Working Remotely and the Supply-Side Impact of COVID-19

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We analyze the supply-side disruptions associated with COVID-19. We find that sectors in which a higher fraction of the workforce is not able to work remotely experienced greater declines in employment and expected revenue growth, worse stock market performance, and higher likelihood of default. The stock market overweights low-exposure industries. Thus, our findings cast light on the disconnect between stock market indices and aggregate outcomes. We combine these ex ante heterogeneous industry exposures with daily financial market data to create a stock return portfolio that tracks news about the supply-side disruptions resulting from the pandemic. (JEL G12, D22, H25, J20, E00)

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The COVID-19 pandemic of 2020 has led to severe disruptions to the supply side of the world economy as entire sectors have shut down. In the first quarter of 2020, U.S. gross domestic output fell by 4.8% in annualized terms, a decline not seen since the Great Recession. This drop underestimates the full economic impact of the pandemic, as the severity of the crisis became fully apparent to the public and private sectors only in the last few weeks of March 2020. Moreover, the effect has been highly asymmetric: restaurants, entertainment, and travel services have suffered significantly more than food or technology services. Naturally, these declines reflect not only the supply-side disruptions due to the effect of government-mandated lockdowns, but also demand-side factors, including the collapse of global consumer demand and expectations of future government policy. This confluence of adverse

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forces obscures the direct effects of the supply-side disruptions of the pandemic.

Our goal is to isolate the supply-side effects from other forces. By *supply-side disruptions* we are referring to disruptions that prevented certain businesses from operating effectively during the pandemic, including disruptions in the production process, difficulties in delivering their product or service to the final customer, and reluctance of consumers to purchase the service due to fears of the pandemic.\(^1\) Our starting point is the assumption that industries in which a higher fraction of the labor force can work remotely are likely to experience less-severe disruptions in their business operations. We build on prior research and construct a metric of industry exposure to the lockdowns using information on the share of the workforce that can work from home (Dingel and Neiman 2020; Alon et al. 2020). Specifically, we follow Alon et al. (2020) and exploit data from the American Time Use Survey (ATUS) of 2017 and 2018, in which workers disclose the extent to which they are able to and have historically had experience working remotely. As noted by Alon et al. (2020), occupations vary immensely in the proportion of workers who report that they are able to telecommute—ranging from 3% for transportation and material moving to 78% for computer programmers. We aggregate these survey responses to build measures of exposure across industries and groups of workers.

In brief, our measure of supply-side disruption for a given industry, termed “COVID-19 work exposure,” is equal to 1 minus the fraction of workers that have telecommuted—more specifically, the fraction that have ever worked full days from home—in each industry. Importantly, there is considerable dispersion in our exposure measure across industries. For example, Software Publishers (NAICS 5112) have an exposure of just 0.38, since much of the production work can be done remotely. By contrast, Meat Production (NAICS 3116) or General Merchandise Stores (NAICS 4523) workers have an exposure close to 1, since most of the employees cannot perform their work remotely.

Government restrictions also play a role in firms’ ability to continue operations. Specifically, local governments typically deem certain industries as critical, namely those that provide “essential infrastructure.” Thus, we also manually classify some industries as “critical.” Since the definition of critical industries varies greatly across states, we aim to be conservative, classifying as critical those industries related to the production and sale of food and beverages, utilities, pharmacies, transportation, waste collection and disposal, and similar.

\(^1\) One could argue that the consumer reluctance is a demand-side effect. We disagree. Reluctance to consume in-person services in the pandemic did not result from a shift in consumer preferences or wealth effects. It resulted from firms’ inability to deliver these services without the risk of infection. We label this a supply-side effect. That said, we cannot rule out the possibility that firms whose workers cannot easily work from home also faced above-average exposure to demand shocks triggered by the decline in aggregate demand. However, personal income actually rose during the recession across the board (due to personal transfers). As such, we believe that it is unlikely that demand-side forces are driving our findings.
and some healthcare and financial services. Data on foot traffic from SafeGraph validate our construction: establishments in industries deemed critical experience significantly smaller declines in traffic than establishments in noncritical industries, while before the pandemic, from January to February 2020, trends in foot traffic in critical industries were nearly identical to those in noncritical industries.

Armed with a measure of industry exposure to these supply-side disruptions, we can answer several important questions regarding the economic impact of the pandemic. Focusing on cross-sectional differences in the feasibility of remote work (COVID-19 work exposure) allows us to isolate the direct impact of the shutdown from other economic forces that would otherwise affect industries across the economy symmetrically.

First, we examine the degree to which differences in COVID-19 work exposure are related to heterogeneity in economic outcomes during the pandemic. In terms of employment, we find that sectors with a larger fraction of workers who cannot work remotely—higher COVID-19 work exposure—experienced significantly larger declines in employment than sectors where more of the workforce can perform tasks remotely. The differences are economically sizable: an increase of one standard deviation in our COVID-19 work exposure measure is associated with an approximately 7% larger decline in employment since April of 2019. The effects of exposure are starker when we restrict the sample to noncritical industries (10%). While there is a partial recovery over the second half of 2020, substantial differences between sectors remain throughout the entire year.

We next focus on firm outcomes. Given the delays in the availability of data on firms’ real activity, we complement data on realized outcomes for 2020 with changes in a set of forward-looking variables that capture future expectations about fundamentals: revisions in analyst forecasts of expected revenue growth, the expected probability of default, and firm survey responses. We find that firms in sectors that are more likely to experience work disruptions also fare significantly worse in terms of these measures during the 2020 pandemic: an increase of one standard deviation in our COVID-19 exposure metric is associated with an 8% decline in analyst revenue forecasts for Q2 and an increase of 0.30 percentage points in the probability of default over the next 2 years. These magnitudes account for a significant share of cross-industry differences in outcomes during this period. Importantly, while financial analysts expect the worst effects to be short lived, our work exposure variable is still a significant predictor of differences in expected revenue growth over the next 2 years, though magnitudes are significantly muted over this longer time horizon. Similar patterns emerge in the differences in projected revenue for noncritical versus critical industries. While analysts project that the annual revenues of firms in noncritical industries will decline by 13%, 10%, and 8% for 2020, 2021, and 2022, respectively, these same projected declines are 3.2%, 2.5%, and 2.3% for firms in
critical industries. While the relationship between longer-run growth projections and exposure is slightly attenuated following positive vaccine news near the end of 2020, substantial differences persist throughout the pandemic period we study. Last, firm-level surveys confirm that our COVID-19 exposure measure is predictive of economic hardship during the pandemic: it is indicative of both employee layoffs and insufficient liquidity.

We next turn our attention to stock market valuations. We find that differences in our COVID-19 work exposure measure are significantly related to differences in stock returns during the early phase of the pandemic (February to May 2020). An increase of one standard deviation in our exposure measure is associated with a 7% decline in stock market performance. A key advantage of financial market variables is that they are available at high frequencies. To this end, we use financial market data to construct a real-time indicator of supply-side disruptions. In particular, we use daily data on stock returns to construct a portfolio that is maximally exposed to the COVID-19 work disruption using the methodology of Fama and MacBeth (1973). The resulting “COVID-19” factor has a long-short portfolio interpretation. It overweights industries whose workers cannot work remotely and underweights industries whose workers can perform their tasks from home. As of May 15, 2020, this portfolio had lost roughly 50% of its value since the beginning of the year, compared to 10% for the broad market index. Naturally, reversing this investment strategy would deliver a portfolio that could significantly hedge future COVID-19-related uncertainty.

Comparing the performance of the stock market to the real economy in 2020 reveals an apparent disconnect. After falling sharply in late February and early March, the stock market almost fully recovers its losses by the middle of the summer. By contrast, the economy is still in a severe recession, as evidenced by high unemployment rates. Our measure sheds some light on this pattern: the composition of listed firms in the stock market is heavily tilted towards industries with low work exposure. As an illustration, we note that when industries are weighted by the market capitalization of listed firms the average industry has an exposure of only 66%, which is considerably lower than the 87% obtained by weighting the same set of industries according to a measure of employment which includes all firms (publicly and privately held) in the sector. Likewise, stock market indices that weigh industries according to the same measure of employment are almost 10 percentage points lower than a market capitalization–weighted index as of midyear, and around 6 percentage points lower as of December 2020.

So far, our analysis indicates that the supply-side disruptions are economically large and are responsible for substantial heterogeneity in outcomes across sectors. Our results thus complement the work of Barrero et al. (2021), which points out that COVID-19 is also a reallocation shock. The relative differences that we uncover validate this view: the COVID-19 pandemic, in addition to having aggregate effects, leads to a reallocation of
resources away from sectors in which remote work is infeasible toward sectors where workers can continue to work remotely. Most importantly, however, this cross-sectoral reallocation is not the only distributional effect of the COVID-19 pandemic. We also find that the pandemic affects workers differentially based on their demographic characteristics. Specifically, a given increase in our COVID-19 work exposure measure is associated with a greater increase in the probability of nonemployment for women and lower-earning workers versus other groups. Among all affected groups, we find that the employment status of female workers with young children and without a college degree is most sensitive: in the cross-section of workers, an increase of one standard deviation in our COVID-19 work exposure measure is associated with a 15% probability of nonemployment for these workers, which is more than three times the magnitude of the baseline coefficient. To the extent these effects are persistent, our findings suggest that the pandemic will increase income inequality and magnify earnings differences between male and female workers.

In response to the pandemic, the U.S. government authorized significant fiscal responses. A key component of the 2020 Coronavirus Aid, Relief, and Economic Security (CARES) Act was the Paycheck Protection Program (PPP), a direct subsidy to firms that took the form of forgivable loans. Our exposure measure can also help judge the efficiency of this response: one might expect that larger amounts of aid would be allocated to the most exposed industries. Perhaps surprisingly, we find the opposite. In particular, we find that almost all small firms applied for PPP financing. Importantly, however, PPP funds are allocated in proportion to total payroll expenses. Since higher-paid employees are more likely to be able to work remotely, tying financing to payroll expenses has the (likely unintended) consequence of allocating more federal funds to the least-affected sectors. For instance, firms in the professional and technical services sectors, one of the least-exposed sectors, received more than $12,400 per employee. By contrast, firms in the accommodation and food services sector, one of the most disrupted sectors, receive approximately $5,000 per worker. Using data at the individual loan level, we find that a change of one standard deviation in our measure of work exposure is associated with a 17% decline in the average loan size per employee. When we limit the sample to noncritical industries, this decline increases to 19%. This negative correlation between the amount of federal aid and the degree workers were affected by the pandemic is likely at odds with an optimal policy prescription (see, e.g. Guerrieri et al. 2020) but consistent with evidence from Granja et al. (2020) suggesting that PPP loans do not disproportionately flow to regions which are more adversely affected. Given the fact that lower-income workers have higher marginal propensities to consume, a more targeted intervention likely would have been a more efficient use of federal funds in stimulating aggregate output (see Kaplan and Violante 2018, for a review of the literature).
Our work contributes to the voluminous economics literature that has emerged in response to the pandemic. The key differentiator of our work is its focus on isolating the supply-side disruptions associated with COVID-19 by exploiting cross-sectional differences in the ability to work remotely. By contrast, existing work has focused on the overall response of the economy during this period.\(^2\) How firms respond during the pandemic is a function of both the underlying supply-side disruptions (our focus) and also firms’ exposures to a decline in consumer demand as a result of expected income losses and increase in uncertainty. Our goal is to isolate the former from the latter channel. In this respect, our work is closer to Bonadio et al. (2020), which focuses on the role of global supply chains, Davis, Hansen, and Seminario-Amez (2020), which estimates firm-level pandemic risk exposures using textual analysis of pre-pandemic 10-K filings, or Hassan et al. (2020), which identifies differences in firms’ exposure based on the transcript of analyst calls.

Our paper is also related to recent work by Dingel and Neiman (2020), Alon et al. (2020), Mongey, Pilossof, and Weinberg (2020) and Koren and Peto (2020). Dingel and Neiman (2020) and Koren and Peto (2020) construct measures of the feasibility of workers to work from home using task descriptions in the O*Net survey. Like us, Alon et al. (2020) construct a measure based on workers’ answers to the American Time Use Survey (ATUS). Though the details of the construction differ, the main idea is similar. Dingel and Neiman (2020) and Alon et al. (2020) mainly focus on demographic differences among workers who can and cannot work remotely; by contrast, we are interested in how the ability to work from home is related to outcomes. In this respect, our work is closest to Mongey et al. (2020) and Koren and Peto (2020), who explore how the feasibility of remote work combined with measures of high physical proximity requirements relate to differential outcomes across workers. Though the first part of our analysis also explores worker-level outcomes, our primary focus is on firms. In contemporaneous work, Pagano, Wagner, and Zechner (2020) examine how the measure developed in Koren and Peto (2020) is related to differences in stock market performance and argue that “pandemic risk” is priced in the 2014–19 period. Our focus instead is on understanding ex post heterogeneity in economic outcomes. In this regard, we view our work as complementary.

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\(^2\) Recent work examines the response of employment (Coibion, Gorodnichenko, and Weber 2020b; Cajner et al. 2020; Campello, Kankanhalli, and Muthukrishnan 2020; Borjas and Cassidy 2020; Couch, Fairlie, and Xu 2020); firm revenue, earnings and dividends, (Barrero et al. 2021; Landier and Thesmar 2020; Gormsen and Kojen 2020); firm exit (Bartik et al. 2020); stock market performance (Ding et al. 2021; Giglio et al. 2020; Baker et al. 2020); or consumer spending (Baker et al. 2020; Coibion, Gorodnichenko, and Weber 2020a) during this period.
1. Measuring COVID-19 Production Disruptions

We begin with a brief description of our construction of exposure measures from the data.

1.1 Workers’ ability to work remotely

Following the rapid increase in cases throughout the U.S., many employers as well as state and local governments quickly imposed restrictions requiring that workers stay at home, leading to what is essentially the largest global experiment in telecommuting in human history. Our starting point is the simple premise that supply-side disruptions are likely to be more severe in occupations/industries for which workers have had little-to-no ability to telework or experience with telework in the past. Accordingly, our measure of industry exposure to work disruptions due to COVID-19 builds on Alon et al. (2020), which uses data from the Leave and Job Flexibilities module of the ATUS in 2017 and 2018 (containing 10,040 observations in total) regarding workers’ ability to work from home and past experiences with working from home. Our preferred measure utilizes responses to two different questions from the ATUS, though the module also includes several additional questions about reasons for and frequency of remote work. We obtain the ATUS microdata from Integrated Public Use Microdata Series.3

Crucially, the survey draws a distinction between workers who are able to telecommute and those who are not, as opposed to those who regularly telecommute and those who do not, as the former is the relevant metric during a pandemic.4 From these questions, we construct an occupation/industry-level metric of the fraction of workers in each occupation that should, in principle, be able to work from home. The first major question asks for a yes/no reply to the following: “As part of your (main) job, can you work at home?” Using the survey’s person weights, approximately 78% of households answer yes to this question. Alon et al. (2020) use this question to identify the share of workers in a given occupation that are able to telecommute and examine the share of workers in various demographic groups who are employed in occupations that can be performed from home.

Our preferred measure also makes use of responses to one additional question, which is only asked to those who say that they are able to work from home: “Are there days when you work only at home?” Around 51% of households who are able to work from home also indicate that they have worked days entirely from home. In our view, this question provides a

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3 S. L. Hofferth, S. M. Flood, M. Sobek and D. Backman. 2020. American Time Use Survey Data Extract Builder: Version 2.8 [dataset]. College Park, MD: University of Maryland and Minneapolis, MN: IPUMS. https://doi.org/10.18128/D060.V2.8

4 For example, the Census Bureau’s American Community Survey asks whether workers worked from home last week, which captures regular telecommuting behavior. According to the Census Bureau, around 4.3% of workers worked from home according to this measure in 2010 (Mateyka, Rapino, and Landivar 2012).
sharper classification of workers who will more likely be able to perform the majority of their job responsibilities from home, as opposed to only a subset of tasks (e.g., answering emails/phone calls) remotely. For example, 64% of computer and information systems managers (Census occupation code 110) say that they can work from home, and 47% of them have worked days entirely from home. These same proportions are 59% and just 13%, respectively, for medical and health services managers (occupation 350), a group that, in our view, is a part of a population of workers who are more likely to be unable to work full time from home effectively.\(^5\)

We classify a surveyed worker as “able to work from home” if they answer “yes” to both questions above. We then compute measures of industry and occupation exposure by aggregating these survey responses across employees according to the industry and occupation codes that appear in the ATUS. Our measure of industry exposure is

\[
\text{COVID - 19 Work Exposure}_i = 1 - \% \text{ of workers able to work from home}_i, \tag{1}
\]

which is computed as a weighted average of individual-level responses aggregated so as to be nationally representative using the person weights from the Bureau of Labor Statistics (BLS). If fewer than five survey respondents are directly employed in a given Census industry, we instead extrapolate using a weighted average of occupation-based measures.\(^6\) Given that individuals’ occupations likely provide a more accurate description of the types of tasks performed on a daily basis, relative to looking at the industry which employs them, we elect to use the occupation-based measure in person-level regressions below, though we obtain similar results if we use the industry-based measure. In general, we also find similar results if we use the more inclusive Alon et al. (2020) measure instead.

As most of our outcomes by industry use NAICS-based classifications, we crosswalk between the ATUS industry codes and NAICS industries.\(^7\) We aggregate most outcomes, when available, to the four-digit NAICS level

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\(^5\) As further evidence of a sharper distinction, among households with nonmissing replies to the question “What is the main reason why you work at home?” 60% of those households who have worked days entirely from home are about twice as likely to list that they do so because their “job requires working at home,” they want to “reduce commuting time or expense,” or they have a “personal preference,” which is significantly higher than the 31% frequency for workers who have not worked an entire day from home (\(t\)-statistic on difference = 12.1). By way of contrast, among workers who have worked from home for part of their workday but not their entire day, the most common answer to this question (36% of responses) is that when they have chosen to work from home, they have done so to “finish or catch up on work.” For workers who have worked entire days from home, that answer is only selected 14% of the time (\(t = 7.3\)).

\(^6\) Specifically, we use data from the (considerably larger) 2016 American Community Survey to estimate the share of employees for each occupation by industry. We choose 2016 so that the occupation and industry codes coincide with those used in ATUS. American Community data are also taken from IPUMS: S. Ruggles, S. Flood, R. Goeken, J. Grover, E. Meyer, J. Pacas and M. Sobek. 2020. IPUMS USA: Version 10.0 [dataset]. Minneapolis, MN: IPUMS. https://doi.org/10.18128/D010.V10.0

\(^7\) We make use of the crosswalks created by Evan Soltas, (https://doi.org/10.7910/DVN/O7JLIC), which we update to use the 2017 NAICS code system.
(NAICS4) given that the industry codes available in the IPUMS ATUS extract roughly correspond with this level of aggregation.

We find that most industries are highly exposed: the mean value of the measure is approximately 85%. Yet there is considerable dispersion across NAICS industries—the cross-sectional standard deviation of our measure across four-digit NAICS industries is approximately 17%. Clearly, some industries are more exposed than others. For example, General Merchandise Stores (NAICS 4523) and Meat Production (NAICS 3116) have an exposure measure of close to 1, since almost none of the workers in those industries report that they can work from home. By contrast, the vast majority of workers employed by Software Publishers (NAICS 5112) report they can work from home, and accordingly their industry has an exposure of just 0.38.

In addition, we perform some manual adjustments to the ATUS work exposure measure. For certain industries which have been almost completely shut down, we set their exposure to 1, giving them “full exposure.” These industries cannot continue business as usual during lockdowns, even if some of their workers have the flexibility to be able to work from home in normal times. These industries include: 4811 Scheduled Air Transportation, 5121 Motion Picture and Video Industries, 5151 Radio and Television Broadcasting, 5615 Travel Arrangement and Reservation Services, 7111 Performing Arts Companies, 7112 Spectator Sports, 7113 Promoters of Performing Arts, Sports, and Similar Events, 7114 Agents and Managers for Artists, Athletes, Entertainers, and Other Public Figures, 7131 Amusement Parks and Arcades.

1.2 Critical industries
While policy responses to the COVID-19 crisis impose severe restrictions on interactions between individuals, governments find it necessary to make some exceptions, classifying industries as essential or nonessential. The Cybersecurity and Infrastructure Security Agency (CISA) provides guidelines to states about what kinds businesses should remain open. Keeping track of essential industries can enhance our analysis because it may be irrelevant if their workers can telecommute if a business is allowed to stay open. We start with Pennsylvania’s guidelines largely because the state provides a list of essential industries at the four-digit NAICS (2017) level based on the CISA guidance. These industries primarily correspond to the production and sale of food and beverages, utilities, pharmacies, transportation, waste collection and disposal, and some healthcare and financial services.

8 The CISA guidance is available at https://www.cisa.gov/publication/guidance-essential-critical-infrastructure-workforce, while the full Pennsylvania list is available at https://pgacs.org/wp-content/uploads/2020/03/452553026-UPDATED-5-45pm-March-21-2020-Industry-Operation-Guidance.pdf
While CISA’s classification of essential industries is a good place to start, we alter it for two basic reasons. First, the classification of essential industries seems too coarse in certain cases. For instance, the NAICS code 4831, Deep Sea, Coastal, and Great Lakes Water Transportation, is listed as essential by Pennsylvania. While some of the firms in this industry are shipping companies, the largest firms in this industry are cruise ships, which clearly are not permitted to maintain business as usual in a pandemic. Second, the CISA list is overly inclusive in what types of industries are classified as providing critical infrastructure. We remove industries from the critical list that faced severe restrictions on operating at a scale close to or even higher than pre-pandemic baselines. For example, restaurants, restaurant suppliers, and airlines are permitted to remain open, but the volume of their business dramatically declines due to quarantines and heavy restrictions on domestic and international travel. While some restaurants remain open for curbside and/or take-out service, it is apparent that their activities are substantially restricted during lockdowns. We have also classified industries as noncritical if they are auxiliary to such firms (such as firms in NAICS code 4244, Grocery and Related Product Merchant Wholesalers, which largely deliver food supplies to restaurants). We exclude critical industries from the bulk of our empirical analysis, and so we view our decision to narrow the scope of critical industries as conservative.\(^9\) Table A.1 provides our list of critical industries.

1.3 Validations using foot traffic data
We validate our critical/noncritical industry classification and exposure measures using weekly foot traffic data from SafeGraph.\(^10\) SafeGraph

\(^9\) As there are 311 industries represented by NAICS4 codes, we do not attempt to explain our justification by industry, but hope to provide some clarification on our thought process, which is primarily disciplined by the CISA guidelines. In the case of manufacturing, for example, the CISA guidelines state that the following workers should be deemed critical: “Workers necessary for the manufacturing of metals (including steel and aluminum), industrial minerals, semiconductors, materials and products needed for medical supply chains and for supply chains associated with transportation, aerospace, energy, communications, information technology, food and agriculture, chemical manufacturing, nuclear facilities, wood products, commodities used as fuel for power generation facilities, the operation of dams, water and wastewater treatment, processing and reprocessing of solid waste, emergency services, and the defense industrial base.” (p. 17).

As steel and aluminum are mentioned explicitly and directly correspond to NAICS codes 3312 (Steel Product Manufacturing from Purchased Steel) and 3313 (Alumina and Aluminum Production and Processing), we include those as critical. We also deem Soap, Cleaning Compound, and Toilet Preparation Manufacturing (3256), Pharmaceutical and Medicine Manufacturing (3254), Plastics Product Manufacturing (3261), Agriculture, Construction, and Mining Machinery Manufacturing (3331), and Medical Equipment and Supplies Manufacturing (3391) as critical, as these clearly fall under the jurisdiction of the quoted CISA guideline. However, as most other manufacturing NAICS codes represent industries that manufacture both products that would fit into the above categories and those that would not, we have largely chosen to designate the remainder of the manufacturing industries as noncritical.

\(^10\) We are grateful to SafeGraph for making the data freely available to our research team and the broader community for COVID-19-related work. Attribution: SafeGraph, a data company that aggregates anonymized location data from numerous applications in order to provide insights about physical places. To enhance privacy, SafeGraph excludes census block group information if fewer than five devices visited an establishment in a month from a given census block group. Further information about the data are available at https://docs.safegraph.com/docs/weekly-patterns. See also, e.g., Mongey et al. (2020) and Farboodi, Jarosch, and Shimer (2021) for additional applications of SafeGraph data to the study of COVID-19.
collects anonymized information on location activity from a large panel of mobile devices. For more than 5 million points of interest (POIs), we observe aggregated daily activity of users in the panel. As activity exhibits strong within-week seasonal patterns, we aggregate the data to the weekly level. Given our focus on workers’ ability to telecommute, we focus on visits to POIs that last for 4 hours or more, which we will refer to as “worker foot traffic.”

For each four-digit industry, we compare activity in week $t$ with a baseline level of average activity: the mean of weekly activity over the period beginning with the week of January 6–12 and ending with the week of February 10–16. In the baseline period, the median NAICS4 industry receives 18,705 worker visits per week, and the distribution of activity is highly right skewed, with the 90th, 95th and 99th percentiles having 560,000, 1.03 million, and 5.60 million hits, respectively.

If our classification of industries that provide critical infrastructure is accurate, we would expect to see a significantly smaller decline in foot traffic in critical industries than in noncritical ones starting from the middle of March 2020, when COVID-19 awareness and state-mandated lockdowns go into effect. To test this hypothesis, we then aggregate foot traffic across all POIs to the NAICS4 level so as to match our critical industry classification. Specifically, we estimate

$$\log \left( \frac{\text{Total Worker Foot Traffic in Week } t \text{ in Industry } I}{\text{Pre-period Average Worker Foot Traffic of Industry } I} \right) = a_i + \delta_i \text{ Critical Industry}_I + \epsilon_{I,t}. \quad (2)$$

When estimating Equation (2), we weight observations by total industry employment, and, to minimize the effect of outliers, we winsorize these industry indices at the 1st and 99th percentiles.

Figure 1 plots the results of our foot traffic analysis. Panel A reports average levels of our activity indices for critical and noncritical industries. Both sets of industries follow essentially identical trends in January and early February 2020, then experience a significant decline in foot traffic, which dramatically accelerates in the middle of March. Though the COVID-19 pandemic affects almost all establishments, we can see that the decline is smaller for industries classified as critical. Panel B examines the differences in traffic between the two industries by plotting the estimated coefficient $\delta_i$ in Equation (2) above. It shows that the decline in worker foot traffic is around

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**Footnotes:**

11 Specifically, SafeGraph makes available data on number of visits by “bucketed dwell time,” which captures the length of time that a device is at each POI. Consistent with the recommendations of SafeGraph researchers, we scale total weekly activity by a moving average of the total number of devices in the panel over the prior week for each POI prior to aggregating.

12 Some industries have very sparse coverage in the pre-period, so we drop the approximately 5% of industries with fewer than 30 average worker hits per week. Our results are not sensitive to increasing this threshold or eliminating it entirely. Total NAICS4 employment is taken from the Census Bureau’s 2017 Statistics of United States Businesses tables, available at https://www.census.gov/data/tables/2017/econ/susb/2017-susb-annual.html.
20% smaller for industries that we identified as providing critical infrastructure. These results support our classifications of industries as “critical” and “noncritical.”
Our foot traffic data also permit a simple validation of our exposure measure. Our hypothesis is that, even in critical industries, workers prefer to minimize their exposures to the disease by working from home to the extent it is feasible. Whereas workers in noncritical industries are essentially prevented from going to their workplaces during the pandemic, the decision to telework is more discretionary for workers in critical industries. Accordingly, we would expect to see larger declines in worker foot traffic (i.e., increased telecommuting) for critical industries in which workers are more easily able to telework. To test this premise, we estimate the following specification for critical (panel C) and noncritical (panel D) industries:

\[
\log \left( \frac{\text{Total Worker Foot Traffic in Week } t \text{ in Industry } I}{\text{Pre-period Average Worker Foot Traffic of Industry } I} \right) = c_t + \gamma_t \text{ COVID Exposure}_I + e_{I,t},
\]

where our prediction is that \( \gamma_t > 0 \) since workers in critical, high-exposure industries will be more likely to go to work relative to the workers who can telecommute more easily. Panel C provides strong evidence in support of this hypothesis: a 1% increase in the fraction of workers who cannot work remotely is associated with 1%–1.5% higher foot traffic throughout the month of April. In contrast, exposure is not correlated with changes in foot traffic in noncritical industries during the same period, which is consistent with the requirement that all workers in noncritical industries work remotely regardless of feasibility constraints.

### 1.4 Heterogeneity in work exposure

Figure 2 plots the distribution of the COVID-19 work exposure measure for critical and noncritical NAICS4 industries. Note that most industries have relatively high values of COVID-19 work exposure, with averages of approximately 0.85 for critical and 0.87 for noncritical industries. More importantly, however, we see there is considerable dispersion in our measure: the cross-sectional standard deviation is approximately 17%. The bulk of our paper explores the extent to which these cross-sectional differences are predictive of differential economic outcomes during the pandemic.

Table 1 illustrates how our industry exposure measure is related to firm characteristics. Due to data availability, we include only publicly listed firms. Panel A shows results for all industries, while panel B shows the same measure for the noncritical industry subsample. Three patterns stand out. First, we see that firms in the high-exposure category tend to be larger. For instance, focusing on the subsample of noncritical industries, the median firm in the top quartile of the COVID-19 work exposure measure has 4,900 employees; by comparison, the median firm in the bottom quartile has 1,500 employees. Second, there is some evidence that firms in the least-exposed industries have more intangibles than firms in the most-exposed industries: firms in the
least-exposed industries have higher market valuations (median Tobin’s Q in noncritical industries of 2.3 for the most exposed versus 1.3 for the least exposed), have lower ratios of physical capital (property, plant and equipment [PPE]) to book assets (0.16 versus 0.58 for the least- and most-exposed industries, respectively), and spend significantly more on research and development (R&D) and selling, general, and administrative expenses (SG&A) than firms in the most-exposed industries. This is consistent with the view that firms with more intangibles have more jobs that can be done remotely than firms that rely more on physical assets. Last, firms in the most-exposed industries are more profitable in terms of bottom-line accounting measures (return on assets), but this difference is driven by higher spending on intangibles and/or fixed costs by firms in the least-exposed industries.

2. COVID-19 Work Exposure and Economic Performance

So far, we have constructed a measure of exposure to COVID-19 work disruptions using data from the 2017 and 2018 ATUS. Here, we explore the extent to which this exposure measure is able to predict differences in

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13 Corrado, Hulten, and Sichel (2009) and Eisfeldt and Papanikolaou (2013) argue that higher SG&A expenditures are associated with higher investment in intangibles. That said, Eisfeldt and Papanikolaou (2013) focus on within-industry differences, whereas these results reflect between-industry patterns. As such, the variation in SG&A could also reflect differences in operating leverage (importance of fixed costs) or accounting practices.
economic performance across industries and individual workers. Our outcome variables include data on employment outcomes at the industry and worker level as well as forward-looking variables that are indicative of future economic performance—analyst forecasts and default probabilities.

Each of these variables has distinct advantages and disadvantages. Data from financial markets and financial analysts are forward looking but are only available for public firms, which may be less exposed to supply-side disruptions than smaller private firms. Employment data are more representative of the universe of firms but are only available with a lag and may not accurately reflect outcomes for firm owners.

### 2.1 Employment

We begin by exploring the extent to which our measure of production disruption due to the pandemic can predict differences in employment declines across industries. First, we focus on aggregated employment data from the Bureau of Labor Statistics (BLS). Each month, the BLS aggregates data from large surveys of establishments in order to construct estimates of total employment by industry. We make use of data from Table B-1a of the April employment report, which provides estimates of seasonally adjusted
employment at the NAICS4 level for the vast majority of nonagricultural industries in the U.S. economy.\textsuperscript{14}

We estimate the following specification

\[
\text{Employment Growth}_I = a + \beta \text{COVID-19 Work Exposure}_I + \epsilon_I. \quad (4)
\]

Here, the unit of observation is a NAICS4 industry and the outcome variable is employment growth. We examine both monthly and annual changes: monthly changes are measured from March to April of 2020, while annual changes are measured from April 2019 to April 2020. Since the sizes of these industries vary greatly, depending on the specification, we also present results in which we weight industries using total employment as of the baseline period used to calculate each growth rate. Last, we report results either using the full sample, or by excluding the critical industries listed in Table A.1.

Table 2 and Figure 3 present our results. Examining panels A and B of the table, we see an economically and statistically significant correlation between our exposure measure and industry-wide declines in employment that is robust across different specifications. In particular, an increase of one standard deviation in our COVID-19 work exposure measure is associated with a 5.6\% to 10.3\% greater decline in employment. The magnitudes are comparable for monthly and annual growth rates and are larger when we exclude critical industries and weight industries by their total employment. These magnitudes are quite significant and comparable to either the average decline in employment during this period (14\%) or the cross-sectional standard deviation (17\%). In panel C, we also report the differences in average employment growth rates between industries which we classify as critical versus noncritical. On an employment-weighted basis, monthly declines in employment are more than 5 times larger in noncritical industries (–22.5\%) relative to critical ones (–4.08\%).

Figure 4, panel A, provides a more aggregated summary of the relationship between our exposure measure and BLS year-on-year employment growth. Specifically, we aggregate across noncritical industries by major two-digit NAICS sector. Even at this level of aggregation, one can observe a strong relationship between exposure and changes in employment. Unsurprisingly, the three hardest-hit sectors are retail, hotels, and entertainment, which are also the three most highly exposed sectors according to our measure.

\section*{2.2 Revisions in revenue forecasts}

We next examine the ability of our measure to predict revisions in analyst forecasts regarding the economic performance of these industries. Specifically, we use consensus forecasts of firms’ revenues over various horizons, sourced from Capital IQ. We begin by looking at the change in revenue

\textsuperscript{14} Employment data are available at https://www.bls.gov/web/empsit/ceseeb1a.htm.
forecasts for the same accounting period (e.g., 2020Q2) across two points in time, February 14 and May 15, 2020. Later, we illustrate how these forecasts evolve on a monthly basis.

We focus on forecast horizons up to 3 years ahead, that is, Q2 through Q4 of 2020, and full-year forecasts for 2020–22. To minimize measurement error, we require that each firm has at least three individual forecasts. Due to this restriction, as well as the fact that underlying forecasts are more sparsely populated at longer horizons, we lose some industries for longer-run forecasts, especially for 2022. For each firm $f$ in the sample, we compute the percent change in revenue forecast from February to May 2020,

### Table 2
COVID-19 work exposure and employment growth

|                          | Weighted by Mar’20 employment | Equal weighted |
|--------------------------|-------------------------------|---------------|
|                          | All Industries | Noncritical | All Industries | Noncritical |
| A. Month-on-month growth (%)|                            |              |               |             |
| COVID-19 work exposure   | -46.8***         | -67.1***     | -30.3***      | -39.0***    |
|                          | (-3.24)          | (-4.47)      | (-4.76)       | (-4.61)     |
| Number of observations   | 217              | 156          | 217           | 156         |
| $R^2$                    | 0.146            | 0.277        | 0.070         | 0.099       |

|                          | Weighted by April’19 employment | Equal weighted |
|--------------------------|----------------------------------|---------------|
|                          | All Industries | Noncritical | All Industries | Noncritical |
| B. Year-on-year growth (%)|                            |              |               |             |
| COVID-19 work exposure   | -52.2***         | -74.2***     | -33.3***      | -42.3***    |
|                          | (-3.40)          | (-4.71)      | (-4.80)       | (-4.62)     |
| Number of observations   | 217              | 156          | 217           | 156         |
| $R^2$                    | 0.157            | 0.294        | 0.076         | 0.105       |

|                          | Month-on-month growth | Year-on-year growth |
|--------------------------|-----------------------|---------------------|
|                          | Weighted | Unweighted | Weighted | Unweighted |
| C. Average, all industries|          |            |          |            |
| Critical industries      | -4.08*** | -6.49***   | -2.86*** | -5.85***   |
|                          | (-4.65)  | (-6.65)    | (-3.29)  | (-5.20)    |
| Noncritical industries   | -22.47*** | -17.54*** | -22.60*** | -17.73***  |
|                          | (-6.09)  | (-12.78)   | (-5.69)  | (-12.29)   |
| Diff: Noncritical–critical| -18.39*** | -11.06*** | -19.75*** | -11.88***  |
|                          | (-4.85)  | (-6.57)    | (-4.86)  | (-6.30)    |
| Number of observations   | 217      | 217        | 217      | 217        |

Panels A and B report the coefficient estimates for the regression of employment growth on COVID-19 work exposure (Equation (4)) using employment-weighted and unweighted specifications ($t$-statistics in parentheses). The dependent variable is expressed in percentage points and constructed using private-sector employment data from the BLS's April 2020 employment report at the NAICS4 level. Standard errors are robust to heteroskedasticity (White, 1980). Panel C reports the average declines in the dependent variable for critical and noncritical industries, as well as the difference between the two averages. The cross-sectional standard deviation of exposure across BLS industries is 13.86%. Given that BLS only reports data for a single NAICS4 agricultural industry (logging), we exclude agriculture from this analysis. The results are not sensitive to this choice. The list of critical industries at the NAICS4 level is in Table A.1.

*p < .05; **p < .01; ***p < .001.
Figure 3
Employment growth and COVID-19 work exposure
Figure plots the correlation between employment growth and our COVID-19 work exposure measure at the NAICS4 level. Panel A plots month-on-month changes (April vs March 2020) while panel B plots year-on-year changes (April 2020 to April 2019). Industries listed as critical (red) are listed in Table A.1.
Figure 4
Real activity of noncritical industries and COVID-19 work exposure by major sector
Panel A plots employment growth rates from April 2020 vs 2019 from the BLS against exposure (aggregated across 2-digit industries using BLS total employment weights). Panels B–F plot stock returns and revisions in revenue forecasts for noncritical industries from mid-February to mid-May versus the COVID-19 work exposure measure. For purposes of generating the graph, when aggregating to the NAICS2 level, we average across 4-digit noncritical industries, weighting by Compustat employment. IT stands for information technology.
Revenue Forecast for Period $\tau$, as of May 2020$ f$  
Revenue Forecast for Period $\tau$, as of February 2020$ f$  

(5)

For purposes of these regressions, we winsorize firm-level measures at the 1st and 99th percentiles, then aggregate the nonmissing firm-level revenue forecasts to the NAICS4 level, weighted by the corresponding level of the firms’ February 2020 forecasts for the same period,

\[ \text{Forecast Revision}_i^f = \frac{\sum_{f \in I} \text{Revenue Forecast for Period } \tau, \text{ as of May } 2020^f}{\sum_{f \in I} \text{Revenue Forecast for Period } \tau, \text{ as of February } 2020^f} - 1. \]  

(6)

We estimate the following equation where the dependent variable is the revision in analyst forecasts described in (6)

\[ \text{Forecast Revision}_i^f = a + \beta_i \text{ COVID – 19 Work Exposure}_i + \epsilon_i. \]  

(7)

Our dependent variable is the revision in analyst revenue forecasts for periods between February and May 2020, aggregated to industry $i$. To conserve space, we focus on our preferred specification in which we restrict the sample to noncritical industries and weight observations by the number of Compustat employees in each industry; using equal weights and weighting by the number of firms leads to quantitatively similar results. Standard errors are robust to heteroskedasticity (White 1980).

Panels A and B of Table 3 present our findings. Panel A shows that, for Q2 2020, an increase of one standard deviation in the exposure measure is associated with a 7.7% decline in analyst revenue forecasts. Importantly, the effect is quite persistent, though the magnitudes do decline with the forecast horizon $\tau$, as we can see from comparing the magnitudes across columns. Figure 5 plots the estimated coefficients as a function of the forecast horizon $\tau$. As of mid-May 2020, financial analysts expect the direct economic cost of the pandemic to subside significantly over the course of 2020: a one-standard-deviation increase in the exposure measure is associated with a 3% decline in revenue for Q3 and a 1.4% decline for Q4. The overall estimate for 2020 is equal to 2.6%. Extending our analysis to 2021 and 2022, we note that our estimates are significantly weaker at 2% and 1.5%, respectively. They are still statistically significant, however, suggesting that analysts expect the costs of these supply-side disruptions to persist for several years. Figures 4 and 6 provide scatterplots for noncritical industries aggregated by major sector and at the NAICS4 level.

In panel C of Table 3, we also report industry-level averages of these revenue forecasts for critical versus noncritical industries (weighted by 2019 employment levels from Compustat). We note that projected declines are roughly three times larger for firms in noncritical industries relative to those in critical ones. In both cases, the largest declines in revenue are expected for
2020Q2 (−27% and −7% for noncritical and critical, respectively), though forecasts suggest that analysts expect noncritical industries to experience substantial long-run declines in output. In particular, noncritical industries are projected to experience revenue declines of 10% and 8% in 2021 and 2022, respectively.15

### Table 3

**COVID-19 work exposure, stock returns and analyst forecasts**

| Stock Analyst forecast revisions (%) | 2020Q2 | 2020Q3 | 2020Q4 | 2020 | 2021 | 2022 |
|------------------------------------|--------|--------|--------|------|------|------|
| A. Regressions for noncritical industries | COVID-19 work exposure | −38.9*** | −43.9*** | −71.1** | −8.3* | −15.1** | −11.6*** | −8.5*** |
| | | (−5.37) | (−4.32) | (−2.45) | (−1.78) | (−2.13) | (−3.35) | (−2.96) |
| | Observations | 141 | 126 | 127 | 127 | 127 | 92 |
| | $R^2$ | 0.295 | 0.229 | 0.099 | 0.053 | 0.077 | 0.151 | 0.134 |
| B. Regressions for noncritical industries with size and profitability controls | COVID-19 work exposure | −37.7*** | −48.0*** | −20.4** | −10.8*** | −18.7** | −12.3*** | −8.0*** |
| | | (−4.81) | (−3.79) | (−2.43) | (−2.08) | (−2.36) | (−3.03) | (−2.39) |
| | log(market cap) | 0.7 | −1.7 | −0.8 | −0.6 | −0.4 | −0.9 | 0.4 |
| | | (0.32) | (−0.76) | (−0.53) | (−0.50) | (−0.34) | (−1.09) | (0.48) |
| | Profitability | 2.2 | 18.2 | 22.5*** | 16.9*** | 33.4*** | −9.3** | 2.7 |
| | | (0.22) | (1.64) | (3.34) | (3.31) | (5.36) | (−2.20) | (0.88) |
| | Observations | 142 | 126 | 127 | 127 | 127 | 92 |
| | $R^2$ | 0.295 | 0.261 | 0.200 | 0.180 | 0.280 | 0.201 | 0.142 |
| C. Averages, all industries | Critical industries | −8.0** | −6.8*** | −4.5*** | −2.7** | −3.2*** | −2.5** | −2.3*** |
| | | (−2.02) | (−3.08) | (−3.17) | (−2.54) | (−2.71) | (−2.15) | (−2.49) |
| | Noncritical industries | −25.6*** | −26.5*** | −15.3*** | −9.4*** | −12.5*** | −9.9*** | −7.9*** |
| | | (−10.53) | (−8.67) | (−8.58) | (−7.90) | (−6.82) | (−10.08) | (−9.57) |
| | Diff: Noncritical–Critical | −17.6*** | −19.7*** | −10.7*** | −6.7*** | −9.2*** | −7.4*** | −5.6*** |
| | | (−3.78) | (−5.24) | (−4.69) | (−4.22) | (−4.43) | (−4.84) | (−4.52) |
| | Number of observations | 203 | 181 | 182 | 182 | 184 | 183 | 140 |

Panel A shows the coefficient estimates from regressions of stock returns and analyst forecasts on our COVID-19 exposure measure for noncritical industries (Equations (7) and (10), t-statistics in parantheses). The dependent variables are constructed using firm data from Compustat and Capital IQ, aggregated to the NAICS4 level. These regression coefficients are based on a snapshot of forecasted default probabilities taken on May 12, 2020. The regression is weighted by total Compustat 2019 employment in each industry. Standard errors are robust to heteroskedasticity (White, 1980). Panel B reports these same regressions but with additional variables that help account for differences in size and profitability across industries. Panel C reports averages of each outcome for critical and noncritical industries, as well as differences between the two. The list of critical industries is in Table A.1. The cross-sectional standard deviation of exposure across critical industries is 17.4%.

* $p < .05$; ** $p < .01$; *** $p < .001$.

2020Q2 (−27% and −7% for noncritical and critical, respectively), though forecasts suggest that analysts expect noncritical industries to experience substantial long-run declines in output. In particular, noncritical industries are projected to experience revenue declines of 10% and 8% in 2021 and 2022, respectively.15

### 2.3 Default probabilities

So far, we have seen that our COVID-19 work exposure measure predicts declines in both employment declines and expected revenue across industries. We next examine another forward-looking measure, expected probabilities of default.

15 See, e.g., Landier and Thesmar (2020) and Barrero et al. (2021) for related evidence on projected aggregate declines.
We obtain estimates of default probabilities from the Risk Management Institute (RMI) of the National University of Singapore. RMI generates forward-looking default probabilities for issuers on a daily basis for maturities of 1, 3, 6, 12, and 24 months ahead using the reduced-form forward-intensity model of Duan, Sun, and Wang (2012). These measures have been shown to work well in forecasting applications and are available for a very wide array of firms (over 70,000 publicly listed firms worldwide). We next compute the first difference of the default probability over the February–May 2020 period and aggregate these default probabilities at the industry level (four-digit NAICS) by averaging across firms (weighted by employment).

We estimate the following specification:

$$\text{Default Probability}_t^\tau = \alpha_\tau + \beta_\tau \text{ COVID – 19 Work Exposure}_t + \epsilon_t^\tau. \quad (8)$$

The outcome variable is the industry-level probability of default over the next $\tau$ months. As before, we restrict the sample to noncritical industries and weight observations by the number of employees in each industry.

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16 For example, Gallagher et al. (2020) use these probability estimates to study changes in portfolio risk of international portfolios of securities owned by US money market funds, and illustrate that the default probabilities closely track CDS spreads. For additional details on the database, see https://rmicri.org/en/.
Figure 6
Revenue forecast revisions and COVID-19 work exposure
Panel A plots the revisions in revenue forecasts for Q2 2020 from mid-February to mid-May 2020 versus the COVID-19 work exposure measure. Panel B plots the corresponding revisions for the year 2020. NAICS4 critical industries (red) are listed in Table A.1.
Table 4
COVID-19 work exposure and default probabilities

|                | Change in probability of default (%) in next |      |      |      |      |
|----------------|---------------------------------------------|------|------|------|------|
|                | 3 months                                   | 6 months | 12 months | 24 months |
| A. Regression coefficients for probability of default in noncritical industries | COVID-19 work exposure | 0.19 | 0.47* | 1.08** | 1.75*** |
|                |                                             | (1.62) | (1.92) | (2.29) | (2.66) |
|                | Observations                               | 155   | 155   | 155   | 155   |
|                | R²                                         | 0.040 | 0.054 | 0.075 | 0.093 |
| B. Additional size and profitability controls | COVID-19 work exposure | 0.15 | 0.43 | 1.12*** | 2.06*** |
|                |                                             | (1.23) | (1.60) | (2.10) | (2.70) |
|                | log(market cap)                            | -0.01 | 0.00  | 0.06  | 0.19  |
|                |                                             | (-0.28) | (0.05) | (0.62) | (1.45) |
|                | profitability                              | 0.28  | 0.57  | 0.85  | 0.46  |
|                |                                             | (1.58) | (1.32) | (0.95) | (0.35) |
|                | Observations                               | 155   | 155   | 155   | 155   |
|                | R²                                         | 0.093 | 0.094 | 0.099 | 0.114 |
| C. Average change in probability of default, all industries | Critical industries | 0.04*** | 0.08*** | 0.15*** | 0.20** |
|                |                                             | (2.90) | (2.87) | (2.73) | (2.23) |
|                | Noncritical industries                      | 0.12**** | 0.26*** | 0.56*** | 0.83*** |
|                |                                             | (5.01) | (4.93) | (4.90) | (4.88) |
|                | Diff: noncritical–critical                  | 0.09**** | 0.20*** | 0.41*** | 0.63*** |
|                |                                             | (3.216) | (3.179) | (3.195) | (3.243) |
|                | Observations                               | 221   | 221   | 221   | 221   |

Panel A reports the coefficient estimates for the regression of change in default probability for noncritical industries from February to May 2020 on COVID-19 work exposure (see Equation (8)) where the dependent variables are constructed using firm data from Compustat and the RMI Credit Research Database, aggregated to the NAICS4 level (t-statistics in parantheses). These regression coefficients are based on a snapshot of forecasted default probabilities taken on May 12, 2020. The dependent variable is expressed in percentage points so that the slope coefficient can be interpreted as the increase, in basis points, of the probability of default associated with a 1 percentage point increase in exposure. The regression is weighted by total Compustat 2019 employment in each industry. Standard errors are robust to heteroskedasticity (White, 1980). The list of critical industries is in Table A.1. Panel B reports these same regressions, but with additional controls to account for differences in market capitalization and profitability across industries. Panel C reports the average default probability for critical and noncritical industries, as well as the difference between the two.

Table 4 shows that differences in our COVID-19 work exposure measure are associated with increased probabilities of default. This correlation is both statistically and economically significant and is monotonically increasing in the forecast horizon τ. For instance, an increase of one standard deviation is associated with a 0.08 percentage point increase in the probability of default over the next 6 months and a 0.30 percentage point increase over the next 2 years. Given that the average probability of default over these horizons is 0.26% and 1.38%, respectively, these magnitudes are quite substantial. We also observe that, consistent with earlier evidence, these increases in default risk are considerably higher for noncritical industries relative to critical industries.17

17 While we winsorize our industry average default measures at the 1st and 99th percentiles to reduce influence of outliers, results are partially driven by a subset of exposed industries experiencing very large increases. In
2.4 Evidence based on firm surveys

Last, in this section we provide additional survey-based evidence that links firms’ experiences during the pandemic to our COVID-19 work exposure measure. We use the Small Business Pulse Survey (SBPS), which was recently introduced by the Census Bureau to provide timely information on how firms are impacted by the crisis. Each week, the Census sends an electronic survey to a large sample of small businesses and reports statistics which are aggregated across respondents by NAICS3 sector.18

The SBPS contains several questions on whether the firm is experiencing material hardship during the pandemic. We assume that a firm is experiencing a major disruption if it responds to the question “Overall, how has business been affected by the COVID-19 pandemic?” with an answer of “large negative effect.” At the mean level of exposure, 49% of firms indicate that the pandemic has had a large negative effect. Next, we consider whether a firm has reduced its employee headcount or hours in the last week, which is captured by answers of “yes, decreased” to the questions “in the last week, did this business have a change in the number of paid employees?” and “in the last week, did this business have a change in the total number of hours worked by paid employees?”

We code a firm as having missed payments if it responds “yes” to the question, “Since March 13, 2020, has this business missed any other scheduled payments, not including loans? Examples of other scheduled payments include rent, utilities, and payroll.” We determine the firm’s liquidity based on their answer to the question “How would you describe the current availability of cash on hand for this business, including any financial assistance or loans? Currently, cash on hand will cover X weeks.” We compute the fraction of firms reporting that they do not have enough cash to cover at least 4 weeks of business operations. We average survey responses across the first six waves of the survey, which corresponds with data collected from April 26 through June 6, 2020.

Table 5 and Figure 7 summarize the relationships between our COVID-19 work exposure measure and these self-reported measures of hardship. In particular, Table 5 reports univariate regressions of the fraction of firms experiencing hardship as measured by each of the SBPS variables on our exposure measure, weighted by employment. We de-mean the exposure measure prior to running the regression, so that the constant may be interpreted as the average response for a firm with the average level of exposure (about 86%). Panel A reports these responses for all industries included in the sampling frame, whereas panel B reports the results for noncritical industries Appendix Table A.3, we find that results are qualitatively similar if we instead estimate regression specifications which are more robust to outliers.

18 The target population is small businesses with fewer than 499 employees. Multi-establishment firms are excluded from the sampling frame. For additional details, see Buffington, Dennis, Dinlersoz et al. (2020). The data are available at https://www.census.gov/data/experimental-data-products/small-business-pulse-survey.html.
only. For brevity, we focus on estimates for noncritical industries in our discussion, though estimates are qualitatively similar for the full sample.

In sum, our COVID-19 work exposure measure is significantly correlated with these hardship measures. An increase of one standard deviation in our exposure measure is associated with a 9.4 percentage point increase in the probability the firm is experiencing a major disruption in operations, 5.7 and 4.0 percentage point increases in the likelihood of reducing headcount and payroll, respectively, a 5.9 percentage point increase in the probability of missing payments, and a 4.3 percentage point increase in the likelihood of having insufficient liquidity.

Panels A through E of Figure 7 illustrate these results graphically. These figures show nonparametric evidence on the relationship between exposure and survey responses via binned scatterplots, in which we separate noncritical industries into 10 bins, then report for each bin the (employment-weighted) means of exposure and the fraction of survey respondents answering yes to each question. These plots confirm the regression results and illustrate that

| Table 5 | COVID-19 work exposure and Small Business Pulse Survey responses |
|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|
|                | Major disruption | Reduced head count | Reduced hours | Missed payments | < 1 month liquidity | Applied PPP |
| A. All industries | COVID-19 work exposure | 65.87*** | 39.46*** | 28.12*** | 36.95** | 30.86*** | 27.16*** |
|                  | Constant | (3.52) | (4.20) | (3.24) | (2.22) | (4.59) | (2.85) |
|                  | Observations | 80 | 80 | 80 | 80 | 80 | 80 |
|                  | R² | 0.219 | 0.377 | 0.203 | 0.163 | 0.239 | 0.158 |
| B. Noncritical industries | COVID-19 work exposure | 73.77*** | 44.72*** | 31.48*** | 46.72** | 34.21*** | 28.48*** |
|                  | Constant | (3.21) | (3.63) | (3.25) | (2.31) | (7.14) | (3.12) |
|                  | Observations | 54 | 54 | 54 | 54 | 54 | 54 |
|                  | R² | 0.279 | 0.453 | 0.378 | 0.259 | 0.526 | 0.365 |

Table reports coefficient estimates (and robust t-statistics in parentheses) from ordinary least squares regressions of the fraction of survey respondents in NAICS3 industries who provided the following answers during the first six waves of the Census Bureau’s Small Business Pulse Survey:

- **Major disruption:** (Q) “Overall, how has business been affected by the COVID-19 pandemic?” (A) Large negative effect.
- **Reduced head count:** (Q) “In the last week, did this business have a change in the number of paid employees?” (A) Yes, decreased.
- **Reduced hours:** (Q) “In the last week, did this business have a change in the total number of hours worked by paid employees?” (A) Yes, decreased.
- **Missed payments:** (Q) “Since March 13, 2020, has this business missed any other scheduled payments, not including loans? Examples of other scheduled payments include rent, utilities, and payroll.” (A) Yes. < 1 month liquidity: (Q) “How would you describe the current availability of cash on hand for this business, including any financial assistance or loans? Currently, cash on hand will cover.” (A) 1–7 days of business operations through 3–4 weeks of business operations. Applied PPP: “Since March 13, 2020, has this business requested financial assistance from the following Federal Sources?” (A) Paycheck Protection Program. The cross-sectional standard deviation of exposure across NAICS3 industries is 12.7%. Regressions are weighted by 2017 employment obtained from the Census Bureau’s Statistics of U.S. Businesses release.

*p < .05; **p < .01; ***p < .001.
COVID is major disruption
Reduced head count
Missed schedule payments
Has < 1 month liquidity
Applied for PPP loan

Figure 7
COVID-19 work exposure and Small Business Survey responses: Binned Scatterplots
Figures plot the percent of respondents from noncritical NAICS3 industries who indicate each of the following in the first six waves of the Census Bureau’s Small Business Pulse Survey against our COVID-19 work exposure measure: A) COVID-19 had caused a major disruption to their business, B) they had reduced employee head count, C) they had reduced employee hours, D) they had missed scheduled payments, E) they had less than 1 month of liquidity, or F) they had applied for a PPP loan. NAICS3 industries are sorted into 10 bins based on exposure, where, to compute bins and means within each bin, observations weighted by 2017 employment obtained from the Census Bureau’s SUSB release. Please see notes to Table 5 for precise definitions of how we code each survey response.
the strong relationships between exposure and measures of economic hardship are not driven by a small set of outliers.

2.5 Medium-term Outcomes
Most of the discussion so far has focused on realized and forecasted outcomes as of the beginning of the pandemic. Here, we briefly examine the dynamic behavior of employment and firm revenue from the end of 2019 through the end of 2020.

Panel A of Figure 8 shows the dynamic response of employment. Examining the figure, we note the stark difference in employment outcomes for workers as a function of our exposure measure. For example, focusing on the peak of the pandemic (April 2020), an increase of one standard deviation in our exposure metric is associated with an approximately 10% higher decline in employment between April 2020 and April 2019. These differences decline by approximately two-thirds through the end of 2020. By the end of 2020, the same difference in our exposure measure is associated with approximately 3.5% lower employment growth relative to the end of 2019. By contrast, employment at critical industries remains roughly unchanged since the pre-pandemic year.

Panel B examines firm revenue, showing log growth rates of industry revenues relative to the same quarter in the prior year. (For this analysis, we exclude firms whose fiscal end dates do not coincide with calendar quarters.) We note that revenue is considerably more volatile than employment: revenue of firms in the most-affected sectors collapses in the second quarter of 2020, recovering by a factor of around 50% but remaining significantly lower than pre-pandemic levels in the third and fourth quarters. Comparing these revenue realizations to their forecasts at the onset of the pandemic in Figure 5, we note that analyst forecasts were fairly accurate regarding these aggregate effects for calendar year 2020.

Overall, the adverse effects of the pandemic on revenue and employment were rather persistent. By the end of 2020, high-exposure industries had recovered approximately two-thirds of the employment losses incurred at the onset of the pandemic. Revenues recovered, but only partially, consistent with the pandemic continuing to act as a drag on firms’ operations through the medium term.

3. COVID-19 and Income Inequality
The recent availability of CPS data allows us to explore outcomes at the level of individual workers. The advantage of doing so is twofold. First, by observing the characteristics of individual workers we can control for some
Figure 8
COVID-19 work exposure, employment and firm revenue over the medium term
The figure shows changes in year-over-year employment and revenue growth for firms if they were to experience a 100% change in their employees’ ability to work from home (e.g., go from all employees working from home to no employees working from home). Regressions are weighted by employment at the beginning of the year in panel A, and start-of-period revenue in panel B. Error bars show a 95% confidence interval, standard errors are heteroskedasticity consistent. Growth rates are winsorized at the 1% level.
variables that may be correlated with our COVID-19 work exposure measure. For instance, workers that can work remotely tend to be in white-collar occupations (see e.g., Dingel and Neiman 2020). By including controls for workers’ level of education, or past earnings, we can ensure that we are comparing otherwise similar workers. Further, analyzing outcomes for individual workers, and how these outcomes vary with worker characteristics, reveals a fuller picture of the effects of the COVID-19 pandemic on heterogeneity in worker outcomes.

We use the April version of the CPS which contains employment information for individual workers.19 We restrict the sample to adults of working age (25 to 60 years) that are present in the March 2020 survey and who report that they were “at work last week” as of March 2020. Our sample contains 23,984 workers. In April of 2020, 19,664 of these workers report they are at work, 2,144 report they are out of a job, and 1,257 report they have a job but were not at work last week. We include the first and last groups in the sample for the regressions described below.

We impose one other substantial restriction on the sample. As of the start of the year, the BLS changed its coding of occupations relative to prior years, and a crosswalk between the older vintage of occupation codes from ATUS and the newer codes in the 2020 CPS has not yet been developed. In part due to this technical reason, and also because several researchers have already documented a disproportionate increase in unemployment for lower-income workers, we restrict attention to workers who appear in the March/April 2020 core CPS and March 2019 Annual Social and Economic Supplement (ASEC-CPS) surveys. This enables us to construct controls for an individual’s prior income and, motivated by evidence on potentially concentrated adverse effects for small businesses, firm size. For each worker, we assign an exposure measure based on their March 2019 occupation which is equal to 1 minus the fraction of ATUS respondents in that occupation (weighted using the ATUS sampling weights) who had worked a full day from home.20

We estimate the following specification:

\[ \text{Not Employed}_i = a + \beta \text{ COVID - 19 Work Exposure}_i + cZ_i + \varepsilon_i. \]  

(9)

Our main outcome variable is a dummy variable that takes the value of 1 if the worker was not “at work last week” in the April 2020 CPS survey, which includes both unemployed and furloughed workers. For ease of

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19 There are some possible selection issues. IPUMS notes, “Interviews for April were conducted exclusively by phone. The two Census Bureau call centers that usually assist with the collection of CPS data remained closed. Response rates continued to be low in April, over 10 percentage points below the average (see below). Response rates continued to be particularly low among rotation groups one and five who would have normally received a visit from the enumerator. Month-in-sample one and five response rates were similar to those same groups in March. Additionally, those households that entered the survey for the first time in March had a similarly low response rate for their second interview in April.”

20 Note that we also assigned an alternative measure based on each worker’s March 2020 industry and obtain similar results.
interpretation, we multiply the dependent variable by 100 to express probabilities in percentage points in tables and figures.

Since the CPS contains information on workers’ occupations, we use the occupation-level version of our COVID-19 work exposure measure rather than the industry aggregate, though using industry aggregates produces comparable results. Depending on the specification, the vector of worker-level controls and interaction terms $Z_i$ includes gender indicator variables, college education, whether the worker has children younger than 14 years old, education (a college graduate indicator), worker age, worker earnings as of 2019 (quartile indicators), and firm-size indicators. We cluster the standard errors by occupation and industry (using Census Bureau codes). Table 6 shows results.

When we examine Table 6, several facts stand out. First, as we see in the first three rows of the table, workers in occupations that are less able to work remotely (higher exposure) are more likely to stop working. These effects are not absorbed by worker characteristics—as we see in second and third columns of the table—suggesting that our exposure measure is not simply capturing differences in the composition of the work force. Further, the point estimates are somewhat larger for noncritical industries relative to critical industries. Focusing on the third column—which includes controls for worker gender, age, education, prior earnings, and firm size—an increase of one standard deviation in our measure is associated with a 4.5 percentage point increase in the probability of a worker in a noncritical industry being without employment in April 2020, compared to a 1.0 percentage point increase for a worker in a critical industry; the difference is, however, statistically not significantly different from zero. Moreover, relative to workers in noncritical industries with similar characteristics, employees in critical industries are 8 percentage points less likely to remain employed. Hence, in the remainder of the paper, we restrict attention to noncritical industries.

One potential concern with these results is that they could simply reflect differential employment trends in white-collar versus blue-collar occupations. In the last column of Table 6 we show the results of a placebo exercise in which we repeat the analysis for the February CPS sample, which was well before the effects of the pandemic became apparent. Examining the results we note that none of the coefficients of interest are statistically different from zero.

We next allow the coefficient $\beta$ on the COVID-19 work exposure measure in Equation (9) to vary with worker characteristics $Z_i$. In all specifications with interactions, we include dummies for all levels of the categorical variable of interest as controls. Doing so reveals how the employment status of different workers varies in response to the same level of work disruption due to COVID-19.\(^{21}\)

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\(^{21}\) In additional specifications, we verify that many of these patterns persist even if we include occupation and/or industry fixed effects, implying that we can detect similar differences even within occupations/industries. These results are suppressed for brevity and are available upon request.
| Critical industry | April 2020 | February 2020 |
|-------------------|------------|---------------|
| Probability worker is not employed (%) | -9.2*** | -8.1*** |
| Noncritical industry × COVID-19 work exposure | 50.6*** | 36.0*** |
| Critical industry × COVID-19 work exposure | 28.4*** | 18.1** |
| Controls | |
| College graduate indicator | -6.3*** | -3.8*** |
| Female indicator | 4.6*** | 3.2** |
| Kids under 14 | -2.3* | -1.7 |
| Female indicator × Kids under 14 | 4.0** | 2.8 |
| College graduate indicator × Kids under 14 | -0.09 | 0.45 |
| Age 30 to 39 | -2.5* | -0.7 |
| Age 40 to 49 | -3.4*** | -1.2 |
| Age 50+ | -2.7** | -0.2 |
| 2019 earnings in bottom quartile | 12.5*** | 1.8*** |
| 2019 earnings in 2nd quartile | 6.2*** | 0.5 |
| 2019 earnings in 3rd quartile | 2.0*** | 0.1 |
| Firm size: under 10 employees | 2.4 | 0.5 |
| Firm size: 10–99 employees | 1.0 | 0.0 |
| Firm size: 100–999 employees | 0.8 | 0.1 |
| Constant | 0.179*** | 0.121*** |
| Number of observations | 9,660 | 9,273 |
| R² | 0.040 | 0.0135 |

Table 6
COVID-19 work exposure and worker employment outcomes

Probability worker is not employed (%)

| Critical industry | Probability worker is not employed (%) |
|-------------------|----------------------------------------|
| Noncritical industry × COVID-19 work exposure | 50.6*** |
| Critical industry × COVID-19 work exposure | 28.4*** |

Table reports the coefficient estimates from the regression where we model the probability that a worker is employed in April (first three data columns) or February (last three column) 2020 as a function of COVID-19 work exposure and selected worker characteristics (see Equation (9)). Standard errors are double-clustered based on occupation and industry (t-statistics in parantheses). The dependent variable is an indicator that equals 1 if an individual does not have a job in April or February 2020. To be included in the sample, workers need to appear in the March 2020 CPS and March 2019 ASEC survey, and either the April or February core CPS sample. The list of critical industries at the NAICS4 level is in Table A.1. We define critical industries as those for which at least 50% of employment is associated with critical NAICS industries. The cross-sectional standard deviation of the exposure measure for workers in our sample is 12.4%.

*p < .05; **p < .01; ***p < .001.
Figure 9 summarizes our findings. In Panel A of the figure, we see an economically and statistically significant difference in how the employment status of workers of different income levels is related to our COVID-19 exposure measure. A one-standard-deviation increase in exposure is associated with a 9.2 percentage point increase in the likelihood of nonemployment for workers at the bottom quartile of the earnings distribution, as compared to just a 1.6 percentage point increase for workers in the top quartile. The fact that we see such a differential response of employment status to the feasibility of remote work for employees with different earnings levels has several possible interpretations. One possibility is that firms try to retain their most able—and highest paid—employees and reduce employment for workers of lower skill levels first. Moreover, in addition to these differences in slope coefficients, low-income workers tend to be less able to work remotely: average exposure is 1.0%, 3.2%, and 7.7% higher for workers in income quartile 1 relative to workers in quartiles 2, 3, and 4, respectively.

Another possibility is that these responses reflect differences in age or the gender pay gap. Panel B of Figure 9 shows that the response of the employment status of young workers to COVID-19 work disruptions is approximately twice that of the status of older workers. However, the coefficients are imprecisely estimated so the difference is not statistically different from zero. Panels C and D condition on gender as well as college attainment and whether or not the household has at least one child under the age of 14. In both cases, we see that estimated sensitivities for women are large relative to those of men, though these differences are not always statistically significant. Workers without college degrees have higher estimated coefficients. In panel D, we observe that, while men with young children who work in noncritical industries have smaller coefficients than men without young children, the opposite appears to be the case for women with young children. The 7.7 percentage point difference in coefficients between men and women with young children is highly significant (t-statistic = 3.4). Panel E shows that these gender differences do not merely reflect the gender pay gap. More importantly though, panel E reveals that the employment status of female workers is more sensitive to work disruptions than the status of male workers for all income levels. Panel F shows that the workers most adversely affected by work disruptions are female workers with young children and without a college degree. For this group, an increase of one standard deviation in our COVID-19 work exposure measure is associated with about a 15 percentage point increase in nonemployment, which is three times higher than the average response among all workers.

In sum, we find that our COVID-19 work exposure measure is an economically significant predictor of employment. Workers in occupations that do not support remote work are significantly more likely to lose their

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22 This gap remains sizable at 5.5 percentage points when we absorb occupation fixed effects.
employment status in April 2020. This correlation is evident both in cross-industry comparisons and in individual-worker regressions.

4. Stock Market and the Pandemic

So far, we have seen that differences in our COVID-19 work exposure measure are correlated with differences in real economic outcomes across firms—both forecasts and realizations. Here, we extend our analysis to stock-return data. This analysis complements the previous section in several ways and
sheds some light on the apparent disconnect between the behavior of the stock market versus the behavior of the real economy in 2020.

4.1 Stock market performance during the first peak of the pandemic

Though analyst forecasts of revenue growth and default probabilities are forward looking, both measures are somewhat subjective and may not necessarily reflect the “average” beliefs in the economy. Our next outcome variable partly addresses this concern, as it focuses on differences in stock market valuations across industries.

We use data on stock returns from the Compustat Daily Update database to calculate holding period returns for various horizons. We restrict our attention to common stocks of firms that have headquarters in the United States and are traded on NYSE, AMEX, or NASDAQ. We eliminate financial and real estate firms (NAICS codes 52 and 53).\(^\text{23}\) Stock returns were negative for nearly all industries during this period, with a cross-sectional average decline of approximately 26%. Yet, there is considerable cross-industry dispersion—the cross-sectional standard deviation is approximately equal to 18%. A select few industries experienced price appreciation: firms in the grocery store industry (NAICS 4451) saw a 21% increase in stock market values, and firms in electronic shopping (NAICS 4541) appreciated by approximately 13%. Others, such as airlines (NAICS 4811), experienced stock market declines of more than 65%.

Figure 10 illustrates our main results graphically via a scatterplot of our exposure measure versus the stock market performance of these industries. Critical industries are in red, while the trend line is estimated with the subsample of noncritical industries. We note some significant outliers that do not fit the line. For example, NAICS code 5414 corresponds to interior designers. Though these workers can work remotely in normal times, they likely face significant impairments to implementing their designs in the current environment. Figure 4 presents the same information aggregated major sector.

We relate differences in our work exposure measure to differences in cumulative stock market performance using the following specification:

\[
\text{Stock Returns}_i = a + \beta \cdot \text{COVID-19 Work Exposure}_i + \epsilon_i. \tag{10}
\]

The dependent variable corresponds to cumulative stock returns from February 14th through May 15, 2020. As before, we restrict the sample to noncritical industries. To ensure that our results are not driven by small industries with high idiosyncratic volatility, we estimate Equation (10) using

\(^{23}\) We also exclude firms in the education sectors (6111–6114), because the remote exposures of employees of the listed firms in these sectors are likely to be quite different from those employed in the nonprofit/government enterprises which employ the majority of workers in these sectors. Likewise, we exclude fast food restaurants (NAICS 722513) from the sample, as their exposure to work disruption is likely to be quite different from that of other firms in the restaurant industry.
weighted least squares, weighting observations by the total number of employees (across firms in our Compustat sample) in each industry. Weighting by the number of firms in each industry leads to quantitatively similar findings. Standard errors are robust to heteroskedasticity (White, 1980).

The first column of Table 3 presents our estimates. Our industry exposure measure accounts for economically and statistically significant differences in the stock market performance across industries. The magnitudes are considerable: an increase of one standard deviation in our exposure measure is associated with a 6.8% decline in stock prices during this period. Given that the cross-sectional standard deviation in noncritical industries’ stock market performance during this period is approximately 16.6%, our measure captures a significant share of the overall dispersion. Stock market declines are considerably larger (26%) in noncritical industries relative to critical ones (8%), as shown in Panel C.

In sum, we find that exposure (which is constructed using 2019 data) is a statistically significant predictor of differences in stock returns across industries during the COVID-19 pandemic. However, the decline in stock prices associated with exposure is substantially larger than the comparable expected declines in 2020 revenue discussed earlier (for longer-horizon forecasts this discrepancy only increases). There are a couple of possibilities that may resolve this tension. First, firms’ profits may be substantially more affected than revenues. Second, the dispersion in stock return performance could also be
driven by heterogeneous increases in systematic risk during this period stemming from the increased uncertainty between January and May of 2020 (see e.g., Baker et al. 2020).

4.2 Real-time estimates of the supply-side disruption

In our analysis so far, we have developed a measure of industry exposure to production disruptions due to COVID-19 and shown that heterogeneity in risk exposures is associated with cross-industry differences in economic performance during the pandemic period. That work is necessarily cross-sectional, because it examines cumulative outcomes aggregated over the entire sample period. In this section, we use our measure in conjunction with high-frequency financial market data to construct a real-time indicator of news associated with production disruptions.

In particular, we re-estimate Equation (10) for the subsample of noncritical industries, while allowing the slope coefficient to vary over time:

\[
\text{Stock Returns}_{i,t} = a + \beta_t \cdot \text{COVID-19 Work Exposure}_i + \epsilon_{i,t}, \quad (11)
\]

We can use the realized time series of the slope estimates \(\beta_t\) to construct a portfolio whose returns are a noisy estimate of the “COVID-19 return factor,” the source of common variation in returns related to the production disruptions stemming from the pandemic (see, e.g., Fama and MacBeth, 1973; Cochrane, 2009, for more details). Intuitively, this factor is a long-short portfolio of industries based on their disruption exposure: it loads positively on industries in which a lower fraction of workers report that they can telecommute, while loading negatively on industries in which a higher fraction of workers report that they can work remotely. Specifically, the return on the COVID-19 factor can be expressed as

\[
\hat{\beta}_t = \sum_i w_i(R_{i,t} - \bar{R}_{i,emp}^t), \quad \text{where } \bar{R}_{i,emp}^t = \frac{1}{N} \sum_{i=1}^{N} \frac{emp_{i,0}}{emp_0} R_{i,t} = \sum_{i=1}^{n} e_i R_{i,t}, \quad (12)
\]

where \(e_i\) is the employment share of industry \(i\). The portfolio weight industry \(i\) receives in the COVID-19 portfolio can be written as

\[
w_i = \frac{e_i[X_i - \sum_{l=1}^{N} e_l X_l]}{\sum_{j=1}^{N} e_j[X_j - \sum_{k=1}^{N} e_k X_k]^2} = \frac{e_i[X_i - \bar{X}^{emp}]}{\sum_{j=1}^{N} e_j[X_j - \bar{X}^{emp}]^2}, \quad (13)
\]

where \(X_i\) is our (predetermined) measure of exposure for firm \(i\), so the portfolio holds long positions in stocks with exposure above the employment-weighted average exposure and short positions otherwise.
The portfolio overweights industries whose workers can perform their tasks from home and underweights sectors where workers cannot work remotely; this information is summarized in Figure 11. Consistent with the discussion so far, we see that firms in retail trade and accommodation and food services receive large positive weights. By contrast, firms in professional services and information technologies receive negative weights. Appendix Table A.2 contains the full list of weights on NAICS4 industries.24

The correlation between our factor and the market portfolio in the 3 months before the pandemic period is significantly negative (approximately −0.4), which suggests that the industries most exposed to the COVID pandemic are industries with low systematic risk during normal times. However, given the dominance of COVID-related news during this period, the correlation with the market during the pandemic period is positive, though modest (it ranges from 0.1 to 0.3 depending on how the factor is constructed). Figure 12 plots the factor portfolio returns in blue and returns on the market portfolio in red, and includes annotations which make clear that extreme daily realizations of our factor are associated with significant news about the pandemic.

As of May 15, 2020, this long-short portfolio has lost roughly 50% of its value since the beginning of the year, compared to 10% for the broad market index. This pattern supports the view that COVID-19 is primarily a reallocation shock as not all sectors are symmetrically affected, echoing the views in

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24 Data on the COVID-19 factor are available here: https://www.thecovidfactor.org/
Barrero et al. (2021). These results also demonstrate that investors could construct significantly hedge portfolio exposure to future COVID-19 related uncertainty by taking a short position in our COVID-19 factor.\textsuperscript{25}

To better understand which parts of the portfolio are driving the returns, we form five value-weighted portfolios using information on exposure and critical-industry status. Figure 13 presents industry returns across different quintiles of exposure. The first portfolio includes all critical industries, while the remaining four portfolios sort noncritical firms into four groups according to our exposure measure. We choose the breakpoints so that approximately 25\% of the market value of noncritical firms is associated with each bin as of February 14, 2020. Panel A shows cumulative returns since the start of 2020. The solid black line plots the value-weighted return of all companies included in our sample, and Panel B shows how stocks have performed relative to this market index since February 14.\textsuperscript{26} We see that during the last 2 weeks of February, critical industries performed modestly better than other industries, and we do not see major differences across the portfolios sorted by COVID exposure. However, starting in early March, there are persistent, substantial differences in cumulative returns between firms with different

\textsuperscript{25} This portfolio would simply be the inverse of the one described in Appendix Table A.2.

\textsuperscript{26} Recall from Section 4.1 that a small number of industries are dropped from the analysis. We exclude them from our market index construction as well. That said, our market index closely tracks movements in other broad market indices. More specifically, panel B shows the difference between the cumulative return on each portfolio since February 14th and the market cumulative return over the same period.
levels of exposure, with returns being inversely related to exposure. The spreads between the most- and least-exposed industries peak at around 25% in mid-March and only shrink slightly into early June. There is some convergence towards the end of calendar year 2020, especially following positive vaccine news in November 2020.

Last, we examine the real-time response of our two other forward-looking variables—revisions in analyst forecasts and estimated default probabilities. Figures 14 and 15 summarize our findings. Similar to our stock-return evidence above, there is an increased divergence in revenue forecasts and expected default probabilities across industries with high and low exposures by the end of March and beginning of April 2020. Comparing the two figures, we see that default probabilities appear to respond a bit earlier than analyst

Figure 13
Buy-and-hold returns for market, critical, and noncritical portfolios sorted by COVID-19 work exposure
Panel A of the figure shows the buy-and-hold returns since January 1, 2020 for the overall market, the portfolio of critical industries, and portfolios of noncritical industries sorted into quartiles of COVID-19 work exposure such that each noncritical industry portfolio has equal market capitalization. Panel B reports the difference between cumulative returns of each portfolio since February 14, 2020 and the cumulative return of the market portfolio over the same period. Portfolios are value-weighted and breakpoints are chosen so that the noncritical portfolios each have approximately the same market cap as of February 14, 2020.
revenue forecasts, and they seem to recover somewhat from their peaks by the end of April. That said, these timing differences may simply reflect the fact that analyst forecasts are released with some delay. Following some positive news in the second half of 2020, these differences attenuate slightly (with the largest improvements for 2022), though cross-sectional differences remain large and statistically significant throughout the year.

Figure 14
Revenue forecast revisions and COVID-19 work exposure over time

Figure plots the slope coefficients of a regression of forecast revisions on COVID-19 work exposure for non-critical industries at a monthly frequency. Panel A of this figure plots the slope coefficient for revisions in revenue forecasts for Q2–Q4 2020. Panel B plots the corresponding revisions for the years 2020 through 2022.
4.3 The apparent disconnect between the stock market and the economy

Despite the fact that many measures of real activity, including initial claims for unemployment and the employment-population ratio, have reached uncharted territory, the stock market quickly rebounds from its March lows. Numerous explanations have been put forward for this. First, the most severe effects of the pandemic recession on overall activity are likely to be fairly transitory in nature, whereas stock prices capitalize the entire present discounted value of future profits of listed firms. Second, both short- and long-term interest rates have declined following large amounts of fiscal and monetary stimulus, a force that pushes valuations higher, ceteris paribus. Third, listed companies tend to be larger, and small firms are thought to be more exposed to the fallout from the virus. For instance, larger firms have better access to capital markets, and fixed compliance costs associated with COVID-19 are likely more manageable for larger firms.

We consider a very simple and complementary explanation to those proposed above. Specifically, the industrial composition of the stock market is not fully representative of the broader (listed and nonlisted) economy. In the vast majority of cases, a market index such as the S&P 500 weights each of its constituents proportionately with its market capitalization. There are well-understood patterns of which types of firms find it most valuable to list publicly (Doidge, Karolyi, and Stulz 2017), and publicly listed firms now comprise a smaller share of aggregate employment relative to the past.
(Schlingemann and Stulz, 2020). For instance, tech firms are substantially overrepresented in market indices relative to their share of overall employment in the U.S. economy. Moreover, as is indeed the case for the tech sector overall, many of these overrepresented sectors turn out to have a larger share of employees who are able to work from home.

We investigate this possibility systematically by considering two different approaches to aggregating our exposure measure, as well as measures of market values and operating activity, across industries. In one approach, we compute weighted averages using each industry’s share of market capitalization as of February 14, 2020. As an alternative approach intended to more accurately reflect the industry mix of the broader nonfinancial corporate sector, we construct industry weights using NAICS4 employment totals as of 2017 from the Census Bureau’s Statistics of U.S. Businesses database.²⁷ We construct a statistical test for the difference between the market value-weighted and employment means by appending two copies of the dataset, where each copy is associated with a distinct set of weights. We then run a pooled (weighted) regression of each industry outcome on an indicator variable equal to 1 for the copy using value weights and equal to 0 for the copy using employment weights, with standard errors clustered at the industry level. We then report the t-statistic on the null hypothesis that this indicator variable equals zero, which is equivalent to the hypothesis that the two weighted means are identical.

These two different weighting schemes provide very different pictures of the overall exposure of the set of industries that include at least one listed firm. When we weight industries according to their market values, average COVID-19 exposure is only 66%, 21 percentage points lower (t = 4.8) than the 87% mean which obtains when we instead use employment weights. The stock market is considerably less exposed to the supply-side shock than the overall economy; moreover, some larger companies (e.g., Amazon.com) have benefited substantially from the sectoral reallocations induced by the pandemic. As an example, the employment share for the information sector (NAICS 51) is only 3.5%, whereas this sector comprises 24% of the market cap of listed firms as of February 2020. Even within the broader (NAICS2) technology sector, the composition of firms is tilted towards less-exposed NAICS4 industries: employment- and market-cap-weighted exposures are 56% and 43%, respectively. A similar pattern emerges for manufacturing industries (NAICS 31–33), which make up about 48% of the total market cap of nonfinancial industries included in our analysis (versus only about 11% of

²⁷ Note that these are buy-and-hold indices. If a stock is delisted, we assume proceeds are held in cash, which is virtually identical to investing in a short-term Treasury bill given short-term interest rates were approximately at the zero lower bound throughout this period. Note that, as before, we exclude finance, insurance, and real estate from these estimates. As both of these sectors experienced larger market declines relative to overall market indices, our value-weighted index actually shows an even stronger rebound relative to others such as the S&P 500 index.
employment). While the employment-weighted average exposure is 85%, the market-cap-weighted exposure of listed firms in these industries is 66%.

Table 7 and Figure 16 report related weighted means for cumulative stock market returns and analyst forecast revisions at various horizons, measured at different dates during the pandemic. Figure 16 presents the same outcomes at a monthly frequency from February 21st onwards. As of March 20th, near the market trough, the employment-weighted index is down by 39%, which is about 7.4 percentage points more than the market-cap-weighted index. This gap, which is statistically significant at all dates, widens to about 10 percentage points at the later horizons. We observe a similar picture for revenue forecast revisions (after allowing for some potential lag for analysts to update them). Across essentially all horizons, as of June 19, declines in the employment-weighted average forecasts are usually about 50% larger relative to the market-cap-weighted averages. For instance, the decline in the forecast for 2022 calendar revenue is 7.2% in the former versus 4.6% in the

| Date   | Statistic           | Stock returns (%) | Analyst revenue forecast revisions (%) |
|--------|---------------------|-------------------|----------------------------------------|
| 3/20   | Employment-weighted | -0.393            | -0.042 -0.021 -0.010 -0.015 -0.018   |
|        | Market cap-weighted | -0.319            | -0.029 -0.020 -0.016 -0.015 -0.016   |
|        | Difference          | -0.074            | -0.013 0.000 0.006 0.001 -0.002     |
|        | t-statistic         | (-3.133)          | (-0.913) (-0.055) (0.992) (0.134) (-0.367) |
| 4/17   | Employment-weighted | -0.242            | -0.176 -0.088 -0.047 -0.051 -0.056   |
|        | Market cap-weighted | -0.145            | -0.109 -0.069 -0.045 -0.045 -0.041   |
|        | Difference          | -0.097            | -0.066 -0.018 -0.002 -0.006 -0.015   |
|        | t-statistic         | (-4.027)          | (-2.000) (-1.054) (-0.151) (-0.671) (-1.339) |
| 5/15   | Employment-weighted | -0.234            | -0.231 -0.139 -0.084 -0.085 -0.072   |
|        | Market cap-weighted | -0.126            | -0.147 -0.099 -0.062 -0.059 -0.046   |
|        | Difference          | -0.108            | -0.085 -0.039 -0.021 -0.027 -0.026   |
|        | t-statistic         | (-3.742)          | (-2.626) (-1.928) (-1.400) (-1.994) (-2.291) |
| 6/19   | Employment-weighted | -0.146            | -0.226 -0.142 -0.089 -0.090 -0.072   |
|        | Market cap-weighted | -0.047            | -0.144 -0.099 -0.062 -0.059 -0.046   |
|        | Difference          | -0.099            | -0.081 -0.043 -0.027 -0.030 -0.026   |
|        | t-statistic         | (-3.614)          | (-2.678) (-2.133) (-1.674) (-2.022) (-2.447) |
| 9/18   | Employment-weighted | -0.017            | -0.219 -0.129 -0.095 -0.086 -0.062   |
|        | Market cap-weighted | 0.035             | -0.139 -0.077 -0.052 -0.043 -0.03    |
|        | Difference          | -0.052            | -0.08 -0.053 -0.043 -0.042 -0.032    |
|        | t-statistic         | (-1.367)          | (-2.617) (-2.300) (-2.169) (-2.322) (-2.164) |
| 12/18  | Employment-weighted | 0.006             | -0.219 -0.127 -0.093 -0.084 -0.05    |
|        | Market cap-weighted | 0.069             | -0.139 -0.076 -0.038 -0.029 -0.019   |
|        | Difference          | -0.063            | -0.08 -0.052 -0.055 -0.055 -0.031    |
|        | t-statistic         | (-1.434)          | (-2.618) (-2.173) (-2.406) (-2.618) (-2.022) |

Table provides estimates of overall aggregated stock market performance and percentage revisions in analyst revenue forecasts from February 14, 2020 at various dates in 2020 under two different weighting schemes. First, we weight observations by total employment of publicly and privately held companies as of 2017. Then, we consider an alternative in which we weight each NAICS4 industry by the market cap of firms as of February 14, 2020. We then report the difference and a t-statistic on the difference between the two estimates, which is using a weighted regression with standard errors clustered at the NAICS4 level. Using these same weighting schemes, average COVID-19 Work Exposure is 87% when weighting by employment and 66% when weighting by market cap, where the difference of 21% is associated with a t-statistic of 4.8.
latter case. With the exception of 2020Q4, these differences are statistically significant at the 95% level. In brief, the stock market disproportionately captures news about a set of industries that are less exposed to the impact of the pandemic recession relative to the broader economy. Over longer horizons, these gaps close modestly following positive news in the second half of 2020, but remain substantial in magnitude (though they are somewhat less precisely estimated).

Figure 16
Stock returns and revenue forecast revisions: Employment versus market-cap weights
Figure plots average revisions in the revenue forecasts from February 14, 2020, for various horizons as well as stock returns on a monthly basis through 2020. In panels A and C, we weight each four-digit NAICS industry by the market cap of firms as of February 14, 2020. In panels B and D, we weight observations by total employment of publicly and privately held companies as of 2017. Panels A and B show stock returns and shorter-horizon revenue forecast revisions, while panels C and D show longer-horizon revenue forecasts. Dates on the horizontal axes correspond with the ends of calendar weeks.
5. Assessing the Fiscal Response to COVID-19

As state and local governments began to impose widespread lockdowns and social-distancing measures, policy makers were quick to respond with fiscal policies intended to limit the damage from the pandemic. While a formal treatment of optimal fiscal transfers is beyond the scope of this paper (see, e.g., Flynn, Patterson, and Sturm 2020, and references therein for a more formal treatment), economic intuition suggests that an optimal insurance policy would provide the highest amount of relief to the hardest-hit businesses—that is, the businesses most likely to cut investment, reduce employment, or shut down operations if they did not receive aid. Here, we explore whether the relief policies implemented in the first half of 2020 appear consistent with this objective.

In March 2020, the U.S. Congress passed the Coronavirus Aid, Relief, and Economic Security (CARES) Act, which included the PPP. The PPP is a $669 billion loan program run by the U.S. Small Business Administration (SBA) and intended to help smaller firms during the crisis. This program is the largest component of the fiscal stimulus provided to firms in the U.S. In order to be eligible for PPP financing, firms have to meet a size threshold; according to SBA, any business that, prior to the crisis, had 500 or fewer U.S.-based employees or met SBA’s alternative revenue/employment-based size standards is eligible to receive funds.28 Approved loan amounts vary based on the applicant’s average payroll costs, with a $100,000 annualized cap per employee and $10 million cap in total per firm. Most loan disbursements are capped at 2.5 times the firm’s average monthly payrolls costs from 2019. SBA guarantees the loans but does not lend directly to firms; rather, firms apply for PPP loans from authorized lenders. Most importantly, SBA forgives the loan if the firm maintains its entire workforce for a minimum of 8 weeks and the loan is only used for payroll, rent, mortgage interest, or utility expenses. Thus PPP is effectively a fiscal transfer to firms.29

The SBPS we discussed in Section 2.4 asks firms whether they applied for a PPP loan. In particular, the survey asks, “Since March 13, 2020, has this business requested financial assistance from the following Federal Sources?” We tabulate the fraction of responses in which the “Paycheck Protection Program” box is checked. We would expect that hardest-hit businesses are more likely to apply for PPP funding. The last column of Table 5 and panel F of Figure 7 show

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28 In addition to firms, any self-employed person, sole proprietor, independent contractor, 501(c)(3) nonprofit organization, 501(c)(19) veterans’ organization, or tribal business is eligible. Restrictions on size were relaxed for some firms in the Accommodations and Food Services sector (NAICS sector 72). Some firms who had currently or recently defaulted on SBA loans were deemed ineligible.

29 The government has recently taken steps to relax certain requirements of the PPP with the PPP Flexibility Act (PPPPA) passed in early June. Originally, businesses had to spend at least 75% of the loan on payroll alone, but the PPPPA lowered this threshold to 60%. Whereas before firms only had only 8 weeks to spend the entirety of the loan, the PPPPA extended the deadline to the end of 2020, giving firms the flexibility to wait and spend after they have reopened.
that this is indeed the case: an increase of one standard deviation in exposure leads to a 3.6 percentage point increase in the likelihood of application. This magnitude is significant but pales in comparison to the intercept: a firm with the average level of exposure has a 75% probability of applying for PPP funds.

It is clear that the vast majority of firms apply for PPP funding. But are funds allocated to the most exposed sectors? To answer this question, we examine the correlation between our exposure measure and the total disbursements from the PPP program through July 10, 2020.\textsuperscript{30} We augment this information with information at the firm level released by the SBA, which gives a more detailed picture of how the money is allocated. For loans less than $150,000, the SBA reports the exact dollar value of the loan, while for loans larger than $150,000, they report a range of dollar values the loan falls within. The data also include a field called “jobs saved,” which we assume corresponds to the number of employees listed on the loan application form.\textsuperscript{31} We interpolate the loan values that are not perfectly observed with the arithmetic mean of the endpoints of the bin. We validate this strategy by comparing our interpolated totals aggregated at the state level to published state-level totals, and while these values are quite close, the interpolated aggregates are biased upward relative to the published summary statistics for state- and industry-level totals. To correct for this bias, we calculate the average percentage miss at the state level and use that to correct the values of the loans that are not perfectly observed. After this correction, our values almost exactly correspond to published totals, as is clear from Figure A.1 in the Appendix.

In Table 8, we report the dollar amount of PPP funding per employee by major sector, as well as relative to the total annual payroll dollar amount. The sector that receives the largest number of PPP loans—and the second-highest total amount of funding—is professional, scientific, and technical services, with 638,220 loans totaling approximately $66 billion, amounting to $12,400 per employee. However, this sector is one of those least exposed to the disruptions associated with the pandemic: according to our calculations, this sector has the highest fraction of workers who can work remotely. By contrast, more-exposed sectors receive significantly less funding from the PPP program; accommodation and food services and arts, entertainment, and recreation, two of the hardest-hit sectors, receive just $5,000 and $5,400 per worker, respectively.

Overall, we see that the least-affected sectors actually receive more PPP funds than the most-affected sectors. What explains this inefficient provision of insurance? We believe this stems from the fact that the PPP treats all firms identically

\textsuperscript{30} The data is available at https://www.sba.gov/document/report-paycheck-protection-program-report-through-july-10-2020.

\textsuperscript{31} This field is sometimes missing or zero, suggesting that some firms elected not to disclose their current employment levels on the initial loan applications. As the distributions of loan sizes are fairly similar between the group of firms that reports employment totals and the group of firms that does not, we replace zero or missing employment totals with the average number of employees reported by firms in the same industry and loan-size bin. Results are qualitatively similar if we instead keep these numbers at zero.
Table 8
COVID-19 work exposure and PPP loan disbursements by major NAICS sector

| Industry category                                      | Work exposure | # Loans | Total amount ($B) | % of total | Employees | Loan amt. / employee (Raw) | Interp. (M) | Loan amt. / employee (Raw) | Interp. (M) |
|--------------------------------------------------------|---------------|---------|-------------------|------------|-----------|----------------------------|-------------|----------------------------|-------------|
| Health Care and Social Assistance                      | 90%           | 506,259 | $66.8             | 13.16%     | 7.52      | $8,103                     |             |                           |             |
| Professional, Scientific, and Technical Services        | 58%           | 638,220 | $65.9             | 12.99%     | 4.85      | $13,399                    |             |                           |             |
| Construction                                            | 94%           | 466,212 | $64.1             | 12.63%     | 5.08      | $11,475                    |             |                           |             |
| Manufacturing                                           | 84%           | 229,559 | $53.7             | 10.58%     | 4.60      | $10,842                    |             |                           |             |
| Accommodation and Food Services                         | 97%           | 367,499 | $41.9             | 8.25%      | 7.58      | $5,054                     |             |                           |             |
| Retail Trade                                            | 94%           | 450,177 | $40.1             | 7.90%      | 4.75      | $7,724                     |             |                           |             |
| Other Services (except Public Administration)           | 86%           | 531,568 | $30.9             | 6.08%      | 4.08      | $6,757                     |             |                           |             |
| Wholesale Trade                                         | 81%           | 167,235 | $27.5             | 5.42%      | 2.35      | $11,700                    |             |                           |             |
| Administrative and Support and Waste Management and Remediation Services | 87%       | 240,932 | $26.2             | 5.16%      | 3.04      | $8,610                     |             |                           |             |
| Transportation and Warehousing                          | 96%           | 191,608 | $16.9             | 3.33%      | 1.69      | $9,013                     |             |                           |             |
| Real Estate and Rental and Leasing                     | 89%           | 245,696 | $15.4             | 3.04%      | 1.46      | $9,541                     |             |                           |             |
| Finance and Insurance                                  | 68%           | 168,460 | $12.0             | 2.36%      | 1.00      | $10,912                    |             |                           |             |
| Educational Services                                    | 80%           | 81,387  | $11.9             | 2.34%      | 1.43      | $7,511                     |             |                           |             |
| Information                                             | 62%           | 69,103  | $9.2              | 1.81%      | 0.71      | $11,907                    |             |                           |             |
| Arts, Entertainment, and Recreation                    | 91%           | 118,331 | $8.0              | 1.57%      | 1.34      | $5,369                     |             |                           |             |
| Agriculture, Forestry, Fishing & Hunting               | 93%           | 139,146 | $7.9              | 1.55%      | 1.05      | $6,811                     |             |                           |             |
| Mining, Quarrying, and Oil & Gas Extraction            | 88%           | 21,568  | $4.5              | 0.88%      | 0.29      | $14,412                    |             |                           |             |
| Management of Companies and Enterprises                | 69%           | 8,893   | $1.6              | 0.31%      | 0.15      | $9,783                     |             |                           |             |
| Utilities                                               | 89%           | 7,928   | $1.5              | 0.29%      | 0.11      | $14,942                    |             |                           |             |
| Public Administration                                   | NA            | 13,423  | $1.7              | 0.34%      | 0.16      | $10,942                    |             |                           |             |

Table reports summary statistics on PPP loan disbursements by major NAICS sector, along with employment and payroll. Information is taken from the published data at the individual loan level. Payroll data are taken from microdata released by the SBA, which reports number of “jobs saved” associated with each loan. The raw employee number is a raw total of this value by sector, while the interpolated employee number is calculated by imputing zero/missing values with industry x loan-size bin averages. The final two columns express total loan disbursements on a per-employee basis by dividing total loan disbursements by each of these total employment figures.

Once they pass its initial screening criteria. Since loans are forgivable, take-up rates for PPP are extremely high and most variation in total lending across eligible firms is driven by caps on benefit amounts. Average earnings per worker are considerably higher in sectors where working remotely is feasible (see, e.g. Dingel and Neiman 2020, and Section 2.1 above). Since benefit amounts are tied to average payroll, sectors with more white-collar workers (and thus higher average compensation) receive more aid per worker. In brief, tying the amount of aid to total payroll has the (likely unintended) consequence of directing a larger share of total spending per employee towards the least-exposed sectors.
With these data in hand, we get a much more detailed picture: rather than only looking at major sectors, we can now look at how the fiscal response is distributed across different NAICS4 industries. As we show in Figure 17 and Table 9, industries that are better able to transition to remote work, and thus experience less supply-side disruption, receive far more dollars per worker than industries that are completely disrupted. An increase of one standard deviation in our exposure measure is associated with a 17.4% decrease in loan value per employee. In dollars, this corresponds to a loss of nearly $1,700 relative to an average loan value of $9,700. Equally striking is that there is no significant difference between the level of aid given to critical and noncritical industries, but the loan values for noncritical industries (which were more disrupted) are actually more sensitive to exposure than those for critical industries: an increase of one standard deviation in our measure is associated with an average decrease in loan value per employee of 13.2% for critical industries and 19.4% for noncritical industries.

An important consideration is that the first round of stimulus was put in place quickly and at a time with immense economic uncertainty. Accordingly,

| Table 9 | COVID-19 work exposure and loan value ($) per employee |
|---------|------------------------------------------------------|
| A. $/employee | Weighted by employment | Equal weighted |
| All industries | Noncritical | All industries | Noncritical |
| COVID-19 work exposure | $-12116.6***$ | $-13691.8***$ | $-7017.4***$ | $-7474.9***$ |
| Number of observations | 217 | 156 | 217 | 156 |
| R² | 0.327 | 0.368 | 0.134 | 0.145 |
| B. log($/employee)*100 | $-125.9***$ | $-139.8***$ | $-70.1***$ | $-72.2***$ |
| COVID-19 work exposure | (-4.96) | (-4.32) | (-5.66) | (-4.60) |
| Number of observations | 217 | 156 | 217 | 156 |
| R² | 0.291 | 0.322 | 0.120 | 0.121 |
| C. Average, all industries | $/employee | log($/employee)*100 |
| Weighted | Unweighted | Weighted | Unweighted |
| Critical industries | $9896.4***$ | $10468.3***$ | $916.3***$ | $922.4***$ |
| (19.20) | (32.11) | (149.01) | (271.56) |
| Noncritical industries | $9547.2***$ | $10406.7***$ | $909.7***$ | $921.2***$ |
| (13.59) | (48.00) | (108.62) | (401.51) |
| Diff: Noncritical–critical | $-349.2$ | $-61.6$ | $-6.6$ | $-1.1$ |
| (-0.40) | (-0.16) | (-0.64) | (-0.27) |
| Number of observations | 217 | 217 | 217 | 217 |

Panel A reports the coefficient estimates for the correlation between dollars of PPP funding per employee and COVID-19 work exposure using employment-weighted (March 2020 BLS) and unweighted specifications (t-statistics in parantheses). Panel B reports the same statistics for the specification where the dependent variable is the log of SPPP per employee. Odd-numbered columns repeat the analysis for the subsample of noncritical industries. The dependent variable is expressed in percentage points and constructed using private-sector employment data from the BLS’s April 2020 employment report at the NAICS4 level. Standard errors are robust to heteroskedasticity (White, 1980). Panel C reports the average of the dependent variable for critical and noncritical industries, as well as the difference between the two averages. The cross-sectional standard deviation across BLS industries of the COVID-19 work exposure measure is 13.86%. Given that BLS only reports data for a single NAICS4 agricultural industry (logging), we exclude agriculture from this analysis. The results are not sensitive to this choice. The list of critical NAICS4 industries is in Table A.1.

* $p < .05$; ** $p < .01$; *** $p < .001$. 

With these data in hand, we get a much more detailed picture: rather than only looking at major sectors, we can now look at how the fiscal response is distributed across different NAICS4 industries. As we show in Figure 17 and Table 9, industries that are better able to transition to remote work, and thus experience less supply-side disruption, receive far more dollars per worker than industries that are completely disrupted. An increase of one standard deviation in our exposure measure is associated with a 17.4% decrease in loan value per employee. In dollars, this corresponds to a loss of nearly $1,700 relative to an average loan value of $9,700. Equally striking is that there is no significant difference between the level of aid given to critical and noncritical industries, but the loan values for noncritical industries (which were more disrupted) are actually more sensitive to exposure than those for critical industries: an increase of one standard deviation in our measure is associated with an average decrease in loan value per employee of 13.2% for critical industries and 19.4% for noncritical industries.

An important consideration is that the first round of stimulus was put in place quickly and at a time with immense economic uncertainty. Accordingly,
policy makers elected to go for a large and broad-based response, offering aid to essentially all small businesses with few restrictions. Yet to mitigate the costs of the pandemic, a more targeted program may be desirable, consistent with the view in Guerrieri et al. (2020). While proposing an optimal policy is outside the scope of this paper, precedents exist. For example, the Department of Labor’s Trade Adjustment Assistance program targets assistance to workers and firms displaced by competition from foreign imports (see, e.g., Hyman 2018, for more details). Providing targeted assistance to workers and firms based on an ex ante measure of exposure to COVID-19 work disruptions could be a more cost-effective way to alleviate the economic impacts of the virus.

6. Conclusion

In this paper, we have characterized the supply-side disruptions associated with COVID-19 by exploiting differences in the ability of workers across industries to work remotely. We have provided a measure of ex ante pandemic risk exposures and a list of critical industries that can be used to study a wide array of questions related to firm and worker outcomes during and in the aftermath of the pandemic.32

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32 Our data are available here: https://www.thecovidfactor.org/
Our exposure metrics are highly predictive of heterogeneity in outcomes during the pandemic. Specifically, sectors in which a higher fraction of the workforce is not able to work remotely have experienced significantly greater declines in employment, much larger reductions in expected revenue growth, worse stock market performance, and higher expected likelihood of default. Lower-paid workers, especially female workers with young children, are far more affected by these disruptions.

Overall, our results uncover predictable differences in economic outcomes for both workers and firms depending on the ability of their industry to transition to remote work. Importantly, these cross-sectional differences are economically sizable and comparable to the magnitude of the aggregate response. Thus, our findings indicate that the pandemic has an economically significant cross-sectional component that is well captured by our exposure measure. These findings lead to several important conclusions.

First, a significant component of these differences in economic outcomes was largely predictable at the beginning of the pandemic using data on the feasibility of remote work. To the extent that government policy aims to insure firms by smoothing unexpected economic shocks, the PPP fell somewhat short of that goal. Specifically, the primary criterion for participation in the program was firm size; PPP funds are allocated in proportion to total payroll expenses. Since higher-paid employees are more likely to be able to work remotely, tying financing to payroll expenses has the (likely unintended) consequence of allocating more federal funds per employee to the least-affected sectors. By restricting eligibility to the most (ex ante) vulnerable sectors, the program could have delivered a similar level of insurance at significantly lower cost.

Second, understanding that the COVID-19 pandemic has led to significant dispersion in outcomes across sectors helps reconcile the disconnect between returns on the stock market and aggregate economic outcomes. Specifically, the composition of listed firms in the stock market is heavily tilted towards high-tech industries, while underweighting small service firms that are disproportionately disrupted by the pandemic. As a result, the stock market has become even less representative of the U.S. economy during the pandemic.

Last, by combining these ex ante firm exposures with high-frequency data on asset returns, we can construct real-time estimates of pandemic-related news. Applying this idea to stock returns, we create a portfolio that closely replicates the supply-side disruptions resulting from the pandemic. As of May 15, 2020, this portfolio had lost roughly 50% of its value since the beginning of 2020—compared to 10% for the broad market index. Large changes in the value of this portfolio are associated with significant pandemic-related news through the end of our period of study. Given the continued disruptions to the global economy from the COVID-19 pandemic and concern about future disruptions, our COVID-19 portfolio factor may play an important role in explaining the pricing of related risks in 2020 and beyond.
### Appendix

#### Table A.1

**List of critical industries**

| NAICS Code | Industry Name                                      |
|------------|---------------------------------------------------|
| 1111       | Oilseed and Grain Farming                         |
| 1112       | Vegetable and Melon Farming                       |
| 1113       | Fruit and Tree Nut Farming                        |
| 1119       | Other Crop Farming                                |
| 1121       | Cattle Ranching and Farming                       |
| 1122       | Hog and Pig Farming                               |
| 1123       | Poultry and Egg Production                        |
| 1124       | Sheep and Goat Farming                            |
| 1129       | Other Animal Production                           |
| 1141       | Fishing                                           |
| 1142       | Hunting and Trapping                              |
| 1151       | Support Activities for Crop Production            |
| 1152       | Support Activities for Animal Production          |
| 2121       | Coal Mining                                       |
| 2122       | Metal Ore Mining                                  |
| 2123       | Nonmetallic Mineral Mining and Quarrying          |
| 2131       | Support Activities for Mining                     |
| 2211       | Electric Power Generation, Transmission and Distribution |
| 2212       | Natural Gas Distribution                          |
| 2213       | Water, Sewage and Other Systems                   |
| 2373       | Highway, Street, and Bridge Construction           |
| 3111       | Animal Food Manufacturing                          |
| 3112       | Grain and Oilseed Milling                         |
| 3113       | Sugar and Confectionery Product Manufacturing      |
| 3114       | Fruit and Vegetable Preserving and Specialty Food Manufacturing |
| 3115       | Dairy Product Manufacturing                       |
| 3116       | Animal Slaughtering and Processing                |
| 3117       | Seafood Product Preparation and Packaging          |
| 3118       | Bakeries and Tortilla Manufacturing                |
| 3119       | Other Food Manufacturing                           |
| 3121       | Beverage Manufacturing                            |
| 3254       | Pharmaceutical and Medicine Manufacturing         |
| 3256       | Soap, Cleaning Compound, and Toilet Preparation Manufacturing |
| 3261       | Plastics Product Manufacturing                    |
| 3312       | Steel Product Manufacturing from Purchased Steel   |
| 3313       | Alumina and Aluminum Production and Processing     |
| 3331       | Agriculture, Construction, and Mining Machinery Manufacturing |
| 3391       | Medical Equipment and Supplies Manufacturing      |
| 4242       | Drugs and Druggists’ Sundries Merchant Wholesalers |
| 4245       | Farm Product Raw Material Wholesalers             |
| 4413       | Automotive Parts, Accessories, and Tire Stores    |
| 4441       | Building Material and Supplies Dealers            |
| 4451       | Grocery Stores                                    |
| 4452       | Specialty Food Stores                             |
| 4453       | Beer, Wine, and Liquor Stores                     |
| 4461       | Health and Personal Care Stores                   |
| 4471       | Gasoline Stations                                 |
| 4523       | General Merchandise Stores, including Warehouse Clubs and Supercenters |
| 4539       | Other Miscellaneous Store Retailers               |
| 4541       | Electronic Shopping and Mail-Order Houses         |
| 4812       | Nonscheduled Air Transportation                    |
| 4841       | General Freight Trucking                          |
| 4842       | Specialized Freight Trucking                      |
| 4851       | Urban Transit Systems                             |
| NAICS Code | Industry Name                                                                 |
|------------|-------------------------------------------------------------------------------|
| 4852       | Interurban and Rural Bus Transportation                                       |
| 4853       | Taxi and Limousine Service                                                    |
| 4859       | Other Transit and Ground Passenger Transportation                             |
| 4861       | Pipeline Transportation of Crude Oil                                         |
| 4862       | Pipeline Transportation of Natural Gas                                        |
| 4885       | Freight Transportation Arrangement                                           |
| 4911       | Postal Service                                                               |
| 4921       | Couriers and Express Delivery Services                                        |
| 4922       | Local Messengers and Local Delivery                                          |
| 4931       | Warehousing and Storage                                                       |
| 5173       | Telecommunications Resellers                                                  |
| 5179       | Other Telecommunications                                                      |
| 5211       | Monetary Authorities-Central Bank                                            |
| 5221       | Depository Credit Intermediation                                              |
| 5222       | Nondepository Credit Intermediation                                           |
| 5223       | Activities Related to Credit Intermediation                                  |
| 5231       | Securities and Commodity Contracts Intermediation and Brokerage               |
| 5232       | Securities and Commodity Exchanges                                            |
| 5239       | Other Financial Investment Activities                                         |
| 5241       | Insurance Carriers                                                           |
| 5242       | Agencies, Brokerages, and Other Insurance Related Activities                 |
| 5251       | Insurance and Employee Benefit Funds                                          |
| 5259       | Other Investment Pools and Funds                                              |
| 5411       | Legal Services                                                                |
| 5412       | Accounting, Tax Preparation, Bookkeeping, and Payroll Services                |
| 5621       | Waste Collection                                                              |
| 5622       | Waste Treatment and Disposal                                                  |
| 5629       | Remediation and Other Waste Management Services                               |
| 6111       | Elementary and Secondary Schools                                              |
| 6211       | Offices of Physicians                                                         |
| 6214       | Outpatient Care Centers                                                       |
| 6215       | Medical and Diagnostic Laboratories                                           |
| 6216       | Home Health Care Services                                                     |
| 6219       | Other Ambulatory Health Care Services                                         |
| 6221       | General Medical and Surgical Hospitals                                        |
| 6222       | Specialty (except Psychiatric and Substance Abuse) Hospitals                  |
| 6231       | Nursing Care Facilities (Skilled Nursing Facilities)                          |
| 6233       | Continuing Care Retirement Communities and Assisted Living Facilities for the Elderly |
| 9211       | Executive, Legislative, and Other General Government Support                  |
| 9221       | Justice, Public Order, and Safety Activities                                  |
| 9231       | Administration of Human Resource Programs                                     |
| 9241       | Administration of Environmental Quality Programs                             |
| 9251       | Administration of Housing Programs, Urban Planning, and Community Development |
| 9261       | Administration of Economic Programs                                           |
| 9271       | Space Research and Technology                                                 |
| 9281       | National Security and International Affairs                                   |
Table A.2
COVID-19 factor, portfolio weights (four-digit NAICS)

| Industry (NAICS) | Portfolio Weight (%) |
|-----------------|----------------------|
| 4481: Clothing Stores | 19.67 |
| 5613: Employment Services | 15.95 |
| 7225: Restaurants and Other Eating Places | 14.62 |
| 7211: Traveler Accommodation | 11.23 |
| 4811: Scheduled Air Transportation | 11.05 |
| 5151: Radio and Television Broadcasting | 8.19 |
| 4522: Department Stores | 6.12 |
| 7223: Special Food Services | 5.99 |
| 3363: Motor Vehicle Parts Manufacturing | 5.59 |
| 4831: Deep Sea, Coastal, and Great Lakes Water Transportation | 5.57 |
| 3361: Motor Vehicle Manufacturing | 5.51 |
| 3344: Semiconductor and Other Electronic Component Manufacturing | 4.50 |
| 3329: Other Fabricated Metal Product Manufacturing | 3.66 |
| 4411: Automobile Dealers | 3.04 |
| 3339: Other General Purpose Machinery Manufacturing | 2.76 |
| 7131: Amusement Parks and Arcades | 2.75 |
| 3221: Pulp, Paper, and Paperboard Mills | 2.66 |
| 5617: Services to Buildings and Dwellings | 2.45 |
| 4244: Grocery and Related Product Merchant Wholesalers | 2.28 |
| 5121: Motion Picture and Video Industries | 2.10 |
| 3262: Rubber Product Manufacturing | 2.02 |
| 3222: Converted Paper Product Manufacturing | 1.96 |
| 4511: Sporting Goods, Hobby, and Musical Instrument Stores | 1.90 |
| 3311: Iron and Steel Mills and Ferroalloy Manufacturing | 1.88 |
| 2382: Building Equipment Contractors | 1.63 |
| 2371: Utility System Construction | 1.60 |
| 3252: Resin, Synthetic Rubber, and Artificial and Synthetic Fibers and Filaments Manufacturing | 1.48 |
| 5616: Investigation and Security Services | 1.44 |
| 3219: Other Wood Product Manufacturing | 1.41 |
| 4431: Electronics and Appliance Stores | 1.32 |
| 3353: Electrical Equipment Manufacturing | 1.29 |
| 4482: Shoe Stores | 1.29 |
| 4231: Motor Vehicle and Motor Vehicle Parts and Supplies Merchant Wholesalers | 1.24 |
| 7132: Gambling Industries | 1.19 |
| 7139: Other Amusement and Recreation Industries | 1.14 |
| 3399: Other Miscellaneous Manufacturing | 1.13 |
| 3141: Textile Furnishings Mills | 1.12 |
| 2362: Nonresidential Building Construction | 1.10 |
| 5152: Cable and Other Subscription Programming | 1.09 |
| 8123: Drycleaning and Laundry Services | 1.02 |
| 3152: Cut and Sew Apparel Manufacturing | 1.02 |
| 3324: Boiler, Tank, and Shipping Container Manufacturing | 1.01 |
| 4236: Household Appliances and Electrical and Electronic Goods Merchant Wholesalers | 1.00 |
| 2379: Other Heavy and Civil Engineering Construction | 0.99 |
| 2361: Residential Building Construction | 0.95 |
| 4532: Office Supplies, Stationery, and Gift Store | 0.94 |
| 3359: Other Electrical Equipment and Component Manufacturing | 0.90 |
| 3334: Ventilation, Heating, Air-Conditioning, and Commercial Refrigeration Equipment Manufacturing | 0.90 |
| 3366: Ship and Boat Building | 0.87 |
| 3323: Architectural and Structural Metals Manufacturing | 0.77 |
| 3231: Printing and Related Support Activities | 0.74 |
| 8121: Personal Care Services | 0.74 |
| 6222: Psychiatric and Substance Abuse Hospitals | 0.71 |
| 4422: Home Furnishings Stores | 0.70 |
| Industry (NAICS) | Portfolio Weight (%) |
|-----------------|----------------------|
| 3322: Cutlery and Handtool Manufacturing | 0.69 |
| 5611: Office Administrative Services | 0.69 |
| 3352: Household Appliance Manufacturing | 0.66 |
| 3272: Glass and Glass Product Manufacturing | 0.66 |
| 3362: Motor Vehicle Body and Trailer Manufacturing | 0.66 |
| 5615: Travel Arrangement and Reservation Services | 0.61 |
| 7113: Promoters of Performing Arts, Sports, and Similar Events | 0.61 |
| 6244: Child Day Care Services | 0.61 |
| 3332: Industrial Machinery Manufacturing | 0.61 |
| 3251: Basic Chemical Manufacturing | 0.55 |
| 3279: Other Nonmetallic Mineral Product Manufacturing | 0.53 |
| 3371: Household and Institutional Furniture and Kitchen Cabinet Manufacturing | 0.51 |
| 3169: Other Leather and Allied Product Manufacturing | 0.47 |
| 3369: Other Transportation Equipment Manufacturing | 0.45 |
| 5614: Business Support Services | 0.43 |
| 3325: Hardware Manufacturing | 0.41 |
| 3372: Office Furniture (including Fixtures) Manufacturing | 0.35 |
| 4883: Jewelry, Luggage, and Leather Goods Stores | 0.33 |
| 3379: Other Furniture Related Product Manufacturing | 0.33 |
| 2383: Building Finishing Contractors | 0.33 |
| 4237: Hardware, and Plumbing and Heating Equipment and Supplies Merchant Wholesalers | 0.32 |
| 7111: Performing Arts Companies | 0.31 |
| 3351: Electric Lighting Equipment Manufacturing | 0.28 |
| 8129: Other Personal Services | 0.25 |
| 5619: Other Support Services | 0.23 |
| 3212: Veneer, Plywood, and Engineered Wood Product Manufacturing | 0.22 |
| 4238: Machinery, Equipment, and Supplies Merchant Wholesalers | 0.19 |
| 3321: Forging and Stamping | 0.18 |
| 3273: Cement and Concrete Product Manufacturing | 0.18 |
| 6116: Other Schools and Instruction | 0.15 |
| 3326: Spring and Wire Product Manufacturing | 0.15 |
| 3132: Fabric Mills | 0.15 |
| 4412: Other Motor Vehicle Dealers | 0.14 |
| 4512: Book Stores and News Dealers | 0.14 |
| 4832: Inland Water Transportation | 0.13 |
| 3259: Other Chemical Product and Preparation Manufacturing | 0.09 |
| 4883: Support Activities for Water Transportation | 0.09 |
| 4421: Furniture Stores | 0.08 |
| 5612: Facilities Support Services | 0.08 |
| 3274: Lime and Gypsum Product Manufacturing | 0.07 |
| 4881: Support Activities for Air Transportation | 0.06 |
| 7224: Drinking Places (Alcoholic Beverages) | 0.05 |
| 4869: Other Pipeline Transportation | 0.04 |
| 4543: Direct Selling Establishment | 0.04 |
| 2372: Land Subdivision | 0.03 |
| 3211: Sawmills and Wood Preservation | 0.03 |
| 6213: Offices of Other Health Practitioners | 0.03 |
| 3335: Metalworking Machinery Manufacturing | 0.02 |
| 4247: Petroleum and Petroleum Products Merchant Wholesalers | 0.01 |
| 4869: Other Support Activities for Transportation | 0.01 |
| 4243: Apparel, Piece Goods, and Notions Merchant Wholesalers | 0.01 |
| 3327: Machine Shops; Turned Product; and Screw, Nut, and Bolt Manufacturing | 0.00 |
| 4442: Lawn and Garden Equipment and Supplies Stores | 0.00 |
| 7114: Agents and Managers for Artists, Athletes, Entertainers, and Other Public Figures | 0.00 |
| 8111: Automotive Repair and Maintenance | 0.00 |
| 7112: Spectator Sports | 0.00 |
| Industry (NAICS) | Portfolio Weight (%) |
|-----------------|----------------------|
| 4239: Miscellaneous Durable Goods Merchant Wholesalers | -0.01 |
| 5174: Satellite Telecommunications | -0.05 |
| 8122: Death Care Services | -0.09 |
| 4251: Wholesale Electronic Markets and Agents and Brokers | -0.09 |
| 4241: Paper and Paper Product Merchant Wholesalers | -0.09 |
| 5414: Specialized Design Services | -0.10 |
| 2111: Oil and Gas Extraction | -0.15 |
| 4246: Chemical and Allied Products Merchant Wholesalers | -0.24 |
| 3343: Audio and Video Equipment Manufacturing | -0.29 |
| 4233: Lumber and Other Construction Materials Merchant Wholesalers | -0.40 |
| 5419: Other Professional, Scientific, and Technical Services | -0.50 |
| 3333: Commercial and Service Industry Machinery Manufacturing | -0.52 |
| 4249: Miscellaneous Nondurable Goods Merchant Wholesalers | -0.57 |
| 5111: Newspaper, Periodical, Book, and Directory Publishers | -0.60 |
| 5418: Advertising, Public Relations, and Related Services | -1.05 |
| 3241: Petroleum and Coal Products Manufacturing | -1.08 |
| 3336: Engine, Turbine, and Power Transmission Equipment Manufacturing | -1.32 |
| 5413: Architectural, Engineering, and Related Services | -1.93 |
| 5416: Management, Scientific, and Technical Consulting Services | -2.33 |
| 3255: Paint, Coating, and Adhesive Manufacturing | -2.70 |
| 5417: Scientific Research and Development Services | -2.91 |
| 4234: Professional and Commercial Equipment and Supplies Merchant Wholesalers | -3.14 |
| 3365: Railroad Rolling Stock Manufacturing | -3.47 |
| 3341: Computer and Peripheral Equipment Manufacturing | -5.69 |
| 3342: Communications Equipment Manufacturing | -10.47 |
| 3345: Navigational, Measuring, Electromedical, and Control Instruments Manufacturing | -10.51 |
| 3364: Aerospace Product and Parts Manufacturing | -14.72 |
| 5112: Software Publishers | -16.97 |
| 5415: Computer Systems Design and Related Services | -31.57 |
| 5182: Data Processing, Hosting, and Related Services | -35.46 |
| 5191: Other Information Services | -41.46 |
Table A.3
Robust regression for default probabilities

| Default Horizon | Work exposure | Std. Error | t-statistic |
|-----------------|---------------|------------|-------------|
| 3 months        | 0.082%        | 0.016%     | 5.091       |
| 6 months        | 0.182%        | 0.037%     | 4.896       |
| 1 year          | 0.497%        | 0.094%     | 5.276       |
| 2 years         | 1.245%        | 0.170%     | 7.327       |

This table reports the same analysis of default probabilities conditional on work exposure from Table 4, but uses Huber robust regression instead of least squares, which helps account for outliers that may be driving the average result. Regression coefficients are estimated via iteratively re-weighted least squares, as implemented in the MASS R package (Venables and Ripley, 2002).

Figure A.1
Accuracy of PPP interpolation method: Interpolated versus actual state totals

This figure compares the aggregated loan dollar amounts constructed by the model’s interpolation vs. the totals reported by the SBA as of Jun 27th, 2020. Because data are partially observed, we interpolate missing values by taking the midpoint of each loan-size bin and multiplying by a constant to adjust for a small multiplicative bias. All loans reported before Jun 27th, 2020 are summed by state and compared to reported values. This plot shows the debiased loan totals per employee, summed at the state level versus the reported state-level loan totals.
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