Learning from Friends in a Pandemic: Social Networks and the Macroeconomic Response of Consumption

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Abstract

This paper studies how shocks to the social network can have aggregate effects. First, using daily consumption data across counties over the COVID-19 pandemic and Facebook's Social Connectedness Index (SCI), we find that a 10% rise in SCI-weighted cases and deaths is associated with a 0.18% and 0.23% decline in consumption expenditures. These consumption effects are concentrated among consumer goods and services that rely more on social-contact, suggesting that individuals incorporate the experiences from their social network to inform their own consumption choices. Second, we calibrate a heterogenous-agent model with market incompleteness where agents form their perceptions about the local infection conditions subject to social influences. Our model shows how the aggregate consumption has further dropped due to the presence of social network amplification given the pandemic outbreaks first took place in well-connected regions. We also show how the size of aggregate responses depends on the location of the initial shocks and structure of the network.

Keywords: Aggregate Demand, Consumption, Coronavirus, COVID-19, Expectations, Peer Effects, Social Networks

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1 Introduction

The ongoing COVID-19 pandemic represents the largest world-wide shock in at least a century, leading to substantial declines in employment (Coibion et al., 2020a; Bartik et al., 2020; Cajner et al., 2020), consumption (Baker et al., 2020b; Coibion et al., 2020b), and output (Makridis and Hartley, 2020; Guerrieri et al., 2020) that surpass even the Great Recession. The vast majority of empirical contributions thus far have focused on the direct effects of the first moment shocks associated with the virus and the resulting national and state quarantine policies.[1]

The primary purpose of this paper is to explore the macroeconomic effects of the pandemic on consumption mediated through the presence of social networks. Since social media is now a primary vehicle for obtaining information in the average household (Westerman et al., 2014), and 74% of individuals view social media as important for staying connected during the pandemic (Ritter, 2020), individuals may adjust their consumption in response to information communicated through friends in connected regions even if their own county has fairly low exposure to the virus. Identifying how individuals make consumption and savings decisions in response to shocks to not only their fundamentals, but also those of their connected friends is important for understanding the sources of aggregate fluctuations, particularly during episodes of uncertainty and panic.

The question posed in this particular context is also related to a generally interesting inquiry in economics: how are individuals' decisions affected by social influences? Identifying these interpersonal influences on economic decisions is usually challenging in empirical research due to the "reflection problem" (Manski, 2000). This paper solves that challenge by exploiting plausibly exogenous variation in individuals' exposure to geographically remote, but socially connected, counties that vary in their friendship formed prior to the pandemic. In other words, we examine how counties

[1] See Baker et al. (2020a) for an exception.

adjust their consumption in response to shocks in their social network. Another advantage of our approach is that it allows us to distinguish the "expectation channel" from the "preference channel" where individuals adjust their consumption based on the social norms and influences of their peers (Heffetz, 2011; De Giorgi et al., 2020). Since we exploit variation in geographically distant social connections that are identified from social network data, we believe that the effects identified here are more likely through expectations rather than preference dependence.

Using a combination of US micro card transaction data from Facteus and the Social Connectedness Index (SCI) from Facebook, this paper quantifies an elasticity of the individual consumption and the composition of consumption in response to the fluctuations of infections in connected counties. We find that a 10% increase in SCI-weighted cases and deaths is associated with a 0.18% and 0.23% decline in consumption, respectively. We also find that these declines are greater among social-contact-based consumption categories and activities away from home. For instance, each 10% increase in SCI-weighted cases is associated with a 0.5% decrease in clothing, footwear, cosmetics, a 1.1% decrease in contact-based service, and a 1.2% decrease in travel. These decreases are two-to-three times as large as the drop in average spending. This finding provides direct evidence for the uneven impacts of the pandemic on different sectors, which, augmented with market incompleteness, could result in a permanent drop in aggregate demand (Guerrieri et al., 2020).

We investigate the mechanisms and show that our results are not driven by time-varying shocks that are also correlated with infections in connected counties. First, we control for state $\times$ day fixed effects, which isolates variation across counties in the same state. Furthermore, we show that increases in SCI-weighted infections are associated with stronger declines in consumption when stay-at-home orders are in place. This is consistent with the idea that social networks are more influential when consumers are unable to gather information through their personal experience around their city. Second, we conduct a wide array of heterogeneity exercises, showing that the heterogeneous treatment effects align with theory (e.g., greater effect in younger counties since social networks are more prevalent with millennials). Finally, we exploit counties' heterogeneous exposure to day-to-day changes in infections across South Korea, Italy, France, and Spain. We find similar results even when we restrict our sample to days between February 15th and March 15th 2020 prior to the U.S. national pandemic response, suggesting that our results reflect an information-driven response.

Motivated by these empirical results, we extend a heterogenous-agent consumption model of an incomplete market with two key features. First, to capture the interaction between the pandemic and the economy, we model the local infection as an idiosyncratic stochastic state that evolves with persistent shocks. Individual income is state-dependent and a higher infection lowers individual income. Since contact and non-contact consumption differ in their exposure to infections, increases in infections also affect consumption by dampening the relative preference for contact-based consumption, and leading to reallocation between the two sectors.

Second, to capture the social network influence, we assume that agents do not perfectly observe their idiosyncratic state. Instead, they form perceptions by taking a weighted average of states from their connected nodes in the network, which is similar to the naive learning by DeMarzo et al. (2003) and Golub and Jackson (2010). The influence weights are determined by pairwise connections as a share of total connections that the receiving node has across the entire network. With social influence unevenly distributed across agents, social networks can propagate local shocks by emphasizing their salience to consumers across the network. In this sense, aggregate fluctuations in consumption in response to the coronavirus shock depend on the locations that the infections hit, their severity, and the structure of the social network.

Given a reasonable calibration of the model to match the pre-pandemic cross-sectional consumption inequality and an externally estimated dynamics of infection, our model generates economically significant impacts of the social network in amplifying the consumption responses to the pandemic.

For instance, following a one-time 10% increase in the infection of random one-third agents in the economy, the social network leads to an additional 0.3 percentage drop in consumption compared to the 1 percentage point drop in full social isolation. We also show that the consumption responses are larger if more influential nodes are shocked and if the network structure gives a more dispersed distribution of the influence in the network.

Our paper directly contributes to a large literature on the household response of consumption to macroeconomic shocks. This literature largely focuses on the impact of income volatility and borrowing constraints (Zeldes, 1989; Pistaferri, 2001; Gourinchas and Parker, 2002), stimulus (Di Maggio et al., 2017; Fuster et al., 2018), and tax rebates (Souleles, 1999; Johnson et al., 2006; Agarwal et al., 2007) on consumption.[2] Quantifying how shocks affect consumption is important for understanding the presence of partial insurance and the pass-through of shocks (Blundell et al., 2008; Kaplan and Violante, 2010, 2014; Heathcote et al., 2014).[3] Our results provide evidence that individuals may adjust their consumption in response to shocks that affected their connections even beyond any direct effects on themselves. While we are not the first to point out the presence of peer effects in economic and financial behavior (Moretti, 2011; Bursztyn et al., 2014; D'Acunto et al., 2019), our results nonetheless build on emerging evidence about the role of social networks and how they influence the decision to rent versus own a home (Bailey et al., 2018a) and the formation of expectations about the state of the national economy (Makridis, 2020).

Our paper also contributes to an older literature on social externalities, specifically the spread of disease (Diamond and Maskin, 1979; Kremer and Morcom, 1998).[4] Recent research has begun investigating the effects of pandemics on economic activity, placing a central role on the optimizing

[2]Closely related is a larger literature on precautionary saving (Carroll, 1992, 1997; Carroll and Samwick, 1998) and the relationship between economic sentiment and consumption (Carroll et al., 1994).

[3]See Jappelli and Pistaferri (2010) for a survey.

[4]There is also a related literature in applied psychology and computational social science that has identified evidence of contagion through the dissemination of information through social networks, i.e. see Kramer et al. (2014), as well as Fowler and Christakis (2008) for some of the early evidence outside of social media.

behavior of households. Whereas Eichenbaum et al. (2020) and Garibaldi et al. (2020) build models featuring households that fail to internalize the risk of infecting others through contact, Krueger et al. (2020) allow for heterogeneity in infection probabilities across sectors. This heterogeneity allows Krueger et al. (2020) to explore how individuals may optimally choose to avoid certain activities because of the risk of infection, meaning that the economy can avoid contagion without as much of a government intervention. Because we show how individuals adjust their consumption in response to information about the severity of the pandemic before stay-at-home orders were even implemented, we provide additional evidence that individuals make adjustments to their behavior in response to information. Our results are also consistent with Farboodi et al. (2020) who use the Safegraph data to quantify the effect of the pandemic on foot traffic.

Finally, our paper is related to an emerging empirical literature on the role of personal experience in expectation formation. Studies have highlighted the role of personal experience in forming beliefs about future returns (Cogley and Sargent, 2008), inflation (Malmendier and Nagel, 2016; Coibion and Gorodnichenko, 2015), energy prices (Binder and Makridis, 2020), housing prices (Kuchler and Zafar, 2019), macroeconomic activity (Malmendier and Nagel, 2011; Makridis, 2020; Makridis and McGuire, 2020), asset prices (Malmendier et al., 2018), political preferences (Giuliano and Spilimbergo, 2014), and consumption (Malmendier and Shen, 2018). By showing how consumption activity is linked with shocks that are diffused throughout the social network, our paper builds closely on Carroll (2003) who finds that household expectations are informed by news reports and the views of professional forecasters. If social networks amplify negative shocks by "spreading the bad news," they can potentially help account for the potentially persistent effect that the pandemic will have on expectations (Kozlowski et al., 2020a).[5] Binder (2020) also finds that individuals

[5] Kozlowski et al. (2020a) builds a model along the lines of Kozlowski et al. (2020b) where transient shocks can have persistent effects on beliefs. If expectations are trending in one direction, but agents experience a large shock, beliefs can take time to recover.

worried about the pandemic also have greater inflation expectations, suggesting that bad news about the pandemic spills over into the broader expectation formations process.

The structure of the paper is as follows. Section 2 describes our data and measurement approach. Section 3 introduces our identification strategy. Section 4 presents our main results and investigates heterogeneity across consumption goods. Section 5 sets up the model and discusses the calibration parameters. Section 6 conducts a variety of experiments based on the model. Section 7 concludes. We are continuing to produce additional results, specifically focusing on taking these empirical patterns to an aggregate model of the economy.

2 Data and Measurement

The transaction-level data is provided by Safegraph and Facteus based on an anonymized panel of roughly 5.18 million debit card users' daily spending records between January 1st, 2017 to June 30th, 2020. Transactions are collected from primarily four types of cards providers across the United States: (1) bank debit cards whose majority users are young people, (2) general-purpose debit cards that are primarily distributed by merchants and retailers, (3) payroll cards used between employers and employees, and (4) government cards. Average nationwide daily spending of the whole sample is 194 million dollars from a total of 2.3 million transactions.

Three features make the data particularly useful to our analysis.[6] First, there is rich geographic heterogeneity. In particular, transactions are partitioned by the residential zipcode of the card user. We then aggregate zip-level transactions into county-level consumption observations of 3051

[6] However, one limitation of our data is that the location of a transaction differs from the location of residence; we only observe the latter. While we suspect that exploiting county-level (rather than zipcode-level) variation mitigates this concern, since people consume locally most of the time, we view potential misclassification as a source of measurement error (Chen et al., 2011). This would bias us against finding a result. We nonetheless conduct robustness where we investigate potential heterogeneous treatment effects in areas that have high versus lower levels mobility in “normal times", i.e. college towns.

counties (out of 3141 in the United States as of 2019). For zip zones that are associated with multiple counties, we allocate total consumption to its multiple corresponding counties based on its population weights. To ensure the county-level consumption is not biased by abnormal individual users' records and extreme values, we restrict our sample to include only county-day observations with more than 30 card users. Daily average consumption expenditures per card user is roughly $40 based on 0.5 transactions.

Second, there is high-frequency variation. In particular, we exploit the daily variation in transactions to identify the response of consumption to news about the pandemic. Since the epidemic crisis has eclipsed nearly ever other national and international event with release of daily news on the number of infections and deaths, daily records provide much cleaner variation than the common alternative of monthly data to recover the effects of news and social media. Although the transaction data goes back to 2017, we restrict the sample to the period between February 1st and June 30th with a total of 152 days and roughly 450,000 county × day observations. This period spans from the early spreading stage of the COVID-19 in Asian and European continents to the peak of the crisis within the United States. Depending on if the focus of analysis is domestic or international, we split our sample with the cutoff date of March 15—a widely acknowledged watershed in nationwide response to the crisis in the country.

Finally, spending transaction is recorded by the merchant's type identified by its merchant classification code (MCC), a commonly adopted classification scheme by major card providers such as Visa/Mastercard. This allows us to study the consumption responses by category. We group each one of the 982 MCCs into 16 broad categories based on its degree of exposure to the infection risks.[7] For instance, eating/drinking/leisure outside the home, contact-based service such as barbershop, and travel are expected to be most severely hit by the infection risk. Grocery and food shopping,

[7] See Section A.1 in the Online Appendix for examples of merchant types that fall into each category.

financial services, and housing utilities, in contrast, are expected to have mild responses to the pandemic news during this period.

Figure 1 plots the average daily spending of each month since February 2020 by consumption category. The bulk of the consumption is accounted for by goods and services that are generally most exposed to the pandemic, including eating and drinking, leisure outside of the home, contact-based services, travel and transportation, and clothing, footwear, and cosmetics. However, some goods and services, such as financial services, grocery shopping, and home leisure, have actually increased in March, relative to the two months prior. One important difference in the data, however, is that grocery shopping and other necessary purchases account for a large share in total spending, reflecting the fact that the composition of consumers in the sample is lower income and younger than a more nationally representative sample.

[INSERT FIGURE 1 HERE]

While the data contains these three important advantages over the traditional sources, we nonetheless are concerned about whether the data is nationally representative enough to map elasticities identified in the micro-data to the aggregate economy. We explore several validation exercises. First, Figure 2 plots monthly total spending in contact and non-contact sectors based on our transaction records and the advanced retail sales provided by the Census Bureau. For each sector, we combine sub-category series to make the retail sales data approximately comparable with that constructed from the transactions. Specifically, the contact-based consumption for retail sales is approximated by the sum of “drinking and eating places” (RSFSDP) and “health and personal car” (RSHPCS). The non-contact consumption is approximated as the total of “grocery store” (RSGCS) and “food and beverage stores” (RSDBS).

As shown in the Figure 2, in both sectors, our separately constructed time series track with each other reasonably well, although they are not apples to apple comparisons—the correlation is 0.55 in non-contact consumption and 0.26 in contact consumption over the four-year period that overlaps.[8] Despite the lower correlation in contact consumption, importantly, both series mark a dramatic drop in spending in March 2020 and a similar recovery since late April. In its trough, the retail sales and food service decreased by around 16.4% from the same month last year. Given our empirical analysis primarily rely upon the subsample of the year 2020, we are additionally assured about the representativeness of our results.

[INSERT FIGURE 2 HERE]

We also draw on the Social Connectedness Index (SCI) from Facebook, introduced originally by Bailey et al. (2018a) to study how information about housing prices is diffused among social networks and affects the decision to rent versus own a home. This data are now used more widely to understand how social ties are related with economic activity (Bailey et al., 2018b) and expectations about macroeconomic activity (Makridis, 2020). The index is constructed from anonymized information between all Facebook users, counting the number of friendship ties between county c and every other county c' in the United States. We use the 2019 data extract. Each user is limited to a total of 5,000 friends on a profile. Network ties require that both sides agree. Finally, we obtain the number of COVID-19 infections and deaths at the county $\times$ day level from the Center for Systems Science and Engineering from Johns Hopkins.

Figures 3 and 4 characterize the spatial distribution of not only infections and deaths, but also SCI-weighted cases and deaths based on exposure to connected counties as of April 1, 2020. While the actual number of infections or deaths in county c are correlated with their SCI-weighted

[8] Some of the differences between the two series may emerge because the sample selects lower-income individuals and does not have complete coverage throughout the country. These low income and younger groups are widely known in the literature to have a high Engel index, i.e. a large share of spending on necessities such as grocery/food. That means the composition of the spending recorded in the transaction is geared toward basic items. Moreover, both low-income and young people tend to have a high marginal propensity to consume (MPC) due to under insurance. This will undoubtedly induce more volatility in consumption spending across different periods.

versions, they display important differences. In particular, the correlation is only 0.40 between infections / deaths and their SCI counterparts. Moreover, the correlation is roughly half as large when comparing SCI-weighted infections and deaths or infections and SCI-weighted deaths.

[INSERT FIGURES 3 AND 4 HERE]

3 Identification Strategy

While several emerging papers now document a substantial drop in consumption and its composition over the course of the pandemic (Baker et al., 2020b; Coibion et al., 2020b), these studies focus on the direct effects of the national quarantine on spending patterns. However, since individual financial behaviors are also a function of peer effects (Moretti, 2011; Bursztyn et al., 2014), we investigate whether there is evidence of a decline in consumption prior to the national quarantine mediated through social networks. In particular, we draw on the Social Connectedness Index (SCI) to produce an SCI-weighted index of COVID-19 cases and deaths:

$$COVID_{c,t}^{SCI} = \sum_{c' \neq c} (COVID_{c',t} \times SCI_{c,c'}) \tag{1}$$

where $COVID_{ct}^{SCI}$ denotes the logged SCI-weighted number of cases or deaths in connected counties, $COVID_{c',t}$ denotes the logged number of cases or deaths in county c', and $SCI_{c,c'}$ denotes our measure of the SCI. We underscore two important features about our construction of $SCI_{c,c'}$.

First, we omit the number of friendship ties between county c and itself, thereby exploiting only the variation in its exposure to other locations. This means that Equation 1 will not "double count" local infections. Second, we normalize the number of friendship ties in a county to its total number of friendship ties, thereby exploiting the relative exposure to other locations. This means that differences in the level of friendship ties will not explain differences in consumption; only relative differences across counties.[9] Using this SCI-weighted index of the number of cases and deaths, we consider regressions of the following form that also control for local infections:

$$y_{c,t}^{k} = \gamma COVID_{c,t}^{SCI} + \phi COVID_{c,t} + \zeta_c + \lambda_t + \epsilon_{c,t} \tag{2}$$

where $y_{c,t}^{k}$ denotes logged consumption for county c on day t for category-k consumption good, and ϕ and λ denote fixed effects on county and day-of-the-year. We cluster standard errors at the county-level to allow for arbitrary degrees of autocorrelation over time (Bertrand et al., 2004).

Our identifying variation in Equation 2 comes from the fact that the social network in a county is pre-determined with respect to the infections that it and others faces over the coronavirus pandemic. Consider, for example, two counties that share the same population, industrial and occupational composition, and education and age distributions. To the extent that they are both heterogeneously connected to different external counties, then their local response might differ as some residents hear more pessimistic versus optimistic information. We believe that the variation in heterogeneous exposure to other counties is plausibly exogenous.

4 Empirical Results

4.1 Main Results

Table 1 documents the results associated with Equation 2. Starting with columns 1 and 5, we find that a 10% rise in SCI-weighted cases and deaths are associated with roughly a 0.42% decline in consumption expenditures. One concern with these results, however, is that we are failing to

[9]For example, suppose that county A has 100 friendship ties with county B and county C. If county D has 1000 ties with both county B and C, then the level of friendship ties would differ, but the relative amount is the same. Because we do not want to confound differences in the level of social media and/or network exposure with consumption, but rather focus on the connectivity to different locations, we normalize our measure. However, we also obtain qualitatively similar results if we leverage the differences in levels too.

control for local infections and deaths. If, for example, counties that are relatively more exposed to counties that have higher infections also have higher infections themselves in some time-varying way, then we may obtain downward biased coefficient estimate.

To address these concerns, columns 2 and 6 control for logged county cases and deaths. Consistent with our concerns about the potential for bias, our point estimate on the SCI-weighted infections index declines by roughly half: a 10% rise in SCI-weighted cases and deaths is associated with a 0.18% and 0.23% decline in consumption expenditures. Moreover, increases in contemporaneous local cases are also associated with declines in consumption, but with a slightly lower magnitude. Local deaths also decrease the consumption by a similar degree and are statistically significant. We have also experimented with one-week and two-week lags on county cases and deaths because of the incubation period for the virus, but the results are not statistically different: if anything, the gradient on SCI-weighted cases is slightly higher.

Turning towards columns 3 and 7, we include both stand-alone and interaction terms of the SCI weighted cases and an indicator for whether the state has enacted a stay-at-home order (SAHO), controlling for other state policies, including non-essential business closures, business reopenings, and school closures. For example, Ali et al. (2020) found that the adoption of SAHOs was associated with a persistent decline in job postings for early care and education, but which could correlate with household consumption. Moreover, if social networks have a causal mediating effect on consumption, then our estimates should be concentrated in states and days that have enacted SAHOs since they keep individuals in doors where they are more likely to rely on social networks for information through, for example, Facebook, rather than through personal experience. Consistent with our hypothesis, we find that a 10% rise in SCI-weighted cases and deaths following the adoption of a SAHO is associated with a 0.32% and 0.44% decline in consumption expenditures, which is roughly twice the magnitude obtained in columns 2 and 6.

Finally, there could still be other time-varying shocks to consumption that we have not detected through our inclusion of the time-varying state policy controls. Columns 4 and 8 introduce state $\times$ month fixed effects, exploiting variation within a county after controlling for all shocks that are common to a given state-month pair. This pushes the data even further by purging variation in consumption that could be correlated with any state policy. We find slightly stronger estimates: a 10% rise in SCI-weighted cases and deaths is associated with a 0.23% and 0.47% decline in consumption expenditures. Moreover, the coefficient estimates on cases and deaths become less economically and statistically significant, although now we find that a 10% increase in the number of deaths in a county is associated with a 0.15% decline in consumption too.

[INSERT TABLE 1 HERE]

How do these information shocks potentially heterogeneously affect spending across different types of consumer goods? Figure 5 documents these results by reporting the coefficients associated with major categories of goods, which we created based on merchant category codes (MCC) in the transaction data. We report the coefficients associated with both the direct effect of infections and the indirect effect through propagation from social networks. Not surprisingly, we find that clothing, footwear, and cosmetic products decline the most, followed by contact-based services, durables, travel, and eating or drinking outside the home. For example, a 10% rise in SCI-weighted infections is associated with nearly a 1.8% decline in clothing, footwear, and cosmetic spending, which is roughly three times as large as the effects obtained on grocery/food or home leisure spending. These results are consistent with Coibion et al. (2020b) who find a 31 log point drop in consumer spending concentrated in travel and clothing.

[INSERT FIGURE 5 HERE]

4.2 Heterogeneous Treatment Effects Across Space

We now turn towards evidence of heterogeneity in the treatment effects by county characteristics. We control for the direct effects of county infections and deaths, focusing on variation in the SCI-weighted infections. We focus on per capita income, the age distribution, population, the share of digitally-intensive employees as defined by Gallipoli and Makridis (2018), and the share of teleworking employees as defined by Dingel and Neiman (2020). We partition each variable based on the median value, allowing for heterogeneity above and below the median. Our results with the digital and telework shares are both estimated on a restricted sample because we obtain them from the American Community Survey micro-data, which does not cover every county.

Table 2 documents these results. While not all the differences across different types of counties are statistically distinguishable from one another, they are consistent with theory. For example, a 10% rise in the SCI-weighted infections is associated with a 0.47% decline in consumption among the counties below the median in per capita income and a 0.12% decline among the rest. This could be consistent with the presence of greater information asymmetries in lower income counties, so individuals have to rely on more informal networks for information. However, given that our consumption data has better coverage in lower income areas, it is possible that we simply have more measurement error in higher income counties.

Turning towards heterogeneity in the age distribution, we distinguish among those counties that rank above and below the median in terms of the share of individuals below age 35 and the share of individuals above age 65. We do not see statistically different effects when we partition by the median share of individuals below the age of 35: in both cases, a 10% rise in SCI-weighted infections is associated with a 0.21-0.25% decline in consumption. However, when we partition on the median share of individuals over age 65, we find that the elasticity is concentrated in counties with lower shares, implying a 0.28% decline in consumption (compared with a 0.14% decline for counties with higher shares of individuals over the age of 65). This is consistent with the fact that younger individuals are more likely to pay attention to information from social media (Smith and Anderson, 2018). We also find that the effects are concentrated among counties with a larger population. Finally, we do not see much of a difference between states that rank higher versus lower in terms of digital intensity (Gallipoli and Makridis, 2018), but we do see a larger elasticity for states that have a higher share of telework (Dingel and Neiman, 2020). This could be consistent with the fact that states with more remote workers are likely to rely more on social networks for information, rather than personal experience.

[INSERT TABLE 2 HERE]

4.3 Understanding the Mechanisms

We have shown that there is an economically and statistically meaningful decline in consumption associated with increases in the number of COVID-19 infections in socially connected counties even after controlling for time invariant characteristics across space and time, as well as time-varying shocks to local health outcomes (e.g., infections and deaths). However, one concern is that these results are plagued by other time-varying omitted variables that jointly affect connected counties and local consumption outcomes. This section provides further evidence that the results reflect a genuine information effect, rather than potential omitted variables.

One of the primary examples of omitted variables bias is the introduction of state-specific policies. For example, one possibility is that the introduction of emergency orders within a state naturally lead to declines in consumption by significantly disrupting foot traffic and leading to closures of businesses. While we show that our results are robust to controlling for state $\times$ day fixed effects, we nonetheless explore this possibility further by exploiting variation in the staggered introduction of state-specific stay-at-home orders (SAHOs) using data from Ali et al. (2020). If, for example, the introduction of SAHOs and other state policies account for the decline in consumption (Coibion et al., 2020b), then we should see that the effect of the SCI-weighted infections loads on the interaction between it and the SAHOs. However, when we estimate these fixed effect specifications, we find a statistically insignificant point estimate of -0.002. This placebo counters the possibility that there are other unobserved and time-varying county-specific policies that vary with both consumption and connected counties.

We further investigate the role of social networks by turning towards measures of international exposure for each county, leveraging the fact that some countries began experiencing the surge in COVID-19 cases much sooner and more severely than the United States. We focus on four countries—South Korea, Italy, Spain, and France—although our results hold on a broader set of countries exposed early on.[10] Each of these four countries successively experienced large number of infections in different scale since late February preceding the United States.

We exploit variation along two dimensions. First, counties vary cross-sectionally in their exposure to these countries. For example, whereas Maricopa County in Arizona has an SCI of 142,771 with France, San Francisco has an SCI of 258,825. Second, countries vary in their intensity of COVID-19 shocks. Figure 6 shows how Italy experienced a sharper and more severe surge in cases than France even though its population is roughly 6 million smaller. We now consider regressions of logged consumption on the product of the cross-sectional exposure to a country and its time series variation in infections, conditional on the usual county and day fixed effects. Importantly, we restrict our sample to the period between February, 15th to March, 15th, which covers the time

[10] Although we would, of course, ideally include China, the Facebook data does not have representative coverage of ties with China because their government prohibits the use of Facebook.

leading up to the full-scale outbreak in the United States.[11] This allows us to purge variation that is possibly correlated with time-varying shocks in the United States.

Table 3 documents these results. We find that there is a robust negative association between the SCI-weighted number of infections / deaths and consumption for each country. For example, a 10% rise in infections (deaths) in Italy for counties that are more closely connected to Italy is associated with a 0.07% (0.52%) decline in consumption. One reason for the potentially larger coefficient on deaths over infections stems from the way that media covers international deaths more intensively than the number of infections, although we cannot say conclusively. We see broadly similar treatment effects for each country, although they are smaller for France, perhaps because the United States had already witnessed the experience of Asian countries, like South Korea, and Spain and Italy earlier in the month of March. Section A.2 of the Online Appendix also presents additional diagnostics that mitigate concerns that our results simply reflect differences in physical distance between connected counties.

[INSERT TABLE 3 HERE]

Our finding that consumption in one county depends on the infections among connected counties—even if they are geographically distant—builds directly on an emerging literature on the real effects of social connectedness (Bailey et al., 2018b,a). However, separately identifying the causal effect of shocks to a network from selection effects is challenging (Goldsmith-Pinkham and Imbens, 2013). Our diagnostics—the combination of domestic and international connectivity—suggest that we are detecting meaningful effects from social networks, rather than just selection effects, but this remains an area of ongoing research. Our paper is also related with recent evidence from Charoenwong et al.

[11] We also conduct the same analysis for the period after March, 15th for a different consideration. Since the Federal government of the U.S. announced the travel ban from Europe in the same week, focusing on this later period potentially shuts down the channel via which socially connected cases posed a real risk of infection. The negative impacts of consumption by SCI weighted cases from each of this country, if any, becomes more significant.

(2020) that finds some counties were more likely to adopt social distancing and restrictions measures based on their exposure to Italy and China, although the data on social connectivity to China is confounded by the fact that use of Facebook is blocked within the country.

5 Quantitative Model

In order to explore whether the effect of social network influences in individual spending through expectation plays into sizable aggregate responses, we build a network-based heterogeneous-agent model to quantify how social networks affect aggregate consumption and to conduct several counterfactual experiments. We extend a standard consumption and savings model with uninsured idiosyncratic income risks and borrowing constraints with one key modification: individuals form beliefs about their idiosyncratic infection state through learning from friends on the social network.

We also allow for two sectors in the model that potentially get affected differently by the pandemic. Since we implicitly consider each agent as representing a county analogous to our data, we use the terms agent, consumer, and county interchangeably. Finally, given our primary focus is the propagation mechanisms of aggregate demand via social networks, we adopt a partial equilibrium approach by taking the supply side of the economy as given. However, nominal rigidity and cross-sector frictions could be added to a general equilibrium model so that the aggregate demand generates real effects in output and unemployment.

5.1 The Consumer's Problem

The economy is populated by N infinitely-lived consumers, indexed by i. Each consumer derives utility from a stream of consumption in the current and all future periods:

$$\max \quad E_0 \sum_{t=0}^{\infty} \beta^t u(c_{i,t}) \tag{3}$$

The instantaneous utility within each period takes a CRRA form with relative risk aversion ρ (and the elasticity of inter-temporal substitution $\frac{1}{\rho}$):

$$u(c) = \frac{c^{1-\rho}}{1-\rho} \tag{4}$$

Total consumption, denoted c_t, in each period is a CES bundle of goods/service from two sectors, denoted as c for contact-based and and n for non-contact-based consumption, respectively:

$$c_{i,t} = (s_{i,t}\phi_c c_{i,c,t}^{\frac{\epsilon-1}{\epsilon}} + (1-\phi_c)c_{i,n,t}^{\frac{\epsilon-1}{\epsilon}})^{\frac{\epsilon}{\epsilon-1}} \tag{5}$$

The elasticity of substitution between two sectors is ϵ and the relative preference weight are ϕ_c and $1-\phi_c$: a larger ϵ implies the two sectors are more substitutable and a larger ϕ_c implies a stronger relative preference toward contact-based consumption. Moreover, the taste shock, denoted as $s_{i,t}$, scales the utility from contact-based consumption. In steady state, it takes a value of 1.

In each period t, the agent receives an idiosyncratic draw of the taste shock, $s_{i,t}$, which varies with the local infections, and this is specified later. Lower $s_{i,t}$ implies less utility from consuming contact-based services due to exposure to infection. This conveniently captures the idea that consuming contact-consumption bears higher health risks from the individual's point of view. A lower utility from contact-based consumption could be either due to self-precautionary actions to avoid infection or compliance of local government containment policies such as stay-at-home orders.

The inter-temporal budget and borrowing constraints of the agent i at time t are:

$$\begin{aligned} c_{i,t} + a_{i,t} &= m_{i,t} \\ m_{i,t} &= y_{i,t} + b_{i,t} \\ b_{i,t+1} &= a_{i,t}(1+r) \\ a_{i,t} &\geq 0 \end{aligned} \tag{6}$$

where $a_{i,t}$ is the end-of-period saving at a real interest rate r, $m_{i,t}$ is the total wealth in hand, consisting of the current bank balance $b_{i,t}$ and the labor income $y_{i,t}$, which is determined by:

$$\begin{aligned} y_{i,t} &= n_{i,t} o_{i,t} z_{i,t} \\ ln(o_{i,t}) &= ln(o_{i,t-1}) + v_{i,t} \\ v_{i,t} &\sim N(-\frac{\sigma_v^2}{2}, \sigma_v^2) \end{aligned} \tag{7}$$

where $n_{i,t}$ is the labor supplied inelastically, which we normalize to one. The labor income received by individual i depends on the realizations of two multiplicative idiosyncratic income shocks: a permanent component $o_{i,t}$, and a transitory (or a persistent) component $z_{i,t}$, which is potentially a function of local infection. The logged permanent income $o_{i,t}$ follows a random walk with i.i.d. shock of size σ_v.[12] The component $z_{i,t}$ is equivalent to a standard transitory income component without the impact from the local infection. During the pandemic, a higher infection

[12]We set its mean to be $-\sigma_v^2/2$ so that the expected value of $o_{i,t}$ is unity given that E(exp(x)) = exp($\mu + \sigma^2$) if $x \sim N(\mu, \sigma^2)$.

will lead to a lower income or unemployment. We specify $z_{i,t}$ as a function of infection later.

5.2 The Pandemic

We model the pandemic as an agent-specific state that evolves subject to idiosyncratic shocks.[13] Each agent i at time t is faced with a local infection state, $\Xi_{i,t}$, which represents the severity of the local epidemic. For example, we can think of it as the actual number of infected cases. We will assume later that $\Xi_{i,t}$ is non-observable in real-time by the agent due to reasons such as under-testing, misreporting, etc. The law of the motion of the state from t to $t+1$ depends on the speed of the transmission of the virus. We build on prior literature, such as Eichenbaum et al. (2020) and Krueger et al. (2020), that provides a micro-foundation for the transmission using epidemiological models, assuming that the number of infections grows exponentially with a constant reproduction rate of e^{θ}, a multiplicative shock $\mathrm{e}^{\eta_{i,t+1}}$, and a rate of ψ from today to tomorrow. Taking the log, we obtain the law of motion of infected cases of each county:

$$\begin{aligned} \Xi_{i,t+1} &= exp(\theta)exp(\eta_{i,t+1})\Xi_{i,t}^{\psi} \\ ln(\Xi_{i,t+1}) \equiv \xi_{i,t+1} &= \theta + \psi\xi_{i,t} + \eta_{i,t+1} \end{aligned} \tag{8}$$

The key assumption to be made in this paper is that agents have no perfect observation of the $\xi_{i,t}$ at time t. Instead, they form subjective contemporaneous perceptions about the underlying state of the pandemic based on their respective local conditions as well as their connected friends on the social network. We will return to this in the next section.

The infection state $\xi_{i,t}$ affects the time-varying taste shock $s_{i,c,t}$ and individual productivity

[13] While the pandemic has affected all areas, some are more adversely affected than others at a given point in time. Aggregate shocks could be added as an extension of the model.

shock $z_{i,t}$ according to following linear functions.

$$\begin{aligned} ln(s_{i,t}) &= \alpha_s \xi_{i,t} + \tau_{i,t} \\ ln(z_{i,t}) &= \alpha_z \xi_{i,t} + \zeta_{i,t} \\ \tau_{i,t} &\sim N(-\frac{\sigma_\tau^2}{2}, \sigma_\tau^2) \\ \zeta_{i,t} &\sim N(-\frac{\sigma_\zeta^2}{2}, \sigma_\zeta^2) \end{aligned} \tag{9}$$

Logged preference $s_{i,t}$ and labor productivity $z_{i.t}$ are both linear functions of the underlying infection state $\xi_{i,t}$ plus i.i.d. shocks $\tau_{i,t}$ and $\zeta_{i,t}$,respectively. The two idiosyncratic shocks follow normal distributions with standard deviations σ_ζ and σ_τ, respectively. Like before, their means are both adjusted so that the expected value of $exp(\zeta_{i,t})$ and $exp(\tau_{i,t})$ are equal to one. The loading parameters from the infection to preference and income are α_s and α_z, respectively. Since higher infections are associated with negative income shocks and a taste shock biased against contact-based consumption, both α_s and α_z are negative by assumption.

5.3 Learning in a Social Network

Agents are connected through a pre-determined social network: we assume away the endogenous formation of the network structure in the model since our focus on a short-time window where newly formed or broken tiles in the network are very limited. Agent i is a particular node in a given social network. Nodes differ from each other, potentially, in its location of the network as well as its experienced idiosyncratic shocks. For the former, more formally, we denote the thickness of the link between any two nodes i and j, analogue of the observed SCI from the data, as $l_{i,j}$. It naturally follows that if county i and j have no connections, $l_{i,j} = 0$. The scale of $l_{i,j}$ reflects the degree of connectedness between the two. Links are undirected, so $l_{i,j} = l_{j,i}$. We assume within each node i there is non-zero connectedness sized of $l_{i,i} = l_i$, which accounts for within-region connections.

The information about infection spreads across the network through connected nodes. The structure of the social connections determines the strength of the node-to-node influence in the information exchange. At economywide level, these influences can be captured by a social influence matrix W. The i, j-th entry of the matrix W, defined as the influence j has on i is the number of friends i has with j as a share of total friends i has.

$$w_{i,j} = \frac{l_{i,j}}{\sum_{k=1}^{N} l_{i,k}} \tag{10}$$

Therefore, each row i of the matrix W reflects the influence weights that node i assigns to all of its connected nodes. Hence, the row sum of the matrix is always equal to 1.

$$\sum_{k=1}^{N} w_{i,k} = 1 \quad \forall i \tag{11}$$

Correspondingly, the column sum of the social influence matrix W is what we define as degree, following the network analysis literature. The degree of node j is a measure of how influential it is among the entire network. [14]

$$d_j = \sum_{i}^{N} w_{i,j} \tag{12}$$

Social influence is not necessarily symmetric between two nodes because the weights are normalized by the node-specific social connectedness. For instance, node a may be the single connected node b has while b is just one of many by a. In addition, since the within-node links are never zero,

[14] Other network studies in a variety of contexts also characterize the network structure using degree distribution, such as social learning (DeMarzo et al., 2003), output-input linkages (Acemoglu et al., 2012), investment network (Lehn and Winberry, 2019) and so forth.

any element in the diagonal of the matrix W is always positive and attains its maximum value of 1 when the node has zero connections with the rest of the network. W equal to an identity matrix is the special case where there is no social influence—each node has only itself as a friend.

We assume that agents form their respective perceptions about the underlying infection state $\xi_{i,t}$ subject to influences from their connected nodes on the social network. In particular, the learning takes a similar form of naive learning formulated by Golub and Jackson (2010) and DeMarzo et al. (2003). An agent's belief about her own infection state $\tilde{\xi}_{i,t}$ in each period is a weighted average of true states of its connected nodes and the weight depends on the pairwise social influences we defined above.[15]

$$\tilde{\xi}_{i,t} = \sum_{i=1}^{N} w_{i,j}\xi_{j,t} \tag{13}$$

The agents here are "naive" for at least two reasons. First, although the infection states of different nodes are idiosyncratic by assumption, each agent uses others' states to form perceptions of her own state. Second, the agents repeatedly discard the prior information and simply use the contemparaneous information. Although this belief-formation is a substantial deviation from the standard Bayesian learning and rational expectation benchmark, we believe it helps illustrate expectation subject to social influences in the most straighfoward way.

We can also stack individual beliefs together into a vector. Use a N-sized vector $\tilde{\Xi}_t$ to denote the perceived states of all individuals, the i-th element of which represents the node i's belief $\tilde{\xi}_{i,t}$. Similarly, use a vector Ξ_t to denote the realized infection states. The relationship between the two can be conveniently written as the following:

[15] Golub and Jackson (2010) shows that the "wisdom of crowds" is attainable, i.e. subjective beliefs converge to the truth only if the influence of the most influential nodes in the network vanish over time as network expands. This explains why the agents could persistently misperceive the true state in our model.

$$\tilde{\Xi}_t = W\Xi_t \tag{14}$$

While many characteristics of the network affects learning dynamics and belief distributions, the distribution of degrees across agents is one of the key determinants. Average degree in the network is always equal to one by definition. But what differentiate networks is its dispersion in degrees. Zero-dispersion represents the case of social isolation, i.e. the social influence matrix being the identity matrix. The higher the degree dispersion is, the more asymmetric the influences are across agents on each other. This results in a distortion in individual and aggregate beliefs, i.e. the average belief held by the agents in the economy is no longer equal to the average truth.

Such a belief-formation also results in possible amplification of idiosyncratic shocks to aggregate belief responses if the initial shocks hit the relatively influential nodes (whose average degree is greater than 1). For instance, imagine a fraction of influential nodes suddenly experienced an increase in infection by 10%. Due to the stronger influence these nodes have on others, the shocks will be amplified through social learning and the average perceived infection held by all the agents will increase by more than 10%. (See the Appendix A.3 for the proof of this result.) This is the key mechanism we will illustrate in Section 14.

5.4 Optimal Consumption

We start by characterizing the optimal consumption policy and sector-specific demand function of the individual consumer. Under perfect understanding of the local infection, individual's optimal consumption depends on actual local infection $\xi_{i,t}$ together with preference shock $\tau_{i,t}$, wealth in hand $m_{i,t}$ and permanent income $o_{i,t}$. Under learning from friends, the perceived state of the infection $\tilde{\xi}_{i,t}$ replaces the true state $\xi_{i,t}$ as the state variable of the individual. This together with the taste shock $\tau_{i,t}$ also affects their perceived preference parameter $\tilde{s}_{i,t}$. Individual's value function at time t is therefore evaluated based on her perceived state $\tilde{\xi}_{i,t}$, the draw of the taste shock $\tau_{i,t}$ in addition to permanent income $o_{i,t}$ and total wealth $m_{i,t}$:

$$V_{i,t}(m_{i,t}, o_{i,t}, \tilde{\xi}_{i,t}, \tau_{i,t}) = \max_{\{c_{i,c,t}, c_{i,n,t}\}} \quad u(c_{i,t}(c_{i,c,t}, c_{i,n,t})) + \beta \tilde{E}_{i,t} V_{i,t+1}(m_{i,t+1}, o_{i,t+1}, \tilde{\xi}_{i,t+1}, \tau_{i,t+1}) \tag{15}$$

This treats the choices in inter-temporal consumption policy and sector-specific demand as one problem. It turns out that we can separately solve the two problems to reduce the number of state variables. This is due to the two-stage budgeting principle. Since the CES aggregator within the period is homothetic, the indirect utility gained within each period from optimal allocation between two sectors becomes independent from the realization of the preference shock. We can first solve the inter-temporal problem by treating the total consumption as the single control variable. The value function associated with the problem can be written as the following:

$$V_{i,t}(m_{i,t}, o_{i,t}, \tilde{\xi}_{i,t}) = \max_{\{c_{i,t}\}} \quad u(c_{i,t}) + \beta \tilde{E}_{i,t} V_{i,t+1}(m_{i,t+1}, o_{i,t+1}, \tilde{\xi}_{i,t+1}) \tag{16}$$

Applying the Envelope Theorem to the value function, we can obtain the households' Euler equation associated with the total consumption $c_{i,t}$ as the following:[16]

$$\tilde{E}_{i,t}[e^{(1-\rho)v_{i,t+1}} u'_{t+1}(\frac{c_{i,t+1}}{o_{i,t+1}})] = \beta(1+r) u'_t(\frac{c_{i,t}}{o_{i,t}}) \tag{17}$$

[16] When solving optimal consumption in the presence of permanent income, one commonly used trick is to normalize consumption and asset by the permanent income level to reduce the number of state variables by 1. We do the same following Gourinchas and Parker (2002) and Carroll (2011).

Intra-temporal optimality requires proportional allocation between c and n depending on the perceived taste shifter $\tilde{s}_{i,t}$, which is a function of the perceived local infection $\tilde{\xi}_{i,t}$. It is solved as an allocation of the total consumption into two categories based on the realized preference and the relative price of the two. We assume the relative nominal price of the two is one.

$$\frac{u_{c_c}(c_{i,c,t}, c_{i,n,t})}{u_{c_n}(c_{i,c,t}, c_{i,n,t})} = \frac{\tilde{s}_{i,t}\phi_c}{1-\phi_c}(\frac{c_{i,c,t}}{c_{i,n,t}})^{-\frac{1}{\epsilon}} = 1 \tag{18}$$

5.5 Calibration parameters

One of the novel additions of this model regards the distinction between two sectors of consumption that bear different infection risk. The literature has not provided an estimate regarding the preference parameters associated with the subcategory demand. We therefore rely upon both Consumer Expenditure Survey (CEX) and the card transaction data to infer them. We group reported subcategory consumption series into contact and non-contact based ones. The steady-state share of contact consumption ϕ_c is then set to be 0.41.

We also estimate the elasticity of substitution (EOS) between the two via a reduced-form regression of the change in one on that of the other. Our estimates suggest an ϵ of 0.75. This indicates that our baseline model assumes the two sectors of consumption are gross complements. We recognize the substantial disagreement on the assumption regarding the substitutability of the two sectors in the recent literature about the pandemic. For instance, Krueger et al. (2020) assumes a baseline EOS of 3 and 11 for the alternative assumptions although no empirical estimates are provided. Guerrieri et al. (2020) discusses the important aggregate demand implications of the value of EOS without taking an empirical stance on it. Given this, we will compare the calibration results by assuming complementarity and substitutability in later sections.

We estimate the parameters for the evolution of infection described by Equation 8 using the weekly panel of reported cases of U.S. counties between Feb 1st to June 30th. The estimates suggest a weekly growth rate of 13%, equivalent to a reproduction rate of $exp(0.13) = 1.14$, a persistence parameter of $\psi = 0.978$ and the size of the shock being $\sigma_\eta = 0.18$. Although the reproduction rate has varied over time, our choice is largely consistent with the time-dependent transmission rate prior to April, which, if anything, was even higher (Hong and Li, 2020).

The second block of parameters regards income process and preferences. The size of permanent income volatility σ_v is set to be 0.15. The size of transitory income volatility σ_ζ is set to be 0.2. These are common in the consumption insurance literature. We jointly choose the two to match the cross-sectional consumption inequality before the run-up of the pandemic. In addition, the loading parameters of the pandemic state onto idiosyncratic preference $s_{i,t}$, and labor income $z_{i,t}$, α_z and α_s are chosen internally within the model to match the elasticity of consumption in responses to local cases. They are also subject to following restrictions: (1) both α_z and α_s are negative to reflect the fact that higher infection leads to lower utility toward contact-based consumption and lower-income, (2) $s_{i,t} < 1$, i.e., infection lowers the weight of the contact sector compared to its steady-state level. Finally, the size of taste shock σ_τ is set to be 1 to match the cross-sectional inequality of contact/non-contact based consumption.

Other preference parameters are standard in the literature. Whenever we can, we follow the standard consumption/saving literature in choosing the preference parameters. Since the model is set at weekly frequency, so both time discount factor and interest rates are converted accordingly. In particular the time discount factor β is set to be $0.96^{1/52}$. The risk-free nominal interest factor $1 + r$ is $1.03^{1/52}$. The relative risk aversion ρ is 2.

The exact procedures of calibration are as followed. (1) Solve the model based on the optimality conditions laid out in the previous section. (2) Simulate the cross-sectional histories of idiosyncratic infections and the corresponding perceptions of individual agents of their state using naive learning rule. (3) Simulate the history of individual consumption streams based on the simulated beliefs and resulting assets and compute the aggregate consumption responses.

6 Model Experiments

6.1 Social Network and Influence Matrix

The social influence matrix W defined in the previous section is directly computed using the SCI from Facebook. We set the number of nodes (consumers) to be equal to the number of counties for which we have data: $N = 3141$. Figure 7 plots the heat map corresponding to the influence matrix. We rank counties by their FIPS code so that counties from the same state are adjacent in the graph. The diagonal blocks have greater weight indicating the dominant influence within the county. The rectangular blocks along the diagonal also have higher weight indicating stronger influence within the same state. There is substantial variation across different counties in terms of both their inward and outward influence.

[INSERT FIGURES 7 HERE]

Figure 8 plots the distribution of degrees from the SCI in the year of 2016 and 2019, respectively. For both years, the distribution is right-skewed with a long tail. This indicates a small fraction of nodes has a disproportionately strong influence within the network. By construction, the average degree in the network is 1. The observed standard deviation, a measure of the dispersion of influences, is 0.27 in 2016 and 0.29 in 2019, respectively. This suggest that social network connections have grown more dispersed over time. An extreme case where all nodes have a degree of 1 thus zero-dispersion represents the case where there is no inter-node influence at all. In contrast, higher dispersion of the degrees implies the nodes have more asymmetric influences on others across the network. A more disperse distribution in 2019 compared to 2016 will lead to higher degree of amplification of local shocks to the whole network, as will see from Section 6.5. These differences in dependencies across the network imply that the aggregate fluctuations in consumption will depend on where the initial shocks take place.

[INSERT FIGURES 8 HERE]

6.2 Benchmark: Pre-pandemic Consumption

Before exploring the implications of the pandemic for the consumption responses, we first calibrate the model for the pre-pandemic period. Specifically, we set the underlying local infection state to be zero $\xi_{i,t} = 0$ deterministically for all agents in the economy. This turns the income process into a standard one with two idiosyncratic components: one permanent and the other transitory. The relative preference for contact versus non-contact consumption now depends solely on the idiosyncratic and transitory draw of the taste shock.

Like many other models featuring with ex-ante homogeneity and uninsured idiosyncratic income risks (Carroll et al., 2017), our model generates ex-post heterogeneity across agents in terms of consumption and wealth. Since the data on cross-county wealth is not available, we focus on consumption inequality. We simulate the pre-pandemic histories of the economy for a large number of periods such that the cross-sectional consumption inequality implied from the simulation broadly matches that from the data, giving us a useful benchmark.

Figure 9 plots the simulated and data-implied Lorenz Curves of total and subcategory consumption across all U.S. counties in our data sample. Since we suspect that the inequality suggested by the raw transaction data is driven by cross-regional differences in the data coverage and other unobservable characteristics, we compute the consumption inequality based on regression residuals of the consumption spending on a broad set of county-specific variables, including: population, GDP per capita, the share of males, the education distribution, and the race distribution. This implies a cross-sectional standard-deviation of log consumption per capita of 0.89 over the period of June 2017 to February 2020. While it is larger than the 0.3 to 0.45 dispersion of log consumption found in other household data, our calibrated parameters nonetheless allow us to broadly match the consumption inequality (Blundell et al., 2008; Heathcote et al., 2010; Kaplan and Violante, 2010; Heathcote et al., 2014; Aguiar and Bils, 2015).

[INSERT FIGURES 9 HERE]

We can also validate the assumption of the model regarding the two sectors by examing the subcategory consumption inequality. We group detailed card spending data into two sectors as we defined in this paper. Lorenz Curves of contact and non-contact-based consumption, which are shown in the middle and right panel in Figure 9 indicates that the consumption inequality within categories is higher than the total consumption, suggesting the role of heterogeneity in preference shocks. This subcategory inequality can help us identify the size of preference shock σ_τ. We pick it such that the Lorenz Curves of both categories match that from data, respectively (e.g., Aguiar and Hurst (2013) and Attanasio and Pistaferri (2016)).

Taking the pre-pandemic wealth distribution as the initial condition, we proceed to explore the aggregate consumption responses after the outbreak of the pandemic. We first simulate some initial history of the outbreak for 10 weeks long to get some cross-sectional distribution of the infections that are not conditioned on the initial spread. Then, we hit a chosen fraction of agents with an infection shock to get the impulse responses of the economy. For the baseline scenario, we assume there is no social network learning and the agents can perfectly observe their true infection state in real-time, allowing us to isolate the role social networks play on consumption.

Figure 10 plots the impulse responses of the aggregate variables in the economy relative to the steady-state scenario following a one-time 10% increase in local infections of all agents at $t = 0$. We define steady state as one where the infections of all agents stay at its initial level before $t = 0$ while individual income keeps drawing new permanent and transitory income shocks.

[INSERT FIGURES 10 HERE]

A one-time increase in the infection of all agents leads to an increase in the average infection by the same magnitude. Its impact gradually subsides over the following periods given the persistence in the evolution of the infection state. It immediately brings down the average income thus wealth by 1%, which is consistent with the assumed income elasticity of the local infection. Under the perfect understanding, the shock in the true infections fully translates into the same degree of change in perceptions held by the agents. This, together with a negative wealth shock, makes agents immediately cut their consumption spending. As to the allocation of consumption between two sectors, because higher infection risk results in a negative preference shock toward contact consumption, it drops more than the total consumption. In addition to lower total consumption and the complementarity between two sectors, non-contact consumption also drops accordingly. Because of fluctuation in preferences, the sub-category shocks show higher volatility than the total consumption. Finally, the dynamics of wealth following the shock depends on the relative size of the two forces. Although lower consumption helps to build up wealth, the increase in infections negatively affects income in the following periods, drawing down income.

6.3 Experiment 1: No Social Network

Now, we compare the baseline scenario with a scenario allowing for the learning from the social networks. According to our framework of learning, the one without a social network can be also seen as a special case where the individual agents only assign the full weight of social influence to his/herself, hence, the true state and perceptions coincide with each other.

In order to see the implications of the social networks, it is important that we generate impulses responses by hitting only a fraction of the agents in the economy instead of via an aggregate shock that affects every agent in the economy. The intuition is very simple. If every agent experiences the exactly same shock, the social influence among agents does not particularly distort the average beliefs. Only local or idiosyncratic shocks will be amplified through the social network into more aggregate responses. Figure 11 shows the impulse responses for a 10% increase in infections of a third of the agents. The social network will induce an overreaction only if the agents who experience the shocks are relatively influential in the network. The exact condition is that the average degree of the shocked nodes is greater than one.

Not surprisingly, a 10% increase in infections for a third of the agents corresponds to a third increase in the average infection in the economy absent social networks. However, in the presence of the social networks, the average perceived infection increases more than the underlying true states would. Although the belief distortion did not change total wealth, since wealth at time $t = 0$ just depends on the realized income/infection states, consumption spending drops more because of a more pessimistic view of the infection conditions. Quantitatively speaking, the social network leads to an additional 0.3 percentage point drop in consumption compared to the 1 percentage point drop in the baseline scenario. By the same token, a higher perception of the infection brings down the contact-consumption more than in the case without social network influences.

[INSERT FIGURES 11 HERE]

6.4 Experiment 2: The Location of the Pandemic Shock

Individual nodes have different influences in the network. Therefore, the aggregate responses may differ depending on where the infection shock takes place. Figure 12 plots the impulse response graphs following the same-sized 10% infection increase in the top, middle, and bottom one-third of the nodes in terms of their social influence measured by their degrees. It is not surprising that the aggregate consumption responds the most if the infection condition worsened in most influential agents in the economy. In that scenario, the drop in consumption is almost two times as big as the response if the shocks affect the bottom one-third nodes.

[INSERT FIGURES 12 HERE]

This location-dependent mechanism of aggregate amplification builds upon related work on networks in macroeconomics based on input-output linkages (Acemoglu et al., 2012; vom Lehn and Winberry, 2020). As our empirical evidence has shown, a similar mechanism is present with the COVID-19 pandemic: increases in infections among an individual's socially-connected counties reduces consumption in that individual's own county even after controlling for their own number of infections. This provides one explanation why consumption may have fallen faster and sharper in counties that were more connected to the early COVID-19 hotspots in the United States, such as Seattle and New York City.

6.5 Experiment 3: Alternative Network Structure

What would have happened to the consumption responses if the economy is set in a social network of different structures? Figure 14 compares the impulse responses to the same shock based on the social network in 2016 and 2019, respectively. Since Figure 8 shows that the social influence has grown more dispersed over time, shocks that take place in the most influential nodes will receive greater weight. The relative responses confirm this conjecture. A lower standard deviation of the degree 0.26 in 2016 compared to 0.29 in 2020 further increases the average beliefs of infection by 0.4%. This further reduced the total consumption by 0.2% from a decrease of 1.6% to 1.8%. The amplified responses can be also seen in the subcategory consumption. In particular, contact-based consumption (non-contact) exhibits an additional drop of 0.5% (0.1%).

The above thought experiment has important implications if we want to understand how the future evolution of the social network will change the macroeconomic response mechanisms. It is fair to conjecture that the social network connections may become more dispersed and social influences will become more asymmetric over time. This will increase the chance that any local shocks, especially those that hit the influential does, play into aggregate shocks.

[INSERT FIGURES 14 HERE]

6.6 Experiment 4: Substitution and Complementarity

In the results thus far, we maintain the assumption that the two sectors of consumption are gross complements. We now compare the impulse responses of following the same shock under a range of values of EOS, 0.75, 0.99 and 1.5. The first is the baseline value we use in the paper. The second represents a case of unit elasticity. The third is when the two sectors become substitutes. Not surprisingly, although the aggregate consumption responses remain the same, the sub-category consumption responses vary substantially depending on the two sectors being substitutable or complementary in consumer's preferences. Figure 13 presents the scenario with complementarity, implying that the 1.3% drop in total consumption consists of 2.3% in contact consumption and a 0.8%

drop in non-contact consumption. In contrast, the scenario with substitution implies a different reallocation: 4% drop in contact consumption and 0.5% drop in non-contact based consumption.

[INSERT FIGURES 13 HERE]

Such heterogeneity in sectoral reallocation has important implications for the macroeconomic effects of the pandemic. First, through the general equilibrium effect, a higher degree of substitution will help mitigate the drop in aggregate consumption. Second, if we further allow the consumption behaviors to endogenously affect the infection, higher substitutability across sectors also reduces the infection risk exposure as a whole. Although our model does not incorporate both mechanisms, these implications are rather self-explanatory.

6.7 Discussion

Although our model built in this paper is tailored towards understanding the quantitative effects of the pandemic on consumption, the framework is flexible and it carries broader implications for how social networks can have an aggregate effect in a more general macroeconomic setting under incomplete markets. In particular, the presence of uninsured income shocks creates ex-post heterogeneity in wealth and the marginal propensity to consume across agents in the economy. This heterogeneity is amplified when agents are exposed to and learn from people in their social network who are experiencing different conditions in their own areas. While we introduce social influence via naive learning, alternative and more sophisticated rules would suffice: the key mechanism is simply that social influence changes individual behaviors by "distorting" their beliefs.

We have seen related literature that has pointed out the important role that beliefs play in the macroeconomy. For example, using plausibly exogenous variation in beliefs, Makridis (2020) and Gillitzer and Prasad (2018) provide causal evidence that economic sentiment has a positive effect on individual-level consumption. Similarly, Kozlowski et al. (2020b) and Kozlowski et al. (2020a) show that large shocks, such as the financial crisis and the pandemic, can have large and persistent aggregate effects on macroeconomic activity. Moreover, Malmendier and Nagel (2011), Malmendier and Nagel (2016), Malmendier and Shen (2018), and Binder and Makridis (2020) emphasize the role of personal experience arising from exposure to macroeconomic fluctuations. Finally, Bianchi et al. (2020) show how distorted beliefs can affect macroeconomic activity.

It is worth emphasizing that in our framework, social networks may still not lead to different aggregate responses to shocks if two of following conditions hold. First, if the shock of the focus is entirely aggregate. Since each individual's perception is simply a weighted average of all connected nodes, social network connections do not distort his/her perceptions. Second, if the social network takes an extreme form of zero connectedness among agents. This means people do not receive any influence from the other nodes. So in order for the social network to matter, we need asymmetric influences across nodes. In general, the structure of the network, thus the social influence weights, and the location of the shock, both matter for the aggregate responses.

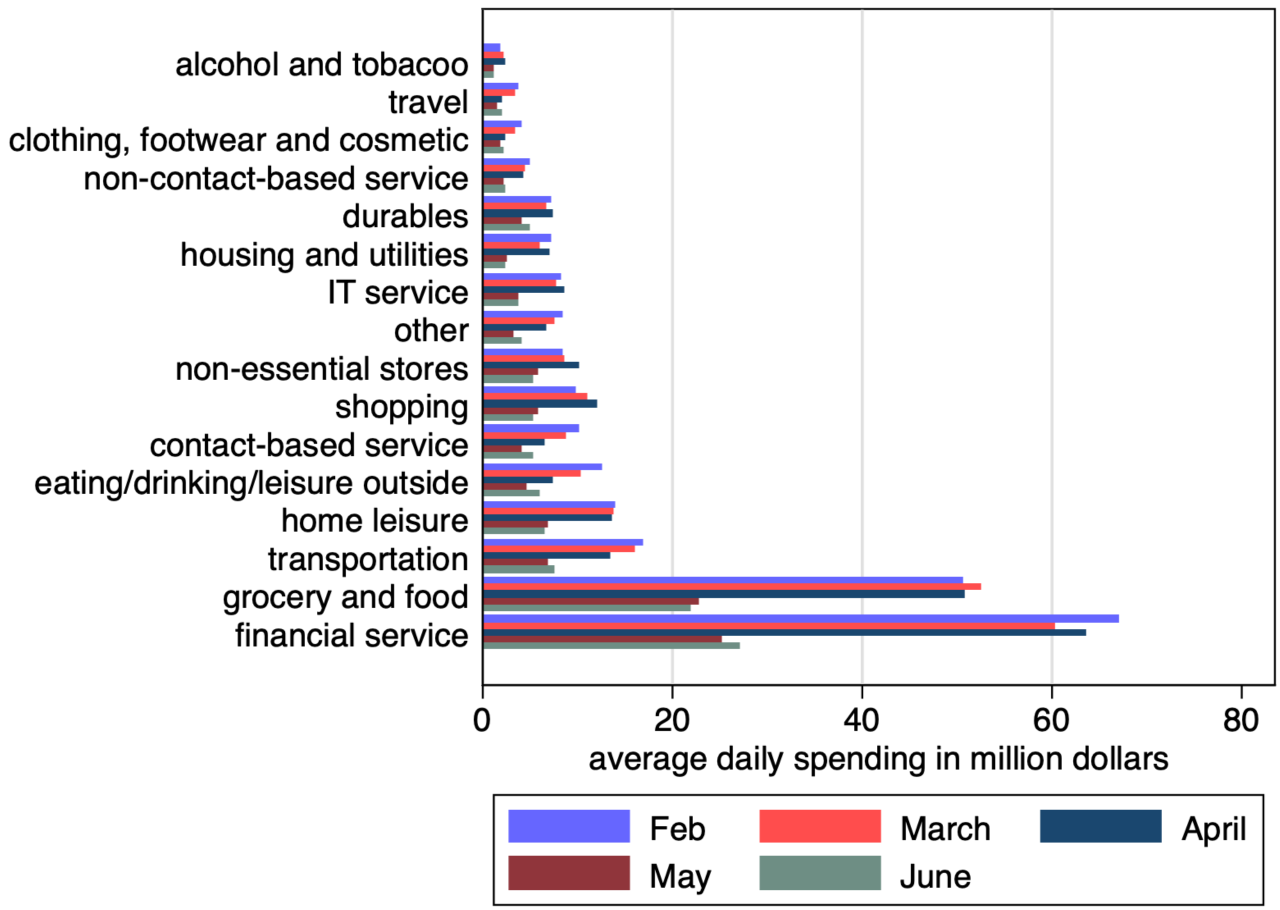
The presence of social network also has cross-sectional implications about the consumption inequality. Since the inclusion of social influence creates a correlation among peoples' perceived idiosyncratic states when they optimize their consumption at a given point in time, our model produces a higher cross-sectional correlation in consumption responses, which reduces cross-sectional inequality in consumption. Taking this into account, the empirical consumption inequality we have observed from data may have been attenuated through social influences, compared to the one that is solely driven by true income and wealth inequality. This has somewhat similar implications as the consumption-peer-effect has for consumption inequality. (Heffetz, 2011; De Giorgi et al., 2020)

7 Conclusion

The COVID-19 pandemic has led to substantial declines in employment (Bartik et al., 2020; Cajner et al., 2020), consumption (Baker et al., 2020b; Coibion et al., 2020b), and output (Makridis and Hartley, 2020; Guerrieri et al., 2020), largely a function of the national quarantine policy. While the emerging empirical literature on the pandemic has focused on the direct effects of specific policies and/or the spread of the virus, this paper focuses on the role that social networks play in potentially propagating the effects on consumption. Using real-time data on consumption expenditures based on 5.18 millions debit card users' transactions, coupled with data on social connectivity across geographies from Facebook, we quantify the response of consumption to changes in a county's COVID-19 exposure based on its social network. Our results suggest that these effects from the social network are larger than the direct effects of the virus on consumption.

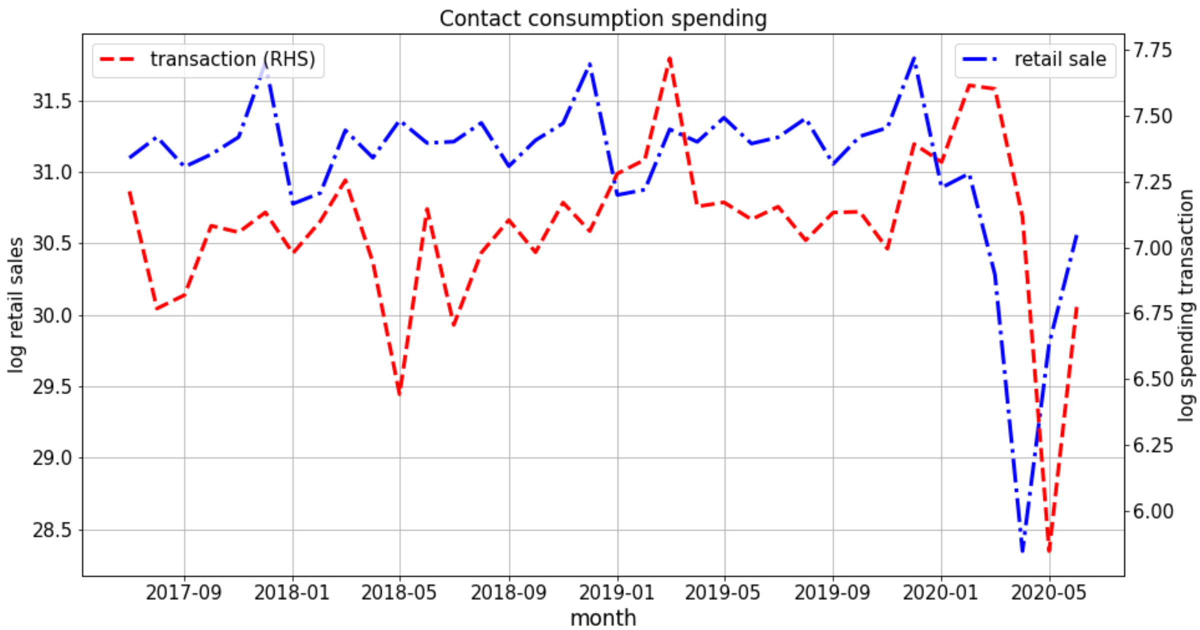
Tables and Figures

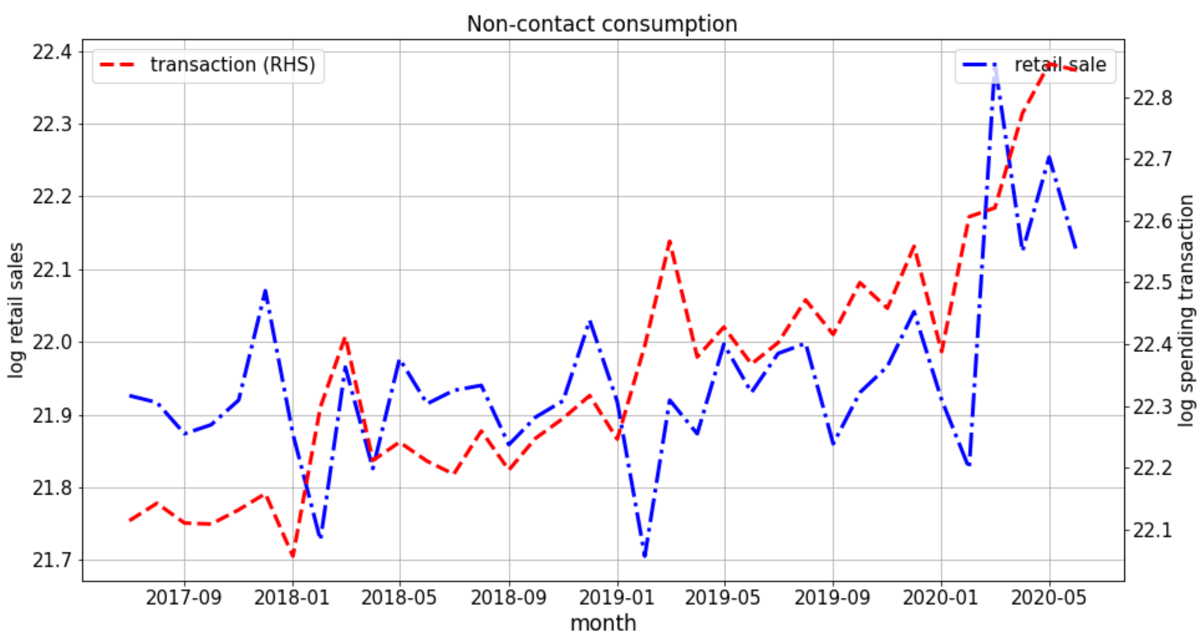
Figure 1: Descriptive Statistics on Consumption Expenditures, by Category



Notes.—Source: Facteus. Average daily consumption by category. Each bar plots the average spending per day in the specific category within each month. See the Appendix for the examples of each consumption category.

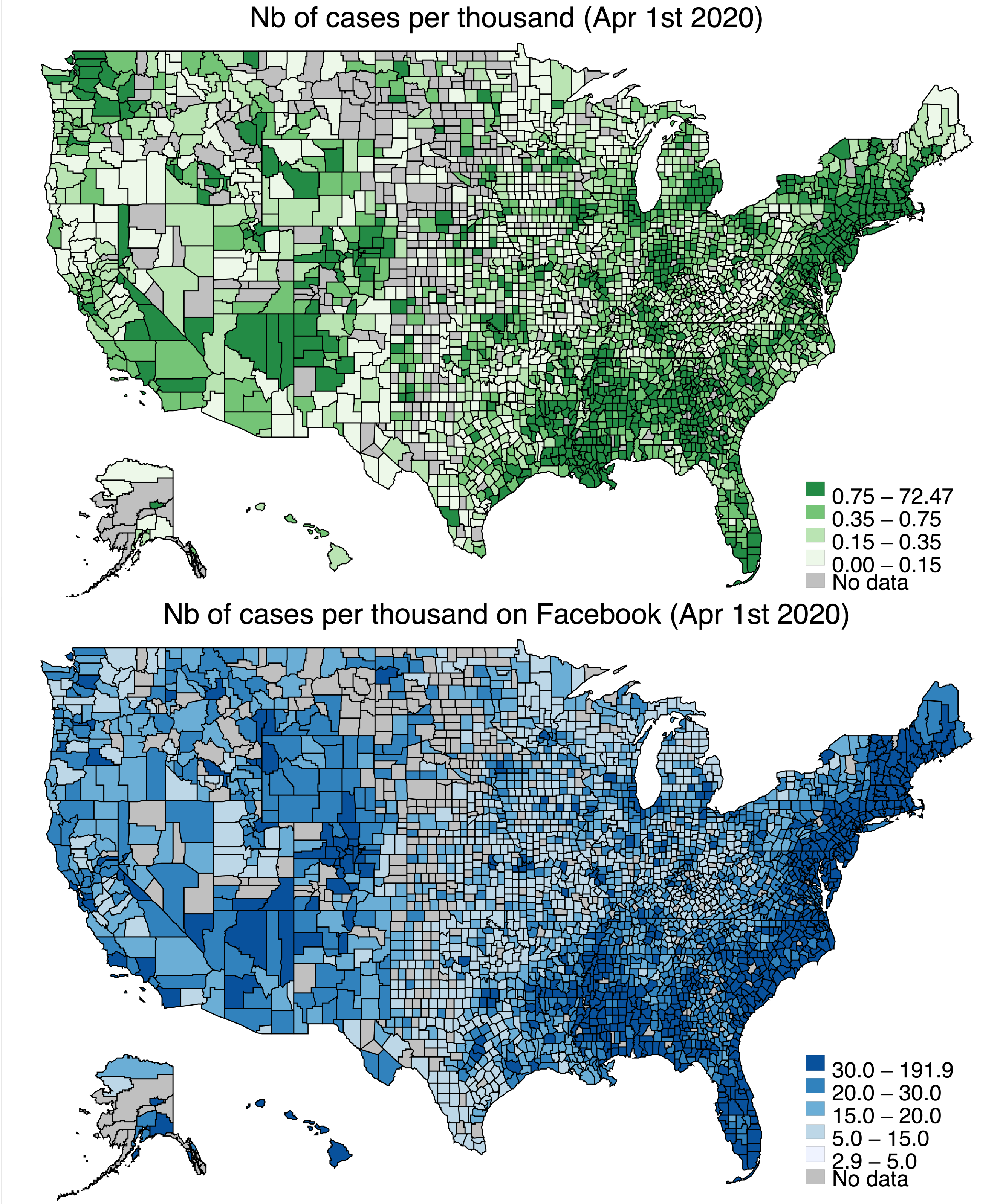
Figure 2: Benchmarking Consumption Expenditures with Retail Sales Over Time





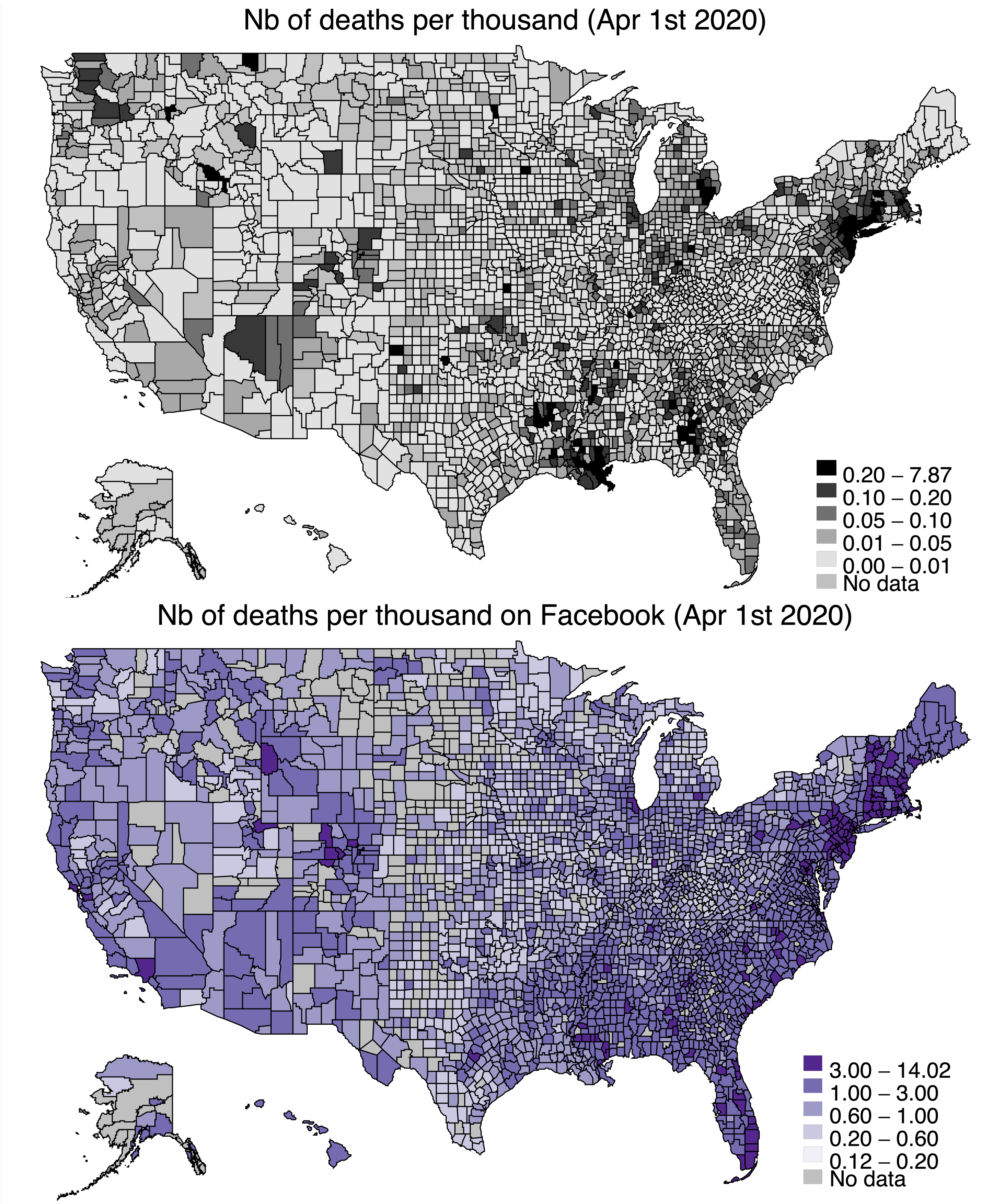
Notes.—Source: retail sales from the Census Bureau and transaction data from Facteus from June 2017 to June 2020. The upper and bottom figures plot the contact and non-contact consumption, respectively. See the appendix for the classification of card transactions. Both retail sales and transactions are without seasonal adjustment and deflated by the PCE price index. Contact-based consumption for retail sales is approximated by the sum of "drinking and eating place" (RSFSDP) and "health and personal care" (RSHPCS). The non-contact consumption is approximated as the total of "grocery stores" (RSGCS) and "food and beverage stores" (RSDBS). The correlation coefficient of the two series is 0.26 and 0.55 on the top and bottom, respectively.

Figure 3: Actual and Socially-connected COVID-19 Case Infections



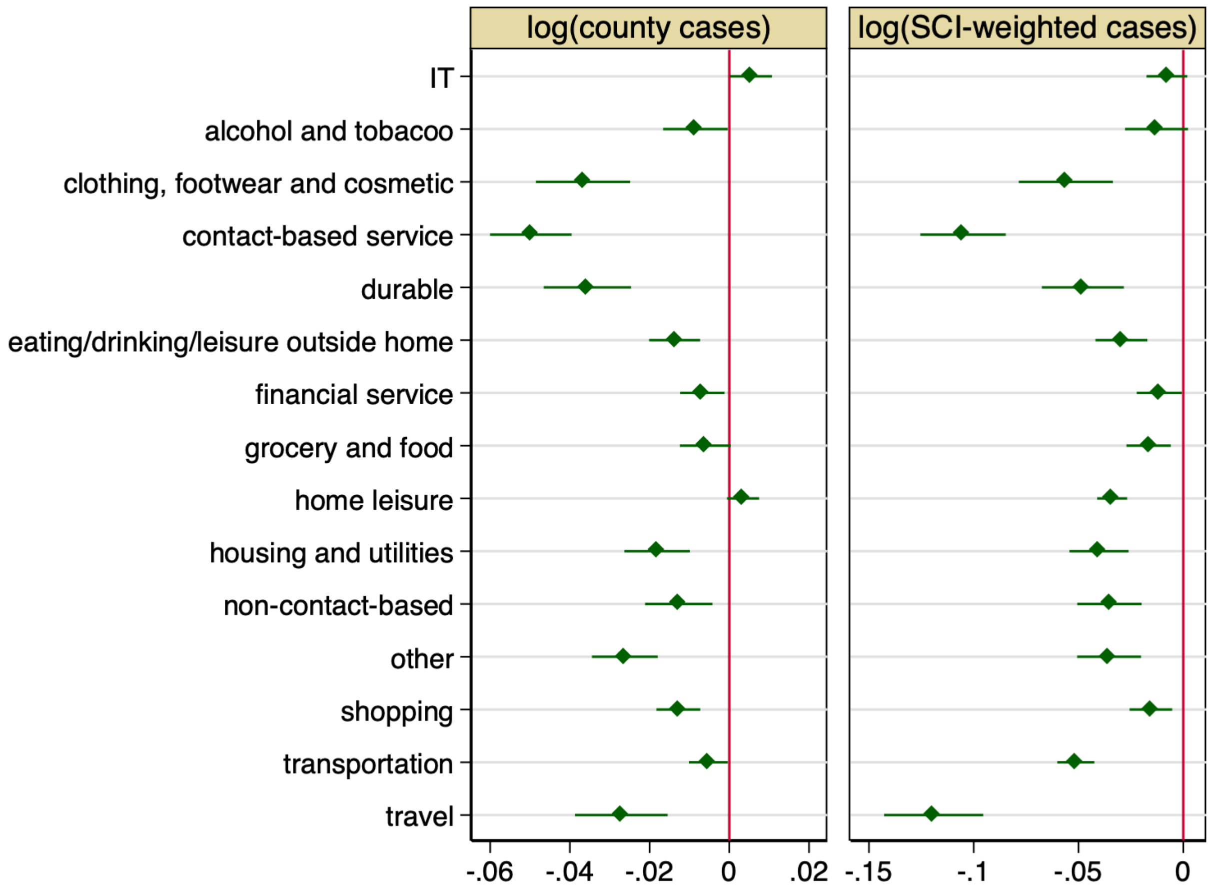
Notes.—Source: Facebook 2019 Social Connectedness Index (SCI). Panel A plots the number of COVID-19 infections per 1,000 individuals within each county as of April 1st, 2020. Panel B plots the SCI-weighted number of infections per 1,000 individuals, obtained by taking the population-weighted average across the product of infections in county c' and the SCI between county c and c'.

Figure 4: Actual and Socially-connected COVID-19 Deaths



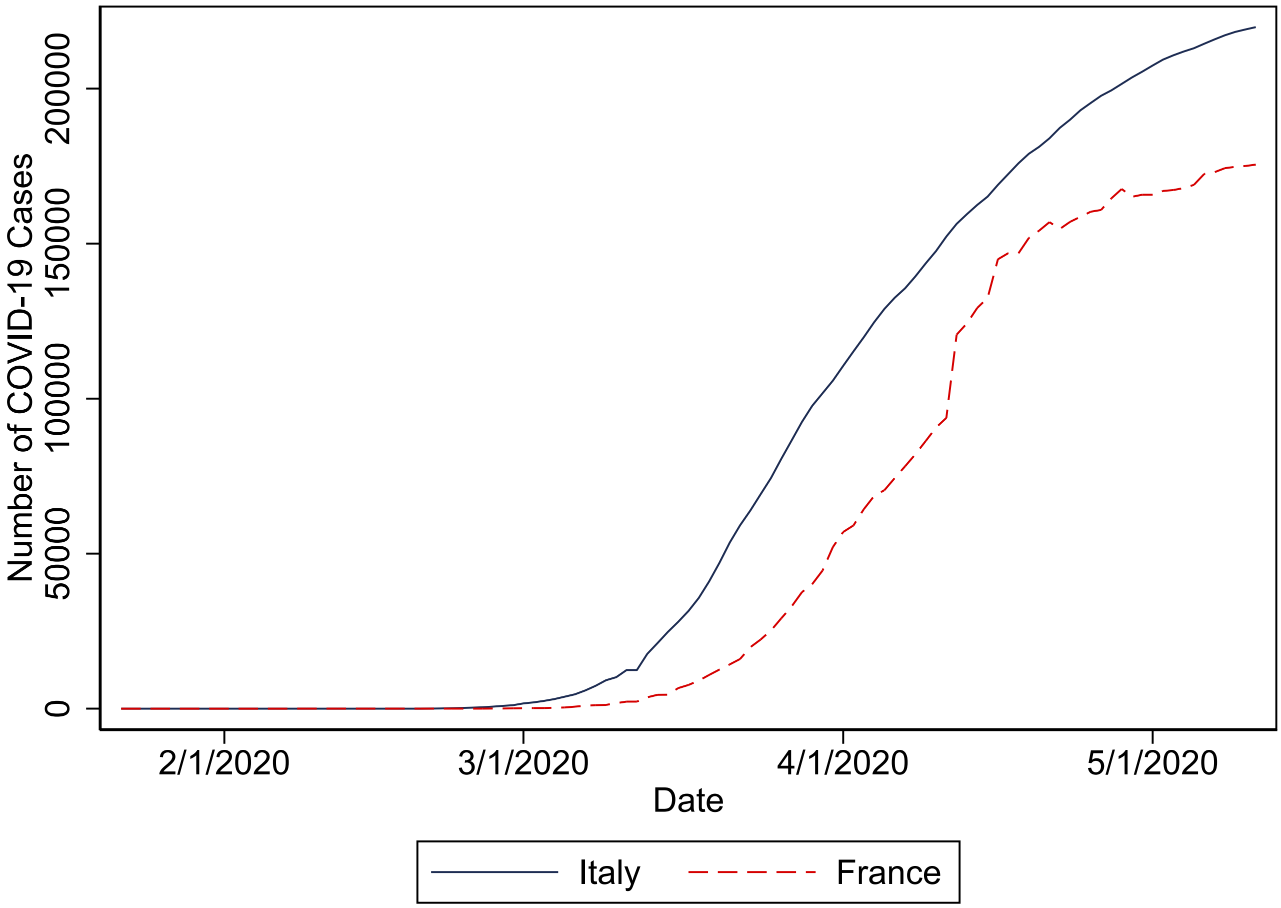
Notes.—Source: Facebook 2019 Social Connectedness Index (SCI). Panel A plots the number of COVID-19 deaths per 1,000 individuals within each county as of April 1st, 2020. Panel B plots the SCI-weighted number of deaths per 1,000 individuals, obtained by taking the population-weighted average across the product of deaths in county c' and the SCI between county c and c'.

Figure 5: Consumption Response to COVID-19 Shocks, by Consumption Category



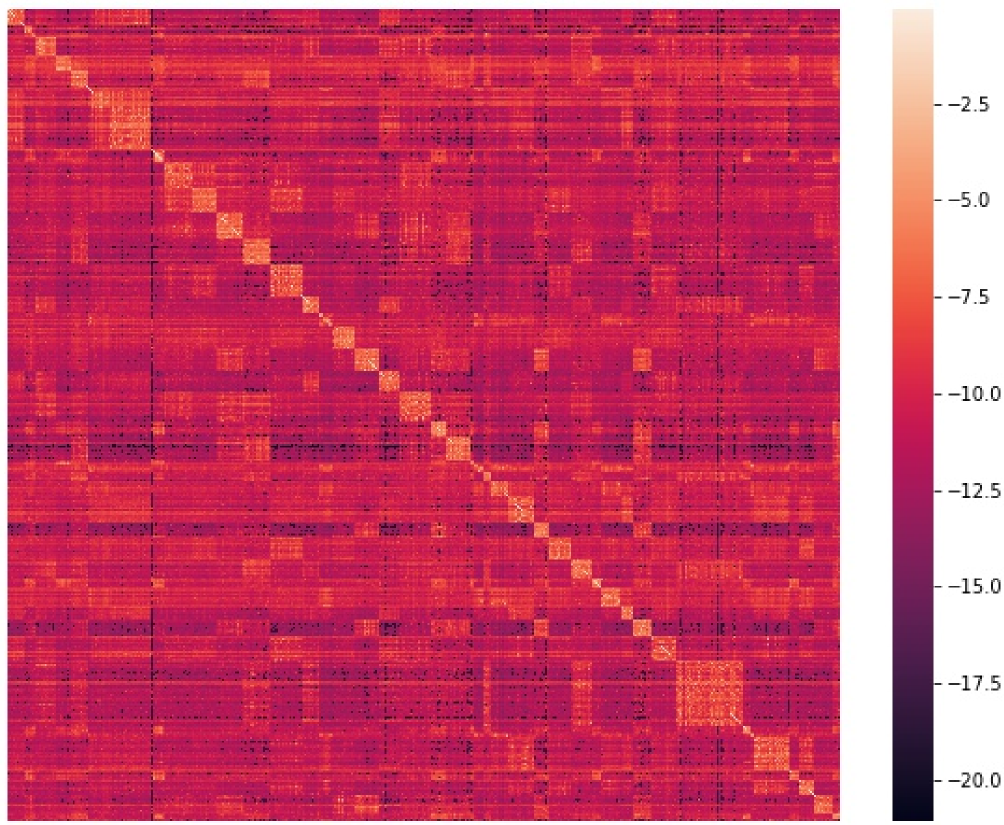
Notes.—Source: Facebook 2019 Social Connectedness Index (SCI) and Facteus. The figure reports the coefficients associated with regressions of logged consumption in a county on the logged number of COVID-19 cases (Panel A) and the logged number of SCI-weighted cases (Panel B) by category of consumption. Each transaction is classified as one of the following category based on its merchant category code (MCC).The sample period is between March 1st to June 30th, 2020

Figure 6: Time Series Patterns in COVID-19 Infections: Italy and France



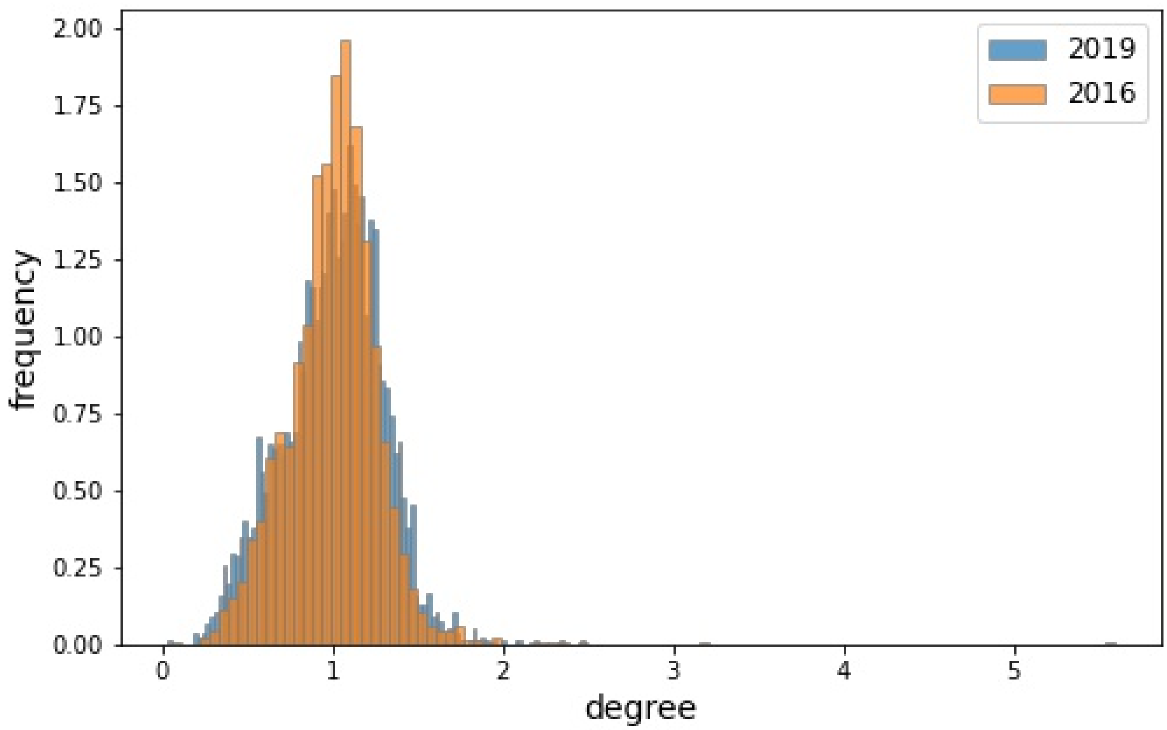
Notes.—Source: Johns Hopkins. The figure plots the number of COVID-19 infections for Italy and France over time.

Figure 7: Social Influence Matrix Across Counties



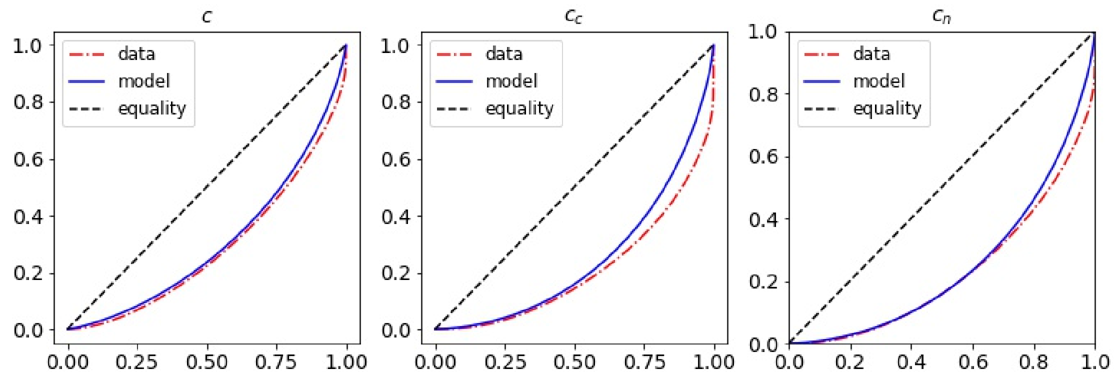
Notes.—Source: Facebook 2019 Social Connectedness Index (SCI). The heatmap plots the logged social influence matrix of 3141 U.S. counties according to SCI data of 2019. The matrix W is defined as in Equation 10. The i-th row and j-th column entry of the W, $w_{i,j}$,represents the social influence the j-th node has on i-th node in the network.

Figure 8: Distribution of the Degree of Social Influence Matrix



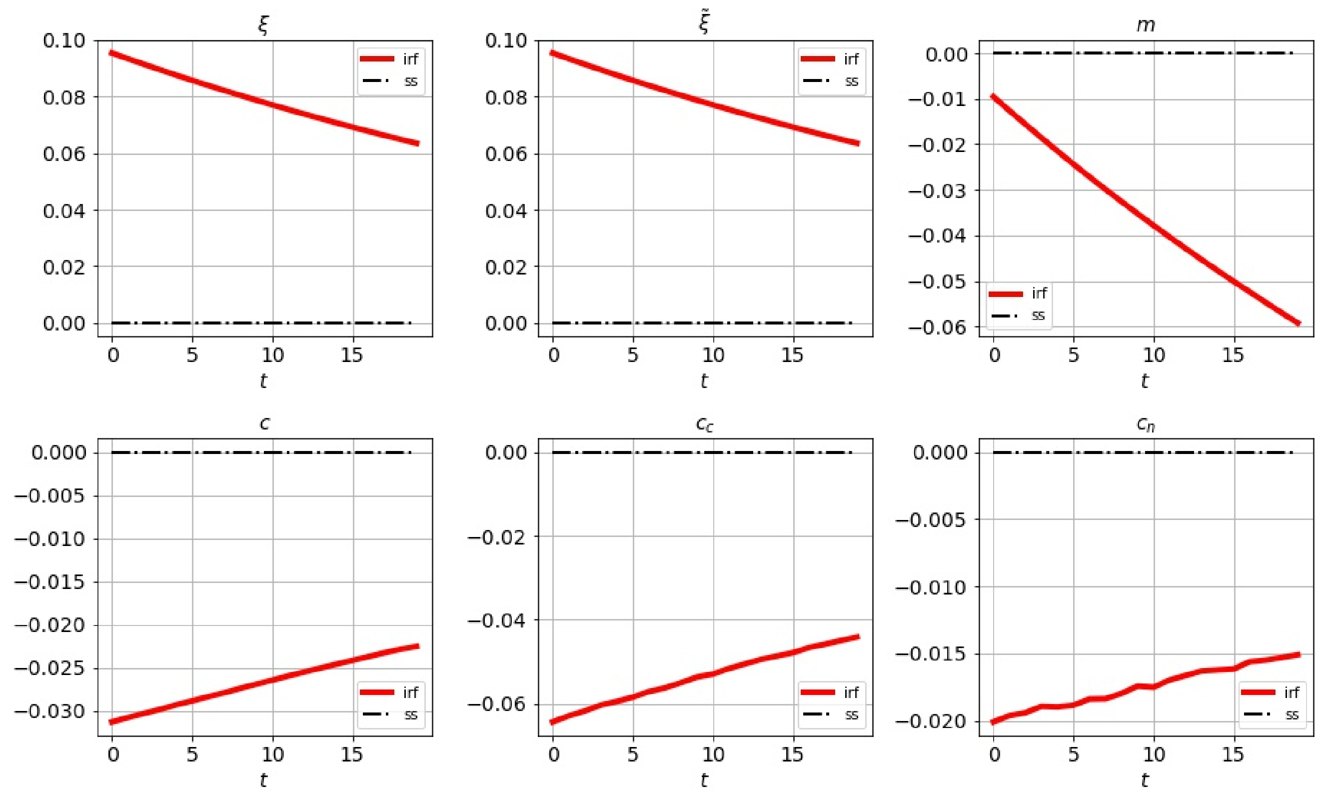
Notes.—Source: Facebook Social Connectedness Index (SCI) for 2016 and 2019. The histogram plots the distribution of degrees of 3141 counties according to SCI's 2016 and 2019 extracts, respectively. The degree is defined as in Equation 12.

Figure 9: Lorenz Curve of Cross-county Consumption before the pandemic



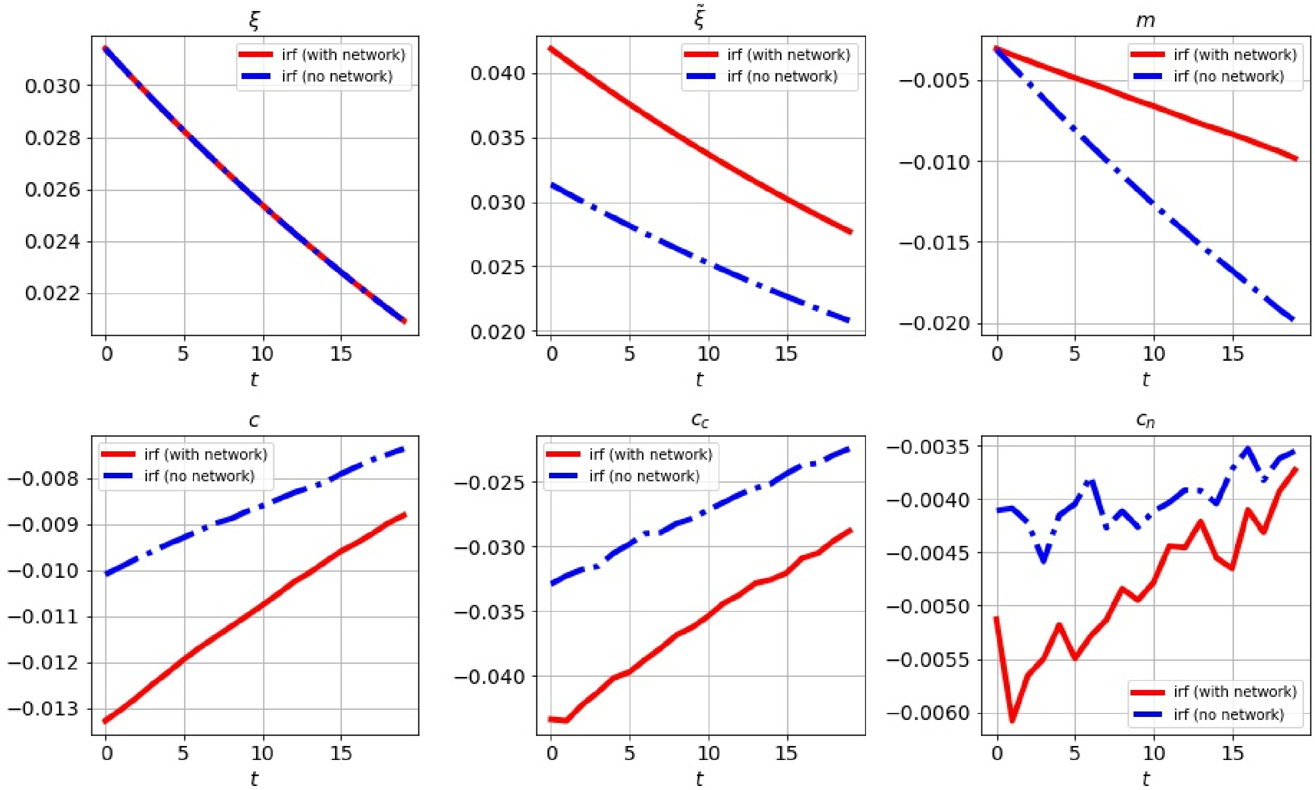
Note: This plot compares the Lorenz Curves of consumption across counties computed from data and simulated from the model. Consumption from data is based on the regression residuals of county-level spending on a list of county-specific demographics. Average consumption between January and February 2020 is used.

Figure 10: Impulse Responses of the Economy to An Infection Shock: Baseline



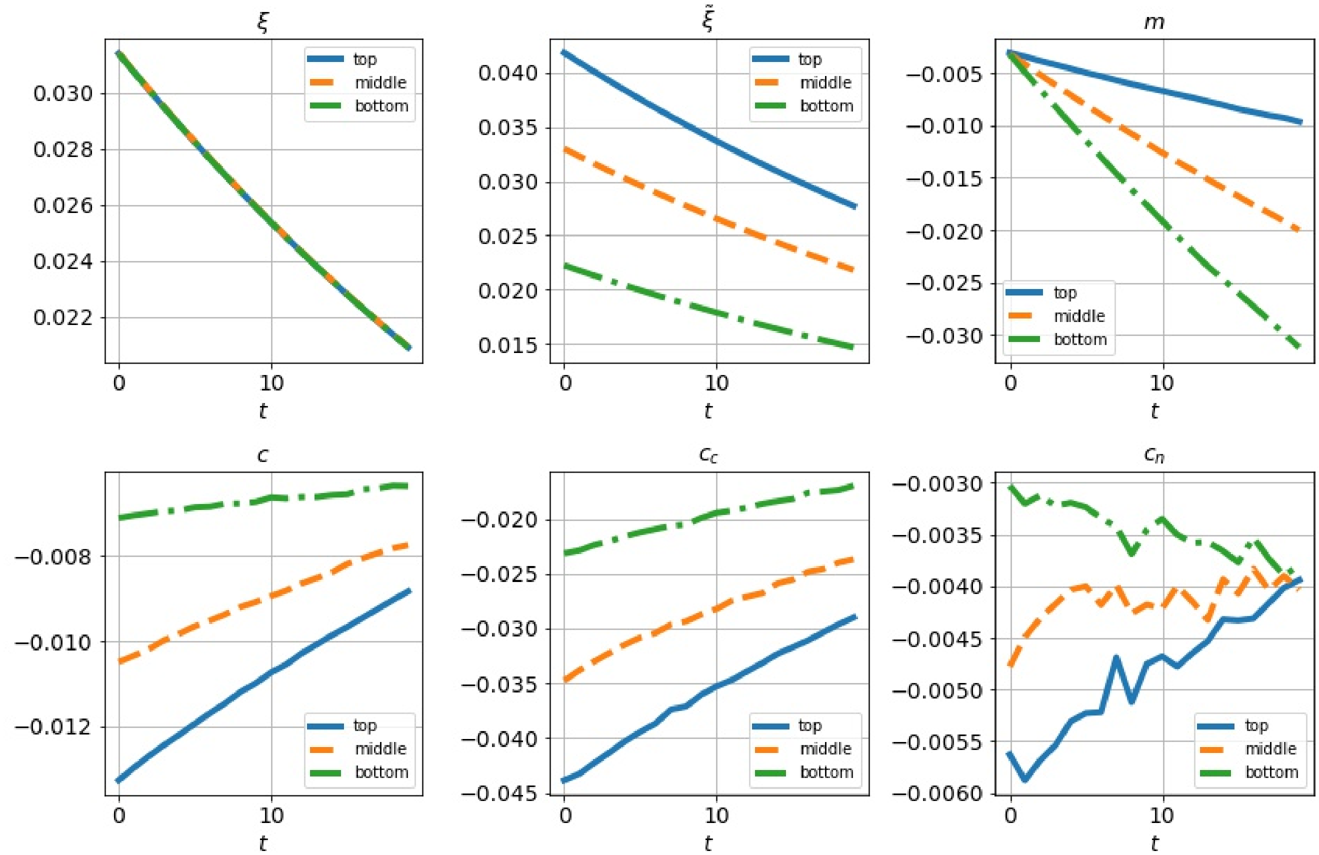
Note: This figure plots the impulse responses of the economy following a 10% increase in infections in one third of the agents in the economy at time $t = 0$ whose average degree is greater than 1. The variables are average local infection ξ, average perceived local infection $\tilde{\xi}$, average wealth m, average total consumption c and average contact-based consumption c_c, and average non-contact consumption c_n.

Figure 11: Impulse Responses of the Economy to An Infection Shock with/without Social Network



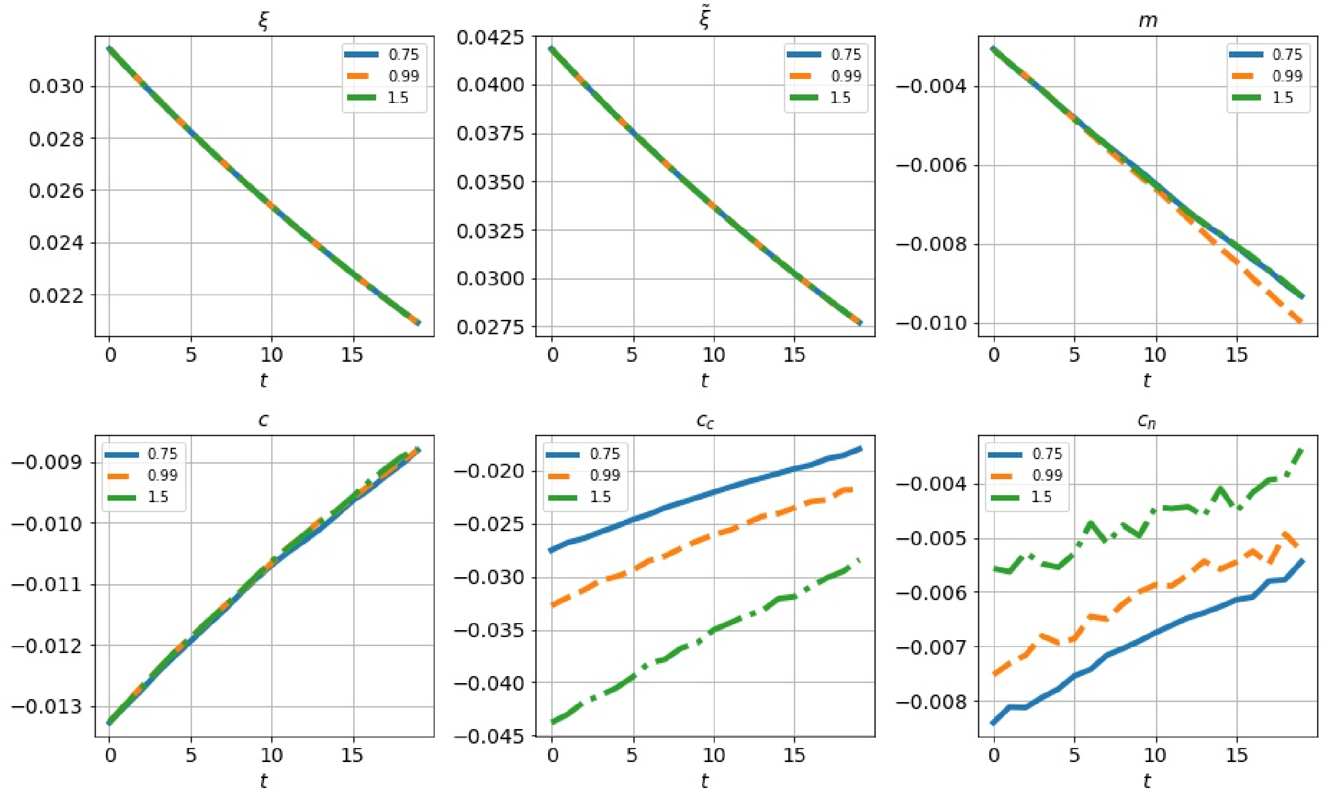
Note: This figure compares the impulse responses of the economy with and without social network influence following a 10% increase in one third of the agents in the economy whose average degree is greater than 1 at time $t = 0$. The variables are average local infection ξ, average perceived local infection $\tilde{\xi}$, average wealth m, average total consumption c and average contact-based consumption c_c, and average non-contact consumption c_n.

Figure 12: Impulse Responses of the Economy to An Infection Shock in Nodes of Degree Degree of Influences



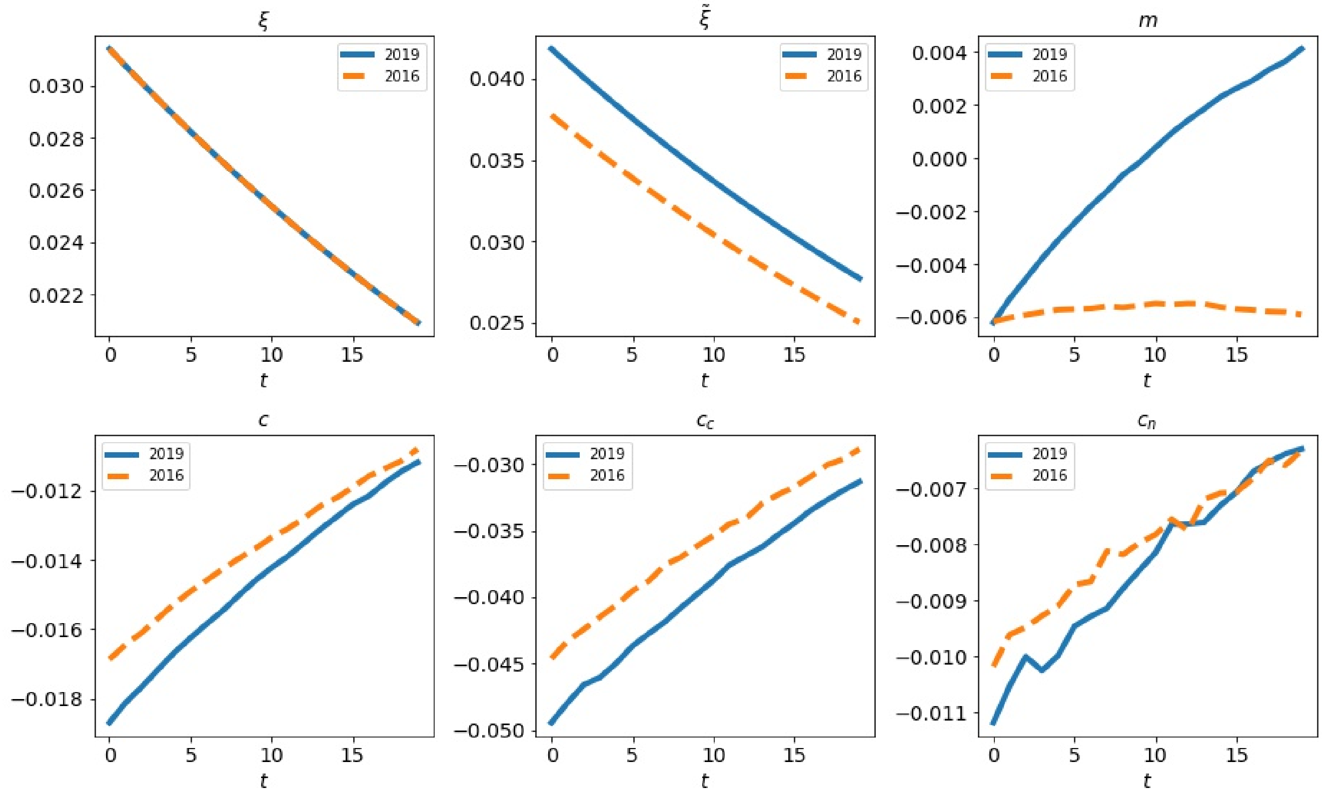
Note: This figure compares the impulse responses of the economy following a 10% increase in a random top/middle/bottom third fraction of the most influential agents in the economy at time $t = 0$. The variables are average local infection ξ, average perceived local infection $\tilde{\xi}$, average wealth m, average total consumption c and average contact-based consumption c_c, and average non-contact consumption c_n .

Figure 13: Impulse Responses of the Economy to An Infection Shock: Different EOS between Contact and Non-contact Consumption



Note: This figure compares the impulse responses of the economy following a 10% increase in the top one third most influential nodes in the economy at time $t = 0$ under degree of elasticity of substitution between two sectors. The variables are average local infection ξ, average perceived local infection $\tilde{\xi}$, average wealth m, average total consumption c and average contact-based consumption c_c, and average non-contact consumption c_n

Figure 14: Impulse Responses of the Economy to An Infection Shock: Social Network at Different Times



Note: This figure compares the impulse responses of the economy following a 10% increase in the top one third most influential nodes in the economy at time $t = 0$ under the social network in 2016 and 2019. The variables are average local infection ξ, average perceived local infection $\tilde{\xi}$, average wealth m, average total consumption c and average contact-based consumption c_c, and average non-contact consumption c_n

Table 1: Consumption Responses to Increases in Socially-connected Coronavirus Cases and Deaths

Dep. var. =	log(Consumption Expenditures)									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Has SAHO			-.058***	.007	-.058***			-.056***	-.044***	-.060***
			[.005]	[.012]	[.005]			[.005]	[.005]	[.005]
log(SCI-weighted Cases)	-.051***	-.015*	-.014*	-.003						
	[.007]	[.008]	[.008]	[.009]						
× SAHO				-.024***						
				[.004]						
log(SCI-weighted Deaths)						-.062***	-.042***	-.063***	-.049***	
						[.008]	[.010]	[.012]	[.013]	
× SAHO									-.026***	
									[.005]	
log(SCI-weighted Cases, Other States)					-.016*					
					[.009]					
log(SCI-weighted Deaths, Other States)										-.059***
										[.012]
log(County Cases)		-.015***	-.006*	-.006	-.006*		-.013***	-.003	-.003	-.005
		[.004]	[.004]	[.004]	[.004]		[.004]	[.003]	[.003]	[.003]
log(County Deaths)		-.015***	-.018***	-.018***	-.017***		-.003	-.006*	-.008**	-.007*
		[.004]	[.003]	[.003]	[.003]		[.004]	[.004]	[.004]	[.004]
R-squared	.97	.97	.97	.97	.97	.97	.97	.97	.97	.97
Sample Size	351645	351645	351645	351645	351645	351645	351645	351645	351645	351645
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State Policies	No	No	Yes	Yes	Yes	No	No	Yes	Yes	Yes
State x Month FE	No	No	Yes	Yes	Yes	No	No	Yes	Yes	Yes

Notes.–Sources: Facebook Social Connectedness Index (SCI) for 2019, Facteus. The table reports the coefficients associated with regressions of logged consumption spending on logged SCI-weighted infections (excluding county c's friendship ties with itself) and logged county infections and deaths, conditional on county and time fixed effects. Consumption is deflated by the national personal consumption expenditure index. Our SCI-weighted cases and death index is constructed as follows: $COVID_{c,t}^{SCI} = \sum_{c'}(COVID_{c',t} \times SCI_{c,c'})$ where $COVID_{ct}^{SCI}$ denotes the logged SCI-weighted number of cases or deaths in connected counties, $COVID_{c',t}$ denotes the logged number of cases or deaths in county c', and $SCI_{c,c'}$ denotes our measure of the SCI. We normalize the scaled number of friendship ties in a county to its total number of friendship ties, thereby exploiting the relative exposure to other locations. Our variables that are denoted "other states" construct the SCI excluding counties within the same state to control for physical proximity. Standard errors are clustered at the county-level. The sample period is between March 1st to June 30th, 2020.

Table 2: Heterogeneous Effects of the COVID-19 Information Shock on Consumption, by County Characteristics

RHS Variable Partition =	Per Capita Income		Share Under Age 35		Share Over Age 65		Population		Digital Intensity		Teleworking Intensity	
	High	Low	High	Low	High	Low	High	Low	High	Low	High	Low
log(SCI-weighted Cases)	-.012	-.047***	-.021**	-.025**	-.014	-.028***	-.044***	.007	-.040***	-.038***	-.042***	-.031***
	[.010]	[.014]	[.010]	[.011]	[.012]	[.010]	[.008]	[.015]	[.009]	[.012]	[.009]	[.011]
log(County Cases)	-.009	-.004	-.002	-.010	-.004	-.008	-.013***	.000	-.014*	-.020***	-.013*	-.020***
	[.006]	[.005]	[.005]	[.007]	[.007]	[.005]	[.005]	[.007]	[.007]	[.007]	[.008]	[.006]
log(County Deaths)	-.021***	-.008	-.006	-.008	-.017**	-.001	.008**	-.039***	.019***	.011*	.015**	.014**
	[.005]	[.005]	[.004]	[.006]	[.007]	[.004]	[.004]	[.010]	[.007]	[.007]	[.007]	[.007]
R-squared	.97	.96	.97	.95	.94	.98	.98	.89	.98	.98	.97	.98
Sample Size	168408	169458	170209	167657	165469	172397	180275	157591	26823	24096	25876	25043
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes.–Sources: American Community Survey (2014-2018), Facebook Social Connectedness Index (SCI) for 2019, Facteus. The table reports the coefficients associated with regressions of logged consumption spending on logged SCI-weighted infections (excluding county c's friendship ties with itself) and logged county infections and deaths, conditional on county, time, and state × month fixed effects, separately for different groups that partition the county (or in the case of digital and telework intensity, the state) based on whether the value ranks above the median of the distribution. Digital and teleworking intensities are obtained from Gallipoli and Makridis (2018) and Dingel and Neiman (2020). Consumption is deflated by the national personal consumption expenditure index. Our SCI-weighted cases and death index is constructed as follows: $COVID^{SCI}_{c,t} = \sum_{c'}(COVID_{c',t} \times SCI_{c,c'})$ where $COVID^{SCI}_{ct}$ denotes the logged SCI-weighted number of cases or deaths in connected counties, $COVID_{c',t}$ denotes the logged number of cases or deaths in county c', and $SCI_{c,c'}$ denotes our measure of the SCI. We normalize the scaled number of friendship ties in a county to its total number of friendship ties, thereby exploiting the relative exposure to other locations. Standard errors are clustered at the county-level. The sample period is between March 1st to June 30th, 2020.

Table 3: Consumption Responses to COVID-19 Information from Other Countries

Dep. var. =	log(spending)							
	ITA	ITA	SPA	SPA	FRA	FRA	SK	SK
log(SCI-weighted cases of the country)	-.007***		-.008***		-.011***		-.011***	
	[.001]		[.001]		[.001]		[.001]	
log(SCI-weighted deaths of the country)		-.052***		-.072***		-.014***		-.081***
		[.001]		[.001]		[.001]		[.002]
log(County Cases)	-.005	.015***	-.005	.003	-.005	-.005	-.005	.012***
	[.003]	[.004]	[.003]	[.004]	[.003]	[.003]	[.003]	[.004]
log(County Deaths)	-.004	-.025	-.004	-.019	-.004	-.004	-.004	-.025
	[.016]	[.018]	[.016]	[.018]	[.016]	[.016]	[.016]	[.018]
R-squared	.97	.98	.97	.98	.97	.97	.97	.98
Sample Size	78550	62925	78550	34148	78550	78550	78550	65552
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day FE	No	No	No	No	No	No	No	No

Notes.–Sources: Facebook, Facteus. The table reports the coefficients associated with regressions of logged consumption spending on logged SCI-weighted infections or deaths of a given foreign country, conditional on county and time fixed effects. These SCI-weighted infections / deaths are obtained by taking the time-varying number of infections in country i and multiplying it by the exposure of county c to country i, producing a Bartik-like measure. The four countries are Italy(ITA), Spain (SPA), France (FRA) and South Korea (SK). The sample period is between February 15th and March 15th, 2020. Standard errors are clustered at the county-level.

A Online Appendix

A.1 Data Description: Consumption Classification

Grocery and food. 1. grocery stores and super markets; 2. convenience stores; 3. drug stores and pharmacies; 4. miscellaneous retail stores; 5. meat provisions; 6. bakery, etc.

Transportation. 1. bus lines; 2. railway stations 3. car rentals; 4. toll and bridge fees, etc.

Home leisure. 1. TV cable fees; 2. digital goods, i.e. games, etc.

Housing and utilities. 1. housing rent payment; 2. home utilities, etc.

Shopping. 1. department stores; 2. discount stores; 3. variety stores; 4. general merchandise; 5. wholesale clubs, etc.

Eating, drinking, and leisure outside the home. 1. restaurants; 2. bars/taverns/clubs; 3. different kinds of parks; 4. outdoor sport and sports events; 5. orchestra and theaters, etc.

Information technology services. 1. computer network; 2. telegraph; 3. telecommunication, etc.

Contact-based services. 1. barber and beauty shops; 2. child care; 3. home cleaning; 4. repair stores; 5. veterinary services; 6. home furnishing; 7. laundry; 8. auto repair, etc.

Durables. 1.vehicles/motorcycle /auto parts; 2. furniture; 3. home appliances; 4. electronics and equipment; 5. home supplies; 6. music instruments, etc.

Non-contact-based services. 1. accounting/auditing; 2. business services; 3. programming; 4. consultations; 5. horticultural/ landscaping, etc.

Clothing, footware, and cosmetics. 1. clothing stores of different kinds; 2. cosmetic stores; 3. footwear and shoe stores, etc.

Alcohol and tobacco. 1. package stores selling wine, beer and other liquor; 2. cigar and tobacco stores, etc.

Travel. 1. airlines; 2. lodging and hotels; 3. duty-free stores; 4. airports; 5. travel agencies, etc.

Financial services. 1. insurance; 2. money orders; 3. wire transfers, etc.

Other. 1. public organizations; 2. government fees; 3. educations; 4. medical spending such as a dental clinic, etc.

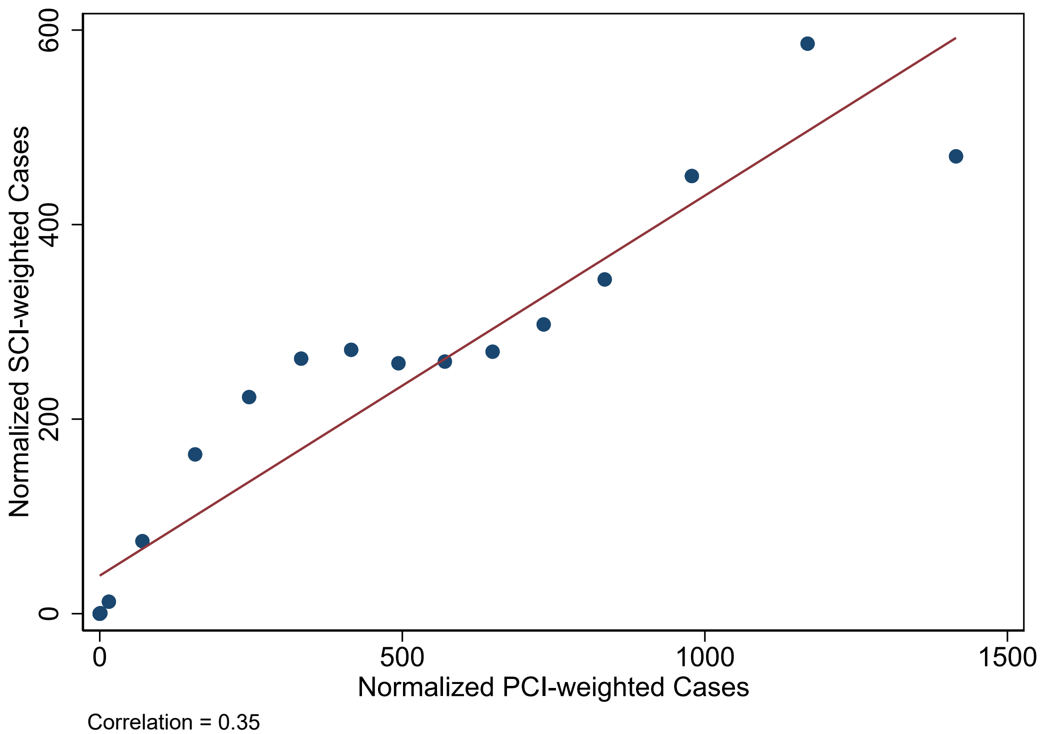
In our model with two broad sectors of consumption, contact-based consumption includes transportation, shopping, eating/drinking/leisure outside the home, contact-based services, durables, clothing/footwear, and cosmetics travel. Non-contact consumption includes grocery and food, home leisure, housing and utilities, information technology services, non-contact-based services, alcohol and tobacco, and financial services.

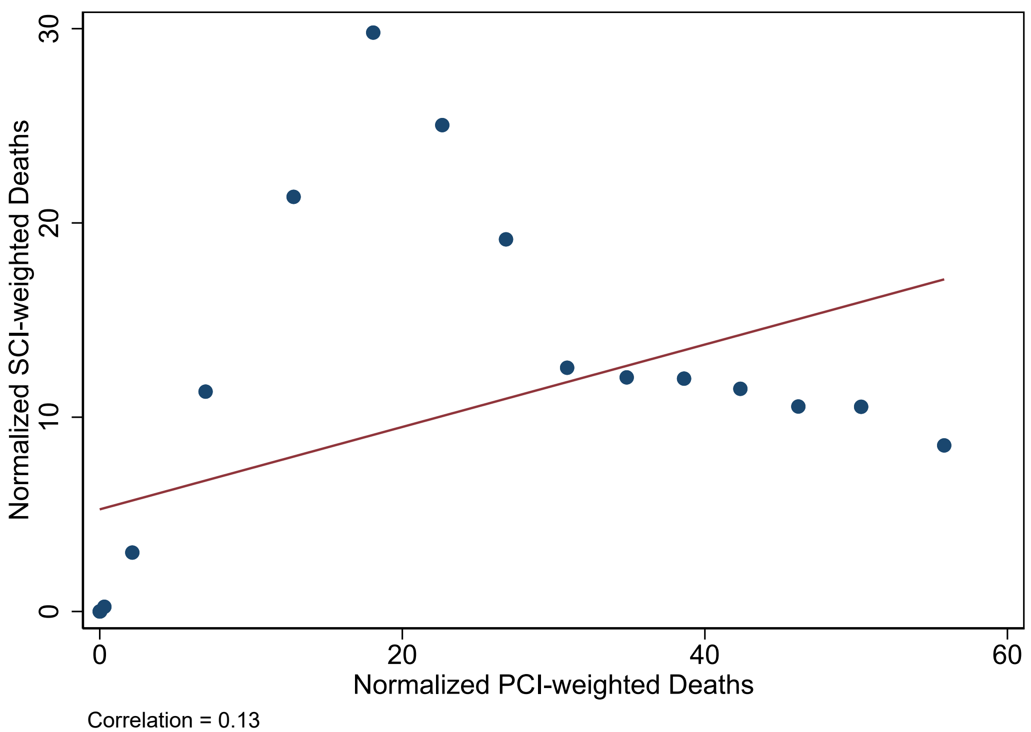
A.2 Supplement to the Empirical Results

We now explore several robustness exercises to our main empirical results that show how increases in the number of SCI-weighted cases are associated with declines in consumption. One of our concerns is that social connectivity is simply a proxy for physical proximity. We examine this concern by obtaining the distance from each county to every other county, just as in our SCI data, and use it to construct a similar index for coronavirus cases, which we call the physical connectedness index (PCI). Figure A.1 documents these results, showing that there is only a correlation of 0.35 (0.13) between the SCI and PCI -weighted number of coronavirus cases (deaths). This suggests that social connectivity is not simply capturing differences in physical distance.

We subsequently investigate the role of physical distance in greater detail by replicating the main results under different specifications with physical distance as a control. Table A.1 documents these results. We present the simple specification in columns 1 and 5: a 10% rise in SCI-weighted cases

Figure A.1: Social and Physical Connectedness -Weighted Coronavirus Cases & Deaths





Notes.—Sources: Facebook Social Connectedness Index and the NBER Physical Distance data. The figure documents the number of coronavirus cases and deaths constructed using the physical and social connectedness indices normalized to the total distance and number of friendship ties.

and deaths is associated with a 0.5% and 0.16% decline in consumption expenditures. After we add PCI-weighted cases and deaths, our main results are not significantly altered: our coefficient on logged SCI-weighted cases is statistically indistinguishable and the coefficient on logged SCI-weighted deaths is even larger (columns 2 and 6). Columns 3 and 7 subsequently add time-varying state policy controls, which only reduces the magnitude of our coefficients marginally. Finally, columns 4 and 8 add two-week lagged values of logged coronavirus cases and deaths. Although the coefficients decline in magnitude, the main results remain statistically and economically significant. We also note that PCI-weighted cases is not associated with consumption, but PCI-weighted deaths is strongly negatively correlated with consumption.

Table A.1: Examining the Role of Physical Distance for Predicting Consumption Responses

Dep. var. =	log(Consumption Expenditures)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
log(SCI-weighted Cases)	-.051***	-.050***	-.042***	-.017**				
	[.004]	[.006]	[.007]	[.008]				
log(SCI-weighted Deaths)					-.016**	-.050***	-.046***	-.023***
					[.007]	[.006]	[.006]	[.009]
log(PCI-weighted Cases)		.007	.006	.026				
		[.018]	[.018]	[.017]				
log(PCI-weighted Deaths)						-.175***	-.175***	-.157***
						[.016]	[.015]	[.015]
log(County Cases), 14 day Lag				-.018***				-.022***
				[.004]				[.004]
log(County Deaths), 14 day Lag				.008				.011**
				[.006]				[.005]
R-squared	.99	.99	.99	.99	.99	.99	.99	.99
Sample Size	351644	351644	351644	351644	351644	351644	351644	351644
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State Policies	No	No	Yes	Yes	No	No	Yes	Yes

Notes.–Sources: Facebook Social Connectedness Index (SCI) for 2019, Facteus. The table reports the coefficients associated with regressions of logged consumption spending on logged SCI and PCI -weighted infections (excluding county c's friendship ties with itself) and logged county infections and deaths, conditional on county and time fixed effects. Consumption is deflated by the national personal consumption expenditure index. Our SCI-weighted cases and death index is constructed as follows: $COVID^{SCI}_{c,t} = \sum_{c'}(COVID_{c',t} \times SCI_{c,c'})$ where $COVID^{SCI}_{ct}$ denotes the logged SCI-weighted number of cases or deaths in connected counties, $COVID_{c',t}$ denotes the logged number of cases or deaths in county c', and $SCI_{c,c'}$ denotes our measure of the SCI. We normalize the scaled number of friendship ties in a county to its total number of friendship ties, thereby exploiting the relative exposure to other locations. The physical connectedness index (PCI) is constructed similar using miles between counties, rather than friendship ties. Our variables that are denoted "other states" construct the SCI excluding counties within the same state to control for physical proximity. Standard errors are clustered at the county-level and observations are weighted by county population. The sample period is between March 1st to June 30th, 2020.

In summary, these results show that our SCI-weighted coronavirus cases and deaths index is not simply capturing variation in physical distance. Moreover, even when we control explicitly for a comparable measure of PCI-weighted cases and deaths, our results remain. These exercises are on top of the baseline specification, which excludes counties in the same state (otherwise closely connected geographies).

Since our consumption data is based on a sample of debit-card users that is disproportionately represented by young and low-income people, it is also worth checking if the empirical results are robust to an alternative measure of consumer spending from separate data source. We utilize the county-level consumer spending of 1481 counties across the United States based on both debit and credit card transaction data provided by Affinity, a commercial provider.[17] Table A.2 reports the results of the same regression as the baseline except for replacing the dependent variable with the growth rate relative to January 2020 of each day. The negative and significant coefficients associated with the SIC weighted cases and deaths remain negative and significant.

A.3 Proofs of two propositions in the model

- The average belief is the degree-weighted truth

$$\tilde{\xi}_t = \frac{\sum_{i=1}^{N} \tilde{\xi}_{i,t}}{N} = \frac{\sum_{i=1}^{N} \sum_{k=1}^{N} w_{i,k} \xi_{k,t}}{N} = \frac{\sum_{k=1}^{N} d_k \xi_{k,t}}{N}$$

- If $d_k = 1 \forall k$, then $\tilde{\xi}_t = \xi_t$.

- WLG, assuming a fraction of nodes $k = 1, 2 \ldots s$ experiences a shock $\Delta\xi$ such that $\sum_{k=1}^{s} d_k / s >$

[17] Chetty et al. (2020) shows that the aggregate series of the transaction data tracks the national retail sales (excluding auto and gas) from the Monthly Retail Trade Survey remarkably well.

Table A.2: Alternative Data Source of Consumption Spending

Dep. var. =	log(Consumption Expenditures) Growth							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Has SAHO			-.011***	.015**			-.010***	-.008**
			[.003]	[.007]			[.003]	[.003]
log(SCI-weighted Cases)	-.028***	-.018***	-.029***	-.025***				
	[.004]	[.005]	[.004]	[.004]				
× SAHO				-.008***				
				[.002]				
log(SCI-weighted Deaths)					-.023***	-.024***	-.042***	-.039***
					[.003]	[.004]	[.005]	[.005]
× SAHO								-.004*
								[.002]
log(County Cases)		.000	.002	.002		-.003*	-.001	-.001
		[.002]	[.002]	[.002]		[.001]	[.001]	[.001]
log(County Deaths)		-.007***	-.007***	-.007***		.003	.001	.001
		[.003]	[.001]	[.001]		[.002]	[.002]	[.002]
R-squared	.84	.84	.75	.75	.73	.73	.75	.75
Sample Size	175857	175857	175857	175857	175857	175857	175857	175857
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State Policies	No	No	Yes	Yes	No	No	Yes	Yes
State x Month FE	No	No	Yes	Yes	No	No	Yes	Yes

Notes.–Sources: Facebook Social Connectedness Index (SCI) for 2019, Affinity Solutions. The table reports the coefficients associated with regressions of logged consumption spending growth from January 1st on logged SCI-weighted infections and logged county infections and deaths, conditional on county and time fixed effects. The consumption spending is from the Affinity Solution, including both debit and credit card transactions of consumption spending at the county level.

1:

$$E(\tilde{\xi}_{t+1}) = \frac{E(\sum_{k=1}^{N} d_k \xi_{k,t+1})}{N}$$
$$= \frac{E(\sum_{k=1}^{s} d_k(\xi_{k,t} + \Delta\xi) + \sum_{k=s+1}^{N} d_k \xi_{k,t+1})}{N}$$
$$> \tilde{\xi}_t + s\Delta\xi$$
$$\rightarrow E(\Delta\tilde{\xi}_{t+1}) > \Delta\xi_{t+1} = s\Delta\xi$$

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