Take it to the Bank!
Local Discourse and Deposits*

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Abstract

Using a hand-collected data set on almost one million local television news stories in the U.S., this paper shows that depositors respond to changes in the intensity of reporting about the COVID-19 pandemic by holding more demand deposits. Counties, where pandemic news stories are 10 percentage points more frequent relative to all news stories hold 1.3% more demand deposits after the onset of the pandemic. This effect holds when controlling for the intensity of the pandemic and several other alternative explanations. Further evidence shows that local news reflects the intensity of local discourse, which in turn causes a spike in deposits, especially in counties with a weaker social structure. The results suggest that the intensity of societal discourse around an event can have significant implications for banks and the real economy.

JEL classification: D14, G14, G21, G51

Keywords: deposits, COVID-19, local discourse, local news

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1 Introduction

The COVID-19 pandemic has led to an unprecedented increase in deposits held at commercial banks (Figure 1). At the same time, there is increasing evidence that the social environment matters for individual decision making. This paper asks whether the significant increases in deposits can – at least in part – be explained by changes in the intensity of discourse around the pandemic. To this end, I collect data on local television news during the pandemic, by scraping the YouTube channels of local TV-stations and analyzing almost one million subtitle files. I find that the intensity of the discussion around the pandemic, as measured by the share of local television stories that discuss the pandemic relative to all other news stories, is strongly associated with the deposit behavior of households. Specifically, deposits increase by about 2.2% more in regions with a one standard deviation higher prevalence of COVID-19 news after the onset of the pandemic, which corresponds to about 1/6th of the overall increase in post-pandemic deposits.

The paper introduces a completely novel self-collected dataset on local television news, by exploiting the increased presence of local U.S. television news channels on YouTube. I manually identify all available local ABC and CBS affiliates with a presence on YouTube and download all video subtitles between January 1st, 2020 and March 31st, 2021. To my knowledge, this is the first large-scale data set using the *content* of television news. In total, the data covers roughly 840,000 news stories (subtitle files) for 203 local news channels, which cover 142 out of 210 media markets in the U.S.

Despite the increasing importance of media consumption online, television in the U.S. still plays a very important role in the local discourse. Local television is still one of the most frequently used news source, with 67% of survey respondents saying they get their news often or sometimes from local television (Pew Research, 2020). Importantly, local news is uniquely representative of local discourse, because it often features interviews with non-professional, ordinary people who perhaps more closely reflect the importance of current topics than professionally trained figures, such as politicians, media spokespersons or newspaper writers. I conduct several tests to confirm this idea and demonstrate that the effects found in the paper are less likely to be driven by the news itself, but rather by the intensity of societal discussions, which is reflected in local news coverage.

The paper's key measure is the intensity of COVID-19 coverage in local news. Using four key words - pandemic, covid, coronavirus and virus - I classify each local news story as pandemic (un-)related. I then calculate the share of pandemic related news stories relative to all stories covered on that day. This measure of the intensity of local discourse is significantly associated with an increase in demand deposits during the pandemic period, even when controlling for alternative factors, such as the pandemic itself, lockdown measures, structural factors and political variables. Deposits also increase, when coverage is more intense in non-local, but socially connected markets. This suggests that the effects are not driven by the TV-coverage itself, because non-local television is rarely watched. Rather, it appears that local news reflect the intensity of societal discourse, which in turn impacts depository behavior.

The effect of the intensity of local discourse on deposits is only weakly affected by economic fundamentals, but strongly impacted by the social environment. Coverage has a larger effect in counties with a larger GDP in absolute terms. However the effect is independent from income per capita and inequality and is also not stronger in counties with a higher share of older individuals, which suggests that people do not act more carefully if they are are threatened more by the economic or health effects of the pandemic. On the other hand, the effect of the intensity of coverage is smaller in stronger communities, for example when membership in religious and non-religious groups is high. In accordance with this results, counties with a high share of votes for Donald Trump in 2020 do not significantly increase their precautionary savings due to an increase in coverage.

The paper contributes to several strands of literature. First, it contributes to the literature about the effects of the COVID-19 pandemic on economic outcomes in general (Chetty et al., 2020; Chen et al., 2021) and on banking in particular (Acharya and Steffen, 2020; Li et al., 2020). It is closely related to Levine et al. (2020), who demonstrate that interest rates on deposits decreased most in areas where the pandemic was more intense. Ruling out several alternative explanations, they make a compelling case that this is likely caused by an increase in deposit supply, stemming from a precautionary savings motive. This paper is in line with their finding, but demonstrates one crucial difference: the driver of deposit inflows appears to be driven not only by the pandemic itself, but also by the intensity of discourse around it.

The paper is also related to the question how people form beliefs, especially in social contexts. A large literature models and demonstrates in the laboratory that people's beliefs depend on the beliefs of others around them **?**Grimm and Mengel (2020). At the same time there is increasing evidence that people overweight the importance of information if they are confronted frequently with it, even when it does not add any additional information (Enke and Zimmermann, 2017; Enke, 2020). The results of this paper are in line with this experimental literature: if societal discourse around a topic becomes more intense, the reaction intensifies as well. The paper is also related to the literature on the effects of sentiment on financial markets (Baker and Wurgler, 2007; Edmans et al., 2007; Da et al., 2015; Soo, 2018; Gao et al., 2020; Edmans et al., 2021). I demonstrate that the intensity of discussion, matters in addition to its sentiment or mood. The main variable of interest – the share of COVID-19 coverage in local news – could also be described as measuring the intensity of the local narrative. In this manner, the paper provides some first empirical evidence that narratives matter for financial behavior.

Lastly, the paper is also related to the discussion around the effects of media more generally and television in particular. There is ample evidence that television content reflects (Gentzkow and Shapiro, 2010) and influences political decisions (Gentzkow and Shapiro, 2006; Gentzkow, 2006; DellaVigna and Kaplan, 2007). There is also recent evidence that television might have had an impact on health outcomes during the pandemic (Bursztyn et al., 2020). While this literature is tries to keenly differentiate between the direct influence of media and media choice simply reflecting existing individual preferences, this paper does not take an explicit stance whether television news is driving or reflective of local sentiment. Yet, because local news is often much less subject to media slant or bias (Martin and McCrain, 2019), it is less likely to try and actively influence its viewership.

2 Data

2.1 Local news media

Local television in the U.S. runs through affiliates of major television networks which include ABC, NBC, CBS, Fox, PBS and the CW. These local affiliates are responsible for broadcasting the network programming in their local media market (sometimes also referred to as a television market or a designated media area (DMA)). In certain time slots – often in the early morning, around noon and in the early evening – local affiliates also broadcast their own programming. This is usually focused around local news, but can also include commentary or small local talk shows. In the past few years, many such local news stations have proceeded to upload their self-produced segments to their own YouTube channels. For each of the 210 media markets in the U.S., I manually search and identify the ABC and CBS affiliate channels on YouTube.[1] In total, I am able to identify 203 local CBS and ABC affiliates in 138 media markets with sufficient uploads. Table A1 displays the full list.

I then download all *subtitle* files for videos uploaded between January 1st, 2020 and March 31st, 2021. What types of videos are uploaded varies significantly between news stations. Using various algorithms, I try to eliminate weather, sports, advertisement and online-exclusive videos from each channel. I also eliminate videos that far exceed the average length of the other videos, because they are often live-streams of press conferences or other non-local events.[2] The goal of this extensive manual cleaning is to keep the scope of videos as large as possible, while eliminating outliers that are not representative of

[1] An extension to include the other major network affiliates is under way.

[2] One very frequent example are the COVID-19 briefings that various governors provided daily during the pandemic. Because the governor addresses the entire state and not just the local media market, these videos are eliminated (while local county updates remain).

what is covered on the local television news. I then clean the text of all stop words and extremely rare words, which are in most cases mistakes or typos from the speech to subtitle conversion process.

The final dataset covers 840,000 videos in 203 local news channels in 138 of the 210 potential media markets. Figure 2 displays the average number of videos the dataset covers by media market. The map demonstrates that the dataset covers a large portion of U.S. media markets quite well. There are only few markets with no coverage and the vast majority of media markets include more than 1 video per day. On average there are 13 videos per day across all media market regions.

– Figure 2 around here –

Figure 3 displays a word map of the most frequent words used in the subtitles of the downloaded videos. Common verbs, conjunctions and other frequent, but by themselves meaningless words have been removed. The full list of the 100 most frequent words is shown in table A2. As can be seen, the most frequent words roughly correspond to words commonly used in television news stories, such as today, morning, day and state. The batch of words with slightly less commonality clearly identify important topics in the news in the year 2020, including several frequent pandemic related words, such as pandemic, coronavirus, virus and covid.[3]

– Figure 3 around here –

To measure the intensity of pandemic coverage in each media market, I compute the share of pandemic related news stories relative to all stories. A story is pandemic related if it contains any of four pandemic related words: *pandemic*, *coronavirus*, *virus* and *covid*. Relative coverage of COVID-19 varies significantly across media markets. Figure

[3]Other topics can also be clearly identified. One can notice the importance of police, because of the black lives matter protests in summer of 2020. The word president also highlights the presence of the fall 2020 presidential election, although the focus is clearly on the more local level (state and county).

4 displays the variation across the U.S.. Interestingly, the intensity of coverage appears to be relatively idiosyncratic and shows very little correlation to the total case numbers per population (figure 5) or other socio-geographic factors. Not even areas which dominated the national news, such as the New York area, have particularly intense coverage when looking at the entire pandemic period. Instead, how intensely the pandemic is covered relative to all other stories appears to follow no discernible logical pattern.

– Figure 4 around here –

– Figure 5 around here –

2.2 Deposits, COVID-19 and other data

Data on deposits stems from the quarterly call reports of banks provided by the FFIEC.[4] The data provide quarterly information on balance sheet items and profit and loss statements and are provided at the *bank* level. Before merging, the data comprise roughly 5,600 institutions. I match the banks via their address to a county using the google maps API. I then sum up all deposits on the county level, in order to arrive at the level of deposits for each county. While these deposits are held at the county level, the depositors do not necessarily need to be local. As a result there is an implicit assumption that deposits held by local banks are held with some regularity by local agents.

I retrieve information on daily confirmed cases of COVID-19 and deaths from COVID-19 for all U.S. counties from Johns Hopkins University Center for Systems Science and Engineering (JHU CSSE).[5] Using population numbers from the same source I then calculate cases and deaths per capita. For easier interpretation of the coefficients, deaths per capita are multiplied by 1000. To get to the quarterly level, cases and deaths are summed up over the entire quarter.

[4]https://cdr.ffiec.gov/public/ManageFacsimiles.aspx

[5]Accessed through github: https://github.com/CSSEGISandData/COVID-19/

To measure the effect of lockdowns, I use data on daily mobility from Apple and Google.[6] Changes in mobility cover both governmental lockdowns, but also self-imposed reductions in participation in public life, which has often preceded official lockdowns (Badr et al., 2020). The Apple data is based the number of requests on Apple maps, relative to January 13th. The data is split into the categories driving, walking and transit, and is provided on a daily basis for each U.S. county.[7] The Google data shows "visitors to (or time spent in) categorized places change compared to our baseline days", where the baseline represents median pre-pandemic days. The data is also provided daily and at the county level. As opposed to the Apple data, Google splits its data not by mode of transport but by places. Both datasets have been frequently used in the epidemiological and economic literature (Cot et al., 2021; Alfaro et al., 2021).

I retrieve data on the socio-economic structure of counties from the U.S. census, in particular its decennial survey.[8] The data used in this paper includes information on education, age, sectoral distribution, inequality (gini coefficient) and the percentage of the population living in urban areas. I also get data on the health of communities from the social capital project created by the Joint Economic Committee - Republicans. The main measure they produce is an index of community health, which is created by aggregating various measures of community activity, such as membership in non-profit groups or religious congregations.

3 Analysis

3.1 Descriptive statistics plausibility checks

Descriptive statistics are displayed in table 1. Detailed variable definitions can be found in table A3 The media coverage measure in the final regression sample is available for 138

[6]Apple: https://covid19.apple.com/mobility ; Google: https://www.google.com/covid19/mobility/
[7]For most counties, only information on driving requests is available
[8]https://data.census.gov/

markets in 1526 counties. Over the entire sample period from January 2019 to March 2021 15% of news stories are pandemic related on average across counties, although this increases to 28% during the pandemic period. The standard deviation is 17 percentage points, with a large geographic distribution as seen in figure 4. Deposits are in line with expectations. On average 1.3 billion U.S.$ rest in demand deposit accounts (transaction accounts) in the average county. The vast majority of these are private deposits by corporations and households (average 1.18 billion U.S.$). Savings accounts (non-transactions accounts) are larger by a factor of about four.

To check if the new COVID-19 coverage measure correlates with behavior according to basic intuition even at a high frequency, I first test how it correlates with daily mobility and display the results in table A4. Coverage of COVID-19 negatively correlates with all mobility measures to places outside of residential areas. This effect remains in place despite controlling for ten lags of case and death numbers in the respective county. This strongly suggests the plausibility of the measure: in regions with more intense coverage of the pandemic, people remain at home more frequently.

3.2 Baseline regression model and estimation

I first study if counties with an intense coverage of the COVID-19 pandemic display a stronger reaction in deposits than counties with less intense coverage. COVID-19 coverage is always 0 before the onset of the pandemic (so from Q1 2019 - Q4 2019). As a result the regression can also be interpreted as a difference-in-difference estimation with time-varying treatment. Concretely, the regression is specified as follows:

$$\ln(\text{deposits})_{iq} = \beta_1 \cdot \text{covid coverage share}_{m(i)q} + \alpha_i + \alpha_q + \epsilon_{iq} \tag{1}$$

where i denotes counties and q denotes the quarter. The sample period starts in Q1

2019 and ends in Q1 2021. The dependent variable $ln(deposits)$ takes three different expressions in the regressions: All demand deposits (transaction accounts), private demand deposits and total savings deposits. Private demand deposits are a subset of all demand deposits. Data is available at the bank-quarter level and gets aggregated to the county-quarter level. α_i and α_q are county and quarter fixed effects, respectively. The COVID-19 coverage measure $covid\ coverage\ share_{m(i)q}$ varies over the pandemic, but is always 0 until the first quarter of 2020. The coefficient β_1 thus provides the marginal effect of a change in COVID-19 coverage on deposits.

The results of estimating equation 1, using clustered standard errors at the media market level, are displayed in table 2. Column (1) displays the results using all demand deposits as the dependent variable. Regions with a 1 percentage point larger share of COVID-19 pandemic coverage hold 0.13% more demand deposits. This means that in regions with a one standard deviation higher coverage after the onset of the pandemic, deposits increase by about 2.21% more than in regions with lower coverage during the pandemic. The effect is slightly larger for private demand deposits (column (2)). This effect is also economically sizable. The overall increase in deposits during the entire sample period is about 15%. This implies that a one standard deviation change is responsible for about 1/6th of the overall increase in deposits during the pandemic.

– Table 2 around here –

The sizable effect of a larger coverage of the COVID-19 pandemic on deposits can also be displayed graphically. Figure 6 plots private demand deposits on the y-axis and the sample period on the x-axis. The solid line represents the development in private deposits for counties with below-median, and the dashed line for counties with above-median COVID-19 pandemic coverage share. The two regions deposits develop similarly before the onset of the pandemic, but diverge significantly when the pandemic starts. This graphically illustrates that more deposits are held when the sentiment about the pandemic is more more intense.

– Figure 6 around here –

The results demonstrate a statistically significant and quite sizable effect of the intensity of coverage of the COVID-19 pandemic on the most liquid deposits. In regions where the pandemic dominated the local narrative, depositors significantly increased their liquid deposit holdings. I propose that this is due to a salience effect: wherever COVID-19 dominates the local news, people are more likely to take the pandemic extremely seriously and thus increase their holdings of liquid deposits. Note that this might be for two reasons. The first reason might be that people are keeping more deposits because they believe they need access to liquidity in the near future, for example because they are experiencing job uncertainty. The other reason could be that a rise in COVID-19 coverage drives people to stay at home more, and as a result they spend less. Later results suggest that the former explanation might be more relevant than the latter.

3.3 Controlling for potential alternative explanations

Is intensity of COVID-19 coverage is only a proxy for the intensity of the pandemic? Or can the results be accounted for by government imposed lockdowns and an increased amount of reporting of such lockdowns? This sections investigates these and other concerns and demonstrates that the intensity of coverage is an important effect on its own, which cannot be easily accounted for by using alternative explanations.

Specifically, I test four different potential confounding effects. First, the intensity of the pandemic, as measured by cases and death numbers in each county-quarter. Second, to proxy the effect of lockdowns, I control for mobility measures from Google and Apple. Because mobility data is only available from Q1 2020, pre-pandemic values are set to zero. Third, I control for several county-level structural factors: The share of the population over 64, to see if coverage and reaction might be stronger in regions more susceptible to the disease, very high and very low education levels, the sectoral distribution, inequality and the share of the urban population. Each of these effects are non-time varying variables, which are by themselves subsumed in county fixed effects. However, it might be true that different county structure leads to a different reaction to the pandemic and thus I specify an interaction with a post-pandemic dummy, which is set to 0 before the pandemic (Q1 2019-Q4 2019) and to 1 after the onset of the pandemic (Q1 2020)-Q1 2021). Lastly I check if political affiliation, specifically the share of votes in the 2020 and prior presidential elections, can account for the effect of coverage intensity on deposits. Formally I estimate the following equation:

$$
\begin{aligned}
\ln(\text{private deposits})_{iq} = {} & \beta_1 \cdot \text{covid coverage share}_{m(i)q} + \\
& \sum \beta \cdot \text{pandemic intensity}_{iq} + \sum \beta \cdot \text{lockdown}_{iq} + \\
& \sum \beta \cdot \text{post}_q \cdot \text{county structure}_i + \sum \beta \cdot \text{post}_q \cdot \text{politics}_i + \\
& + \alpha_i + \alpha_q + \epsilon_{iq} \qquad (2)
\end{aligned}
$$

The results of the estimation using private demand deposits as the dependent variable are displayed in table 3. Estimation results for all dependent variables used in table 2 can be found in table A8, A9, A10, A11, A12. Column (1) controls for parameters trying to capture the intensity of the pandemic. The most plausible explanation for the results might be that the pandemic itself is responsible for changes in coverage and a simultaneous increase in precautionary savings. In fact, under perfect information and rational belief formation this is precisely what we might expect and it is thus no surprise that the literature has found evidence of it (Levine et al., 2020). However, column (1) in table 3 shows that once controlling for the intensity of pandemic sentiment, the actual intensity of the pandemic does not predict an increase in deposits. If anything, an increase in cases leads to a decrease in deposits, although the effect is only significant at the 10% level. Deaths due to the pandemic have even less predictive power in the model. On the other hand, the effect of the intensity of coverage remains positive and statistically significant, with little change from the baseline estimate. This provides clear evidence that the rise in demand deposits is likely not driven by actual pandemic risk, but rather by the perception of risk that is reflected in (or driven by) local news media coverage.

– Table 3 around here –

If it were the case that lockdown measures – whether government- or self imposed – were keeping depositors from spending money, we would expect that areas with higher relative mobility compared to pre-pandemic levels would hold relatively fewer deposits. Column (2) provides no evidence in this regard. Changes in the Google or Apple mobility indexes do not have a significant effect on deposits. The effect of intense COVID-19 coverage on deposits, however, remains statistically and economically significant, even when accounting for changes in mobility. This result provides an indication that the increase in deposits is not significantly driven by involuntary savings. Deposits increase significantly in response to increased coverage, even when controlling for the ability to spend via a mobility proxy.

Lastly, structural factors or politics might be driving deposits post-pandemic. Columns (3) demonstrates that this appears not to be the case. One might expect that counties with an older population, in which COVID-19 poses a higher risk of death, deposits and the intensity of coverage might jointly increase, which appears not to be the case. Intensity of coverage and the reaction in deposits is also not driven by a high share of the population without a high school degree or counties with a larger share of college graduates. There is also not a stronger reaction in counties with higher inequality, or in more urban counties, which might have been more impacted by the spread of disease. There is a slightly higher reaction in counties with a larger share of industries that were more likely to suffer from shut downs, such as manufacturing and service. However none of the factors can explain a significant fraction of the effect of coverage intensity, which remains statistically and economically important.

An interesting observation can be made about political preferences: counties with a high share of votes for Donald Trump in 2020 experience a much lower change in deposits. For a 1 percentage point increase in Trump's voter share, deposits decrease by 0.7%, which is quite sizable, but still does not account for the original effect (column (4)). When all factors are included jointly (column (5)), all of the previously mentioned effects disappear, the only exception being the pandemic intensity measure, which remains statistically significant and similar in size to the baseline estimation.

All in all, none of the factors under investigation can account for the effect of increased pandemic coverage on deposits. The findings support the idea that while other factors also matter for the behavior of depositors in a pandemic, the most consistent predictor of depositor behavior appears to be the intensity of coverage of the pandemic on local television around the pandemic as measured through the intensity of COVID-19 coverage.

3.4 Channel

Does TV coverage drive people to hold more deposits? Because we know from the literature that television can change peoples voting outcomes (DellaVigna and Kaplan, 2007; Gentzkow and Shapiro, 2010), this is a plausible potential explanation for the findings. However, this section suggests that a different explanation is more likely: local news is reflective of local discourse, which in turn drives depositors decisions.

The first piece of evidence is anecdotal: Local news is usually less politically motivated than national news.[9] As a result, it is less likely *intending* to influence their audience's opinion in one way or another. Another important fact about local news is that it is often less professionalized than national news. Interviewees are often not trained politicians and media spokespersons, as they are in national news. As a result, local news coverage is more likely to cover "ordinary" events and to feature more regular people, who are likely to accurately reflect local discourse.

[9]This appears to be the majority view of Americans: https://news.gallup.com/poll/268160/local-news-media-considered-less-biased-national-news.aspx

– Table 4 around here –

However, there is also empirical evidence in support of this hypothesis. If it were true that local news coverage is influencing precautionary savings decisions, we would expect that it can only have an effect in the region where local news can be watched. If discourse is the underlying factor, we would likely also see an impact of connected regions on local depositors. This is precisely what I find. Using the social connectedness (**?**) between counties, I construct a measure capturing the social closeness to news coverage intensity for each county. I multiply the pandemic coverage in county j with the social connectedness between counties i and j and the population in county j and then average this social connectedness to news coverage for each county i. The resulting measure is a measure of exposure to non-local news through social networks (in absolute terms). The results in column (1) of table 4 demonstrate that this measure is significantly positively correlated with local deposits. This implies that even if the intensity of local news cannot be directly observed, the sentiment resulting from intensive coverage in other regions influences decisions about precautionary savings through social networks.

I next turn to a different idea: the timing of the pandemic. Societal discourse was particularly intense in March 2020, when the pandemic swept through the United States and Europe. The WHO declared COVID-19 a pandemic on March 11th, which is also the timing of the first spike in deposits.[10] At the same time, the idea that local news can causally impact behavior in just a few days, is much less reasonable. Thus, if there is an effect of coverage that is exclusive to the early days of the pandemic, it might be interpreted as evidence that local news is reflective of discourse rather than being causal itself. Column (2) of table 4 demonstrates exactly this: The effect of news coverage intensity on deposits is largely focused around the first quarter of the pandemic.

[10]The same week also saw the canceling of many sports leagues and the shutdown of the U.S. border.

3.5 Economic fundamentals or social cohesion?

How can more intense discourse affect precautionary savings? Are people reacting to (expected) changes in expectations about incomes or their economic environment? Or does the explanation require a more complex social explanation? I try to answer this question, using triple interactions with the baseline difference-in-differences estimation. The regression equation for this is displayed in equation 3. The results of these regressions are displayed in table 5.

$$\begin{aligned}\ln(\text{private deposits})_{iq} = {} & \beta_1 \cdot \text{covid coverage share (avg)}_{m(i)q} + \\ & \beta_2 \cdot \text{covid coverage share (avg)}_{m(i)q} \cdot \text{ampl. fac.}_{i/s(i)} + \\ & + \alpha_i + \alpha_q + \epsilon_{iq} \end{aligned} \tag{3}$$

The first potential explanation for the strong reaction of deposits to changes in the intensity of local discourse rests in economic uncertainty. Through an intense discourse, or even through local news coverage itself, depositors might be picking up useful information about their economic outlook. As a result they might simply be better informed than their counterparts in low-coverage counties and adjust their precautionary savings accordingly. If this were the case, we'd expect a particularly strong reaction in lower-income regions, where negative future economic outlooks might be more worrying. The results in table 5 do not suggest that this is the case. Higher income regions – counties with per capita income above the median – react more strongly to increases in local discourse, although the effect is not statistically significant (column (1)). In fact, the majority of the reaction comes from rich countries, measured in terms of absolute GDP levels. Counties with an above median absolute GDP react much more strongly that smaller, poorer counties (column (2)). Economic uncertainty might also be more important in more unequal counties, but there is no statistically significant evidence that the reaction is stronger in counties with a higher Gini coefficient (column (3)).

Information should also be much more impactful in counties where the virus in more dangerous, i.e. in counties with a large share of the older population. Column (4) demonstrates that, if anything, older counties react less strongly to an increase in pandemic coverage, despite the fact that more intense coverage and discourse should lead them to be better informed about the risks of COVID-19.

– Table 5 around here –

Another potential explanation might be that more intense discourse increases the level of uncertainty due to social reasons. If people are talking a lot about the pandemic, it might lead it to being on peoples minds a lot, in turn leading them to increase their precautionary savings because the perceive an unspecified uncertainty about the future. If this is true, we would expect regions where there exists a lot social and emotional support to react less strongly to an increase in the intensity of discourse.

To this end, I first exploit data from the Joint Economic Committee of Congress, which provides an indicator of community health at the county level. The indicator aggregates memberships in religious and non-religious organizations and data on civic engagement into a measure of community health. Estimation results using this community health index as an interaction are displayed in column (5). The results indicate that healthy communities are significantly more resilient to the effects of an increase in the intensity of local discourse. I then separately investigate the effect of membership in religious and non-religious organizations, which shows a similar effect.

Increasingly, political ideology has also become an important factor in how discourse develops and is perceived. I thus test in column (7), if counties that voted for Donald Trump in 2020 might react differently to an increase in discourse intensity. In fact, the results indicate that counties with an above-median share of votes for Donald Trump in the 2020 election, do not react at all to an increase in news coverage. The effect that an increase in local news coverage leads to an increase in precautionary savings appears to be largely limited to Democratic discourse.

3.6 Effects on bank lending

If deposits are influenced by the intensity of coverage during the pandemic, it raises questions about the effects of such a sentiment-induced deposit shock on banks balance sheets. I investigate the effects on the asset side of the balance sheet in table 6.

– Table 6 around here –

Column (1) suggests that there is little effect on credit card loans. This is in line with expectations that typical credit card spending (e.g. restaurants) might have been harder during the pandemic. On the other hand column (2) indicates that loans for consumer purchases have increased in response to higher coverage. Taken together these results might suggest that bank customers made less frequent everyday purchases, which are typically made with a credit card and instead turned to buying larger consumer goods, such as fridges and washing machines, which are frequently financed with consumer credit.

Column (3) suggest a positive, but statistically insignificant effect on commercial loans. On the other hand there is some evidence that real estate lending increases slightly, in response to a spike in deposits from increased local discourse (column (4)). All in all these results result in a statistically significant increase in total loans (column (5)).

Overall the results suggest that the spike in deposits is inducing changes on the asset side of the banks balance sheet, by encouraging them to give out more loans. This is in line with cheaper financing conditions in Levine et al. (2020) and other papers demonstrating that a spike in deposits can generally entail an increase in lending Gilje et al. (2016). The finding implies that the intensity of local discourse as measured through local news has significant implications not only for the financing of banks, but also for their lending business and as a result it will also likely entail some real-economic effects.

4 Conclusion

Using a completely new dataset on 840,000 local television news stories retrieved from YouTube, this paper demonstrates that the intensity of discussion around the pandemic is significantly associated with an increase in demand deposits during the pandemic. I calculate the share of pandemic related news stories, relative to all other news stories and and show that an increase in COVID-19 coverage by 10 percentage points is associated with an increase in checking deposits by 1.3%. A one standard deviation increase in the intensity of COVID-19 news coverage is responsible for about 15% of the overall increase in deposits since the beginning of the pandemic.

This effect cannot be explained by the intensity of the pandemic itself, as measured by COVID-19 cases and deaths. It also cannot be explained by observable structural factors of counties, or the politics of the county. The effect does not only hold for news in the local county, but there is also a measurable effect of intense news coverage from non-local but connected counties, which indicates that news coverage reflects the intensity of local discourse, rather than being causal itself. Intense local discourse has much smaller effects in Republican counties and in counties with stronger local communities, but is not amplified by economic effects, which suggest a social amplification mechanism.

The paper demonstrates that household finance decisions can be significantly affected by the relative prominence of a topic in societal discourse. Wherever the pandemic is particularly salient, households are more prone to take action, in this case by increasing precautionary savings. This finding is highly relevant, especially wherever multiple equilibria exist. If prominent societal narratives can significantly impact household behavior, even beyond fundamentally observable factors, it can also induce a shift of equilibrium outcome. As a result it seems important to further understand how and why discourse around certain topics intensifies.

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Figures and tables

Figure 1: Deposits in U.S. banks over time

The figure displays total U.S. bank deposits in all commercial banks over time from April 1996-July 2021. Data stems from the Board of Governors of the Federal Reserve System (US) and is retrieved from the Federal Reserve Bank of St. Louis (FRED).

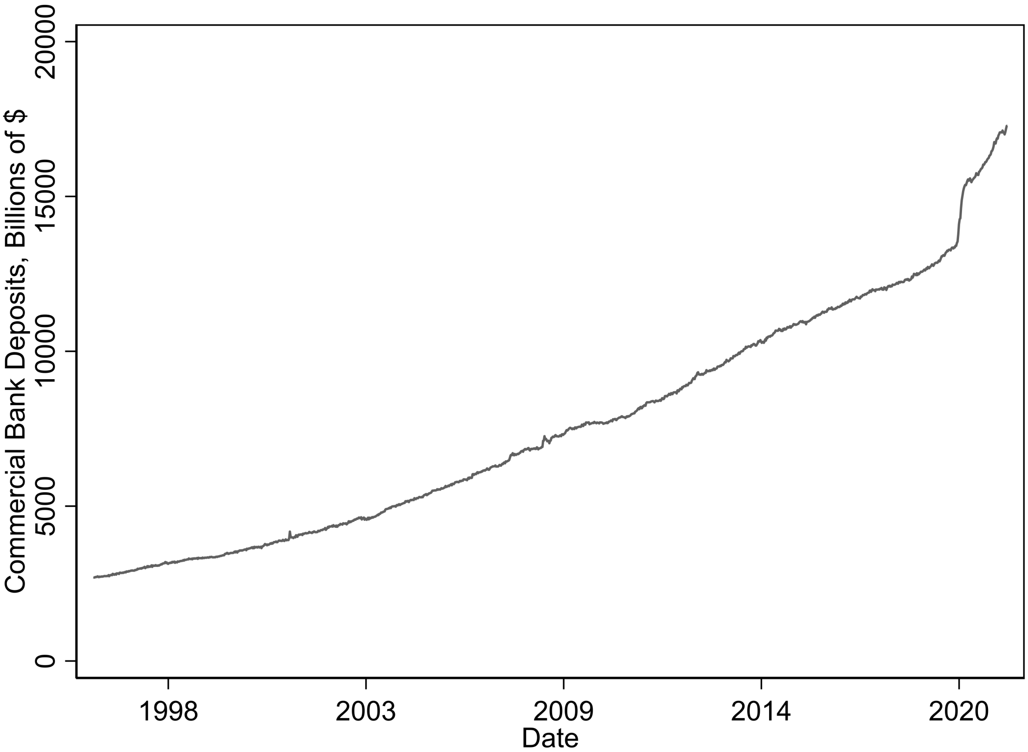

Figure 2: Average daily videos by media market

The figure displays the distribution of available videos per day in each of the 210 media markets in the U.S.. Darker shaded markets have a higher availability of videos. White areas indicate that there is no data available for the market. The data stems from a hand-collection of videos of local television news channels via YouTube. See section 2 for details.

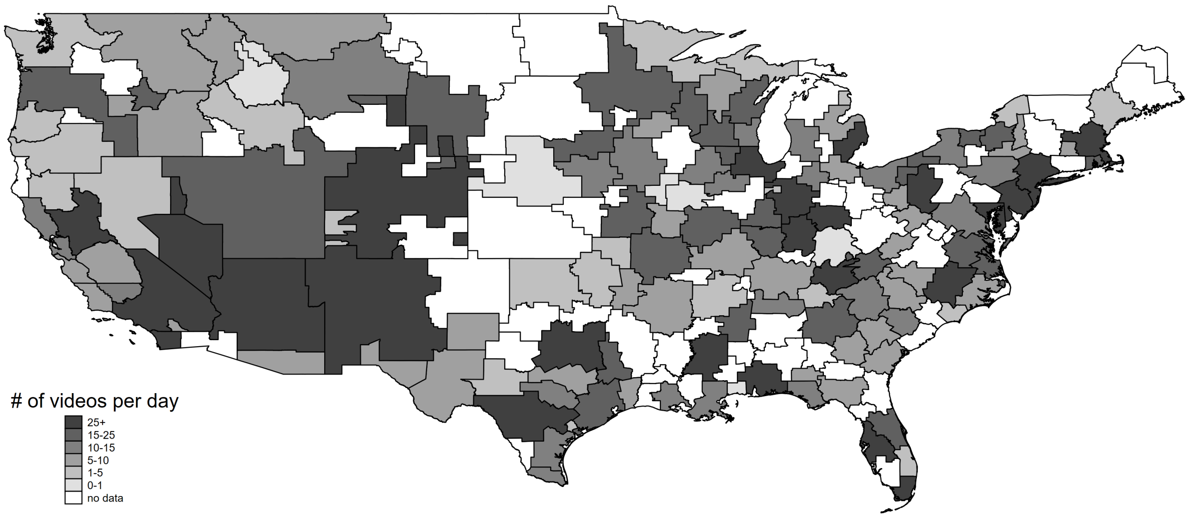

Figure 3: Word Cloud of all 840,000 local news stories

The figure displays a word cloud of the most frequently used words across all 840,000 local news stories included in the dataset. More frequently appearing terms are displayed in a larger font. Word Cloud is created using pythons WordCloud environment.

Figure 4: Relative Frequency of Pandemic related stories in %

The figure displays the frequency of COVID-19 pandemic news stories relative to all other stories. Darker shaded areas indicate a larger share of COVID-19 related stories. The data is captured on the media market level, but county borders are displayed for ease of comparison with figure 5. A local news story is pandemic related if it contains any of the following key words: pandemic, covid, coronavirus or virus.

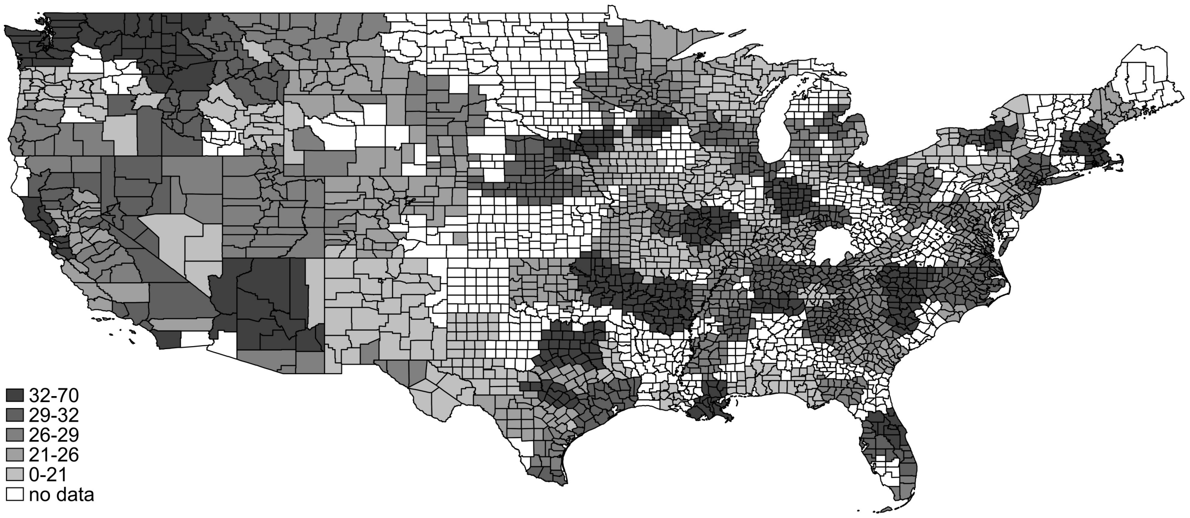

Figure 5: Total cases per capita until March 2021 in %

This figure displays Total COVID-19 cases by county from the beginning of the pandemic until March 2021. Darker shaded areas indicate more total cases. The data stems from Johns Johns Hopkins University.

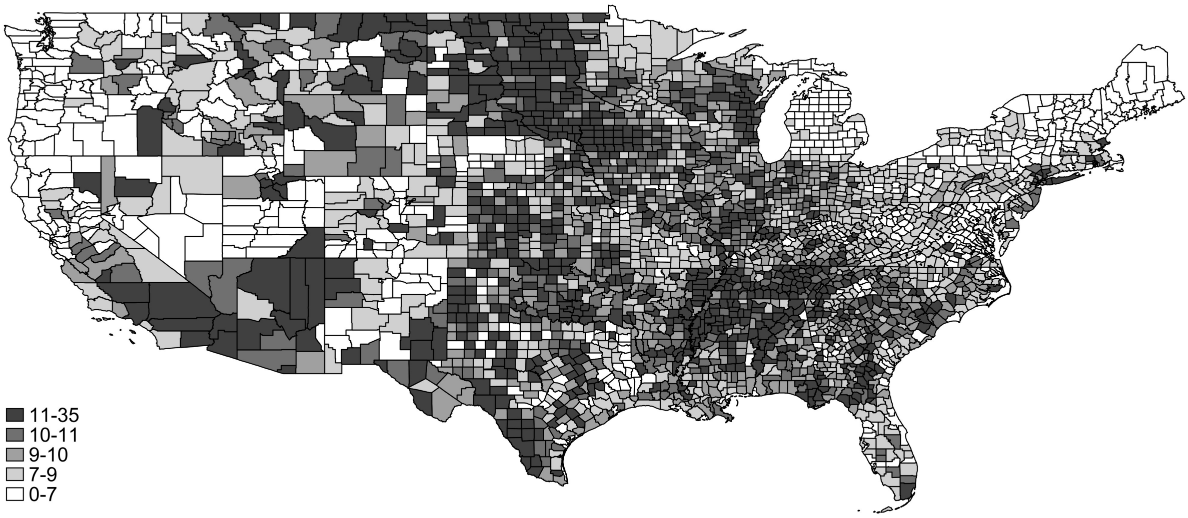

Figure 6: Deposits in private checking accounts over time by intensity of pandemic coverage

This figure displays the development of private checking deposits over time, split by regions with below-median pandemic coverage and regions with above median pandemic coverage. Pandemic coverage is defined as the share of COVID-19 related local news stories as a share of all local stories. A local news story is pandemic related if it contains any of the following key words: pandemic, covid, coronavirus or virus. The variable is then avaraged over the sample duration (January 2020-March 2021).

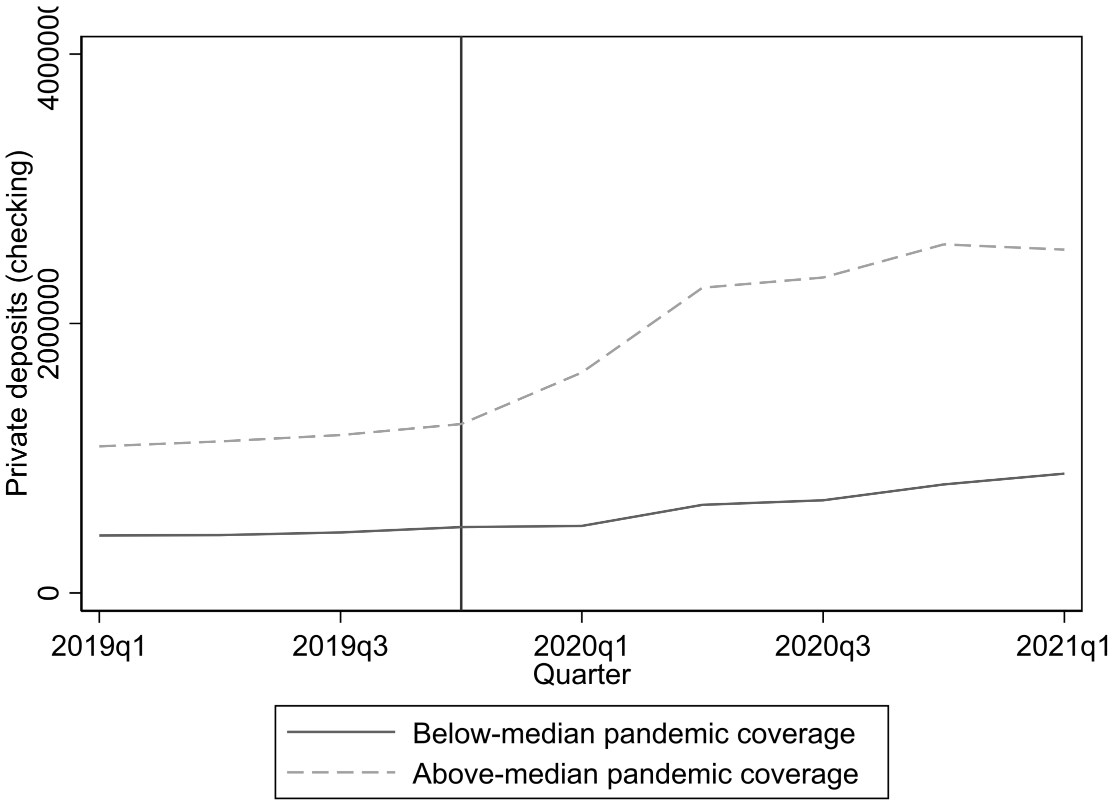

Table 1: Descriptive Statistics

This table displays descriptive statistics for all variables used in the regressions. Covid coverage share stems from hand-collected data, see section 2 for details. Bank level data stems from Quarterly Call Reports from the FDIC. Control and amplification variables are from Johns Hopkins University, Google, Apple, the U.S. census, the U.S. Congress. All bank level variables are in millions of U.S.$. Table A3 provides detailed definitions of all variables.

	N	Mean	Median	SD
Media coverage measure:				
Covid coverage share	13,605	0.15	0.13	0.17
Main dependent variables				
Deposits (checking)	13,605	1,310	144	14,055
Private deposits (checking)	13,605	1,181	122	12,810
Deposits (saving)	13,605	5,109	271	48,429
Control variables				
Total cases per capita	13,605	0.09	0.10	0.03
Total deaths per capita (x1000)	13,605	1.76	1.65	0.92
Mobility: retail	12,220	-13.06	-11.47	12.01
Mobility: driving	10,263	34.86	32.32	27.52
% pop over 64 yrs	13,605	15.13	14.70	3.83
% pop no high school	13,605	16.35	14.70	7.22
% pop w/ college degree	13,605	27.48	25.60	9.79
% construction	13,605	7.84	7.53	2.41
% manufacturing	13,605	13.58	12.86	7.02
% service	13,605	73.04	73.06	7.85
Gini	13,605	0.43	0.43	0.03
% Urban	13,605	48.08	47.78	30.56
% Republican (00-16)	13,605	59.10	60.94	13.47
% Republican 2020	13,596	63.77	67.26	16.27
Additional variables				
Credit card loans	13,605	301	0	5,233
Consumer loans	13,605	166	5	2,079
Commercial loans	13,605	358	41	1,660
Real estate loans	13,605	2,281	244	15,114
Total loans	13,605	4,569	323	38,411
Amplification variables				
Per capita income 2014-2019	13,575	43,174	40,722	12,614
Cases Q1 2020 (x1000)	13,605	226.59	84.47	625.27
Community health	13,605	-0.14	-0.30	0.84
Share of single households	13,605	27.80	27.90	4.22

Table 2: Intensity of discourse around COVID-19 affects deposits: baseline

The table provides estimates how different categories of deposits are affected after the onset of pandemic depending on the relative amount of COVID-19 coverage. The dependent variables are: all demand deposits, private demand deposits and all savings deposits. All dependent variables are used in logs in the regression. Covid coverage share is the share of pandemic related local news stories relative to all news stories, in each quarter from Q1 2019 through Q1 2021. Covid coverage share is 0 before the onset of the pandemic in Q1 2020. A local news story is pandemic related if it contains any of the following key words: pandemic, covid, coronavirus or virus. Table A3 defines all variables and section 2 describes the data collection process in detail. County and quarter fixed effects are included in all regressions. Clustered standard errors on the media market level of the point estimates are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Dependent variable:	Demand deposits		Saving deposits
	All	Private	All
	(1)	(2)	(3)
Covid coverage share	0.129**	0.141**	0.025
	(0.053)	(0.055)	(0.023)
Quarter FE	Yes	Yes	Yes
County FE	Yes	Yes	Yes
No. of obs.	13,605	13,605	13,605
No. of media markets	138	138	138
R^2	0.967	0.965	0.986
Within R^2	0.002	0.002	0.000

Table 3: Testing alternative explanations

The table adds controls of potential confounding factors from table A14 to the baseline regression. The dependent variable is the log of deposits in private checking accounts. Column (1) adds controls to account for the intensity of the pandemic. Column (2) controls for mobility as a proxy for local stay-at-home measures. Column (3) adds for structural factors. Column (4) adds controls for past election results. Column (5) adds all factors at the same time. Covid coverage share is 0 before the onset of the pandemic in Q1 2020. A local news story is pandemic related if it contains any of the following key words: pandemic, covid, coronavirus or virus. Table A3 defines all variables and section 2 describes the data collection process in detail. County and quarter fixed effects are included in all regressions. Clustered standard errors on the media market level of the point estimates are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Cases	Mobility	Structural	Politics	All
Dependent variable:	Private demand deposits				
	(1)	(2)	(3)	(4)	(5)
Covid coverage share	0.145**	0.215***	0.112**	0.121***	0.200***
	(0.056)	(0.064)	(0.044)	(0.046)	(0.059)
Cases per capita	-0.817*				-0.827
	(0.465)				(0.658)
Deaths per capita (x1000)	-0.018				0.001
	(0.012)				(0.014)
Post × mobility: retail		-0.001			0.000
		(0.001)			(0.001)
Post × mobility: driving		0.000			0.000*
		(0.000)			(0.000)
Post × % pop over 64 yrs			-0.002		-0.001
			(0.003)		(0.004)
Post × % pop no highschool			-0.000		0.000
			(0.003)		(0.003)
Post × % pop w/ college degree			0.003		0.003
			(0.002)		(0.003)
Post × % construction			0.007		0.002
			(0.004)		(0.007)
Post × % manufacturing			0.004**		0.002
			(0.002)		(0.003)
Post × % service			0.004*		0.001
			(0.002)		(0.004)
Post × gini			0.199		0.320
			(0.379)		(0.464)
Post × % Urban			0.000		0.001
			(0.001)		(0.001)
Post × % Republican (00-16)				0.005	0.001
				(0.003)	(0.003)
Post × % Republican 2020				-0.007***	-0.002
				(0.002)	(0.003)
Quarter FE	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes
No. of obs.	13,605	9,859	13,605	13,596	9,859
No. of media markets	138	138	138	138	138
R^2	0.965	0.962	0.966	0.966	0.962
Within R^2	0.003	0.003	0.013	0.012	0.011

Table 4: Discourse, not news: investigating the channel

The table investigates the channel through which pandemic coverage is affecting local deposits. Social connectedness to non-local coverage is the product of pandemic coverage in county j, the social connectedness between counties i and j and the population in county j, averaged for each county i. County and quarter fixed effects are included in all regressions. Clustered standard errors on the media market level of the point estimates are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Social centrality	Early pandemic
Dependent variable:	Private demand deposits	
	(1)	(2)
Social connectedness to non-local coverage	0.033**	
	(0.015)	
Covid coverage share $\times$ early pandemic cases		0.192***
		(0.064)
Covid coverage share		0.032
		(0.029)
Post $\times$ early pandemic cases		0.034
		(0.021)
Cases per capita	-0.824*	-0.741
	(0.467)	(0.449)
Deaths per capita (x1000)	-0.019	-0.017
	(0.012)	(0.011)
Quarter FE	Yes	Yes
County FE	Yes	Yes
No. of obs.	13,605	13,605
No. of media markets	138	138
R^2	0.965	0.966
Within R^2	0.002	0.010

Table 5: Effect of media coverage under different circumstances

The table presents results of triple interactions with the baseline difference-in-differences results from table 2, in order to identify variables which might amplify or dampen the baseline effect. Each interaction is specified with a median-split dummy of the respective variable. Community health is n indicator of the stability of the community of each county, provided by the U.S. congress. The dependent variable for all columns is the log of private deposits in checking accounts. Covid coverage share is the share of pandemic related local news stories relative to all news stories. A local news story is pandemic related if it contains any of the following key words: pandemic, covid, coronavirus or virus. Table A3 defines all variables and section 2 describes the data collection process in detail. County and quarter fixed effects are included in all regressions. Clustered standard errors on the media market level of the point estimates are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Economic Factors				Social Environment		
	Income p.c.	GDP	Gini	Age	Comm health	Organizations	Politics
Dependent variable:	Private demand deposits						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Covid coverage share	0.107**	0.017	0.098*	0.187***	0.198***	0.222***	0.316***
	(0.046)	(0.029)	(0.058)	(0.062)	(0.067)	(0.069)	(0.060)
Covid coverage share × high income per capita	0.047						
	(0.058)						
Covid coverage share × high total GDP		0.288***					
		(0.049)					
Covid coverage share × high Gini			0.055				
			(0.057)				
Covid coverage share × high share of pop > 64				-0.117**			
				(0.055)			
Covid coverage share × community health					-0.143**		
					(0.067)		
Covid coverage share × membership in organizations						-0.184***	
						(0.066)	
Covid coverage share × share of Trump voters (2020)							-0.288***
							(0.056)
Post × cases per capita	-1.055**	-0.932**	-1.065**	-1.122**	-1.111**	-1.090**	-0.782*
	(0.465)	(0.449)	(0.470)	(0.460)	(0.466)	(0.465)	(0.447)
Post × deaths per capita	-0.024**	-0.020*	-0.027**	-0.023**	-0.028**	-0.025**	-0.021**
	(0.011)	(0.010)	(0.011)	(0.010)	(0.011)	(0.010)	(0.010)
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of obs.	13,605	13,605	13,605	13,605	13,605	13,605	13,605
No. of media markets	138	138	138	138	138	138	138
R^2	0.966	0.966	0.966	0.966	0.966	0.966	0.966
Within R^2	0.009	0.016	0.009	0.010	0.011	0.012	0.016

Table 6: COVID-19 sentiment and bank lending: the asset side

The table displays estimates of equation 1 using three dependent variables from the asset side of the balance sheet: credit card loans (column(1)), consumer loans (column(2)), commercial loans (column(3)), real estate loans (column(4)) and total loans (column(5)). All dependent variables are aggregated to the county level and are used in logs in the regression. Post is a dummy set equal to 0 from Q1 2019-Q4 2019 and set equal to 1 from Q1 2020- Q1 2021. Covid coverage share is the share of pandemic related local news stories relative to all news stories, averaged over the sample period from January 2020 through March 2021. A local news story is pandemic related if it contains any of the following key words: pandemic, covid, coronavirus or virus. Table A3 defines all variables and section 2 describes the data collection process in detail. County and quarter fixed effects are included in all regressions. Clustered standard errors on the media market level of the point estimates are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Dependent variable:	Credit card loans	Consumer loans	Commercial loans	Real estate loans	Total loans
	(1)	(2)	(3)	(4)	(5)
Covid coverage share	0.062	0.094**	0.074	0.047*	0.057**
	(0.121)	(0.046)	(0.058)	(0.026)	(0.026)
Quarter FE	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes
No. of obs.	4,107	13,539	13,518	13,604	13,605
No. of counties	120	137	138	138	138
R^2	0.971	0.967	0.972	0.987	0.986
Within R^2	0.000	0.001	0.000	0.000	0.001

Appendix

4.1 What drives media coverage?

How much the pandemic is covered is likely due to the intensity of the pandemic itself, but might also be driven by other factors. To check for the potential influence of other important factors, I estimate an OLS regressions using the COVID-19 coverage share as the dependent variable:

$$\begin{aligned}\text{Covid coverage share (avg)}_{m(i)} = & \sum_{k=1} \beta_k \cdot \text{pandemic intensity}_{ki} + \sum_{k=3} \beta_k \cdot \text{lockdown}_{ki} \\ & + \sum_{k=5} \beta_k \cdot \text{county structure}_{ki} + \sum_{k=12} \beta_k \cdot \text{politics}_{ki} + \epsilon_i\end{aligned} \tag{4}$$

Specifically, I check for four sets of factors. First, I test whether the intensity of the pandemic influences the amount of COVID-19 coverage. To this end I correlate total case and total death numbers over the sample period with the coverage measure.

Next, I investigate the effect of lockdown measures. Due to the host of measures at different levels of government, it is difficult to quantify lockdown measures for each county. However, mobility data is available from Apple and Google, which effectively control for how much people reduce their mobility. Because it is well known that individuals adjust their mobility even before official governmental lockdowns are put in place (Badr et al., 2020), mobility measures cannot only account for governmental, but also for self imposed lockdowns. I focus on the most frequently available mobility data: the Apple driving index, which provides information on the the frequency of car routes relative to pre-pandemic levels and the Google mobility index for retail and recreational establishments, which are most likely to experience reductions in visits during the pandemic. Both indexes are averaged over the sample period for the purposes of the regression.

The third factors under investigation are of a structural nature. I investigate the counties education level, measured by both the share of people without a high school diploma and the people with at least a college degree, the sectoral distribution of the counties' workforce, the inequality in the county measured by the Gini coefficient and the share of the population living in urban areas. All factors might be significantly correlated with both the importance and the quality of local news in general, but also might cause differences in reporting during the pandemic. Lastly I look at the politics of the county. Similar to (Levine et al., 2020), I look at the voting share of Donald Trump in 2020 and the voting tendency over the previous presidential elections from 2000-2016.

The most important takeaway from table A14 is shown in column (1), which demonstrates that there is little correlation between the intensity of the pandemic and the coverage about it, at least over the entire sample length. Cases in the county show no correlation with the COVID-19 coverage share. Deaths from COVID-19 show a statistically significant negative correlation. An increase in 1 death per 1000 people is associated with a decrease in the COVID-19 coverage share by about 1.3 percentage points, which is not a very large effect.

– Table A14 around here –

Similarly, there appears to be little effect of lockdowns, whether government- or self-imposed, as proxied by Apple and Google mobility indexes (column (2)). On the other hand, structural factors appear to have some relevance in explaining how much the pandemic is covered in local news (column (3)). Interestingly, both high and low levels of education are correlated with larger coverage shares. We also see slightly higher coverage in counties with larger shares of the population working in the construction, manufacturing and service sectors. There is also a large statistically significant positive effect of inequality on the amount of coverage. Unequal counties cover the pandemic significantly more. A one standard deviation increase in the Gini coefficient (0.03) is associated with a 5.4 percentage point higher coverage share. Somewhat surprisingly, the pandemic is reported a little bit less in urban counties. However, the effect is so small, that the difference is not economically important. An interesting predictor of the COVID-19 coverage share appears to be the political situation. Traditionally republican areas cover the pandemic more, but areas with a high share of people who voted for Donald Trump in the 2020 election are less likely to report more on the pandemic.

4.2 Tables and Figures

Table A1: List of television stations by media market in the dataset

The table provides the full list of local television stations used in the main dataset and their associated media market. Some names are abbreviated as to fit the table on the page.

Media Market	State	ABC Affiliate	CBS Affiliate
Albuquerque-Santa Fe	New Mexico	KOAT	KRQE
Alpena	Michigan	WBKBTV	
Atlanta	Georgia		CBS46 Atlanta
Augusta-Aiken	Georgia	WJBF	
Austin	Texas	KVUE	
Bakersfield	California	23 ABC News KERO	
Baltimore	Maryland	WMAR-2 News	WJZ
Beaumont-Port Arthur	Texas	12NewsNow	
Billings	Montana		KTVQ News
Biloxi-Gulfport	Mississippi	WLOX-TV	
Binghamton	New York	NewsChannel 34	
Bluefield-Beckley-Oak Hill	West Virginia	WOAY TV	59 News
Boise	Idaho	Idaho News 6	
Boston (Manchester)	Massachusetts	WCVB Channel 5 Boston	CBS Boston
Buffalo	New York	WKBW TV Buffalo NY	
Butte-Bozeman	Montana		KXLF News Channel
Champaign-Springfield-Decatur	Illinois		WCIA News
Charlotte	North Carolina	WSOCTV9	
Chattanooga	Tennessee	WTVC NewsChannel 9	
Chicago	Illinois	ABC 7 Chicago	CBS Chicago
Chico-Redding	California		Action News Now
Cincinnati	Ohio	WCPO 9	
Clarksburg-Weston	West Virginia	WBOY 12 News	
Cleveland-Akron (Canton)	Ohio	News 5 Cleveland	
Columbia, SC	South Carolina		News 19 WLTX
Columbia-Jefferson City	Missouri	ABC 17 News	
Columbus	Ohio		WBNS 10TV
Columbus-Tupelo-West Point-Houston	Mississippi		WCBI
Corpus Christi	Texas	KIII 3 News	KZTV Action 10 News
Dallas-Fort Worth	Texas	WFAA	CBSDFW
Davenport-Rock Island-Moline	Iowa		Local 4 News WHBF
Denver	Colorado	Denver7 - The Denver Channel	CBS Denver
Des Moines-Ames	Iowa		KCCI
Detroit	Michigan	WXYZ-TV Detroit Channel 7	
Dothan	Alabama	WDHN	
Duluth-Superior, WI	Minnesota		CBS 3 Duluth
El Paso (Las Cruces)	Texas	KVIA ABC-7	
Erie	Pennsylvania	JET24 FOX66 YourErie	
Eugene	Oregon	KEZI 9	
Evansville	Indiana	Eyewitness News WEHT WTVW	
Flint-Saginaw-Bay City	Michigan		WNEM TV5
Fort Smith-Fayetteville-Springdale-Rogers	Arkansas	40 29 News	
Fort Wayne	Indiana	ABC21 WPTA	WANE 15 News
Fresno-Visalia	California		CBS47 KSEE24
Grand Junction-Montrose	Colorado		KREX News 5
Grand Rapids-Kalamazoo-Battle Creek	Michigan	13 ON YOUR SIDE	
Great Falls	Montana		KRTV NEWS
Green Bay-Appleton	Wisconsin		WFRV Local 5
Greensboro-High Point-Winston Salem	North Carolina		WFMY News 2
Greenville-New Bern-Washington	North Carolina		WNCT-TV 9 On Your Side
Greenville-Spartanburg-Asheville-Anderson	South Carolina		WSPA 7News
Harlingen-Weslaco-Brownsville-McAllen	Texas	KRGV	KVEO
Hartford-New Haven	Connecticut		WFSB 3
Helena	Montana		KXLH NEWS
Honolulu	Hawaii		Hawaii News Now

Houston	Texas	ABC13 Houston	KHOU 11
Huntsville-Decatur (Florence)	Alabama	WAAY-TV 31 News	
Idaho Falls-Pocatello (Jackson)	Idaho	Local News 8	
Indianapolis	Indiana	WRTV Indianapolis	
Jackson, MS	Mississippi	16 WAPT News Jackson	WJTV 12 News
Jacksonville	Mississippi		News4JAX
Joplin-Pittsburg	Missouri		KOAM News Now
Kansas City	Missouri	KMBC 9	KCTV5 News
Knoxville	Tennessee	WATE 6 On Your Side	
La Crosse-Eau Claire	Wisconsin	WQOW News 18	
Lafayette, IN	Indiana		WLFITV
Lafayette, LA	Louisiana	KATC	
Las Vegas	Nevada	KTNV Channel 13 Las Vegas	8 News NOW Las Vegas
Lexington	Kentucky		WYMT Television
Lincoln-Hastings-Kearney	Nebraska	Channel 8 KLKN-TV	
Little Rock-Pine Bluff	Arkansas		THV11
Los Angeles	California	ABC7 LA	CBS Los Angeles
Louisville	Kentucky	WHAS11	WLKY News Louisville
Lubbock	Texas	Everything Lubbock	
Macon	Georgia		13WMAZ
Madison	Wisconsin	WKOW 27 NEWS	Channel 3000
Marquette	Michigan		WJMN Local 3
Medford-Klamath Falls	Oregon	NewsWatch 12	
Memphis	Tennessee	Local 24 Memphis	
Miami-Fort Lauderdale	Florida	WPLG Local 10	CBS Miami
Milwaukee	Wisconsin	WISN 12 News	
Minneapolis-St. Paul	Minnesota	KSTP	
Missoula	Montana		KPAX-TV
Mobile-Pensacola (Fort Walton Beach)	Alabama		WKRG
Monterey-Salinas	California	KSBW Action News 8	
Nashville	Tennessee		NewsChannel 5
New Orleans	Louisiana		WWLTV
New York	New York	Eyewitness News ABC7NY	CBS New York
Norfolk-Portsmouth-Newport News	Virginia	13News Now	
Odessa-Midland	Texas	Big 2 News	
Oklahoma City	Oklahoma	KOCO 5 News	
Omaha	Nebraska	KETV NewsWatch 7	KMTV 3 News Now
Orlando-Daytona Beach-Melbourne	Florida		WKMG News 6 ClickOrlando
Ottumwa-Kirksville	Iowa	KTVOtv	
Paducah-Cape Girardeau-Harrisburg	Kentucky	WSIL News 3	
Palm Springs	California	KESQ NewsChannel 3	
Panama City	Florida	WMBB News 13	
Peoria-Bloomington	Illinois		WMBD News
Philadelphia	Pennsylvania		CBS Philly
Phoenix (Prescott)	Arizona	ABC15 Arizona	azfamily
Pittsburgh	Pennsylvania		CBS Pittsburgh
Portland, OR	Oregon		KOIN 6
Portland-Auburn	Maine	WMTW-TV	
Providence-New Bedford	Rhode Island		WPRI
Quincy-Hannibal-Keokuk	Illinois		KHQA
Raleigh-Durham (Fayetteville)	North Carolina		CBS 17
Rapid City	South Dakota		KELOLAND News
Reno	Nevada		KTVN Channel 2 News
Richmond-Petersburg	Virginia		WTVR CBS 6
Rochester, NY	New York		News 8 WROC
Rochester-Mason City-Austin	Minnesota		KIMT News 3
Rockford	Illinois	Eyewitness News WTVO WQRF	
Sacramento-Stockton-Modesto	California	ABC10	CBS Sacramento
Salt Lake City	Utah	abc4utah	
San Angelo	Texas		KLST-TV KSAN-TV
San Antonio	Texas	KSAT 12	KENS 5 -
San Diego	California	ABC 10 News	CBS 8 San Diego
San Francisco-Oakland-San Jose	California	ABC7 News Bay Area	KPIX CBS SF Bay Area
Santa Barbara-Santa Maria-San Luis Obispo	California	NewsChannel 3-12	
Savannah	Georgia	WJCL News	
Seattle-Tacoma	Washington		KIRO 7 News
Sioux City	Iowa	KCAU-TV Sioux City	
Spokane	Washington		KREM 2 News
Springfield, MO	Missouri		KOLR10 News
Springfield-Holyoke	Massachusetts	Western Mass News	
St. Louis	Missouri		KMOV St. Louis
Syracuse	New York	NewsChannel 9 WSYR Syracuse	
Tallahassee-Thomasville	Florida	WTXL - Tallahassee FL	
Tampa-St. Petersburg (Sarasota)	Florida	ABC Action News	10 Tampa Bay
Terre Haute	Indiana	WTWO WAWV TV	WTHI-TV
Toledo	Ohio		WTOL11
Tri-Cities, TN-VA	Tennessee	WJHL	
Tucson (Sierra Vista)	Arizona	KGUN9	
Tulsa	Oklahoma	NewsChannel 8 Tulsa	
Tyler-Longview (Lufkin-Nacogdoches)	Texas	KETK NBC	CBS19
Utica	New York		WKTVNEWSChannel2
Victoria	Texas		CrossroadsToday
Waco-Temple-Bryan	Texas	25 News KXXV	
Washington (Hagerstown)	District of Columbia		WUSA9
Watertown	New York	ABC50 InformNNY	
Wausau-Rhinelander	Wisconsin	WAOW	
West Palm Beach-Fort Pierce	Florida		CBS 12 News - WPEC
Wheeling-Steubenville, OH	West Virginia	WTRF 7News	
Wilkes Barre-Scranton	Pennsylvania		PAHomepage.com
Wilmington	North Carolina	WWAY NEWS	
Youngstown	Ohio		WKBN27

Table A2: List of most frequent words in all subtitle files

The table displays the list of the most frequently used words across all local news media stories included in the data. The frequency indicates how often they are used. For example, the word "people" appears 422,007 times in 840,000 news stories. Words can appear multiple times in one story.

word	frequency	word	frequency	word	frequency
people	422007	tonight	125414	across	87910
time	261486	come	121737	president	86953
day	245494	said	121647	something	85763
today	242111	high	121129	great	85176
news	239381	community	118131	working	84537
county	236781	live	116124	three	84174
year	232985	covid	115751	thank	84078
morning	205826	coming	115497	old	82751
first	196272	work	112538	every	82546
state	191345	things	112406	few	81764
good	189026	pandemic	110944	part	81249
not	181597	tomorrow	105853	kind	80777
want	174916	local	105585	should	80679
lot	174862	again	105015	number	79057
down	172016	years	104527	afternoon	78792
think	170793	may	103033	open	77873
make	170300	cases	102777	department	77830
little	165802	family	99023	do	77756
help	161507	start	98938	to	76255
week	161054	keep	96610	does	75009
take	160210	bit	95612	kids	74567
look	159983	days	95263	actually	74220
home	159129	able	94731	since	74045
last	158290	big	94644	weekend	73934
police	158277	students	94129	place	73729
health	155296	during	92754	coronavirus	73653
way	155058	another	91970	put	73409
need	152630	rain	90807	abc	73136
school	152489	looking	90428	reporter	72163
other	150388	night	89684	youre	71819
city	147350	area	88974	stay	70723
two	146812	temperatures	88653	care	70135
next	139361	position	88363	long	69382

Table A3: Variable definitions

This table provides variable definitions for all variables used in the main body tables.

Media coverage measure:	
Covid coverage share	Number of COVID-19 related news stories divided by all news stories. A COVID-19 related is defined as a news story that contains any of the following four words: covid, coronavirus, virus & pandemic. Source: own download.
Main dependent variables:	
Demand deposits	Total transaction account volume in thousands of USD (RCON2215). Aggregated to the county level. Source: FDIC / FFIEC Quarterly Call Reports.
Private demand deposits	Total transaction account volume of individuals, partnerships, and corporations in thousands of USD (RCONB549). Aggregated to the county level. Source: FDIC / FFIEC Quarterly Call Reports.
Savings deposits	Nontransaction accounts total in thousands of USD (RCON2385). Aggregated to the county level. Source: FDIC / FFIEC Quarterly Call Reports.
Control variables	
Total cases per capita	Total COVID-19 cases per county per quarter. County level. Source: Johns Hopkins University Center for Systems Science and Engineering (JHU CSSE). Accessed through github: https://github.com/CSSEGISandData/COVID-19/.
Total deaths per capita (x1000)	Total COVID-19 deaths per county per quarter. County level. Source: County level. Source: Johns Hopkins University Center for Systems Science and Engineering (JHU CSSE). Accessed through github: https://github.com/CSSEGISandData/COVID-19/.
Mobility: retail	Google mobility index (quarter average) for retail & recreation, places like restaurants, cafes, shopping centers, theme parks, museums, libraries, and movie theaters. County level. Source: Google.
Mobility: driving	Apple mobility index (quarter average) for driving as the mode of transport. County level. Source: Apple.
Mobility: residential	Google mobility index (quarter average) for places of residence. County level. Source: Google.
% pop over 64 yrs	Share of the population over the age of 64. County level. Source: US Census.
% pop no high school	% of the population 25 or older without a high school degree or equivalent. County level. Source: US Census.
% pop w/ college degree	% of the population 25 or older with a college degree or equivalent. County level. Source: US Census.
% construction	% of the employed population 16 or older working in the construction sector. County level. Source: US Census.
% manufacturing	% of the employed population 16 or older working in the manufacturing sector. County level. Source: US Census.
% service	% of the employed population 16 or older working in the service sector. County level. Source: US Census.
Gini	County level gini coefficient. County level. Source: US Census.
% Urban	% of the employed population in urban areas. County level. Source: US Census.
% Republican (00-16)	Vote share of the republican candidate for president in %. Average over the years 2000-2016. County level. Source: Harvard Datalab.
% Republican 2020	Vote share of the republican candidate for president in 2020 in %. County level. Source: Harvard Datalab.

Sources: Apple Mobility Data: https://covid19.apple.com/mobility
Google Mobility Reports: https://www.google.com/covid19/mobility/
COVID-19 Data: https://github.com/CSSEGISandData/COVID-19/tree/master/csse_covid_19_data/csse_covid_19 _time_series
Census Data: https://data.census.gov/cedsci/
Election Data: https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/VOQCHQ

Variable definitions - continued

Additional dependent variables	
Total deposits	Total deposits. Sum of all checking deposits and all savings deposits (RCON2200). Aggregated to the county level. Source: FDIC / FFIEC Quarterly Call Reports.
Total liabilities	Total liabilities (RCON2948). Aggregated to the county level. Source: FDIC / FFIEC Quarterly Call Reports.
Total equity	Total equity capital (RCONG105). Aggregated to the county level. Source: FDIC / FFIEC Quarterly Call Reports.
Credit card loans	Loans to individuals for household, family, and other personal expenditures - credit cards (RCONB538). Aggregated to the county level. Source: FDIC / FFIEC Quarterly Call Reports.
Consumer loans	Loans to individuals for household, family, and other personal expenditures - Other consumer loans (includes single payment and installment, loans other than automobile loans, and all student loans) (RCONK207). Aggregated to the county level. Source: FDIC / FFIEC Quarterly Call Reports.
Commercial loans	Commercial and industrial loans (RCON1766). Aggregated to the county level. Source: FDIC / FFIEC Quarterly Call Reports.
Real estate loans	All loans secured by real estate (RCONF158 + RCONF159 + RCON1420 + RCON1797 + RCON5367 + RCON5368 + RCON1460 + RCONF160 + RCONF161). Aggregated to the county level. Source: FDIC / FFIEC Quarterly Call Reports.
Total loans	Total loans and leases held for investment and held for sale (RCON2122). ggregated to the county level. Source: FDIC / FFIEC Quarterly Call Reports.
Amplification variables	
Cases Q1 2020 (x1000)	Total case numbers in each county at the beginning of the pandemic (Q1 2020). Source: County level. Source: Johns Hopkins University Center for Systems Science and Engineering (JHU CSSE). Accessed through github: https://github.com/CSSEGISandData/COVID-19/
Community health	Measure of community health, aggregating information on memberships in religious and non-religious organizations and civic engagement. Source: Joint Economic Committee - Republicans.
GPS: patience	Measure of individuals time preference from the Global Preference Survey. Aggregated to the U.S. state level for the analysis. Source: Falk et al. (2018).
GPS: risk taking	Measure of individuals risk preference from the Global Preference Survey. Aggregated to the U.S. state level for the analysis. Source: Falk et al. (2018).
GPS: negative reciprocity	Measure of individuals willingness to punish others for bad behavior or to take revenge from the Global Preference Survey. Aggregated to the U.S. state level for the analysis. Source: Falk et al. (2018).
GPS: trust	Measure of individual's assumption that other people have good intentions from the Global Preference Survey. Aggregated to the U.S. state level for the analysis. Source: Falk et al. (2018).

Table A4: Effect of news media coverage on mobility

The table displays regression results using six mobility indices from google as the dependent variables. Dependent and independent variables vary over counties and days. All mobility indices are provided by Google. Work indicates mobility at workplaces. Transit indicates mobility at transit hubs. Retail and recreation indicates mobility at retail and recreational establishments. Grocery indicates mobility at grocery stores. Residential indicates mobility in residential areas. Parks indicates mobility in parks. Covid coverage share is the share of pandemic related local news stories relative to all news stories. A local news story is pandemic related if it contains any of the following key words: pandemic, covid, coronavirus or virus. Day fixed effects are included in all regressions. Clustered standard errors on the county level of the point estimates are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Dependent variable:	Work	Transit	Retail & rec.	Grocery	Residential	Parks
	(1)	(2)	(3)	(4)	(5)	(6)
Covid coverage share	-1.049*	-6.360**	-4.066***	-4.142***	1.185***	-13.785***
	(0.564)	(2.622)	(1.482)	(1.263)	(0.311)	(4.624)
L1.log(NewCases)	-0.139***	-0.435***	-0.076*	-0.137***	0.093***	-0.149
	(0.034)	(0.082)	(0.045)	(0.040)	(0.014)	(0.184)
L1.log(NewDeaths)	-0.013	-0.128	-0.109	-0.123*	0.002	-1.569***
	(0.060)	(0.138)	(0.077)	(0.069)	(0.027)	(0.296)
Day FE	Yes	Yes	Yes	Yes	Yes	Yes
Lags	Yes	Yes	Yes	Yes	Yes	Yes
No. of obs.	121,303	121,303	121,303	121,303	121,303	121,303
No. of counties	576	576	576	576	576	576
R^2	0.806	0.330	0.644	0.532	0.739	0.319

Table A5: Correlating media coverage and deposits: simple OLS regression

The table regresses various deposit types on covid coverage share. Covid coverage share is the share of pandemic related local news stories relative to all news stories, averaged over each quarter. A local news story is pandemic related if it contains any of the following key words: pandemic, covid, coronavirus or virus. Quarter fixed effects are included in all regressions. Clustered standard errors on the county level of the point estimates are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively

	Checking			Saving
Dependent Variable (deposits):	All	Private	Demand	All
	(1)	(2)	(3)	(4)
Covid coverage share	0.721***	0.750***	0.785***	1.097***
	(0.217)	(0.221)	(0.233)	(0.272)
Cases per capita	-0.918	-1.335	-1.465	-3.210
	(1.783)	(1.810)	(1.891)	(2.109)
Deaths per capita (x1000)	-0.219***	-0.234***	-0.245***	-0.241***
	(0.053)	(0.054)	(0.056)	(0.067)
Quarter FE	Yes	Yes	Yes	Yes
No. of obs.	7,415	7,415	7,415	7,415
No. of counties	1,514	1,514	1,514	1,514
R^2	0.019	0.021	0.021	0.011

Table A6: Correlating media coverage and deposits: county fixed effect

The table regresses various deposit types on covid coverage share including county fixed effects. Covid coverage share is the share of pandemic related local news stories relative to all news stories, averaged over each quarter. A local news story is pandemic related if it contains any of the following key words: pandemic, covid, coronavirus or virus. Quarter and county fixed effects are included in all regressions. Clustered standard errors on the county level of the point estimates are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively

	Checking			Saving
Dependent Variable (deposits):	All	Private	Demand	All
	(1)	(2)	(3)	(4)
Covid coverage share	0.042	0.046	0.062*	-0.015
	(0.030)	(0.032)	(0.035)	(0.015)
Cases per capita	-0.436*	-0.300	-0.309	-0.142
	(0.248)	(0.265)	(0.265)	(0.158)
Deaths per capita (x1000)	-0.006	-0.002	-0.000	-0.001
	(0.008)	(0.008)	(0.009)	(0.007)
Quarter FE	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
No. of obs.	7,415	7,415	7,415	7,415
No. of counties	1,514	1,514	1,514	1,514
R^2	0.982	0.980	0.982	0.994

Table A7: Correlating media coverage and deposits: media market fixed effect

The table regresses various deposit types on covid coverage share including media market fixed effects. Covid coverage share is the share of pandemic related local news stories relative to all news stories, averaged over each quarter. A local news story is pandemic related if it contains any of the following key words: pandemic, covid, coronavirus or virus. Quarter and media market fixed effects are included in all regressions. Clustered standard errors on the county level of the point estimates are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively

		Checking		Saving
Dependent Variable (deposits):	All	Private	Demand	All
	(1)	(2)	(3)	(4)
Covid coverage share	0.049	0.056	0.071*	-0.014
	(0.033)	(0.035)	(0.038)	(0.021)
Cases per capita	5.310***	5.392***	6.115***	7.202***
	(1.458)	(1.475)	(1.528)	(1.712)
Deaths per capita (x1000)	-0.262***	-0.271***	-0.295***	-0.264***
	(0.042)	(0.043)	(0.045)	(0.051)
Quarter FE	Yes	Yes	Yes	Yes
Media market FE	Yes	Yes	Yes	Yes
No. of obs.	7,415	7,415	7,415	7,415
No. of counties	1,514	1,514	1,514	1,514
R^2	0.213	0.219	0.225	0.268

Table A8: Media coverage and deposits: pandemic intensity controls

The table displays the results from column (1) of table 3 for all dependent variables used in table 2. The interaction is designed to control for the intensity of the pandemic. Cases per capita are total COVID-19 related cases per capita in each county over the sample period. Deaths per capita are totoal COVID-19 related deaths per capita in each county over the sample period. The data stems from Johns Hopkins University. Detailed variable definitions and explanations can be found in table A3 and section 2. The dependent variables are: all deposits, private deposits and demand deposits in checking accounts, as well as deposits in all savings accounts. All dependent variables are used in logs in the regression. Post is a dummy set equal to 0 from Q1 2019-Q4 2019 and set equal to 1 from Q1 2020- Q1 2021. Covid coverage share is the share of pandemic related local news stories relative to all news stories, averaged over the sample period from January 2020 through March 2021. A local news story is pandemic related if it contains any of the following key words: pandemic, covid, coronavirus or virus. County and quarter fixed effects are included in all regressions. Clustered standard errors on the county level of the point estimates are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

		Checking		Saving
Dependent Variable (deposits):	All	Private	Demand	All
	(1)	(2)	(3)	(4)
Post × covid coverage share (avg)	0.206**	0.242***	0.234**	0.032
	(0.090)	(0.087)	(0.096)	(0.063)
Post × cases per capita	-1.008***	-1.085***	-0.795**	-0.187
	(0.364)	(0.381)	(0.387)	(0.291)
Post × deaths per capita	-0.020**	-0.024**	-0.022*	-0.005
	(0.010)	(0.010)	(0.012)	(0.012)
Quarter FE	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
No. of obs.	13,605	13,605	13,605	13,605
No. of counties	1,526	1,526	1,526	1,526
R^2	0.968	0.966	0.963	0.986

Table A9: Media coverage and deposits: lockdown & mobility controls

The table displays the results from column (2) of table 3 for all dependent variables used in table 2. The mobility interaction is intended to control for the effect of government- and self-imposed lock-down measures. Mobility: retail is an index of mobility at retail and recreational establishments for each county. The index stems from google and is averaged over the sample period. Mobility: driving is an index of mobility using a car as mode of transportation. The index stems from search requests in Apple maps and is average over the sample period. Detailed variable definitions and explanations can be found in table A3 and section 2. The dependent variables are: all deposits, private deposits and demand deposits in checking accounts, as well as deposits in all savings accounts. All dependent variables are used in logs in the regression. Post is a dummy set equal to 0 from Q1 2019-Q4 2019 and set equal to 1 from Q1 2020- Q1 2021. Covid coverage share is the share of pandemic related local news stories relative to all news stories, averaged over the sample period from January 2020 through March 2021. A local news story is pandemic related if it contains any of the following key words: pandemic, covid, coronavirus or virus. County and quarter fixed effects are included in all regressions. Clustered standard errors on the county level of the point estimates are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

		Checking		Saving
Dependent Variable (deposits):	All	Private	Demand	All
	(1)	(2)	(3)	(4)
Post × covid coverage share (avg)	0.238**	0.319***	0.266**	0.065
	(0.119)	(0.113)	(0.131)	(0.086)
Post × mobility: retail	-0.002***	-0.002**	-0.002*	0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Post × mobility: driving	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Quarter FE	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
No. of obs.	10,245	10,245	10,245	10,245
No. of counties	1,149	1,149	1,149	1,149
R^2	0.964	0.962	0.958	0.985

Table A10: Media coverage and deposits: structural and cultural controls

The table displays the results from column (3) of table 3 for all dependent variables used in table 2. The interactions are designed to control for structural factors which might be related to coverage of the pandemic. All variables are used at the county level and do not vary over time. The data stems from the U.S. census. Detailed variable definitions and explanations can be found in table A3 and section 2. The dependent variables are: all deposits, private deposits and demand deposits in checking accounts, as well as deposits in all savings accounts. All dependent variables are used in logs in the regression. Post is a dummy set equal to 0 from Q1 2019-Q4 2019 and set equal to 1 from Q1 2020-Q1 2021. Covid coverage share is the share of pandemic related local news stories relative to all news stories, averaged over the sample period from January 2020 through March 2021. A local news story is pandemic related if it contains any of the following key words: pandemic, covid, coronavirus or virus. County and quarter fixed effects are included in all regressions. Clustered standard errors on the county level of the point estimates are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Checking			Saving
Dependent Variable (deposits):	All	Private	Demand	All
	(1)	(2)	(3)	(4)
Post × covid coverage share (avg)	0.183**	0.222**	0.210**	0.053
	(0.090)	(0.087)	(0.096)	(0.062)
Post × % pop no high school	0.000	0.000	0.000	0.001
	(0.002)	(0.002)	(0.002)	(0.002)
Post × % pop w/ college degree	0.003	0.003	0.003	0.001
	(0.002)	(0.002)	(0.002)	(0.001)
Post × % construction	0.007**	0.007*	0.007	0.006
	(0.004)	(0.004)	(0.004)	(0.004)
Post × % manufacturing	0.003**	0.004**	0.005***	0.002*
	(0.001)	(0.002)	(0.002)	(0.001)
Post × % service	0.003	0.004**	0.004**	-0.002
	(0.002)	(0.002)	(0.002)	(0.001)
Post × gini	0.164	0.107	0.082	-0.386
	(0.349)	(0.390)	(0.396)	(0.286)
Post × % Urban	0.001	0.001	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Quarter FE	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
No. of obs.	13,605	13,605	13,605	13,605
No. of counties	1,526	1,526	1,526	1,526
R^2	0.968	0.966	0.963	0.986

Table A11: Media coverage and deposits: political controls

The table displays the results from column (4) of table 3 for all dependent variables used in table 2. The interactions are designed to control for political factors which might be related to coverage of the pandemic. % Republican (00-16) is the average voter share of republicans candidates for president from 2000-2016 in each county. % Republican 2020 is the share of voters that voted for Donald Trump in the 2020 election in each county. Detailed variable definitions and explanations can be found in table A3 and section 2. The dependent variables are: all deposits, private deposits and demand deposits in checking accounts, as well as deposits in all savings accounts. All dependent variables are used in logs in the regression. Post is a dummy set equal to 0 from Q1 2019-Q4 2019 and set equal to 1 from Q1 2020-Q1 2021. Covid coverage share is the share of pandemic related local news stories relative to all news stories, averaged over the sample period from January 2020 through March 2021. A local news story is pandemic related if it contains any of the following key words: pandemic, covid, coronavirus or virus. County and quarter fixed effects are included in all regressions. Clustered standard errors on the county level of the point estimates are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Checking			Saving
Dependent Variable (deposits):	All	Private	Demand	All
	(1)	(2)	(3)	(4)
Post × covid coverage share (avg)	0.205**	0.244***	0.239**	0.044
	(0.087)	(0.082)	(0.093)	(0.062)
Post × % Republican (00-16)	0.004	0.004	0.003	0.000
	(0.003)	(0.003)	(0.003)	(0.002)
Post × % Republican 2020	-0.006**	-0.007***	-0.005*	0.000
	(0.002)	(0.003)	(0.003)	(0.002)
Quarter FE	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
No. of obs.	13,596	13,596	13,596	13,596
No. of counties	1,525	1,525	1,525	1,525
R^2	0.968	0.966	0.963	0.986

Table A12: Media coverage and deposits: all controls

The table displays the results from column (5) of table 3 for all dependent variables used in table 2. The table jointly includes all potential alternative explanations of the previous tables. Detailed variable definitions and explanations can be found in table A3 and section 2. The dependent variables are: all deposits, private deposits and demand deposits in checking accounts, as well as deposits in all savings accounts. All dependent variables are used in logs in the regression. Post is a dummy set equal to 0 from Q1 2019-Q4 2019 and set equal to 1 from Q1 2020- Q1 2021. Covid coverage share is the share of pandemic related local news stories relative to all news stories, averaged over the sample period from January 2020 through March 2021. A local news story is pandemic related if it contains any of the following key words: pandemic, covid, coronavirus or virus. County and quarter fixed effects are included in all regressions. Clustered standard errors on the county level of the point estimates are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

		Checking		Saving
Dependent Variable (deposits):	All	Private	Demand	All
	(1)	(2)	(3)	(4)
Post × covid coverage share (avg)	0.178	0.250**	0.206	0.074
	(0.116)	(0.110)	(0.126)	(0.082)
Post × cases per capita	-0.841*	-0.856	-0.650	-0.662
	(0.507)	(0.526)	(0.528)	(0.421)
Post × deaths per capita	-0.004	-0.009	-0.003	0.018
	(0.015)	(0.016)	(0.019)	(0.016)
Post × mobility: retail	-0.000	0.000	-0.000	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)
Post × mobility: driving	0.001*	0.001*	0.001	0.000*
	(0.000)	(0.000)	(0.000)	(0.000)
Post × % pop no highschool	0.002	0.001	0.002	0.001
	(0.003)	(0.003)	(0.003)	(0.002)
Post × % pop w/ college degree	0.003	0.002	0.002	0.002
	(0.003)	(0.003)	(0.003)	(0.002)
Post × % construction	0.002	0.001	0.001	0.005
	(0.006)	(0.007)	(0.007)	(0.005)
Post × % manufacturing	0.002	0.003	0.005	0.003
	(0.003)	(0.003)	(0.003)	(0.002)
Post × % service	0.000	0.001	0.002	-0.002
	(0.003)	(0.003)	(0.003)	(0.003)
Post × gini	0.173	0.282	0.093	-0.556
	(0.443)	(0.473)	(0.539)	(0.409)
Post × % Urban	0.001*	0.001*	0.001	0.000
	(0.001)	(0.001)	(0.001)	(0.000)
Post × % Republican (00-16)	0.001	0.001	0.001	0.002
	(0.004)	(0.004)	(0.004)	(0.003)
Post × % Republican 2020	-0.001	-0.001	-0.001	-0.001
	(0.003)	(0.003)	(0.004)	(0.003)
Quarter FE	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
No. of obs.	10,245	10,245	10,245	10,245
No. of counties	1,149	1,149	1,149	1,149
R^2	0.964	0.962	0.958	0.985

Table A13: Effect of media coverage under different circumstances

The table presents results of additional triple interactions, analogous to table 5. Non-profit denotes membership in non-profit organizations. Religious congregations denotes membership in religious congregations. Membership denotes membership in any organization. Associations denotes memberships in recreational establishments. Charity denotes the share of charitable contributions as a share of average income. Positive reciprocity describes the propensity to act in a reciprocal manner. Altruism denotes the tendency towards altruistic actions. Math denotes math skills. Global Preference survey (Falk et al., 2018) measures are state level aggregates. The other variables stem from the Social Capital in America Project and vary on the county level. The dependent variable for all columns is the log of private deposits in checking accounts. Post is a dummy set equal to 0 from Q1 2019-Q4 2019 and set equal to 1 from Q1 2020- Q1 2021. Covid coverage share is the share of pandemic related local news stories relative to all news stories, averaged over the sample period from January 2020 through March 2021. A local news story is pandemic related if it contains any of the following key words: pandemic, covid, coronavirus or virus. County and quarter fixed effects are included in all regressions. Clustered standard errors on the county level of the point estimates are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Dependent variable: Private deposits (checking)						Global preference survey:		
	non-profit	religious congregations	membership	associations	charity	pos. reciprocity	altruism	math
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post × covid coverage share (avg)	0.341***	0.553***	0.365***	0.383***	0.421***	0.239***	0.245***	0.283
	(0.101)	(0.118)	(0.113)	(0.110)	(0.121)	(0.088)	(0.088)	(0.350)
Post × covid coverage share (avg) × Non-profits	-0.030*							
	(0.017)							
Post × covid coverage share (avg) × Religious congregation		-0.152***						
		(0.029)						
Post × covid coverage share (avg) × Membership in org.			-0.013**					
			(0.006)					
Post × covid coverage share (avg) × Associations				-0.015***				
				(0.005)				
Post × covid coverage share (avg) × Charity					-0.042**			
					(0.021)			
Post × covid coverage share (avg) × GPS: pos. rec.						-0.021		
						(0.127)		
Post × covid coverage share (avg) × GPS: altruism							-0.013	
							(0.148)	
Post × covid coverage share (avg) × GPS: math skills								-0.006
								(0.053)
Post × cases per capita	-1.205***	-0.837**	-1.054***	-0.982**	-0.968**	-1.090***	-1.088***	-1.087***
	(0.389)	(0.380)	(0.382)	(0.386)	(0.378)	(0.384)	(0.385)	(0.382)
Post × deaths per capita	-0.026**	-0.014	-0.023**	-0.023**	-0.020*	-0.024**	-0.024**	-0.024**
	(0.010)	(0.010)	(0.010)	(0.010)	(0.011)	(0.010)	(0.010)	(0.010)
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of obs.	13,605	13,605	13,605	13,605	13,605	13,605	13,605	13,605
No. of counties	1,526	1,526	1,526	1,526	1,526	1,526	1,526	1,526
R^2	0.966	0.966	0.966	0.966	0.966	0.966	0.966	0.966

Table A14: Determinants of media coverage

This table investigates the determinants of COVID-19 coverage. The dependent variable is the covid coverage share. There are four different sets of independent variables of interest: pandemic measures to control for the intensity of the pandemic (column (1)), mobility variables to control for lock-downs (column (2)), structural variables to control for cultural and socio-economic determinants (column (3)) and political variables (column (3)). Column (5) controls for all sets of predictors at the same time. All variables are time invariant. Covid coverage share is the share of pandemic related local news stories relative to all news stories, averaged over the sample period from January 2020 through March 2021. A local news story is pandemic related if it contains any of the following key words: pandemic, covid, coronavirus or virus. Table A3 defines all variables and section 2 describes the data collection process in detail. Clustered standard errors on the media market level of the point estimates are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Dependent variable:	Covid coverage share (avg)				
	Cases	Mobility	Structural	Politics	All
	(1)	(2)	(3)	(4)	(5)
Cases per capita	0.231				0.241
	(0.429)				(0.521)
Deaths per capita (x1000)	-0.003				0.000
	(0.008)				(0.013)
Mobility: retail		-0.000			-0.000
		(0.000)			(0.000)
Mobility: driving		-0.000			-0.000
		(0.000)			(0.000)
% pop no high school			0.001**		0.001*
			(0.001)		(0.001)
% pop w/ college degree			0.001***		0.001
			(0.000)		(0.001)
% construction			0.002**		0.004***
			(0.001)		(0.001)
% manufacturing			0.001**		0.001
			(0.000)		(0.001)
% service			0.001*		0.001
			(0.000)		(0.001)
Gini			0.047		0.014
			(0.053)		(0.066)
% Urban			-0.000		-0.000
			(0.000)		(0.000)
% Republican (00-16)				0.000	-0.000
				(0.001)	(0.001)
% Republican 2020				-0.001	-0.000
				(0.000)	(0.001)
Mobility: residential					0.002*
					(0.001)
Quarter FE	Yes	Yes	Yes	Yes	Yes
County FE	No	No	No	No	No
No. of obs.	13,605	10,245	13,605	13,596	8,949
No. of media markets	138	138	138	138	138
R^2	0.709	0.750	0.713	0.710	0.762

Table A15: Expanding the view: the effect on liabilities

The table displays estimates of equation 1 using three dependent variables from the passive side of the balance sheet: total deposits, total liabilities and total equity. All dependent variables are aggregated to the county level and are used in logs in the regression. Post is a dummy set equal to 0 from Q1 2019-Q4 2019 and set equal to 1 from Q1 2020- Q1 2021. Covid coverage share is the share of pandemic related local news stories relative to all news stories, averaged over the sample period from January 2020 through March 2021. A local news story is pandemic related if it contains any of the following key words: pandemic, covid, coronavirus or virus. Table A3 defines all variables and section 2 describes the data collection process in detail. County and quarter fixed effects are included in all regressions. Clustered standard errors on the county level of the point estimates are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Dependent variable:	Total deposits	Total liabilities	Total equity
	(1)	(2)	(3)
Post $\times$ covid coverage share (avg)	0.103	0.053	-0.013
	(0.063)	(0.065)	(0.064)
Quarter FE	Yes	Yes	Yes
County FE	Yes	Yes	Yes
No. of obs.	13,605	13,592	13,592
No. of counties	1,526	1,525	1,525
R^2	0.986	0.986	0.986