma_t + \epsilon_{i,t}, \quad (6)$$

where the dependent variable is the delinquency rate, measured as the share of loans that are at least one month delinquent, in county i and year t . The right-hand variables remain the same as in our baseline specification in equation (1).

To further explore the mechanism, we test whether product categories that drive the stronger consumption spillovers also generate the larger effects on financial distress by running the following regression.

$$Delinquency_{i,t} = \beta \text{Log}(\widehat{Consumption}_{j,t-1,g}) + \Gamma C_{i,t} + \delta_i + \gamma_t + \epsilon_{i,t}. \quad (7)$$

In regression (7), the goods characteristics g can be *socially salient*, *socially nonsalient*, *expensive*, or *cheap*. Since socially salient and expensive goods trigger larger consumption

increases than non-salient and cheap goods, we expect that these same categories from the connected county also have stronger impacts on the focal county's delinquency rates if peer-induced spending is indeed straining household financial stability. Observing these patterns would reinforce the interpretation that visible peer consumption leads households to overextend financially, linking the social contagion of consumption to subsequent financial stress.

Table 8 presents the results of regressions (6) and (7). Column (1) shows that a 1% increase in the connected county j 's consumption leads to a 0.06% increase in the focal county i 's delinquency rate. This effect is statistically significant and indicates that household financial stress rises in tandem with peer-driven spending spikes — when people spend more because their friends are spending more, they appear to struggle to meet their own debt obligations.

Columns (2) through (5) examine how different product categories of the connected county's consumption are associated with the focal county's delinquency rate. Columns (2) and (3) show that a 1% increase in the connected county j 's consumption of salient goods is associated with the focal county i 's delinquency rate by 0.074%, compared to just 0.053% for non-salient goods. Columns (4) and (5) show that the gap is even larger for expensive versus cheap goods: expensive goods are associated with an increase in delinquency by 0.098%, which compares to only 0.029% for cheap goods. These results confirm our prediction that product categories driving stronger consumption responses also generate larger increases in financial distress, demonstrating how visibility-driven social contagion directly undermines household financial stability. Moreover, the increase in delinquency rates indicates that financially constrained households drive the average spillover effects,

as unconstrained households would not experience repayment difficulties from increased spending.

For the robustness test, we rely on an alternative definition of the delinquency measure, defined as the share of loans with more than two months past due, instead of at least one month, and repeat our analysis. Online Appendix Table A6 shows the consistent findings: the focal county's delinquency rate rises following consumption increases in connected counties, with salient and expensive goods having stronger effects than non-salient and cheap goods. This consistency underscores that the implication of the social transmission of consumption extends beyond spending patterns to household financial stability.

In summary, we document a sizable social multiplier in consumption: households increase spending when observing friends' spending more, despite no change in their own income. This effect operates through visible and expensive goods and is most pronounced among socially connected households. However, this peer-driven spending undermines financial stability, as reflected in higher delinquency rates. Our findings shed new light on how biased social observation can propagate both consumption patterns and contribute to financial vulnerability.

5 Conclusion

This paper demonstrates that consumption can be socially contagious: households tend to spend more when they observe their peers spending more. By leveraging an exogenous shock to one set of households' consumption (through fracking-driven income gains) and tracing its effects on connected households, we establish a clear causal link in this social transmission of consumption. The evidence indicates that a significant part of this spillover

is driven by visibility bias – the tendency to be influenced by conspicuous consumption. We find that households with greater exposure to friends (through online networks or children’s activities) respond the most, and that the contagion is strongest for highly visible goods. In contrast to standard economic spillovers, which would raise broad consumption through higher income or confidence, the pattern we document is more specific: observers, especially those low-income ones, increase their consumption of cheaper items, rather than expensive products, when they see their peers spending more.

Our findings have meaningful implications for both theory and policy. From a theoretical perspective, our results provide empirical validation for models of social behavior and inattention that predict overconsumption when people observe others’ spending patterns ([Han et al., 2023](#)). They suggest that social networks serve as a conduit for demand shocks, amplifying consumption changes across communities even without concomitant income changes. This mechanism could contribute to aggregate demand fluctuations and may help explain why consumption booms and busts sometimes cluster geographically or temporally beyond what economic fundamentals would predict. Moreover, the policy implications are equally significant. Our finding that peer-induced spending sprees lead to higher debt delinquency potentially raises concerns about financial stability: When households increase their spending to match their peers rather than because their financial situation has improved, they become more vulnerable to income disruptions. This social transmission of consumption patterns can push families to overextend themselves financially. Policymakers and lenders should be aware that surges in visible consumption (for example, during holiday seasons or in conspicuous goods) could foreshadow rising credit risks if driven by social emulation rather than improved fundamentals.

This study highlights that the ripple effects of one group's positive economic shock can extend well beyond direct economic linkages, operating through the psychology of observation and biased social perception. Future research could explore interventions to mitigate excessive peer influence—such as improved financial education about these biased perceptions, or social media designs that downplay conspicuous consumption. It could also be fruitful to examine whether similar social multipliers of consumption occur in other contexts (e.g., in emerging markets or with different types of shocks) and how they interact with formal economic policies. By illuminating the channels through which peer observation influences spending in the modern, connected economy, our work contributes to a deeper understanding of consumption dynamics and financial well-being in the age of social networks.

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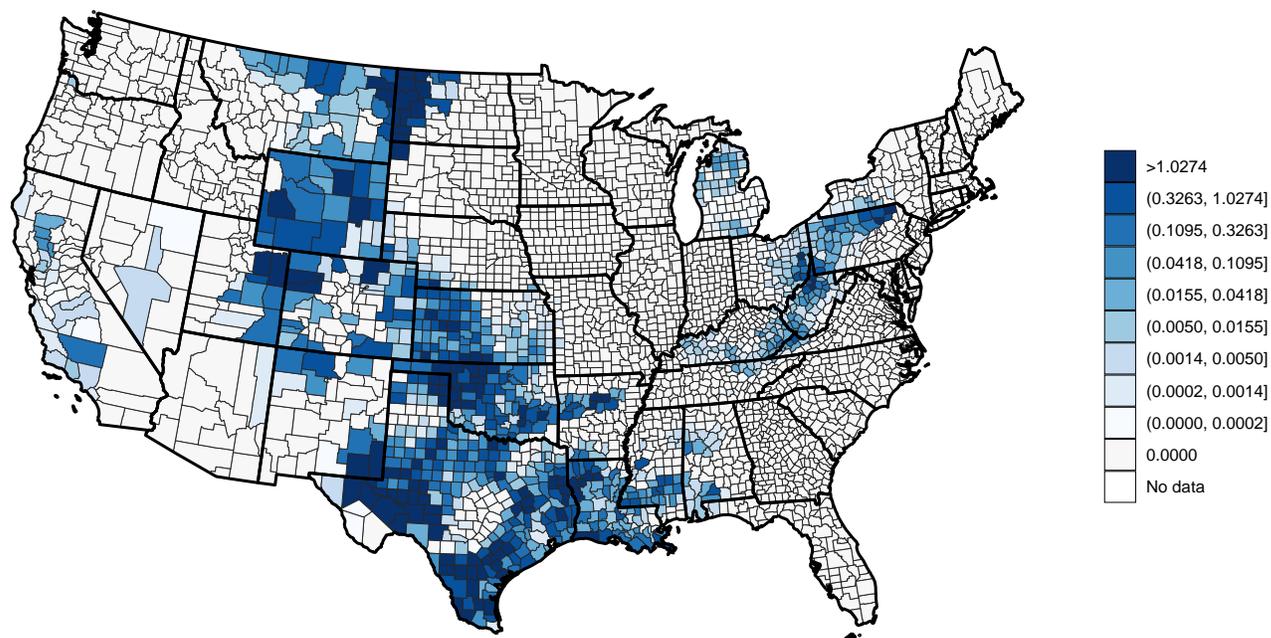


Figure 1. New Production From Fracking

This figure plots each county's cumulative value of new production per capita from 2004 to 2014.

Table 1. Summary statistics

| | N | Mean | SD | P1 | P10 | P50 | p90 | p99 |
|---|------|---------|--------|---------|---------|---------|--------|--------|
| Consumption | 9744 | 8.214 | 0.408 | 7.084 | 7.696 | 8.237 | 8.703 | 9.129 |
| Consumption of households with Internet | 8712 | 8.253 | 0.406 | 7.115 | 7.737 | 8.276 | 8.740 | 9.142 |
| Consumption of households without Internet | 4686 | 8.043 | 0.482 | 6.773 | 7.419 | 8.061 | 8.643 | 9.117 |
| Consumption of households with young children | 3332 | 8.493 | 0.403 | 7.368 | 7.962 | 8.533 | 8.971 | 9.332 |
| Consumption of households without young children | 9259 | 8.161 | 0.411 | 7.020 | 7.640 | 8.184 | 8.659 | 9.092 |
| Consumption on salient goods | 9744 | 7.664 | 0.434 | 6.455 | 7.111 | 7.688 | 8.200 | 8.593 |
| Consumption on nonsalient goods | 9744 | 7.329 | 0.429 | 6.059 | 6.797 | 7.351 | 7.839 | 8.319 |
| Consumption on expensive goods | 9744 | 7.787 | 0.494 | 6.359 | 7.151 | 7.827 | 8.367 | 8.855 |
| Consumption on cheap goods | 9744 | 7.075 | 0.435 | 5.854 | 6.538 | 7.095 | 7.606 | 8.030 |
| Consumption in connected county | 9744 | 8.231 | 0.413 | 7.060 | 7.716 | 8.253 | 8.727 | 9.182 |
| Consumption on salient goods in connected county | 9744 | 7.678 | 0.440 | 6.442 | 7.119 | 7.699 | 8.217 | 8.627 |
| Consumption on nonsalient goods in connected county | 9744 | 7.352 | 0.433 | 6.081 | 6.823 | 7.373 | 7.875 | 8.388 |
| Consumption on expensive goods in connected county | 9744 | 7.800 | 0.494 | 6.389 | 7.159 | 7.839 | 8.385 | 8.867 |
| Consumption on cheap goods in connected county | 9744 | 7.099 | 0.454 | 5.799 | 6.528 | 7.130 | 7.650 | 8.093 |
| Delinquency measure 1 | 2845 | 0.033 | 0.019 | 0.003 | 0.014 | 0.029 | 0.054 | 0.109 |
| Delinquency measure 2 | 2845 | 0.018 | 0.015 | 0.000 | 0.005 | 0.015 | 0.033 | 0.079 |
| NewValueCapita in thousand USD | 9744 | 0.183 | 6.427 | 0.000 | 0.000 | 0.000 | 0.000 | 0.591 |
| NewValueCapita (conditional on > 0) in thousand USD | 560 | 3.178 | 26.654 | 0.000 | 0.000 | 0.020 | 2.253 | 48.694 |
| Log(GDP per capita) | 9744 | 10.579 | 0.397 | 9.707 | 10.100 | 10.569 | 11.055 | 11.616 |
| GDP per capita growth | 9744 | 0.004 | 0.063 | -0.142 | -0.053 | 0.004 | 0.060 | 0.161 |
| Unemployment | 9744 | 2.046 | 0.170 | 1.619 | 1.833 | 2.050 | 2.268 | 2.411 |
| Unemployment growth | 9744 | 0.018 | 0.210 | -0.295 | -0.182 | -0.040 | 0.379 | 0.622 |
| Population growth | 9744 | 0.006 | 0.012 | -0.017 | -0.006 | 0.004 | 0.020 | 0.045 |
| HPI growth | 9744 | -0.024 | 0.056 | -0.185 | -0.086 | -0.023 | 0.037 | 0.125 |
| Voting share | 9744 | 55.116 | 13.448 | 19.642 | 38.280 | 55.755 | 71.741 | 82.662 |
| Interacted voting share | 9744 | -29.399 | 47.955 | -81.447 | -69.671 | -49.269 | 59.252 | 75.737 |

This table provides summary statistics of county-year level variables used in this paper. All the consumption variables are the log of real consumption based on the total consumption of each household. N denotes the number of observations. $Mean$ denotes the arithmetic mean of the variable. SD the standard deviation of the variable. PX denotes X th-percentile of the variable. Nominal values are converted to real values using the 2012 dollar. The variable definition is in Appendix Table A1.

Table 2. **Baseline**

| | Log(Consumption _{<i>j,t-1</i>}) (1) | Log(Consumption _{<i>i,t</i>}) (2) |
|---|--|--|
| NewValueCapita _{<i>j,t-1</i>} | 0.0006*** (0.0001) | |
| Log($\widehat{\text{Consumption}}_{j,t-1}$) | | 0.348*** (0.13) |
| County controls | ✓ | ✓ |
| County FE | ✓ | ✓ |
| Year FE | ✓ | ✓ |
| N | 9744 | 9744 |
| Kleibergen-Paap Wald F-Stat | 25.07 | 25.07 |

This table presents the 2SLS regression of log consumption of county i in year t on its most connected county j 's log consumption in year $t - 1$, predicted by county j 's production from new oil and natural gas wells in year $t - 1$. Column (1) presents the first stage result and column (2) present the second stage result. We control for county i 's log real GDP per capita, real GDP growth, unemployment rate, unemployment rate growth, population growth, housing price change, and political position. County and year fixed effects are controlled. Standard errors clustered by county are in parentheses. Kleibergen-Paap Wald F-statistic for the first stage regression is reported. ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively. The variable definition is in Appendix Table A1.

Table 3. OLS and reduced form

| | Dep. var. Log(Consumption _{<i>i,t</i>}) | | | |
|---|---|--|--|----------------------|
| | Full sample (1) | Positive shock in connected county (2) | Zero shock in connected county (3) | Full sample (4) |
| Log(Consumption _{<i>j,t-1</i>}) | 0.003 (0.01) | 0.117** (0.06) | 0.001 (0.02) | |
| NewValueCapita _{<i>j,t-1</i>} | | | | 0.0002** (0.0001) |
| County controls | ✓ | ✓ | ✓ | ✓ |
| County FE | ✓ | ✓ | ✓ | ✓ |
| Year FE | ✓ | ✓ | ✓ | ✓ |
| N | 9744 | 521 | 9165 | 9744 |

This table presents the OLS regressions of county i 's log consumption in year t on its most connected county j 's log consumption in year $t - 1$ in columns (1) to (3). Column (1) presents the result for the full sample. Column (2) presents the result for observations where the connected county has a positive fracking shock, and column (3) presents the result for observations where the connected county has a zero fracking shock. Column (4) presents the reduced form result. We control for county i 's log real GDP per capita, real GDP growth, unemployment rate, unemployment rate growth, population growth, housing price change, and political position. County and year fixed effects are controlled. Standard errors clustered by county are in parentheses. ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively. The variable definition is in Appendix Table A1.

Table 4. Household heterogeneity

| | Dep. var. Log(Consumption _{<i>i,t,h</i>}) | | | |
|---|---|------------------------------------|---------------------------------------|--|
| | Households with Internet (1) | Households without Internet (2) | Households with young children (3) | Households without young children (4) |
| Log($\widehat{\text{Consumption}}_{j,t-1}$) | 0.412*** (0.13) | -0.651 (1.08) | 1.040*** (0.26) | 0.286** (0.13) |
| County controls | ✓ | ✓ | ✓ | ✓ |
| County FE | ✓ | ✓ | ✓ | ✓ |
| Year FE | ✓ | ✓ | ✓ | ✓ |
| N | 8702 | 4609 | 3281 | 9249 |
| Kleibergen-Paap Wald F-Stat | 24.82 | 24.20 | 38.35 | 22.98 |

This table presents the 2SLS regressions of log consumption of county i 's certain types of households in year t on its most connected county j 's log consumption in year $t - 1$, predicted by county j 's production from new oil and natural gas wells in year $t - 1$. We control for county i 's log real GDP per capita, real GDP growth, unemployment rate, unemployment rate growth, population growth, housing price change, and political position. County and year fixed effects are controlled. Standard errors clustered by county are in parentheses. Kleibergen-Paap Wald F-statistics for the first stage regressions are reported. ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively. The variable definition is in Appendix Table A1.

Table 5. **Product heterogeneity: effects of the connected county's consumption types**

| | Dep. var. Log(Consumption _{<i>i,t,g</i>}) | | | |
|---|---|-------------------|--------------------|-------------------|
| | (1) | (2) | (3) | (4) |
| Log($\widehat{\text{Consumption}}_{j,t-1,g}$) Salient goods | 0.443*** (0.14) | | | |
| Log($\widehat{\text{Consumption}}_{j,t-1,g}$) Nonsalient goods | | 0.295** (0.13) | | |
| Log($\widehat{\text{Consumption}}_{j,t-1,g}$) Expensive goods | | | 0.531*** (0.18) | |
| Log($\widehat{\text{Consumption}}_{j,t-1,g}$) Cheap goods | | | | 0.161** (0.07) |
| County controls | ✓ | ✓ | ✓ | ✓ |
| County FE | ✓ | ✓ | ✓ | ✓ |
| Year FE | ✓ | ✓ | ✓ | ✓ |
| N | 9744 | 9744 | 9744 | 9744 |
| Kleibergen-Paap Wald F-Stat | 18.41 | 16.17 | 14.33 | 21.59 |

This table presents the 2SLS regressions of county i 's log consumption in year t on its most connected county j 's log consumption of certain types of goods in year $t - 1$, predicted by county j 's production from new oil and natural gas wells in year $t - 1$. We control for county i 's log real GDP per capita, real GDP growth, unemployment rate, unemployment rate growth, population growth, housing price change, and political position. County and year fixed effects are controlled. Standard errors clustered by county are in parentheses. Kleibergen-Paap Wald F-statistics for the first stage regressions are reported. ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively. The variable definition is in Appendix Table A1.

Table 6. Product heterogeneity: responses of the focal county's consumption types

| | Dep. var. Log(Consumption _{<i>i,t,g</i>}) | | | |
|--|---|-------------------------|------------------------|--------------------|
| | Salient goods (1) | Nonsalient goods (2) | Expensive goods (3) | Cheap goods (4) |
| Log(Consumption _{<i>j,t-1</i>}) All goods | 0.188 (0.15) | 0.577* (0.33) | 0.169 (0.23) | 0.692*** (0.18) |
| County controls | ✓ | ✓ | ✓ | ✓ |
| County FE | ✓ | ✓ | ✓ | ✓ |
| Year FE | ✓ | ✓ | ✓ | ✓ |
| N | 9744 | 9744 | 9744 | 9744 |
| Kleibergen-Paap Wald F-Stat | 25.07 | 25.07 | 25.07 | 25.07 |

This table presents the 2SLS regressions of county *i*'s log consumption of certain types of goods in year *t* on its most connected county *j*'s log consumption in year *t* - 1, predicted by county *j*'s production from new oil and natural gas wells in year *t* - 1. We control for county *i*'s log real GDP per capita, real GDP growth, unemployment rate, unemployment rate growth, population growth, housing price change, and political position. County and year fixed effects are controlled. Standard errors clustered by county are in parentheses. Kleibergen-Paap Wald F-statistics for the first stage regressions are reported. ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively. The variable definition is in Appendix Table A1.

Table 7. Interaction of household income and goods price

| | Dep. var. Log(Consumption _{<i>i,t,h,g</i>}) | | | |
|---|---|----------------------------------|---------------------------------------|-----------------------------------|
| | Low income Expensive goods (1) | Low income Cheap goods (2) | High income Expensive goods (3) | High income Cheap goods (4) |
| Log($\widehat{\text{Consumption}}_{j,t-1}$) | -0.416 (0.42) | 0.426*** (0.16) | 1.787*** (0.30) | 0.781*** (0.27) |
| County controls | ✓ | ✓ | ✓ | ✓ |
| County FE | ✓ | ✓ | ✓ | ✓ |
| Year FE | ✓ | ✓ | ✓ | ✓ |
| N | 9744 | 9744 | 9744 | 9744 |
| Kleibergen-Paap Wald F-Stat | 25.07 | 25.07 | 25.07 | 25.07 |

This table presents the 2SLS regressions of county i 's log consumption of certain types of households and goods in year t on its most connected county j 's log consumption in year $t - 1$, predicted by county j 's production from new oil and natural gas wells in year $t - 1$. We control for county i 's log real GDP per capita, real GDP growth, unemployment rate, unemployment rate growth, population growth, housing price change, and political position. County and year fixed effects are controlled. Standard errors clustered by county are in parentheses. Kleibergen-Paap Wald F-statistics for the first stage regressions are reported. ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively. The variable definition is in Appendix Table A1.

Table 8. Delinquency

| | Dep. var. Delinquency _{<i>i,t</i>} | | | | |
|---|---|--------------------|--------------------|-------------------|--------------------|
| | (1) | (2) | (3) | (4) | (5) |
| Log($\widehat{\text{Consumption}}_{j,t-1}$) All goods | 0.060*** (0.02) | | | | |
| Log($\widehat{\text{Consumption}}_{j,t-1,g}$) Salient goods | | 0.074*** (0.03) | | | |
| Log($\widehat{\text{Consumption}}_{j,t-1,g}$) Nonsalient goods | | | 0.053*** (0.02) | | |
| Log($\widehat{\text{Consumption}}_{j,t-1,g}$) Expensive goods | | | | 0.098** (0.05) | |
| Log($\widehat{\text{Consumption}}_{j,t-1,g}$) Cheap goods | | | | | 0.029*** (0.01) |
| N | 2845 | 2845 | 2845 | 2845 | 2845 |
| Kleibergen-Paap Wald F-Stat | 20.76 | 13.67 | 18.21 | 5.68 | 55.67 |

This table presents the 2SLS regressions of county i 's delinquency rate in year t on its most connected county j 's log consumption of certain types of goods in year $t - 1$, predicted by county j 's production from new oil and natural gas wells in year $t - 1$. Delinquency is measured as percentage of loans that are one or more months past due. We control for county i 's log real GDP per capita, real GDP growth, unemployment rate, unemployment rate growth, population growth, housing price change, and political position. County and year fixed effects are controlled. Standard errors clustered by county are in parentheses. Kleibergen-Paap Wald F-statistics for the first stage regressions are reported. ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively. The variable definition is in Appendix Table A1.

Online Appendix to “Social Transmission of Consumption”

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Table A1. Variable definitions

| Variable | Description | Source |
|---|--|--|
| Consumption | Log of average household consumption | NielsenIQ |
| Consumption of households with Internet | Log of average consumption of households with Internet | NielsenIQ |
| Consumption of households without Internet | Log of average consumption of households without Internet | NielsenIQ |
| Consumption of households with young children | Log of average consumption of households with young children | NielsenIQ |
| Consumption of households without young children | Log of average consumption of households without young children | NielsenIQ |
| Consumption on salient goods | Log of average household consumption on salient goods | NielsenIQ |
| Consumption on nonsalient goods | Log of average household consumption on nonsalient goods | NielsenIQ |
| Consumption on expensive goods | Log of average household consumption on expensive goods | NielsenIQ |
| Consumption on cheap goods | Log of average household consumption on cheap goods | NielsenIQ |
| Consumption in connected county | Similarly defined for the connected county | NielsenIQ |
| Consumption on salient goods in connected county | Similarly defined for the connected county | NielsenIQ |
| Consumption on nonsalient goods in connected county | Similarly defined for the connected county | NielsenIQ |
| Consumption on expensive goods in connected county | Similarly defined for the connected county | NielsenIQ |
| Consumption on cheap goods in connected county | Similarly defined for the connected county | NielsenIQ |
| Delinquency measure 1 | Percentage of loans that are one or more months past due | Fannie Mae's and Freddie Mac's |
| Delinquency measure 2 | Percentage of loans that are two or more months past due | Fannie Mae's and Freddie Mac's |
| NewValueCapita in thousand USD | Value of production of oil and natural gas per capita from new wells | Feyrer et al. (2017) sourced from drillinginfo.com and BLS |
| Log(GDP per capita) | Log of real GDP per capita | BEA |
| GDP per capita growth | Log growth in real GDP per capita | BEA |
| Population growth | Log growth in population | BEA |
| Unemployment | Log of the number of unemployed workers | BLS |
| Unemployment growth | Log growth in unemployment | BLS |
| HPI growth | Log growth in House Price Index | FHFA |
| Voting share | Voting share for Republican | MIT Election Data and Science Lab |
| Interacted voting share | $(\text{Voting share} - 0.5) \times \text{whether Republican wins the election}$ | MIT Election Data and Science Lab |

This table provides the definitions of variables. All the consumption variables are the log of real consumption based on the total consumption of each household.

Table A2. Household heterogeneity

| | Dep. var. Log(Consumption _{<i>i,t,h</i>}) | | | |
|---|---|------------------------------------|---------------------------------------|--|
| | Households with Internet (1) | Households without Internet (2) | Households with young children (3) | Households without young children (4) |
| Log(Consumption _{<i>j,t-1</i>}) | 1.119** (0.54) | -0.672 (1.20) | 1.101*** (0.37) | 0.704** (0.27) |
| County controls | ✓ | ✓ | ✓ | ✓ |
| County FE | ✓ | ✓ | ✓ | ✓ |
| Year FE | ✓ | ✓ | ✓ | ✓ |
| N | 3608 | 3608 | 2810 | 2810 |
| Kleibergen-Paap Wald F-Stat | 29.29 | 29.29 | 25.30 | 25.30 |

This table presents the 2SLS regressions of log consumption of county i 's certain types of households in year t on its most connected county j 's log consumption in year $t - 1$, predicted by county j 's production from new oil and natural gas wells in year $t - 1$. Observations are restricted to county-years that have both types of households. Namely, observations in columns (1) and (2) have both households with Internet and households without Internet. Observations in columns (3) and (4) have both households with young children and households without young children. We control for county i 's log real GDP per capita, real GDP growth, unemployment rate, unemployment rate growth, population growth, housing price change, and political position. County and year fixed effects are controlled. Standard errors clustered by county are in parentheses. Kleibergen-Paap Wald F-statistics for the first stage regressions are reported. ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively. The variable definition is in Appendix Table A1.

Table A3. The most salient and the least salient products

| Product Modules | Score | Product Modules | Score |
|--|-------|---|-------|
| Panel A: The most salient products | | Panel B: The least salient products | |
| ALCOHOLIC COCKTAILS | 10 | ... | |
| BEER | 10 | AMMONIA | 1 |
| BRANDY/COGNAC | 10 | BLEACH - DRY | 1 |
| CAMERAS | 10 | BLOOD URINE STOOL TEST PRODUCTS | 1 |
| CELLULAR PHONE | 10 | CIGARETTE AND CIGAR PAPER | 1 |
| ARTIST AND HOBBY PAINT AND SUPPLY | 9 | CIGARETTES | 1 |
| BABY ACCESSORY | 9 | CLAM JUICE | 1 |
| BABY CARE PRODUCTS-LOTIONS | 9 | CONTRACEPTIVES-FEMALE | 1 |
| BABY CARE PRODUCTS-POWDER | 9 | DIARRHEA REMEDIES | 1 |
| BABY FOOD - JUNIOR | 9 | ENEMAS-READY-TO-USE | 1 |
| BABY MILK AND MILK FLAVORING | 9 | INSECTICIDE-ANT & ROACH-CRACK & CREVICE-SPRAY | 1 |
| CAKE DECORATIONS & ICING | 9 | IPECAC PRODUCT | 1 |
| GIFT PACKAGE WITH CANDY OR GUM | 9 | LAXATIVES | 1 |
| BAKERY - BREAD - FRESH | 8 | PERISHABLE MUFFIN | 1 |
| BAKERY-BREAKFAST CAKES/SWEET ROLLS-FRESH | 8 | PERISHABLE SUGAR | 1 |
| BAKERY-CAKES-FRESH | 8 | PESTICIDES - REMAINING | 1 |
| BAKERY-CHEESECAKE-FRESH | 8 | RECTAL MEDICATION | 1 |
| BAKERY-DOUGHNUTS-FRESH | 8 | RODENTICIDES | 1 |
| BAKERY-MUFFINS-FRESH | 8 | SEXUAL ENHANCING DEVICE | 1 |
| BAKERY-PIES-FRESH | 8 | SKIN BLEACHING/TONING PRODUCTS | 1 |
| BAKERY-ROLLS-FRESH | 8 | SMOKING ACCESSORIES | 1 |
| BAKING CHIPS - MILK CHOCOLATE | 8 | TOBACCO-SMOKING | 1 |
| PET CARE - PET FOOD | 8 | UNCLASSIFIED INSECTICDS/PESTICDS/RODENTICDS | 1 |
| ... | | YEAST-REFRIGERATED | 1 |

This table presents the most salient and the least salient products. We rate the social-media sharing likelihood of each product category in our data on a 1–10 scale.

Table A4. **Product heterogeneity: salient versus nonsalient goods**

| | Dep. var. Log(Consumption _{<i>i,t,g</i>}) | | | |
|---|---|-------------------------|----------------------|-------------------------|
| | Salient goods (1) | Nonsalient goods (2) | Salient goods (3) | Nonsalient goods (4) |
| Log($\widehat{\text{Consumption}}_{j,t-1,g}$) Salient goods | 0.240 (0.20) | 0.734** (0.37) | | |
| Log($\widehat{\text{Consumption}}_{j,t-1,g}$) Nonsalient goods | | | 0.160 (0.12) | 0.489 (0.33) |
| County controls | ✓ | ✓ | ✓ | ✓ |
| County FE | ✓ | ✓ | ✓ | ✓ |
| Year FE | ✓ | ✓ | ✓ | ✓ |
| N | 9744 | 9744 | 9744 | 9744 |
| Kleibergen-Paap Wald F-Stat | 18.41 | 18.41 | 16.17 | 16.17 |

This table presents the 2SLS regressions of county i 's log consumption of certain types of goods in year t on its most connected county j 's log consumption of certain types of goods in year $t - 1$, predicted by county j 's production from new oil and natural gas wells in year $t - 1$. We control for county i 's log real GDP per capita, real GDP growth, unemployment rate, unemployment rate growth, population growth, housing price change, and political position. County and year fixed effects are controlled. Standard errors clustered by county are in parentheses. Kleibergen-Paap Wald F-statistics for the first stage regressions are reported. ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively. The variable definition is in Appendix Table A1.

Table A5. **Product heterogeneity: expensive versus cheap goods**

| | Dep. var. Log(Consumption _{<i>i,t,g</i>}) | | | |
|--|---|--------------------|------------------------|--------------------|
| | Expensive goods (1) | Cheap goods (2) | Expensive goods (3) | Cheap goods (4) |
| Log(Consumption _{<i>j,t-1,g</i>}) Expensive goods | 0.258 (0.33) | 1.058*** (0.36) | | |
| Log(Consumption _{<i>j,t-1,g</i>}) Cheap goods | | | 0.078 (0.11) | 0.321*** (0.08) |
| County controls | ✓ | ✓ | ✓ | ✓ |
| County FE | ✓ | ✓ | ✓ | ✓ |
| Year FE | ✓ | ✓ | ✓ | ✓ |
| N | 9744 | 9744 | 9744 | 9744 |
| Kleibergen-Paap Wald F-Stat | 14.33 | 14.33 | 21.59 | 21.59 |

This table presents the 2SLS regressions of county i 's log consumption of certain types of goods in year t on its most connected county j 's log consumption of certain types of goods in year $t - 1$, predicted by county j 's production from new oil and natural gas wells in year $t - 1$. We control for county i 's log real GDP per capita, real GDP growth, unemployment rate, unemployment rate growth, population growth, housing price change, and political position. County and year fixed effects are controlled. Standard errors clustered by county are in parentheses. Kleibergen-Paap Wald F-statistics for the first stage regressions are reported. ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively. The variable definition is in Appendix Table A1.

Table A6. Delinquency: alternative measure

| | Dep. var. Delinquency _{<i>i,t</i>} | | | | |
|---|---|--------------------|--------------------|-------------------|--------------------|
| | (1) | (2) | (3) | (4) | (5) |
| Log($\widehat{\text{Consumption}}_{j,t-1}$) All goods | 0.071*** (0.02) | | | | |
| Log($\widehat{\text{Consumption}}_{j,t-1,g}$) Salient goods | | 0.088*** (0.03) | | | |
| Log($\widehat{\text{Consumption}}_{j,t-1,g}$) Nonsalient goods | | | 0.063*** (0.02) | | |
| Log($\widehat{\text{Consumption}}_{j,t-1,g}$) Expensive goods | | | | 0.115** (0.05) | |
| Log($\widehat{\text{Consumption}}_{j,t-1,g}$) Cheap goods | | | | | 0.034*** (0.01) |
| N | 2845 | 2845 | 2845 | 2845 | 2845 |
| Kleibergen-Paap Wald F-Stat | 20.76 | 13.67 | 18.21 | 5.68 | 55.67 |

This table presents the 2SLS regressions of county i 's delinquency rate in year t on its most connected county j 's log consumption of certain types of goods in year $t - 1$, predicted by county j 's production from new oil and natural gas wells in year $t - 1$. Delinquency is measured as percentage of loans that are two or more months past due. We control for county i 's log real GDP per capita, real GDP growth, unemployment rate, unemployment rate growth, population growth, housing price change, and political position. County and year fixed effects are controlled. Standard errors clustered by county are in parentheses. Kleibergen-Paap Wald F-statistics for the first stage regressions are reported. ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively. The variable definition is in Appendix Table A1.