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

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Abstract

Aggregate events often start locally, with households learning about the unfolding of events through social communication. Using plausibly exogenous variation in counties' social network exposure to geographically remote regions during the COVID-19 pandemic, we quantify the propagation of idiosyncratic COVID-19 social network weighted shocks to consumption spending. We present a wide array of tests that directly control for the role of physical mobility, and physical distance, and isolate the role of geographically distant counties to show that the detected consumption responses were primarily through the channel of expectations, rather than physical infection risks or other common economic and policy shocks.

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

JEL Codes: D14, E21, E71, G51

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1 Introduction

Household expectations are increasingly recognized as a central driver of aggregate macroeconomic activity, including most recently over COVID-19 (Bailey et al., 2024),[1] but much less is known about their determinants, especially how social networks can transmit shocks via their effects on agents' expectations. In particular, individuals may adjust their consumption as a function of not only direct shocks and changes in their information set, but also what their friends convey to them, particularly with the growing importance of social media (Westerman et al., 2014; Ritter, 2020).

Isolating the role of social networks with only data on individual outcomes is challenging because of the "reflection problem" (Manski, 1993, 2000): fluctuations in individual consumption may simply reflect unobserved and correlated shocks to others in the same social network. We tackle this challenge by identifying high-frequency consumption responses to heterogeneous and time-varying exposure to only geographically remote, but socially connected, counties during a period of low physical mobility in 2020—a feature that is rarely feasible. We ask: did people cut their consumption spending more if they were connected on online social networks to those who faced more severe epidemic risks, conditional on the direct responses to their local circumstances?

This paper finds direct empirical evidence that information propagated through social networks has an effect on consumption. Using a combination of transaction-level data of 5.18 million consumers from Facteus and the Social Connectedness Index (SCI) from Facebook (Bailey et al., 2018a), we find that a 10% increase in SCI-weighted cases and deaths is associated with a 0.15% and 0.42% 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

[1]For other work that studies the impacts of social mechanisms on economic expectations, see, for example, Shiller and Pound (1989); Hirshleifer et al. (2023) on stock investment, Carroll (2003) on inflation expectations, and Piazzesi and Schneider (2009), Burnside et al. (2016), Bailey et al. (2018a), Bailey et al. (2019) on housing investment and mortgage choices. Carroll and Wang (2023) does an extensive survey of this literature.

10% increase in SCI-weighted cases is associated with a 0.5% decrease in clothing, footwear, and cosmetics, a 1.1% decrease in contract-based service, and a 1.2% decrease in travel. These decreases are two to three times as large as the drop in average spending. We implement several robustness exercises. 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 online social networks are more influential when consumers are unable to gather information through local in-person communications. 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 in 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.

Our paper most closely contributes to empirical studies on the effects of social networks on economic decisions (Bailey et al., 2018a, 2019, 2024; Makridis, 2022). Unlike the large body of work on peer-effects via preference dependence, this literature emphasizes the role of influence channeled via expectations, although direct evidence using belief data is rare. Our paper is closely related to van Rooij et al. (2024) who implement a randomized control study where treated households are informed about either the average income or debt of individuals like them. They find evidence of peer effects in the short-run, particularly with individuals exposed to the information treatment reallocating from non-durables to durables, but effects are modest in the months that follow the experiment. Our results on the transmission effects of COVID-19 infections, particularly for durables, are consistent with van Rooij et al. (2024). Our paper also builds on Makridis (2022) who exploits variation in the social transmission of house price growth as an instrument for economic sentiment. We build on these results by leveraging the SCI data to construct another measure of social transmission of beliefs related to COVID-19. Our results are also consistent with Eichenbaum et al. (2022) who show how accounting for consumer expectations about COVID-19 can explain the decline in expenditures, although they cannot distinguish durables and non-durables.

We also contribute to a large literature on the household response of consumption to macroeconomic shocks, which 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), tax rebates (Souleles, 1999; Johnson et al., 2006; Agarwal et al., 2007), sentiment (Carroll et al., 1994; Gillitzer and Prasad, 2018; Makridis, 2022; Lagerborg et al., 2023) on consumption. 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).[2] Our results highlight how social networks can transmit idiosyncratic shocks in a more realistic setting of imperfect information and affect household consumption.

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, 2022), asset prices (Malmendier et al., 2018), and consumption (Malmendier and Shen, 2024). Our evidence on social communications corroborates this literature as well, as essentially communications are part of the experiences, and it is fair to conjecture that the effects of experiences on expectations are by and large reinforced via interpersonal communications. This is reminiscent of models of macroeconomic expectation formation of average households via interpersonal communications (Carroll, 2003).

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

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 to June 30th, 2020.[3] Average nationwide daily spending of the whole sample is 194 million dollars from a total of 2.3 million transactions. Despite some limitations, three features make the data particularly useful to our analysis.[4] First, there is rich geographic heterogeneity. In particular, transactions are partitioned by the residential zip code 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 their 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. The value of daily spending per card user was roughly $40, and within each county and day, one out of two users are observed to have made a card transaction.

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 every other national and international event with the 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. We use a sample

[3] Transactions are collected from primarily four types of card 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.

[4] 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 of mobility in “normal times", i.e. college towns, producing similar results.

of transaction data between January 1st and June 30th 2020, yielding roughly 450,000 county $\times$ day observations. This period spans from the early spreading stage of COVID-19 in Asian and European continents to the peak of the crisis within the United States.

Finally, the 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 their degree of exposure to the infection risks.[5] For instance, eating/drinking/leisure outside the home, contact-based services such as barbershops, 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. In Appendix A.1, we validate that both the category coverage and time-series pattern from our constructed series of consumption represent the pattern in the commonly used macro consumption data series well.

We also draw on the Social Connectedness Index (SCI) from Facebook[6], introduced originally by Bailey et al. (2018b) to study how information about housing prices is diffused among social networks and affects the decision to rent versus own a home. These data are now used more widely to understand how social ties are related to economic activity (Bailey et al., 2018b), expectations about macroeconomic activity (Makridis, 2022), and mobility (Bailey et al., 2024). 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

[5] See Section A.2 in the Online Appendix for examples of merchant types that fall into each category.

[6] Till 2011, there were about 149 million users of Facebook in the U.S. out of the 260-million eligible population, 15.9 billion edges, an average of 214 friend ties per user (Ugander et al. (2011)).

$\times$ day level from the Center for Systems Science and Engineering at Johns Hopkins.[7]

3 Empirical Evidence

3.1 Identification Strategy

In order to identify an individual county's consumption responses to heterogeneous information exposure to COVID news, 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 of 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.[8] 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:

[7] See Figures A.3 and A.4 in Section A.3 of the Online Appendix.

[8] 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.

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

where $y_{c,t}^{k}$ denotes logged consumption for county c on day t for category-k consumption good, and ϕ and λ denote county and day fixed effects. We cluster standard errors at the county level to allow for arbitrary degrees of autocorrelation over time.[9]

Our plausibly exogenous identifying variation in Equation 2 comes the social network in a county being pre-determined with respect to the infections that it and others face over the 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, and such exposure is time-varying, then their local response might differ as some residents hear more pessimistic versus optimistic information. We believe that the variation in heterogeneous and time-varying exposure to other counties is plausibly exogenous. We also consider additional robustness exercises where we exploit the exposure of different *countries* to the pandemic based on their social connectivity before the quarantines began in the United States in March 2020.

To ensure that our results are not contaminated by unobserved local shocks, we undertake several diagnostics. First, we use Google Mobility data to control physical mobility. Second, we isolate variation in geographically distant counties, namely those that are over 500 miles away. Our results hold. We also show that our estimates are unique to the 2020 period when there was significant uncertainty and ambiguity, while our estimates dampened in 2021 and vanished for 2022 when the pandemic had subsided. This pandemic period provides an unprecedented opportunity to study the propagation effects of social networks when mobility came to a halt.

A final issue, which we examine in Section A.4 of the Online Appendix relates with the exogeneity

[9]We also show robustness to our main results in Table A.2 clustering on both date and time.

of infections and deaths. Tables A.4-A.7 present robustness to our main results by residualizing local infections and deaths from time fixed effects, and further orthgonalize them by taking a first-difference, thereby purging any unobserved heterogeneity that could be correlated with aggregate fluctuations over this period. In particular, these new measures, which only strengthen our results, reflect the truly idiosyncratic component in local pandemic shocks.[10]

3.2 Main Results

Table 1 documents the results associated with Equation 2. We begin with a standard fixed effects estimator in columns 1 and 6, exploit variation within the same county over time. We find that a 10% rise in SCI-weighted cases and deaths are associated with a 0.51% and 0.62% decline in consumption expenditures, respectively. One concern with these results, however, is that we are failing to control for local infections and deaths. If, for example, counties that are relatively more exposed to counties with 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 7 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: a 10% rise in SCI-weighted cases and deaths is associated with a 0.15% and 0.42% decline in consumption expenditures respectively. Moreover, increases in contemporaneous local cases are also associated with declines in consumption, but with a lower magnitude. Local deaths also decrease consumption by a similar degree but 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

[10]We thank an anonymous referee for raising this concern about local infections and deaths.

gradient on SCI-weighted cases is slightly higher.[11]

Yet another concern is that state policies vary considerably over these months. Even though there was a national quarantine, states introduced policies of varying restrictiveness, including stay-at-home orders (SAHOs). For example, Ali et al. (2021) find that the adoption of SAHOs is associated with a persistent decline in job postings for early care and education. This may also impact consumption by shifting the composition of goods and the overall amount of goods as people stay home. Consistent with this interpretation, columns 3 and 8 show that the adoption of an SAHO is associated with a 5.6-5.8% decline in consumption. Moreover, increases in SCI-weighted cases and deaths continue to have a negative association with consumption.

Next, we exploit variation in SAHOs to provide an additional diagnostic into the potential causal interpretation of our estimates. 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 indoors where they are more likely to rely on social networks for information through, for example, Facebook, rather than through in-person interactions. Consistent with our hypothesis, columns 4 and 9 show that a 10% rise in SCI-weighted cases and deaths following the adoption of an SAHO is associated with an additional 0.24% and 0.26% decline in consumption expenditures, which is roughly twice the magnitude obtained in columns 2 and 7. These coefficients are also more precisely estimated, significant at the 1% level.

Although we have taken measures to control for local infections and focused on areas with low mobility due to SAHOs, it is still possible to question whether individuals' consumption responses to online exposures are primarily driven by concerns about immediate physical infection risk in their neighborhoods. This is because people are more likely to be connected online to others who

[11] Another possible concern would be if our results simply pick up some spurious correlation because of the use of the level of spending as the dependent variable, Table A.1 in the Online Appendix also shows that these SCI-weighted shocks also affect the growth rate of consumption negatively.

are physically close to them. To address this concern, we conducted several robustness analyses in Columns 5 and 10 using alternative SCI-weighted measures that only include connected counties outside the state. Remarkably, we found that the coefficients in these columns remain significantly negative. Specifically, a 10% increase in out-of-state SCI-weighted cases and deaths is associated with a decline in consumption spending of 0.16% and 0.59%, respectively.

Table 1: Consumption Responses to Increases in Socially-connected COVID 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 and 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: $COVID^{SCI}_{c,t} = \sum_{c'}(COVID_{c',t} \times SCI_{c,c'})$ 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. 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. *, ** and *** denote significance at the 10%, 5% and 1% level, respectively.

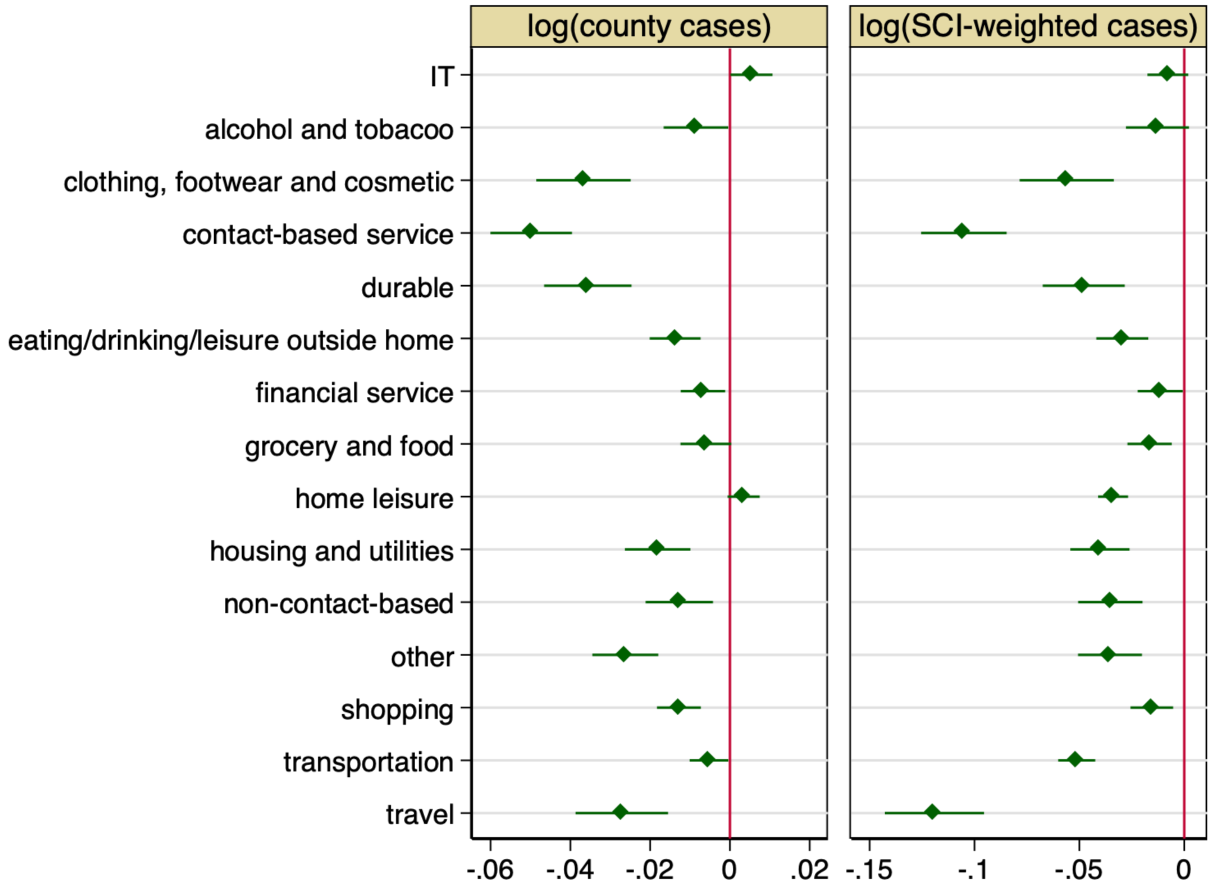
Did the spending responses differ across different types of consumption? If the reactions were mostly due to concerns about the infection risk, instead of about the economic conditions of the connected regions, the responses should be the strongest in the types that bear the highest risk of COVID. We did find that this is the case. Figure 1 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. Both the direct effect of infections and the indirect effects of social communications are reported. 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 0.5% decline in clothing, footwear, and cosmetic spending, whereas the effects on grocery/food or home leisure spending are nearly zero. These results are consistent with Coibion et al. (2020) who find a 31 log point drop in consumer spending concentrated in travel and clothing. Similarly, we see the largest association for contact-based consumption: a 10% rise in SCI-weighted infections is associated with a 1.3% decline in consumption, consistent with theory on the most elastic categories.

Another possibility is that the strength of the response depends on initial beliefs. While the absence of individual-level data prevents us from being able to test this hypothesis directly, we draw on related results by Canes-Wrone et al. (2023) who have panel data on individuals throughout three years of the pandemic. They find that initial beliefs, through the lens of partisanship, matter, but they can be tempered by state policies that coincide with the individual's beliefs about the proper reaction to the pandemic. In this sense, we anticipate that individuals with greater pessimism about the economy could have a potentially larger response to negative shocks to their network, but that the net effect could be dampened by other, possibly conflicting, policies.

3.3 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, age distribution, population, the share of digitally-intensive employees as defined by Gallipoli and Makridis (2018), and the share of tele-

Figure 1: 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 categories based on its merchant category code (MCC).The sample period is between March 1st to June 30th, 2020

working 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 microdata, 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 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 errors 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 based on occupational composition (Gallipoli and Makridis, 2018, 2022), 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.

3.4 The Role of Physical Distance

An obvious concern with our results thus far are that our estimated SCI-weighted elasticities with respect to consumption are contaminated by shocks to physical mobility. For instance, there could

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: $COVID_{c,t}^{SCI} = \sum_{c'}(COVID_{c',t} \times SCI_{c,c'})$ 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. Standard errors are clustered at the county level. The sample period is between March 1st to June 30th, 2020. *, ** and *** denote significance at the 10%, 5% and 1% level, respectively.

be inflows or outflows in an area based on a correlation with social connectedness (i.e., see Figure A.6, giving a correlation of 0.35 (0.13) for cases (deaths), respectively). Nonetheless, we turn to formal tests where we either directly control for distance/mobility or exclude nearby counties.

First, we replicate our main results using physical distance as an alternative weighting strategy with cases and deaths, which we denote PCI-weighted cases and deaths. Table 3 documents these results. We present the simple specification in columns 1 and 5: a 10% rise in SCI-weighted cases and deaths is associated with a 0.5% and 0.16% decline in consumption expenditures. Next, we add PCI-weighted cases and deaths, showing that 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 are not associated with consumption, but PCI-weighted deaths are strongly negatively correlated with consumption, which is also comforting.

Second, although we had previously shown robustness excluding counties in the same state, now we recalculate our SCI-weighted cases and death measure, excluding counties that are within 500 miles of the home county. Table 4 documents these results with the exactly same specifications as in the baseline Table 1. The magnitudes are in line with previous results.

Third, and finally, we directly control for physical mobility in Table 5 using county $\times$ day specific mobility statistics, which are measured by the time spent in different locations such as at home, at workplace, away from home, and transit, from Google Mobility data.[12] We treat these mobility statistics, especially the time in transit stations, as a proxy for the intensity of physical

[12]See Chetty et al. (2024) and Economic Tracker (`https://www.tracktherecovery.org/`) for the construction of these measures.

Table 3: Robustness Controlling for 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 similarly 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. *, ** and *** denote significance at the 10%, 5% and 1% level, respectively.

Table 4: Robustness Using Only Geographically Remote Counties (Over 500 Miles)

Dep. var. =	log(Consumption Expenditures)									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Has SAHO			-.014**	-.043***	-.014**			-.016**	-.026***	-.016**
			[.007]	[.012]	[.007]			[.007]	[.008]	[.007]
SCI-weighted Cases Far	-.036***	-.020***	-.013**	-.021***						
	[.004]	[.006]	[.005]	[.006]						
× SAHO				.021***						
				[.005]						
SCI-weighted Deaths Far						-.157***	-.074***	-.042**	-.103***	
						[.017]	[.018]	[.018]	[.022]	
× SAHO									.116***	
									[.026]	
SCI-weighted Cases Far, Other States					-.013**					
					[.005]					
SCI-weighted Deaths Far, Other States										-.043**
										[.018]
log(County Cases)		-.009***	-.008***	-.007***	-.008***		-.011***	-.011***	-.010***	-.010***
		[.003]	[.002]	[.002]	[.002]		[.001]	[.002]	[.002]	[.002]
log(County Deaths)		-.001	.004	-.000	.004		.005	.006*	.003	.006*
		[.003]	[.003]	[.003]	[.003]		[.003]	[.003]	[.003]	[.003]
R-squared	.99	.99	.97	.97	.97	.97	.97	.97	.97	.97
Sample Size	195156	195156	195156	195156	195156	195156	195156	195156	195156	195156
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. The table reports the coefficients associated with regressions of logged consumption spending on SCI-weighted cases and deaths in connected but geographically remote (>500 miles) counties and logged county infections and deaths, conditional on county and time-fixed effects. The consumption spending is from the Facteus. The sample period is between January 1st to March 30th 2020. *, ** and *** denote significance at the 10%, 5% and 1% level, respectively.

movements (including inward and outward traffic in the county). While the correlation between various mobility statistics and consumption spending are all significant and intuitive, the coefficients of SCI-weighted cases and deaths remain similar to the baseline result.

Table 5: Robustness Controlling Directly for Physical Mobility

Dep. var. =	log(Consumption Expenditures)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
log(SCI-weighted Cases)	-.018*	-.021***	-.022***	-.020***				
	[.009]	[.007]	[.006]	[.006]				
log(SCI-weighted Deaths)					-.036***	-.037***	-.024***	.066***
					[.010]	[.009]	[.008]	[.011]
log(County Cases)	-.005	.002	.003	.004	-.007**	-.000	.000	-.018***
	[.004]	[.003]	[.004]	[.004]	[.003]	[.003]	[.003]	[.004]
log(County Deaths)	-.013***	-.014***	-.008***	-.009***	-.006*	-.007**	-.004	-.004
	[.003]	[.002]	[.003]	[.003]	[.004]	[.003]	[.003]	[.007]
time at home			-.868***				-.881***	
			[.080]				[.079]	
time at workplace		.220***				.221***		
		[.040]				[.041]		
time away from home				.694***				1.654***
				[.068]				[.129]
time at transit	.040*				.037*			
	[.021]				[.020]			
R-squared	.99	.98	.99	.99	.99	.98	.99	.99
Sample Size	119048	258089	155170	155170	119048	258089	155170	155170
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State Policies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State x Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes.–Sources: Facebook Social Connectedness Index (SCI) for 2019 and Google Covid-19 community mobility reports. The table reports the coefficients associated with regressions of logged consumption spending on logged SCI-weighted Covid cases and deaths and logged county infections and deaths, conditional on county and time-fixed effects. The consumption spending is from the Facteus. *, ** and *** denote significance at the 10%, 5% and 1% level, respectively.

4 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). We believe that these results reflect the effects of the dissemination of information on social media. For example, Bailey et al. (2024) provides evidence consistent with this hypothesis: increases in exposure to more connected counties are linked with declines in mobility, which they show is related to the frequency of posts by Facebook friends in support groups. Nonetheless, one concern is that these results are plagued by other time-varying omitted variables that jointly affect connected counties and local consumption outcomes.

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 leads 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. (2021) and Ali et al. (2024). 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 on the interaction. 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 of each county, recognizing 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, as reported in our online Appendix. [13] Each of these four countries successively experienced

[13] 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.

a large number of infections in a different scale since late February preceding the U.S.

We exploit variation along two dimensions. First, counties vary cross-sectionally in their pre-pandemic exposure to foreign countries. For example, whereas Maricopa County in Arizona has an SCI of 142,771 with France, San Francisco has an SCI of 258,825. We normalize these SCI ties by the county's total population. Second, countries vary in their COVID-19 dynamics. Figure A.5 in the Appendix 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 normalized cross-sectional SCI 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 after March 15th, when 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.

Table 6 documents these results. We find a robust negative association between the SCI-weighted number of infections/deaths and consumption for each country. For example, a 1% rise in infections (deaths) in Italy for counties that are more closely connected to Italy is associated with a 0.39% (0.29%) decline in consumption. We see similar treatment effects by Spain. In comparison, the size of the coefficients is much bigger for South Korea and is smaller and non-significant for France. The differences in treatment effects might stem from the relative timing of the Covid outbreak in these countries. The responses were stronger to the exposure to early epicenters.[14]

Table A.9 in the Online Appendix reports a related robustness exercise. In particular, we ask whether the relationship that we have found between SCI-weighted cases/deaths and consumption holds over time. If our theory about social communication is correct, then we should see a decline

[14] See Table A.10 for results with other countries. Section A.4 of the Online Appendix also presents additional diagnostics that mitigate concerns that our results simply reflect differences in physical distance between connected counties.

Table 6: Consumption Responses to COVID-19 Information from Other Countries

Dep. var. =	log(Consumption Expenditures)							
	ITA	ITA	SPA	SPA	FRA	FRA	SK	SK
log(SCI-weighted Cases)	-.393***		-.291***		-.002		-2.806***	
	[.149]		[.108]		[.074]		[.660]	
log(SCI-weighted Deaths)		-.293***		-.213***		.007		-.702***
		[.113]		[.081]		[.043]		[.159]
log(County Cases)	-.003	-.003	-.003	-.003	-.003	-.003	-.002	-.002
	[.004]	[.004]	[.004]	[.004]	[.004]	[.004]	[.004]	[.004]
log(County Deaths)	-.030***	-.030***	-.030***	-.031***	-.033***	-.033***	-.031***	-.031***
	[.003]	[.003]	[.003]	[.003]	[.003]	[.003]	[.003]	[.003]
R-squared	.97	.97	.97	.97	.97	.97	.97	.97
Sample Size	165146	165146	165146	165146	165146	165146	165146	165146
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes.–Sources: Facebook and Facteus. The table reports the coefficients associated with regressions of logged consumption spending on SCI-weighted logged 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 logged time-varying number of infections in country i and multiplying it by the exposure of county c to country i normalized by the total population of country c, 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. *, ** and *** denote significance at the 10%, 5% and 1% level, respectively.

in statistical significance over time. Indeed, that is what we see with the estimate fading by 2022.

Our finding that consumption in one county depends on the infections among connected counties—even if they are geographically distant—builds on an emerging literature on the economic impacts of social network (Bailey et al., 2018a, 2019, 2024). 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 to recent evidence from Charoenwong et al. (2020) who find that some counties were more likely to adopt social distancing and restrictions measures based on their exposure to Italy and China, as well as Bailey et al. (2024) who find similar results using the full data from Facebook.

5 Conclusion

We study the role of social networks in shaping household consumption patterns in the face of macroeconomic shocks, specifically during the COVID-19 pandemic. By leveraging data that combines consumer transaction data with the Social Connectedness Index (SCI), our analysis reveals that information propagated through social networks leads to significant adjustments in consumption spending. Specifically, we find that increases in SCI-weighted COVID-19 cases and deaths are associated with notable declines in consumption, particularly in categories that involve social interaction and activities away from home. These findings underscore the importance of considering social influence mechanisms in understanding economic behavior, especially in times of crisis.

Our results contribute to a large literature on the effects of social networks on economic decisions, highlighting the transmission of shocks via expectations and the significant role that online social networks play in this process. Furthermore, our study adds to the understanding of household consumption response to macroeconomic shocks, showing that social media can act as a conduit for these shocks, amplifying their effects through the transmission of information and influencing consumption decisions even in the presence of stay-at-home orders and reduced physical mobility.

Our results point to at least two implications for policymakers. First, social networks matter for influencing the response to policy. For example, Eichenbaum et al. (2022) point out that an even more aggressive lockdown policy in the U.S. would have had even greater consequences for consumption because individuals were already self-regulating out of fear. Second, our study underscores the need to incorporate social dynamics and expectation formation mechanisms into models of economic behavior to better predict and understand the impact of macroeconomic shocks on consumption. Nonetheless, many questions for future research remain, especially how social media interacts with other channels for information dissemination (e.g., traditional media) and how individuals form beliefs over the long-run in response to both media and personal experience.

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A Online Appendix

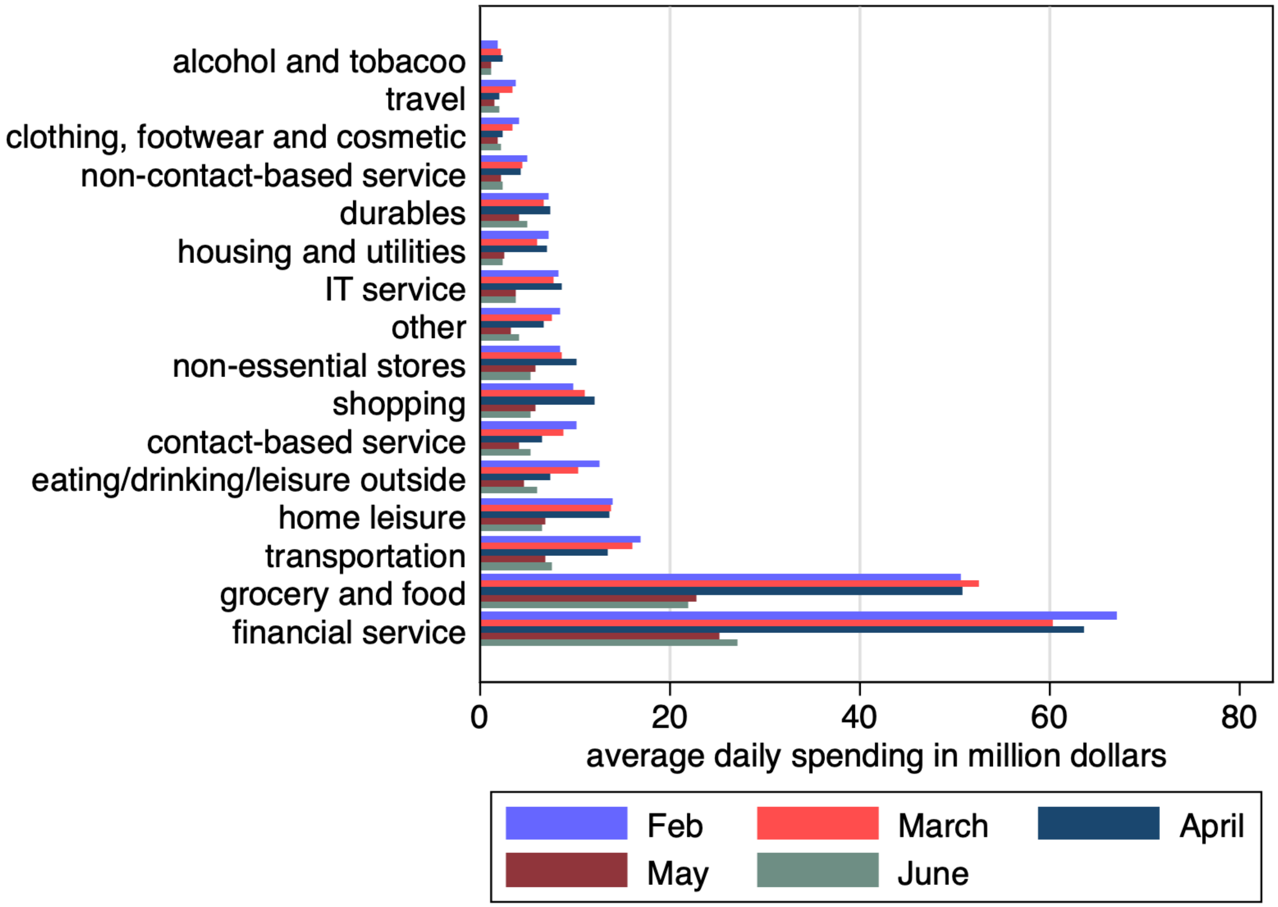
A.1 Validating the Consumption Data

Figure A.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 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 of total spending, reflecting the fact that the composition of consumers in the sample is lower income and younger than a more nationally representative sample.

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 microdata to the aggregate economy. We explore several validation exercises. First, Figure A.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 Figure A.2, in both sectors, our separately constructed time series track with

Figure A.1: Descriptive Statistics on Consumption Expenditures, by Category



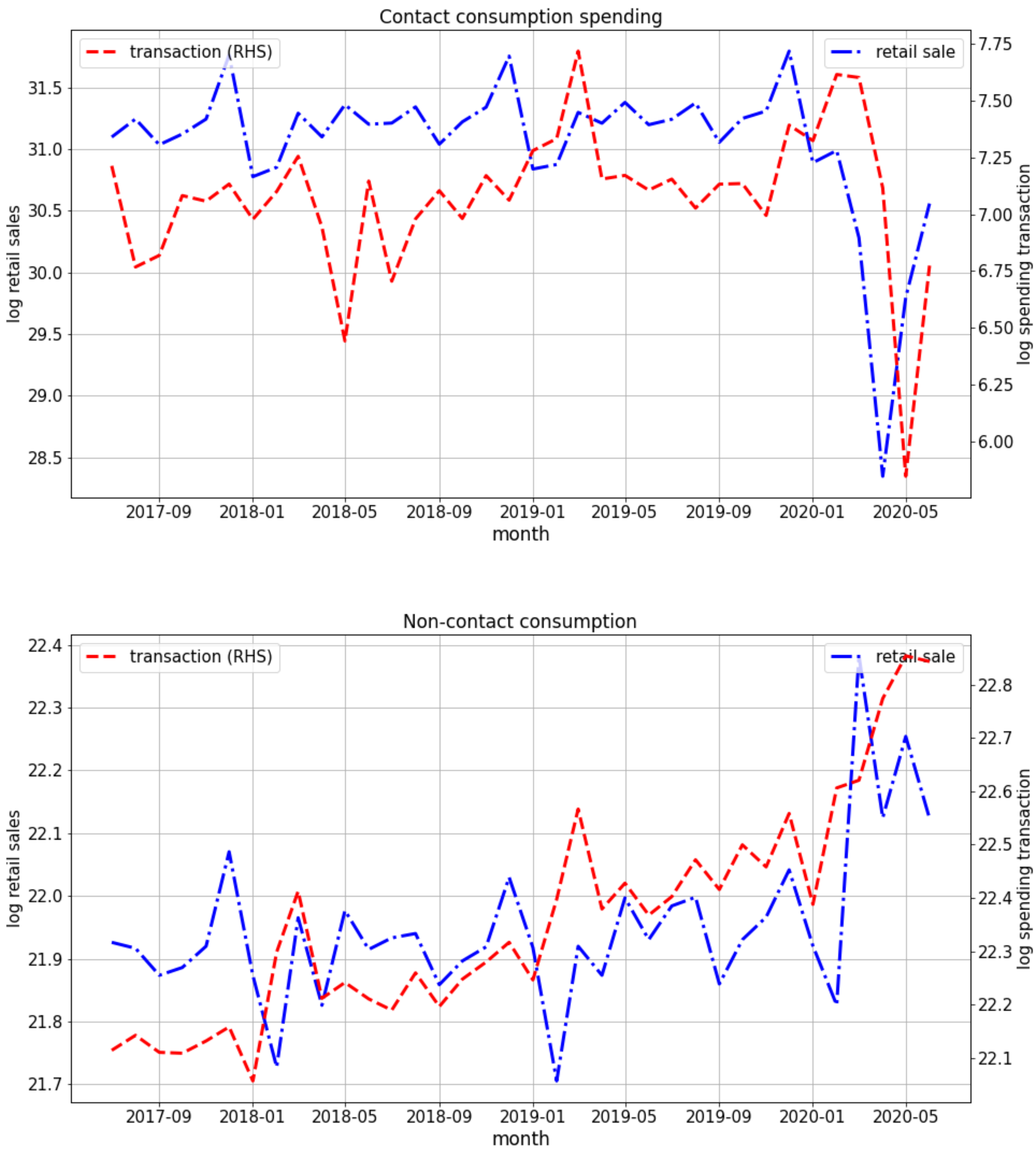
Notes.—Source: Facteus. Average daily consumption by category. Each bar plots the average spending per day in the specific category within each month in 2020. See the Appendix for the examples of each consumption category.

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.[15] 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 relies upon the subsample of the year 2020, we are additionally assured

[15]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.

about the representativeness of our results.

Figure A.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.

A.2 Data Description: Consumption Classification

One of the contributions of our paper is the classification of consumption categories from the data and subsequently into contact and non-contact based aggregate consumption categories. We now enumerate these:

Grocery and food. 1. grocery stores and supermarkets; 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, footwear, 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.

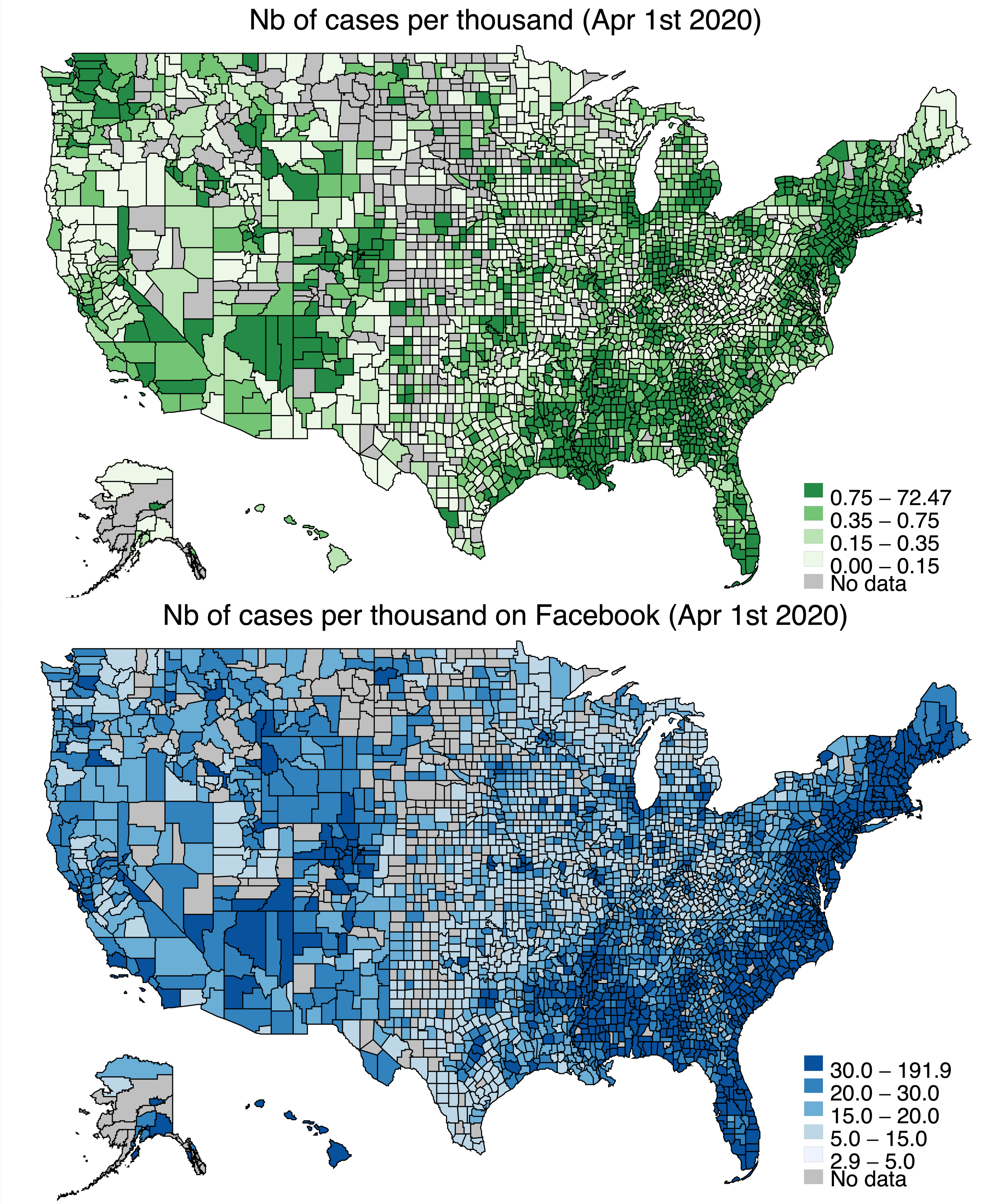
Financial services. 1. insurance; 2. money orders; 3. wire transfers, etc.

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

A.3 Data Description: Social Connectedness Index

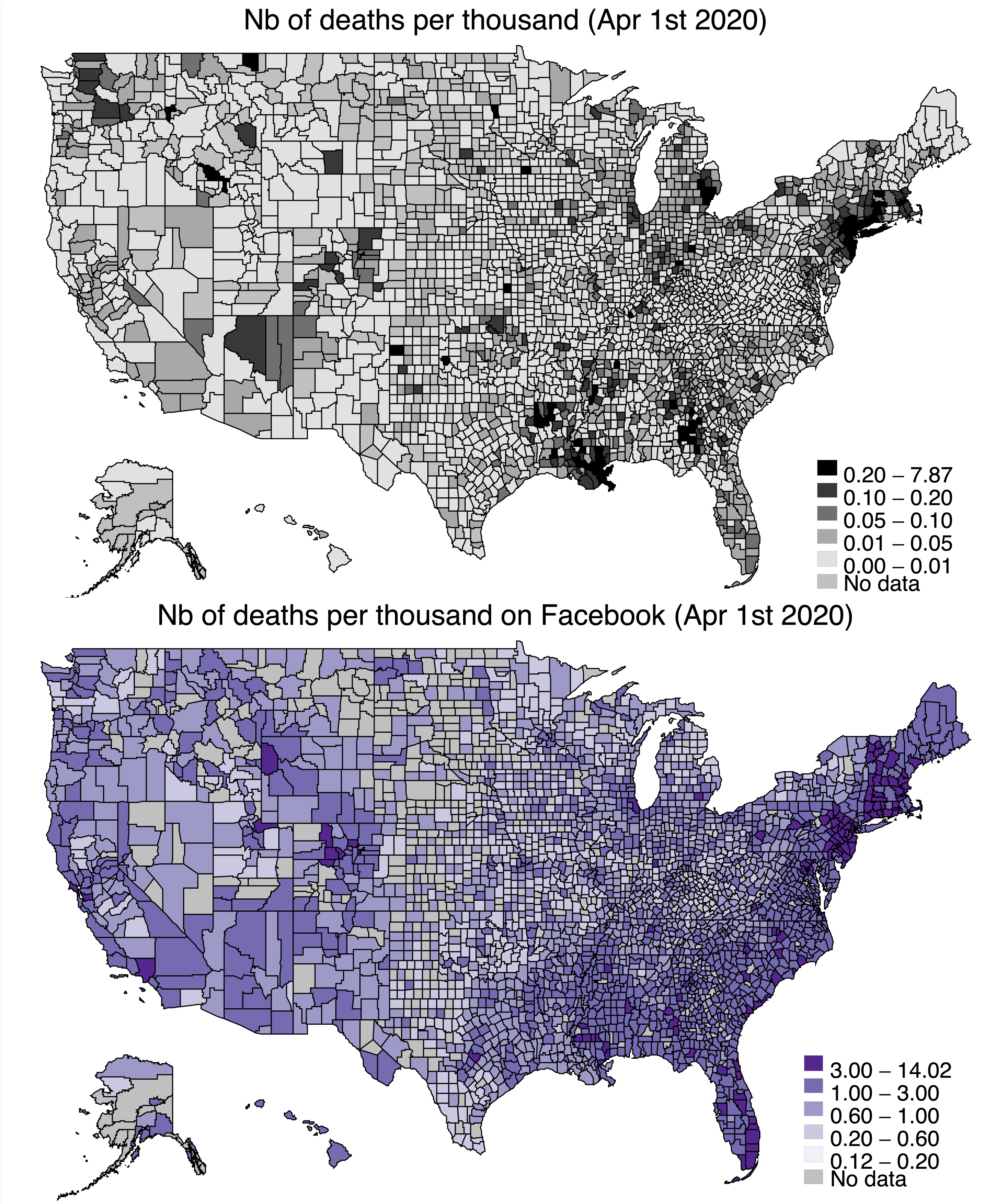
Figures A.3 and A.4 characterize the spatial distribution of not only infections and deaths but also SCI-weighted cases and deaths based on exposure to connected counties as of April 1, 2020. While the actual number of infections or deaths in a county c are correlated with their SCI-weighted versions,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

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



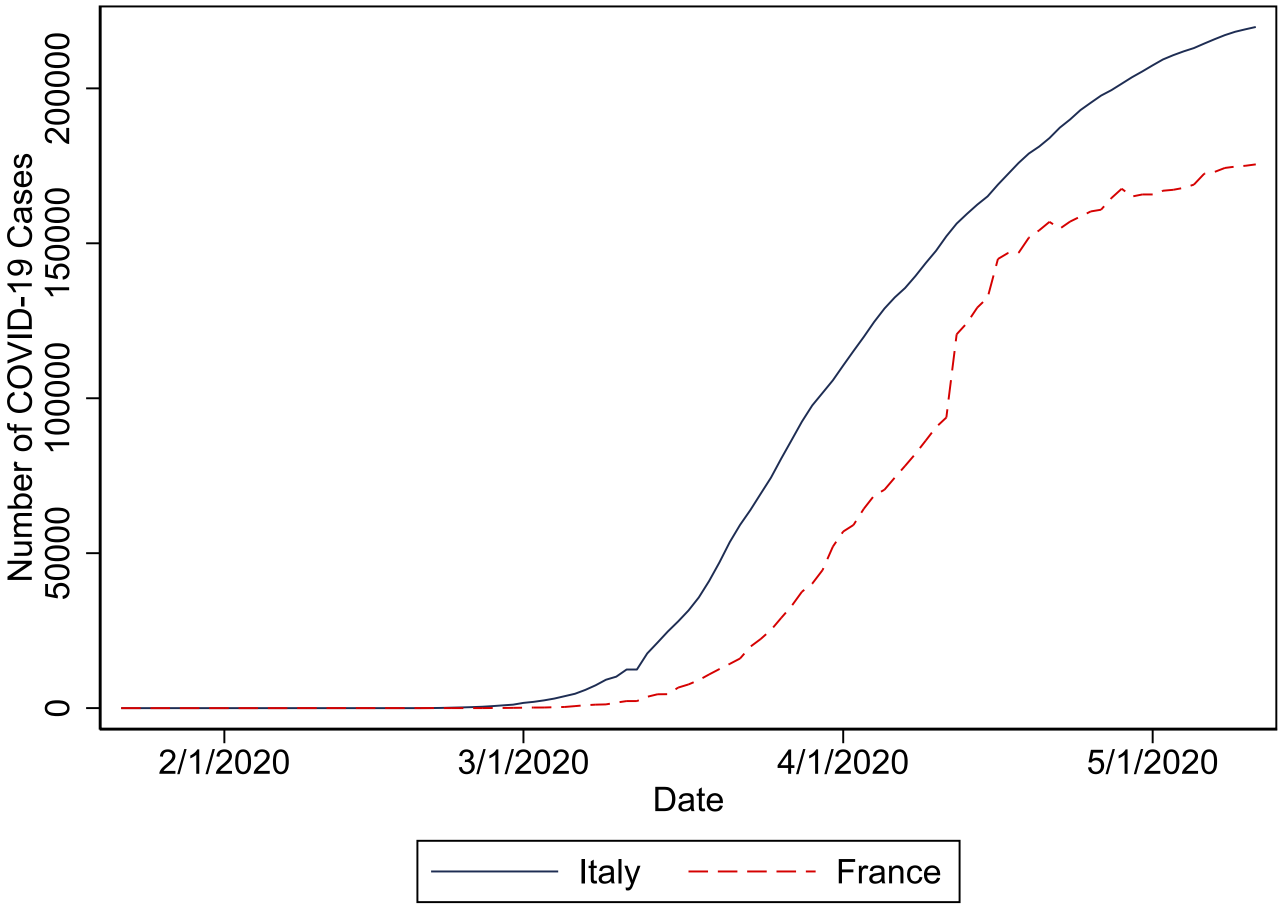
Notes.—Source: Facebook 2019 Social Connectedness Index (SCI). Panel A plots the number of COVID-19 infections per 1,000 individuals within each county as of April 1st, 2020. Panel B plots the SCI-weighted number of infections per 1,000 individuals, obtained by taking the population-weighted average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

Figure A.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 A.5: Time Series Patterns in COVID-19 Infections: Italy and France



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

A.4 Supplement to the Empirical Results

Relatedly, Table A.3 directly examines the impacts of SCI-weighted idiosyncratic consumption shocks in connected counties on each county's consumption. The consumption shocks are generated from a cross-sectional panel regression of daily growth rates of consumption excluding time-fixed effects. The results suggest that despite the specificity of the pandemic, there exists in general consumption spill-over effects from idiosyncratic shocks to socially connected counties. We leave these results for future analysis.

Table A.1: Extension Using Consumption Growth as the Dependent Variable

Dep. var. =	log spending growth							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
log(SCI-weighted Cases) growth	-.008**	-.021***	-.026***	-.022*				
	[.003]	[.007]	[.007]	[.013]				
log(SCI-weighted Deaths) growth					-.007***	-.006	-.010**	.002
					[.003]	[.004]	[.004]	[.009]
log(County Cases)		.008**	.008**	.011***		.009**	.009**	.011***
		[.004]	[.004]	[.004]		[.004]	[.004]	[.004]
log(County Deaths)		-.009***	-.010***	-.008***		-.008***	-.008***	-.008***
		[.003]	[.003]	[.003]		[.003]	[.003]	[.003]
R-squared	.30	.42	.42	.54	.30	.42	.42	.54
Sample Size	246709	87060	87060	87054	246709	87060	87060	87054
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State/Time FE	No	No	No	Yes	No	No	No	Yes
State Polices	No	No	Yes	No	No	No	Yes	No
Day FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes.–Sources: Facebook Social Connectedness Index (SCI) for 2019. 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. *, ** and *** denote significance at the 10%, 5% and 1% level, respectively.

All our results to date are using COVID-19 cases and deaths directly to compute the SCI-weighted measure. Here, we take several steps to create more exogenous Covid shocks both cross-sectionally and intertemporarily. In the first step, instead of using the level of the cases and deaths, we use the daily percent changes of them as the inputs of the weight measure. (Table A.1) In the second step, we obtain the idiosyncratic shocks to county-day cases and deaths by excluding the time-fixed effects estimated across all counties (Table A.6 and A.7). In the third step, we further orthogonalize the idiosyncratic shocks from step 2 by taking the first difference of them. This removes the possible serial correlation of local dynamics induced by very persistent components in driving local Covid dynamics (Table A.4 and A.5). The coefficients of SCI-weighted measures remain negative and significant in all of these specifications. The size of the coefficients based on the shocks from step 3, if any, are actually larger than those in the baseline estimates.

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

Table A.2: Robustness to Baseline Using Double Clustered Standard Errors

Dep. var. =	log(Consumption Expenditures)									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Has SAHO			-.014	-.048***	-.016			-.015	-.030***	-.017
			[.011]	[.013]	[.011]			[.010]	[.010]	[.011]
log(SCI-weighted Cases)	-.033	-.026***	-.022***	-.026***						
	[.]	[.009]	[.005]	[.006]						
× SAHO				.014**						
				[.006]						
log(SCI-weighted Deaths)						-.069	-.040*	-.027	-.080***	
						[.]	[.021]	[.018]	[.019]	
× SAHO									.068***	
									[.014]	
log(SCI-weighted Cases, Other States)					-.020***					
					[.006]					
log(SCI-weighted Deaths, Other States)										-.040
										[.026]
log(County Cases)		-.004	-.003	-.003	-.005*		-.010***	-.010***	-.008***	-.010***
		[.004]	[.002]	[.002]	[.003]		[.003]	[.003]	[.003]	[.003]
log(County Deaths)		-.001	.003	-.001	.003		.009**	.009**	.006*	.007**
		[.006]	[.004]	[.003]	[.004]		[.004]	[.004]	[.004]	[.003]
R-squared	.99	.99	.97	.97	.97	.97	.97	.97	.97	.97
Sample Size	195156	195156	195156	195156	195156	195156	195156	195156	195156	195156
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. Regression results as in baseline Table 1 except for using standard errors clustered by both date and the county. *, ** and *** denote significance at the 10%, 5% and 1% level, respectively.

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.6 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.

As our results in the main text show, our SCI-weighted coronavirus cases and deaths index is not simply capturing variation in infection risk directly posed by physical movements between connected or nearby regions. Moreover, even when we control explicitly for a comparable measure of PCI-weighted cases and deaths, our results remain. These exercises complement the baseline specification, which excludes counties in the same state (otherwise closely connected areas).

Since our consumption data is based on a sample of debit-card users that is disproportionately

Table A.3: Extension Using SCI-weighted Consumption Shocks to Measure Spillovers

Dep. var. =	log(Consumption Expenditures)							
	2020H1	2020H1	2020H2	2020H2	2021	2021	2022	2022
SCI-weighted Shocks to Spending	1.600***		.752***		.739***		.515***	
	[.044]		[.042]		[.039]		[.037]	
SCI-weighted Shocks to Spending, Other States		3.249***		1.610***		1.393***		1.023***
		[.236]		[.206]		[.139]		[.138]
log(County Cases)	-.006***	-.009***	-.003**	-.004***	.006	.009	-.011	-.010
	[.001]	[.001]	[.001]	[.002]	[.006]	[.007]	[.019]	[.019]
log(County Deaths)	-.001	.001	.002	.003**	.004	.002	-.010	-.010
	[.001]	[.001]	[.001]	[.001]	[.004]	[.005]	[.008]	[.008]
R-squared	.68	.64	.65	.65	.63	.63	.67	.67
Sample Size	259326	259326	344112	344112	586919	586919	250848	250848
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes.–Sources: Facebook Social Connectedness Index (SCI) for 2019 and Affinity Solutions. The table reports the coefficients associated with regressions of logged consumption spending growth relative to January 1st, 2020 on SCI-weighted *consumption* shocks and logged county infections and deaths, conditional on county and time-fixed effects. The consumption spending is measured by total debit and credit card transactions at the county level. *, ** and *** denote significance at the 10%, 5% and 1% level, respectively.

Table A.4: Using Idiosyncratic Covid Shocks (Cases)

Dep. var. =	log(Consumption Expenditures)				
	(1)	(2)	(3)	(4)	(5)
Has SAHO			-.056***	-.057***	-.059***
			[.005]	[.005]	[.005]
SCI-weighted Shocks to Cases	-.041***	-.012	-.036***	-.034***	
	[.005]	[.008]	[.009]	[.010]	
× SAHO				-.004	
				[.004]	
SCI-weighted Shocks to Cases, Other States					-.121***
					[.027]
log(County Cases)		-.028***	-.000	-.000	-.003
		[.004]	[.004]	[.004]	[.004]
log(County Deaths)		.005	-.019***	-.019***	-.016***
		[.006]	[.003]	[.003]	[.003]
R-squared	.99	.99	.97	.97	.97
Sample Size	351766	351766	351766	351766	351766
County FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
State Policies	No	No	Yes	Yes	Yes
State x Month FE	No	No	Yes	Yes	Yes

Notes.–Sources: Facebook Social Connectedness Index (SCI) for 2019. The table reports the coefficients associated with regressions of logged consumption spending on logged SCI-weighted *idiosyncratic shocks* to infections in connected counties and logged county infections and deaths, conditional on county and time-fixed effects. The idiosyncratic shocks are panel regression residuals of county-day Covid cases net of time-fixed effects. The consumption spending is from the Facteus. The sample period is between January 1st to March 30th 2020. *, ** and *** denote significance at the 10%, 5% and 1% level, respectively.

Table A.5: Using Idiosyncratic Covid Shocks (Deaths)

Dep. var. =	log(Consumption Expenditures)				
	(1)	(2)	(3)	(4)	(5)
Has SAHO			-.057***	-.059***	-.059***
			[.005]	[.005]	[.005]
SCI-weighted Shocks to Deaths	-.092***	-.083***	-.067***	-.062***	
	[.009]	[.010]	[.012]	[.012]	
× SAHO				-.018***	
				[.005]	
SCI-weighted Shocks to Deaths, Other States					-.165***
					[.036]
log(County Cases)		-.011***	-.005	-.005	-.007**
		[.004]	[.003]	[.003]	[.003]
log(County Deaths)		.004	-.010***	-.010***	-.011***
		[.004]	[.003]	[.003]	[.003]
R-squared	.97	.97	.97	.97	.97
Sample Size	351766	351766	351766	351766	351766
County FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
State Policies	No	No	Yes	Yes	Yes
State x Month FE	No	No	Yes	Yes	Yes

Notes.–Sources: Facebook Social Connectedness Index (SCI) for 2019. The table reports the coefficients associated with regressions of logged consumption spending on SCI-weighted *idiosyncratic shocks* to Covid deaths in connected counties and logged county infections and deaths, conditional on county and time-fixed effects. The idiosyncratic shocks are panel regression residuals of county-day Covid deaths net of time-fixed effects. The consumption spending is from the Facteus.The sample period is between January 1st to March 30th 2020. *, ** and *** denote significance at the 10%, 5% and 1% level, respectively.

Table A.6: Using Orthogonalized Idiosyncratic Covid Shocks (Cases)

Dep. var. =	log(Consumption Expenditures)				
	(1)	(2)	(3)	(4)	(5)
Has SAHO			-.017**	-.017**	-.018***
			[.007]	[.007]	[.007]
SCI-weighted Shocks to Cases	-.227***	-.100***	-.101***	-.116***	
	[.022]	[.019]	[.019]	[.021]	
× SAHO				.079	
				[.050]	
SCI-weighted Shocks to Cases, Other States					-.393***
					[.079]
log(County Cases)		-.012***	-.010***	-.010***	-.010***
		[.002]	[.001]	[.001]	[.002]
log(County Deaths)		-.004	.001	.001	.002
		[.004]	[.003]	[.003]	[.003]
R-squared	.99	.99	.97	.97	.97
Sample Size	195156	195156	195156	195156	195156
County FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
State Policies	No	No	Yes	Yes	Yes
State x Month FE	No	No	Yes	Yes	Yes

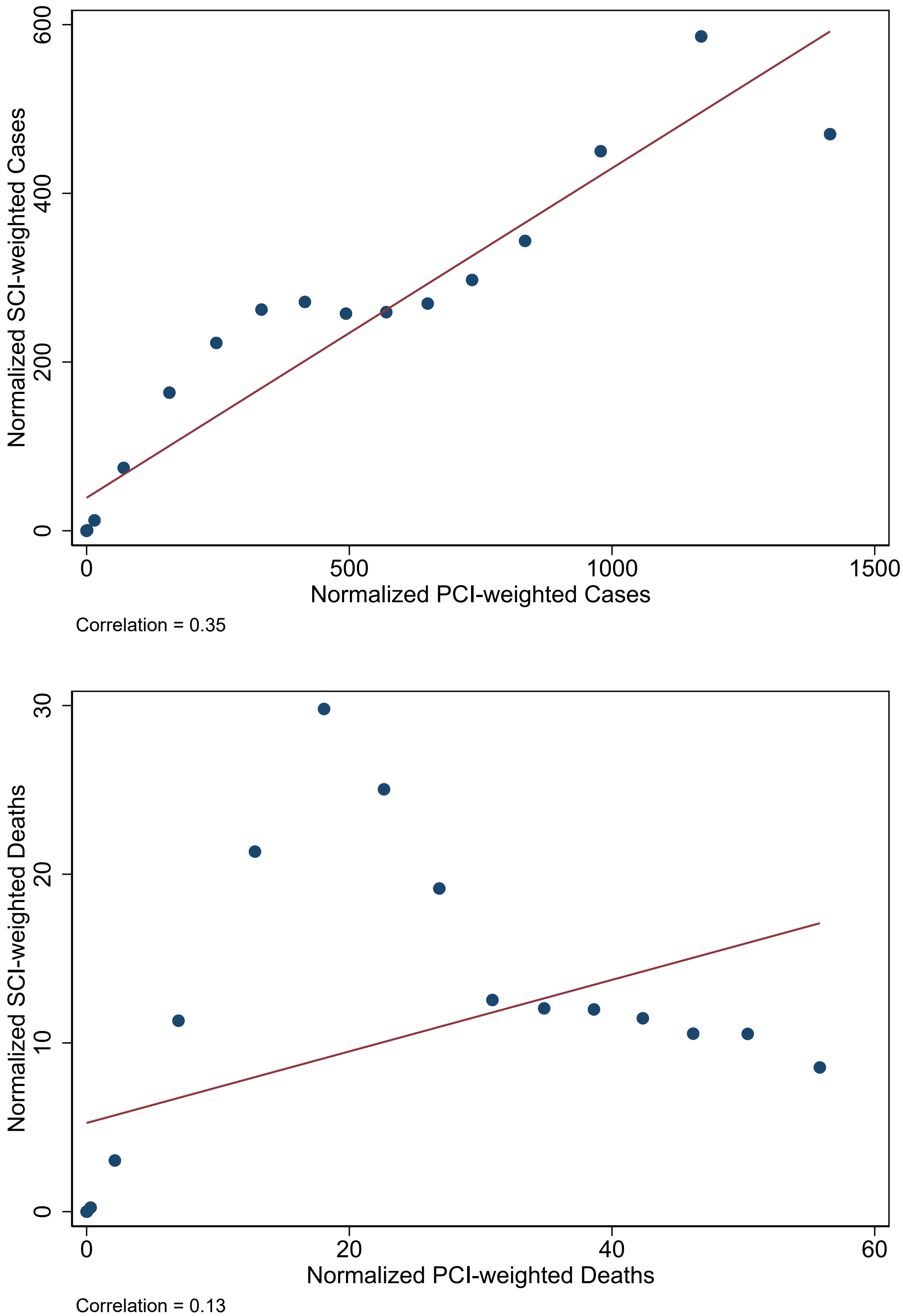
Notes.–Sources: Facebook Social Connectedness Index (SCI) for 2019. The table reports the coefficients associated with regressions of logged consumption spending on logged SCI-weighted *idiosyncratic shocks* to infections in connected counties and logged county infections and deaths, conditional on county and time-fixed effects. The shocks are approximated as the first difference of the idiosyncratic residuals from a panel regression of county-day cases net of time-fixed effects. The consumption spending is from the Facteus. The sample period is between January 1st to March 30th 2020. *, ** and *** denote significance at the 10%, 5% and 1% level, respectively.

Table A.7: Using Orthogonalized Idiosyncratic Covid Shocks (Deaths)

Dep. var. =	log(Consumption Expenditures)				
	(1)	(2)	(3)	(4)	(5)
Has SAHO			-.017**	-.018***	-.017***
			[.007]	[.007]	[.007]
SCI-weighted Shocks to Deaths	-.201***	.030	.010	.098	
	[.072]	[.075]	[.074]	[.087]	
× SAHO				-.165	
				[.134]	
SCI-weighted Shocks to Deaths, Other States					-1.068**
					[.503]
log(County Cases)		-.014***	-.012***	-.012***	-.010***
		[.001]	[.002]	[.002]	[.002]
log(County Deaths)		.000	.003	.004	.005
		[.003]	[.003]	[.003]	[.003]
R-squared	.97	.97	.97	.97	.97
Sample Size	195156	195156	195156	195156	195156
County FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
State Policies	No	No	Yes	Yes	Yes
State x Month FE	No	No	Yes	Yes	Yes

Notes.–Sources: Facebook Social Connectedness Index (SCI) for 2019. The table reports the coefficients associated with regressions of logged consumption spending on SCI-weighted *idiosyncratic shocks* to Covid deaths in connected counties and logged county infections and deaths, conditional on county and time-fixed effects. The shocks are approximated as the first difference of the idiosyncratic residuals from a panel regression of county-day deaths net of time-fixed effects. The consumption spending is from the Facteus. The sample period is between January 1st to March 30th 2020.

Figure A.6: 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.

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 a 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.[16] Table A.8 reports the results of the same regression as the baseline, except for replacing the dependent variable with the daily growth rate in consumption spending relative to January 1st, 2020. The coefficients associated with the SCI-weighted cases and deaths remain negative and significant.

Table A.8: Robustness Using 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, 2020 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. *, ** and *** denote significance at the 10%, 5% and 1% level, respectively.

Next, we use this same data to see whether our the relationship between SCI-weighted cases/deaths

[16]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.

and consumption holds in later years. We posit that the relationship should grow weaker since the pandemic subsided substantially in 2022 across a variety of dimensions. Consistent with this hypothesis, Table A.9 shows that the social communication impacts on consumption spending no longer last in the later phase of the pandemic, as indicated by the non-significance of the SCE-weighted measures in most of the sample from June 2020 onward till 2022.

Table A.9: The Relationship Between SCI-weighted Cases/Deaths and Consumption Across Time

Dep. var. =	log(Consumption Expenditures) Growth					
	2020H2	2020H2	2021	2021	2022	2022
log(SCI-weighted Cases)	-.008		.024		.082	
	[.008]		[.025]		[.059]	
log(SCI-weighted Deaths)		.007		-.041**		-.012
		[.007]		[.017]		[.049]
log(County Cases)	-.008**	-.011***	.011	.018***	-.031	-.006
	[.003]	[.002]	[.010]	[.007]	[.021]	[.014]
log(County Deaths)	.008***	.006***	-.017***	-.006	-.012	-.010
	[.002]	[.002]	[.005]	[.006]	[.008]	[.016]
R-squared	.76	.76	.75	.75	.81	.81
Sample Size	344112	344112	586919	586919	250848	250848
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes.–Sources: Facebook Social Connectedness Index (SCI) for 2019 and Affinity Solutions. The table reports the coefficients associated with regressions of logged consumption spending growth relative to January 1st, 2020 on logged SCI-weighted infections and logged county infections and deaths, conditional on county and time-fixed effects. The consumption spending is measured by total debit and credit card transactions at the county level. *, ** and *** denote significance at the 10%, 5% and 1% level, respectively.

Table A.10: International Evidence from Additional Countries

Dep. var. =	log(Consumption Expenditures)			
	JAP	JAP	SINGA	SINGA
log(County Cases)	-.003	-.003	-.003	-.003
	[.004]	[.004]	[.004]	[.004]
log(County Deaths)	-.029***	-.029***	-.032***	-.032***
	[.003]	[.003]	[.003]	[.003]
log(SCI-weighted Cases)	-.406***		-.065**	
	[.084]		[.032]	
log(SCI-weighted Deaths)		-.424***		-.077**
		[.090]		[.038]
Constant	9.851***	9.820***	9.783***	9.776***
	[.019]	[.014]	[.010]	[.009]
R-squared	.97	.97	.97	.97
Sample Size	165146	165146	165146	165146
County FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes

Notes.–Sources: Facebook and Facteus. The table reports the coefficients associated with regressions of logged consumption spending on SCI-weighted logged 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 logged time-varying number of infections in country i and multiplying it by the exposure of county c to country i normalized by the total population of country c, producing a Bartik-like measure. The two additional countries are Japan (JAP) and Singapore (SINGA). The sample period is between February 15th and March 15th, 2020. Standard errors are clustered at the county level. *, ** and *** denote significance at the 10%, 5% and 1% level, respectively.