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

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Abstract

How do individuals adjust their consumption in response to information disseminated through peers and the social network? Using United States data on consumption, coupled with geographic friendship ties to measure social connectivity, this paper quantifies the role of social networks as a propagation mechanism for understanding aggregate fluctuations in consumption. Using the COVID-19 pandemic as a source of variation, we find that a 10% rise in cases and deaths in counties connected through the social network is associated with a 0.64% and 0.33% decline in consumption expenditures–roughly three to seven times as large as the direct effects of local cases or deaths. Counties more socially connected to epicenter countries of the pandemic also saw a bigger drop in consumption. These 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. We are working on incorporating this microeconomic evidence into a heterogeneous agent model and social interaction to study the aggregate demand implications.

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

JEL Codes: D14, E21, E71, G51

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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 (Bartik et al., 2020; Cajner et al., 2020), consumption (Baker et al., 2020b; Coibion et al., 2020), and output (Makridis and Hartley, 2020; Guerrieri et al., 2020). 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 quarantine.[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 networks are now a primary vehicle for obtaining information in the average household (Westerman et al., 2014), 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. Quantifying 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.

This paper quantifies an elasticity of the individual consumption and the composition of consumption in response to fluctuations in infections in connected counties. Using a combination of US micro card transaction data from Facteus and the Social Connectedness Index (SCI) from Facebook, we exploit plausibly exogenous variation in individuals' exposure to different geographically remote counties based on ties in their social network that were formed prior to the pandemic. We find that a 10% increase in SCI-weighted cases and deaths is associated with 0.64% and 0.33% decline in consumption, respectively. We also find that these declines are greater among social-

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

contact-based consumption categories and activities away from home. For instance, each 10% increase in socially-connected cases is associated with a 2% decrease in clothing/footwear/cosmetics, a 1.3% decrease in contract-based service, and a 1.1% decrease in travel. These are twice to three times as large as the drop in average spending. This finding provide 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. As a placebo, we also show that increases in infections among connected counties do not have systematically different effects on consumption in states after the adoption of stay-at-home orders, which we would expect them to have if the results were driven by state-specific policies that simply curtailed foot traffic. 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. Restricting our sample to February 15th to March 15th before the United States' national emergency was launched in full force, we find similar results, suggesting that our results reflect an information-driven response.

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 to affect their "friends" 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), our results nonetheless build on emerging literature that points to the real economic consequences of social networks, as in the case of renting versus owning in the housing market (Bailey et al., 2018a).

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 began investigating the effects of pandemics on economic activity, placing a central role on the optimizing 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 severe of 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)

[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.

who use the Safegraph data to quantify the effect of the pandemic on foot traffic.

Finally, our paper is related with 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 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 investigates the prospective social networks mechanism. Section 6 concludes. We are continuing to produce additional results, specifically focusing on taking these empirical patterns to an aggregate model of the economy.

[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.

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 April 17th, 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. (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 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

[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.

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 15th and April 17th with a total of 60 days and roughly 250,000 county $\times$ 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 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 17 broad categories based on its degree of exposure to the infection risks, as well as its demand elasticity.[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, 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

[7]See Section 6 for examples of merchant types that fall into each category.

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 based on our transaction records and the monthly total retail sales provided by the Census Bureau. To ensure that the series are as comparable as possible, we exclude from the card spending both financial services (e.g., insurance premiums and wire transfers) and housing rent and utilities, leaving the purchase of durable and non-durable goods and services. The two series track each other fairly well given that they are not apples to apples comparisons—the correlation is 0.41 over the three-year period that overlaps. Some of these differences may emerge because the sample selects lower-income individuals and does not have complete coverage throughout the country.[8]

[INSERT FIGURE 2 HERE]

In addition, we also compare the transaction series with subcategory of consumption separately reported by the Census Bureau. The positive correlation remains between our series with categories

[8] 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.

such as grocery shopping, food and beverage stores, general merchandise and eating/drinking places, for which the correlation coefficients are all above 0.4.

Another major dataset used in this analysis measures the social network connectedness between different pairs of counties and between a U.S. county to different foreign countries. We combine these data with the Social Connectedness Index (SCI) from Facebook. Introduced by Bailey et al. (2018a) to study the role of social networks in propagating housing price shocks across space, these data are beginning to be used more widely to understand how social ties are related with economic activity (Bailey et al., 2018b). The index is constructed off of aggregated and 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. Friendship ties require that both sides agree. We also draw upon 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.[9]

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., 2020), 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:

$$COVID_{ct}^{SCI} = \sum_{c'}(COVID_{ct}^{d} \times SCI_{c,c'})$$

where $COVID_{ct}^{SCI}$ denotes the logged SCI-weighted number of cases or deaths in connected counties, $COVID_{ct}^{d}$ denotes the (direct) logged number of cases or deaths in the county. Importantly, we constructed Equation 3 by excluding ties between county c and all other counties c' within the same state to avoid potential mechanical effects between state-level policies and infections. 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:

$$Y_{ct} = \gamma COVID_{ct}^{SCI} + \phi COVID_{ct}^{d} + \zeta_c + \lambda_t + \epsilon_{ct}$$

where y_{ict}^{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).

Equation 3 exploits plausibly exogenous variation in the exposure of an individual to counties that have more versus less severe COVID-19 shocks over time. For instance, whereas Maricopa County in Arizona has a scaled SCI with King County (Seattle) in Washington of 3,626, San Francisco in California has a scaled SCI of 12,294 with King County. Then, because Seattle was one of the hardest hit cities at first, we would expect that individuals in San Francisco would experience a greater drop in their consumption, relative to Maricopa County. Moreover, since we are controlling for the direct effects of COVID-19 in county c, we are exploiting only the variation that arises from social networks. We also explore potentially heterogeneous treatment effects.

4 Empirical Results

4.1 Main Results

Table 1 documents the results associated with Equation 3. Starting with columns 1 and 4, we find that a 10% rise in SCI-weighted cases and deaths are associated with a 0.64% and 0.33% decline in consumption expenditures. Throughout all specifications, our SCI-weighted index excludes connections among counties within the same state as we focus on the effect through social networks instead of physical connect. Compared to column (1) and (4), columns (2), (3) (5), and (6) control for local (county) cases and deaths. While our coefficients decline slightly in magnitude, they remain statistically significant at a 1% level.

Importantly, the gradients on our SCI-weighted index of cases and deaths are roughly three to seven times as large as the direct effects of cases and deaths. This suggests that information transmitted through social networks might be even more quantitatively significant at informing consumption decisions than local activity does. Finally, recognizing the presence of time-varying state-specific containment policies, which are associated with meaningful effects on different activities such as job postings (Ali et al., 2020), we control for state × day fixed effects, isolating variation in counties' heterogeneous social networks even in the same state. Table 2 replicates these results using consumption growth and SCI-weighted growth in cases and deaths, producing almost identical results.

[INSERT TABLES 1 AND 2 HERE]

How do these information shocks potentially heterogeneously affect spending across different types of consumption 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 comsetic 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 3% decline in contact-based service spending, which is roughly three-times as large as the effects obtained on grocery / food or home leisure spending. These results are also consistent with Coibion et al. (2020) who find a 31 log point drop in consumer spending concentrated with a decline 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 3 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 0.54% decline in consumption among the counties below the median in per capita income, but a 0.46% decline among the rest. This could be consistent with the fact that counties with higher per capita income also have higher social capital and hygiene (Makridis and Wu, 2020). 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.

Interestingly, we see that the effects are concentrated in counties that rank above the median share of individuals below age 35 and below the median share of individuals above age 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 lower population counties have a nearly two-times as large of an elasticity, which could be explained by the fact that individuals in urban areas learn faster through their own surroundings. Finally, we see that counties with lower shares of digitally-intensive and teleworking employees are more adversely affected. Since both of these measures from Gallipoli and Makridis (2018) and Dingel and Neiman (2020) are measuring occupational tasks that cushion against the national quarantine—since digital services and teleworking (unlike, for example, hotels) are not directly affected by the national quarantine—we would expect to see that the counties with fewer of such workers being the ones that are harder hit.

[INSERT TABLE 3 HERE]

5 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., 2020), 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 remains 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

[10]Although we would, of course, ideally include China, the Facebook data does not have representative coverage

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

Table 4 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.

of ties with China because their government prohibits the use of Facebook.

[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.

[INSERT TABLE 4 HERE]

Our finding that consumption in one county depends in part on the effects of 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. (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.

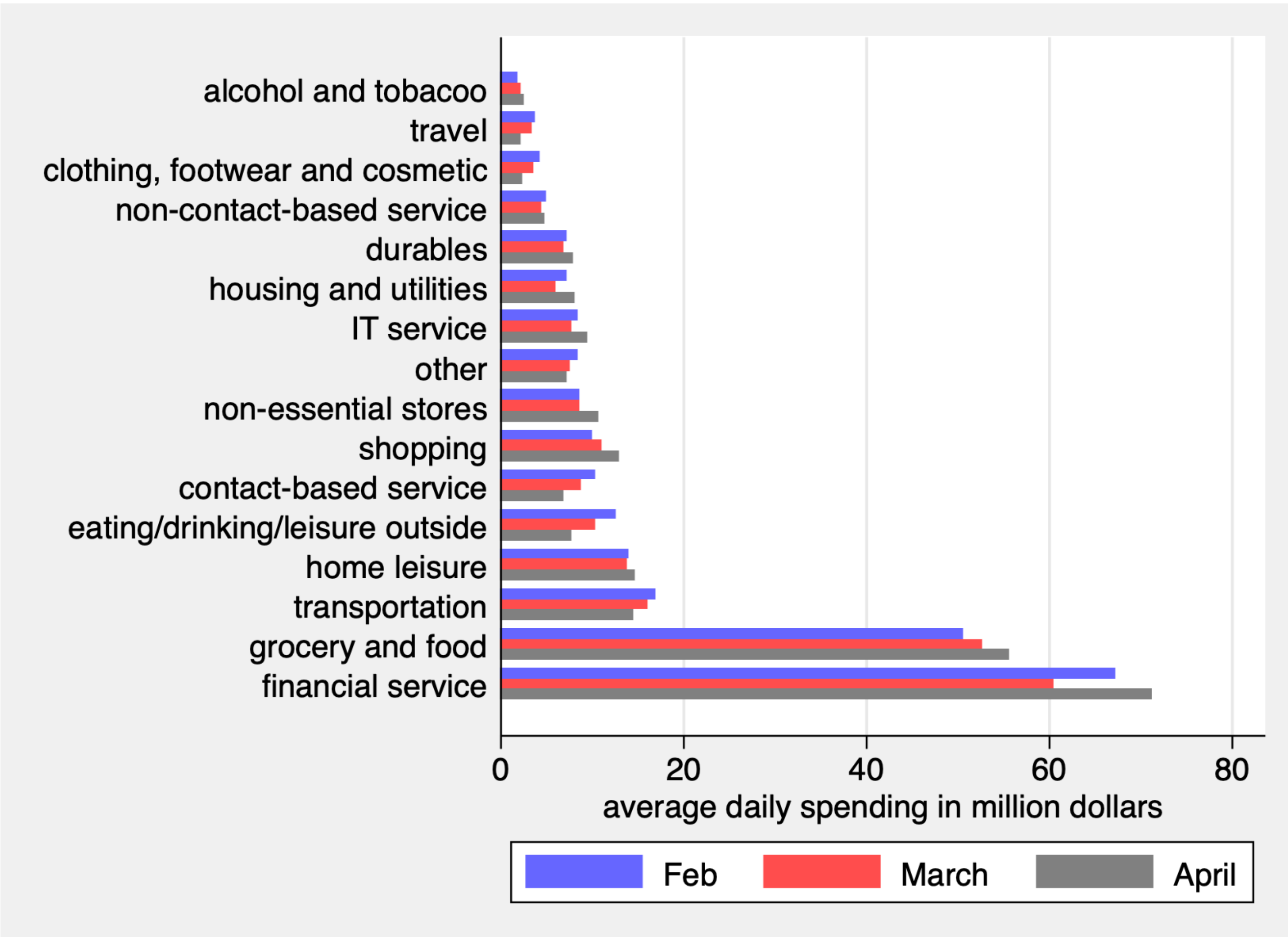
6 Conclusion

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., 2020), 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' transaction, 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 significantly larger than the direct effects of the virus on consumption.

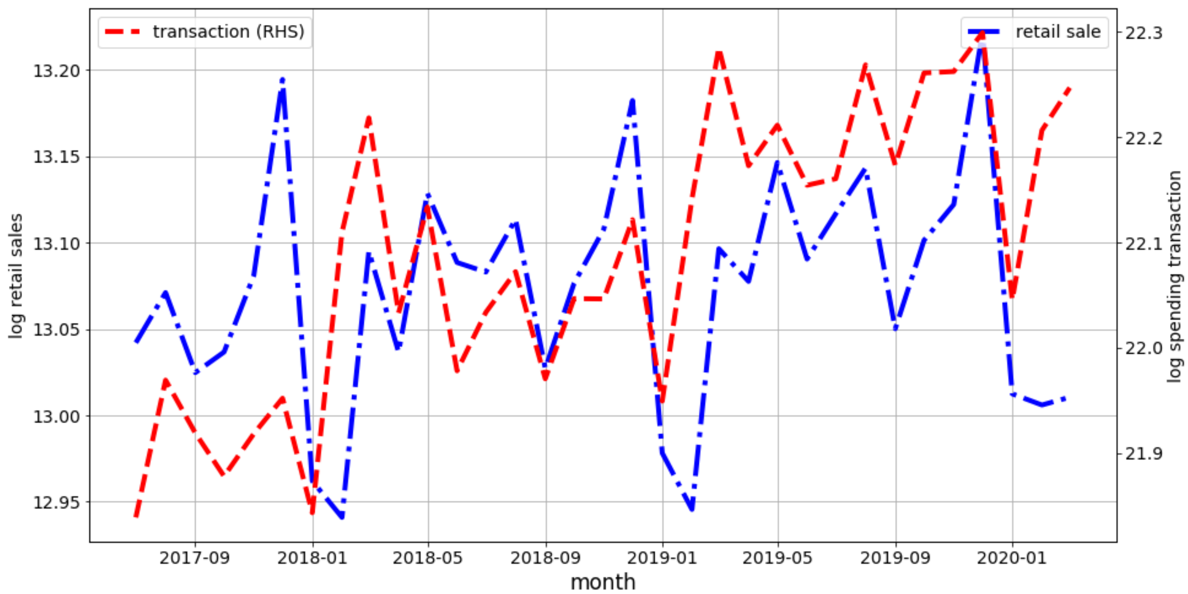
Tables and Figures

Figure 1: Descriptive Statistics on Consumption Expenditures, by Category



Notes.—Source: Facteus. Average daily consumption by category. Each bar plots the average spending in the specific category within each month. Data till the 17th is used for the average of April. 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. Both are without seasonal adjustment and deflated by PCE price index. The total card transaction excludes financial-service-related such as insurance premium and wire transfer, as well as housing and utilities expenses. The retail sale uses the series "retail and food services, (total)", directly provided by the Census Bureau. The correlation coefficient of the two series is 0.41.

Table 1: Consumption Responses to the COVID-19 Information on Facebook

Dep. var. =	log(spending)					
	(1)	(2)	(3)	(4)	(5)	(6)
log(SCI-weighted Cases)	-.064***	-.054***	-.067***			
	[.006]	[.006]	[.014]			
log(SCI-weighted Deaths)				-.033***	-.027***	-.054***
				[.003]	[.003]	[.008]
log(County Cases)		-.008***	-.006***		-.008***	-.006***
		[.001]	[.001]		[.001]	[.001]
log(County Deaths)		-.008***	-.007***		-.007***	-.006**
		[.002]	[.002]		[.002]	[.002]
R-squared	.97	.97	.98	.97	.97	.98
Sample Size	126106	126100	126086	126106	126100	126086
County FE	Yes	Yes	Yes	Yes	Yes	Yes
State/Time FE	No	No	Yes	No	No	Yes
Day FE	Yes	Yes	No	Yes	Yes	No

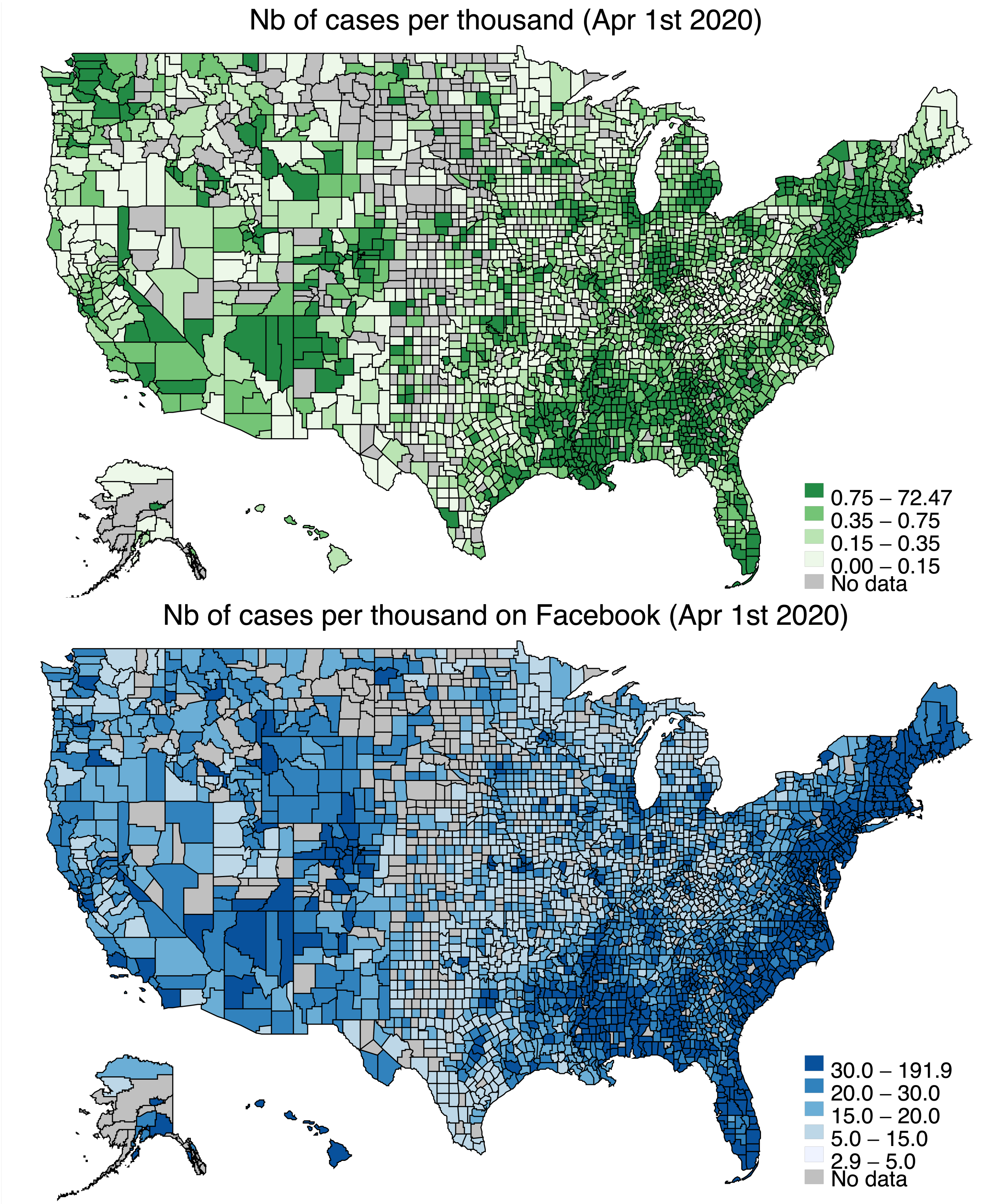
Notes.–Sources: Facebook, Facteus. The table reports the coefficients associated with regressions of logged consumption spending on logged SCI-weighted infections (excluding the counties in the same state) and logged county infections and deaths, conditional on county and time fixed effects. Standard errors are clustered at the county-level. The sample period is between March, 1st to April 17th, 2020

Table 2: Growth in Consumption and the COVID-19 News from Facebook

Dep. var. =	log spending growth					
	(1)	(2)	(3)	(4)	(5)	(6)
log(SCI-weighted Cases) growth	-.056***	-.053***	-.025			
	[.012]	[.012]	[.025]			
log(SCI-weighted Deaths) growth				-.014**	-.013**	-.039**
				[.006]	[.006]	[.016]
log(County Cases)		.005***	.001		.005***	.001
		[.001]	[.002]		[.001]	[.001]
log(County Deaths)		-.006***	-.005*		-.006**	-.005**
		[.002]	[.003]		[.002]	[.002]
R-squared	.33	.33	.42	.33	.33	.42
Sample Size	105606	105596	105589	105606	105596	105589
County FE	Yes	Yes	Yes	Yes	Yes	Yes
State/Time FE	No	No	Yes	No	No	Yes
Day FE	Yes	Yes	No	Yes	Yes	No

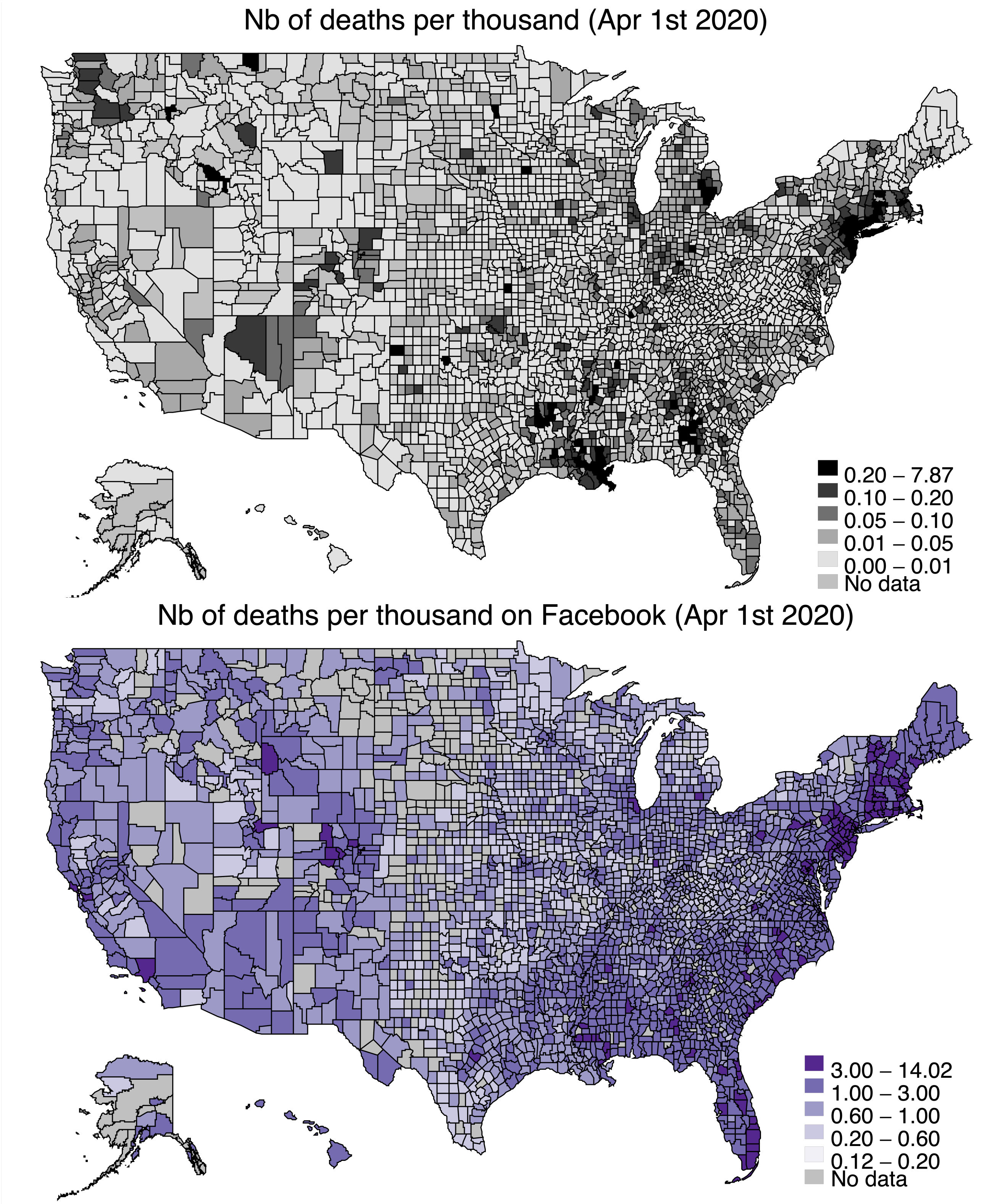
Notes.–Sources: Facebook, Facteus. The table reports the coefficients associated with regressions of logged consumption spending on week-to-week growth in SCI-weighted infections (excluding the counties in the same state) and logged county infections and deaths, conditional on county and time fixed effects. Standard errors are clustered at the county-level.The sample period is between March, 1st to April 17th, 2020

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



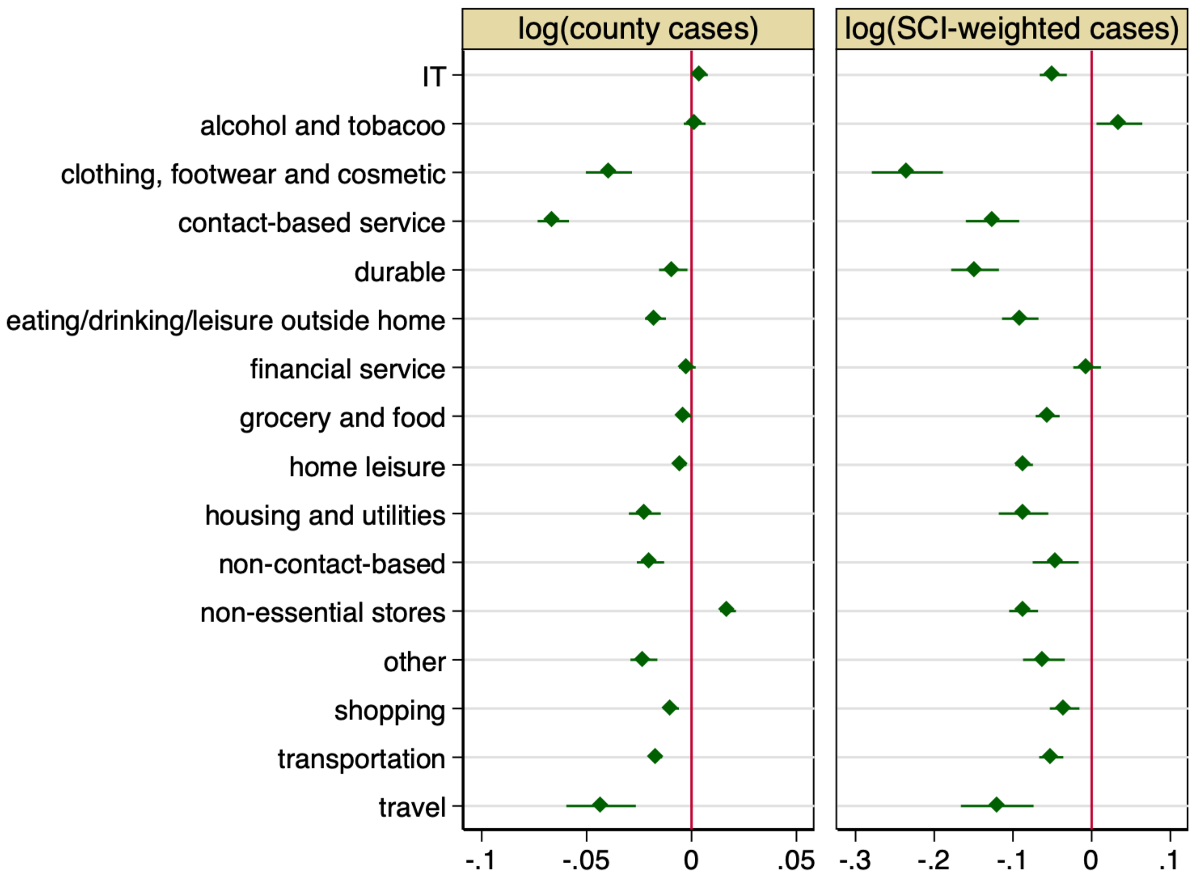
Notes.—Source: Facebook 2019 Social Connectedness Index (SCI). Panel A plots the number of COVID-19 infections per 1,000 individuals within each county as of April 1st, 2020. Panel B plots the SCI-weighted number of infections per 1,000 individuals, obtained by taking the population-weighted average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



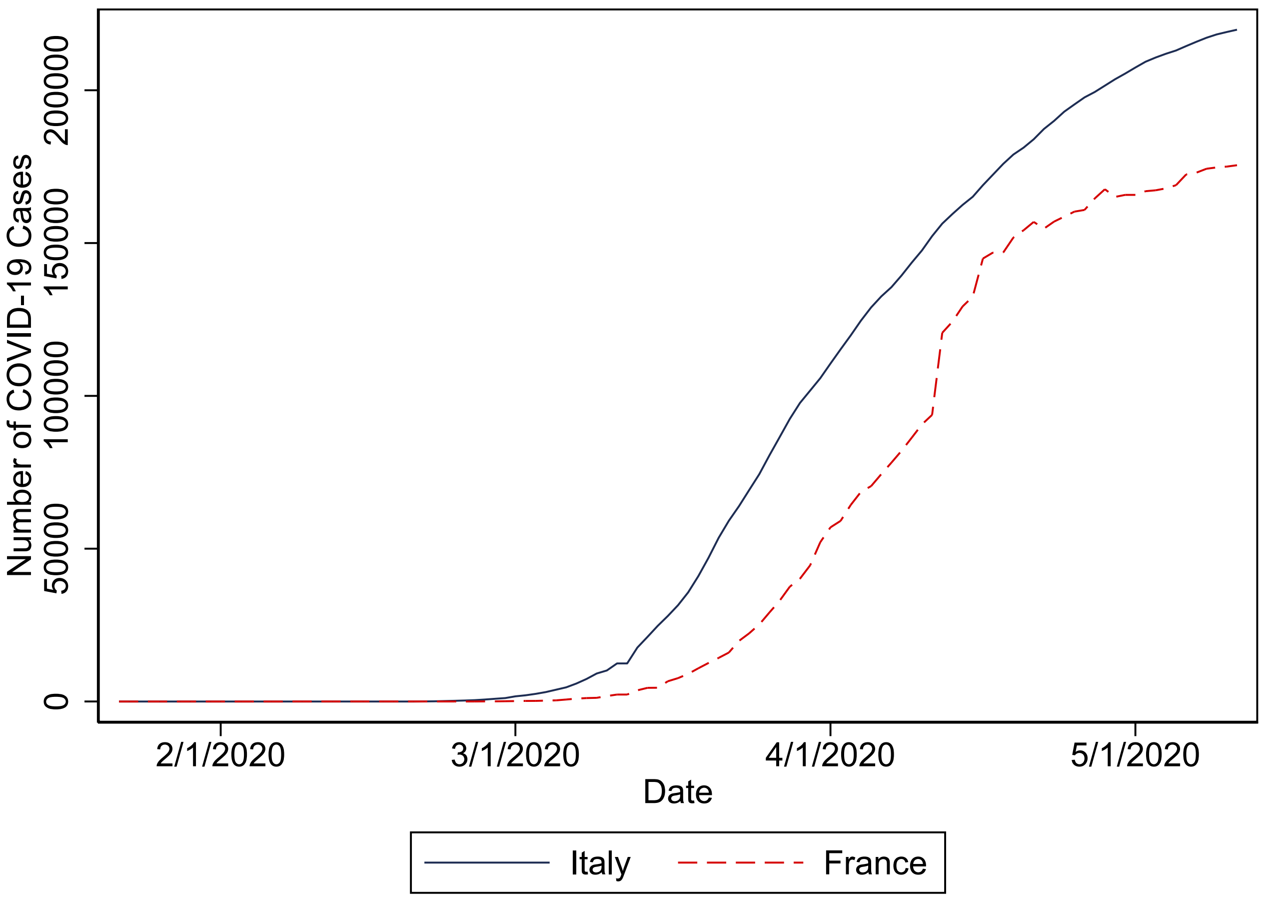
Notes.—Source: Facebook 2019 Social Connectedness Index (SCI) and Facteus. The figure reports the coefficients associated with regressions of logged consumption in a county on the logged number of COVID-19 cases (Panel A) and the logged number of SCI-weighted cases (Panel B) by category of consumption. 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 April 17th, 2020

Table 3: 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)	-.046***	-.054***	-.070***	-.046***	-.046***	-.064***	-.038***	-.074***	-.019**	-.032***	-.021***	-.031***
	[.007]	[.009]	[.008]	[.009]	[.009]	[.007]	[.005]	[.012]	[.008]	[.010]	[.008]	[.010]
log(County Cases)	-.009***	-.009***	-.006***	-.006**	-.007***	-.005***	-.006***	-.013***	-.007**	-.003	-.006**	-.004
	[.002]	[.002]	[.002]	[.002]	[.003]	[.002]	[.001]	[.004]	[.003]	[.003]	[.003]	[.003]
log(County Deaths)	-.008***	-.004	-.005**	-.014***	-.005	-.008***	-.009***	-.005	-.007**	-.005	-.005	-.006
	[.002]	[.005]	[.002]	[.004]	[.006]	[.002]	[.002]	[.013]	[.003]	[.004]	[.003]	[.005]
R-squared	.98	.96	.98	.96	.95	.98	.98	.90	.98	.97	.98	.98
Sample Size	62235	63865	64855	61245	59862	66238	70597	55503	10741	9483	10360	9864
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: Facebook, Facteus, Census Bureau. The table reports the coefficients associated with regressions of logged consumption spending on logged SCI-weighted infections (excluding the counties in the same state) on logged county infections, conditional on county and time fixed effects. Standard errors are clustered at the county-level.

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.

Table 4: 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.

Online Appendix

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.

Non-essential stores. 1.antique stores; 2. book stores; 3. art dealers, etc.

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

References

Agarwal, S., Liu, C., and Souleles, N. S. (2007). The reaction of consumer spending and debt to tax rebates: Evidence from consumer credit data. *Journal of Political Economy*, 115(6):986–1019.

Ali, U., Herbst, C. M., and Makridis, C. A. (2020). No More Home Alone: The Effects of Stay-at-Home Orders on the U.S. Child Care Market. *Working paper*.

Bailey, M., Cao, R., Kuchler, T., and Stroebel, J. (2018a). The economic effects of social networks: Evidence from the housing market. *Journal of Political Economy*, 126(6):2224–2276.

Bailey, M., Cao, R., Kuchler, T., Stroebel, J., and Wong, A. (2018b). Social connectedness: Measurement, determinants, and effects. *Journal of Economic Perspectives*, 32(3):259–280.

Baker, S. R., Bloom, N., Davis, S. J., and Terry, S. J. (2020a). COVID-induced economic uncertainty. *NBER working paper*.

Baker, S. R., Farrokhnia, R. A., Meyer, S., Pagel, M., and Yannelis, C. (2020b). How Does Household Spending Respond to an Epidemic? Consumption During the 2020 COVID-19 Pandemic. *Working paper*.

Bartik, A. W., Betrand, M., Lin, F., Rothstein, J., and Unrath, M. (2020). Labor market impacts of COVID-19 on hourly workers in small- and medium- size businesses: Four facts from HomeBase data. *Chicago Booth Rustandy Center, Working Paper*.

Bertrand, M., Duflo, E., and Mullainathan, S. (2004). How much should we trust differences-in-differences estimates? *Quarterly Journal of Economics*, 119(1):249–275.

Binder, C. (2020). Coronavirus Fears and Macroeconomic Expectations. *Review of Economics and Statistics*, forthcoming.

Binder, C. and Makridis, C. A. (2020). Stuck in the Seventies: Gas Prices and Macroeconomic Expectation. *Review of Economics & Statistics, R&R*.

Blundell, R., Pistaferri, L., and Preston, I. (2008). Consumption inequality and partial insurance. *American Economic Review*, 98(5):1887–1921.

Bursztyn, L., Ederer, F., Ferman, B., and Yucghtman, N. (2014). Understanding mechanisms underlying peer effects: Evidence from a field experiment. *Econometrica*, 82(4):1273–1301.

Cajner, T., Crane, L., Decker, R. A., Grigsby, J., Hamins-Puertolas, A., Hurst, E., Kurz, C., and Yildirmaz, A. (2020). The U.S. labor market during the beginning of the pandemic recession. *BFI working paper*.

Carroll, C. (1992). The buffer-stock theory of saving: Some macroeconomic evidence. *Brookings Papers on Economic Activity*, 23(2):61–156.

Carroll, C. D. (1997). Buffer-stock saving and the life cycle/permanent income hypothesis. *Quarterly Journal of Economics*, 112(1):1–55.

Carroll, C. D. (2003). Macroeconomic Expectations of Households and Professional Forecasters. *Quarterly Journal of Economics*, 118(1):269–298.

Carroll, C. D., Fuhrer, J. C., and Wilcox, D. W. (1994). Does consumer sentiment forecast household spending? If so, why? *American Economic Review*, 84(5):1397–1408.

Carroll, C. D. and Samwick, A. A. (1998). How important is precautionary saving? *Review of Economics and Statistics*, 80(3):410–419.

Charoenwong, B., Kwan, A., and Pursiainen, V. (2020). Social connections with COVID-19 affected areas increase compliance with mobility restrictions. *Working paper*.

Chen, X., Hong, H., and Nekipelov, D. (2011). Nonlinear models of measurement errors. *Journal of Economic Literature*, 49(4):901–937.

Cogley, T. and Sargent, T. J. (2008). The market price of risk and the equity premium: A legacy of the Great Depression. *Journal of Monetary Economics*, 55(3):454–476.

Coibion, O. and Gorodnichenko, Y. (2015). Information Rigidity and the Expectations Formation Process: A Simple Framework and New Facts. *American Economic Review*, 105(8):2644–2678.

Coibion, O., Gorodnichenko, Y., and Weber, M. (2020). The cost of the COVID-19 crisis: Lockdowns, macroeconomic expectations, and consumer spending. *NBER working paper*.

Di Maggio, M., Kermani, A., Keys, B. J., Piskorski, T., Ramcharan, R., Seru, A., and Yao, V. (2017). Interest rate pass-through: Mortgage rates, household consumption, and voluntary deleveraging. *American Economic Review*, 107(11):3550–3588.

Diamond, P. A. and Maskin, E. (1979). An equilibrium analysis of search and breach of contract, I: Steady states. *Bell Journal of Economics*, 10(1):282–316.

Dingel, J. I. and Neiman, B. (2020). How many jobs can be done at home. *BFI working paper*.

Eichenbaum, M., Rebelo, S., and Trabandt, M. (2020). The macroeconomics of epidemics. *NBER working paper*.

Farboodi, M., Jarosch, G., and Shimer, R. (2020). Internal and external effects of social distancing in a pandemic. *BFI working paper*.

Fowler, J. H. and Christakis, N. A. (2008). Dynamic spread of happiness in a large social network: longitudinal analysis over 20 years in the Framingham Heart Study. *BMJ*, 337.

Fuster, A., Kaplan, G., and Zafar, B. (2018). Wht would you do with $500? Spending responses to gains, losses, news and loans. *NBER working paper*, Review of Economic Studies, R&R.

Gallipoli, G. and Makridis, C. (2018). Structural Transformation and the Rise of Information Technology. *Journal of Monetary Economics*, 97:91–110.

Garibaldi, P., Moen, E. R., and Pissarides, C. A. (2020). Modeling contacts and transitions in the SIR epidemics model. *Covid Economics, CEPR Press*, 5(16).

Giuliano, P. and Spilimbergo, A. (2014). Growing up in a Recession. *Review of Economic Studies*, 81(2):787–817.

Goldsmith-Pinkham, P. and Imbens, G. W. (2013). Social Networks and the Identification of Peer Effects. *Journal of Business & Economic Statistics*, 31(3):253–264.

Gourinchas, P.-O. and Parker, J. A. (2002). Consumption over the life cycle. *Econometrica*, 70(1):47–89.

Guerrieri, V., Lorenzoni, G., Straub, L., and Werning, I. (2020). Macroeconomic implications of COVID-19: Can negative supply shocks cause demand shortages. *Working paper*.

Heathcote, J., Storesletten, K., and Violante, G. L. (2014). Consumption and labor supply with partial insurance: An analytical framework. *American Economic Review*, 104(7):1–52.

Jappelli, T. and Pistaferri, L. (2010). The consumption response to income changes. *Annual Review of Economics*, 2:479–506.

Johnson, D. S., Parker, J. A., and Souleles, N. S. (2006). Household expenditure and the income tax rebates of 2001. *American Economic Review*, 96(5):1589–1610.

Kaplan, G. and Violante, G. L. (2010). How much consumption insurance beyond self-insurance. *American Economic Journal: Macroeconomics*, 2(4):53–87.

Kaplan, G. and Violante, G. L. (2014). A model of the consumption response to fiscal stimulus payments. *Econometrica*, 82(4):1199–1239.

Kozlowski, J., Veldkamp, L., and Venkateswaran, V. (2020a). Scarring body and mind: The long-term belief-scarring effects of COVID-19. *Working paper*.

Kozlowski, J., Veldkamp, L., and Venkateswaran, V. (2020b). The tail that wags the economy: Beliefs and persistence stagnation. *Journal of Political Economy*, forthcoming.

Kramer, A. D. I., Guillory, J. E., and Hancock, J. T. (2014). Experimental evidence of massivescale emotional contagion through social networks. *Proceedings of the National Academy of Sciences*, 111(24):8788–8790.

Kremer, M. and Morcom, C. (1998). The effect of changing sexual activity on HIV prevalence. *Mathematical Biosciences*, 151(1):99–122.

Krueger, D., Uhlig, H., and Xie, T. (2020). Macroeconomic dynamics and reallocation in an epidemic. *NBER working paper.*

Kuchler, T. and Zafar, B. (2019). Personal experiences and expectations about aggregate outcomes. *Journal of Finance*, 74(5):2491–2542.

Makridis, C. (2020). Sentimental Business Cycles and the Protracted Great Recession. *Working paper.*

Makridis, C. A. and Hartley, J. (2020). The cost of COVID-19: A rough estimate of the 2020 GDP impact. *Mercatus Center, Policy Brief Special Edition.*

Makridis, C. A. and McGuire, E. (2020). Refined by Fire: The Great Depression and Entrepreneurship. *Working paper.*

Makridis, C. A. and Wu, C. (2020). Ties that Bind (and Social Distance): How Social Capital Helps Communities Weather the COVID-19 Pandemic. *SSRN working paper.*

Malmendier, U. and Nagel, S. (2011). Depression babies: Do macroeconomic experienes affect risk taking? *Quarterly Journal of Economics*, 126(1):373–416.

Malmendier, U. and Nagel, S. (2016). Learning from inflation experiences. *Quarterly Journal of Economics*, 131(1):53–87.

Malmendier, U., Pouzo, D., and Vanasco, V. (2018). Investor experiences and financial market dynamics. *NBER Working Paper 24697*.

Malmendier, U. and Shen, L. S. (2018). Scarred consumption. *NBER working paper*.

Moretti, E. (2011). Social learning and peer effects in consumption: Evidence from movie sales. *Review of Economic Studies*, 78(1):356–393.

Pistaferri, L. (2001). Superior information, income shocks, and the permanent income hypothesis. *Review of Economics and Statistics*, 83(3):465–476.

Smith, A. and Anderson, M. (2018). Social media use in 2018. *Pew Center*.

Souleles, N. S. (1999). The response of household consumption to income tax refunds. *American Economic Review*, 89(4):947–958.

Westerman, D., Spence, P. R., and Van Der Heide, B. (2014). Social media as information source: Recency of updates and credibility of information. *Journal of Computer-Mediated Communication*, 19(2):171–183.

Zeldes, S. P. (1989). Consumption and liquidity constraints: An empirical investigation. *Journal of Political Economy*, 97(2):305–346.