The Value of Mobile Labor during Immobile Times:
Evidence from the COVID-19 Pandemic

Abstract

We examine whether and how mobile labor influences firm resilience to the COVID exposure. Using a sample of U.S. firms during the first two quarters of 2020, we find that firms with mobile labor experience less negative stock returns and less decline in operating profit in response to the COVID exposure. These results suggest that mobile labor helps firms fare better and stay resilient to the COVID exposure. Further analyses uncover three channels through which this effect takes place: in response to the COVID exposure, mobile employees (1) can be redeployed to do additional work at a lower cost due to the lower pay for their general skills, (2) to do alternative work more easily due to their broader expertise, and (3) can better adapt to the new environment due to their various experiences at different jobs, which in turn helps their firms stay resilient. Overall, our evidence points to the value of mobile labor during the COVID pandemic and has implications for regulators and practitioners who have been exploring ways for firms to stay resilient during the pandemic.

Keywords: Labor mobility; COVID; Firm resilience; Stock returns

1. Introduction

The novel coronavirus (COVID-19) has created unprecedented upheaval and challenges for companies and triggered a global public health crisis. By the end of June 2020, the COVID-19 pandemic had infected over 10 million people and caused over 0.53 million deaths. Numerous companies experienced serious losses in revenue and the number of companies that defaulted or filed for bankruptcy increased during the pandemic. Stock markets around the world crashed – during the first six months of 2020, the S&P 500 declined by 34% from its high to its low, while the stock exchanges in Brazil, Hong Kong, Italy, and Japan went down by 46%, 25%, 41%, and 31%, respectively (Statista Research Department 2021). Given the extraordinary nature of this health crisis, it is pressing to understand factors and forces that help companies stay resilient to the exposure to the COVID-19 pandemic, which may involve supply-chain disruption, labor disruption, customer demand change, liquidity crunch, among other things (hereafter, the COVID exposure).[1] In this paper, we examine whether mobile labor helps firms fare better and stay resilient to the COVID exposure and identify the underlying channels.[2]

We focus on mobile labor because, as a critical resource for a modern corporation, labor has been directly affected by the COVID-19 pandemic, and their mobility, in particular, has been seriously constrained. Labor input has become increasingly important for modern economic growth due to the rising demand for quality improvement and process innovation (Hart and Moore 1990; Zingales 2000).[3] The COVID-19 pandemic, however, has had a direct and adverse impact on labor force (e.g., Campello, Murillo, and Kankanhalli 2021). To control the spread of COVID-

[1] Following Harvard Business Review (2020), we define resilience as "a company's capacity to absorb stress, recover critical functionality, and thrive in altered circumstances."
[2] Similar to Donangelo (2014), we define labor mobility as employees' flexibility to move to other jobs due to their more general skills.
[3] Human relations theories (e.g., Maslow 1943; Hertzberg 1959; McGregor 1960) consider employees to be critical assets of an organization that can generate substantial value through inventing new products or developing client relationships.

19, many governments mandated mask wearing, social distancing, lockdowns, and instituted travel restrictions. These mandates and restrictions together with the COVID-19 spread and the concern for the spread substantially affect workers' physical health, mental health, financial health, and productivity, among other things (e.g., Cheema-Fox, LaPerla, Serafeim, and Wang, 2020). Labor mobility has been seriously constrained by these mandates and restrictions coupled with the limited outside opportunities (e.g., Campello, Murillo, and Kankanhalli 2021).[4] Using data from the *normal* times, the literature has long largely viewed mobile employees as being costly to the firm, as they have the flexibility to leave the current employer in response to better opportunities elsewhere (e.g., Donangelo 2014; Leung, Mazouz, Chen, and Wood 2018; Shen 2018). But during the *abnormal* COVID-19 pandemic, when employees become immobile, it remains unclear what the implication of mobile labor is for the firm.

We expect that mobile labor could increase firm resilience to the COVID exposure through three channels. First, with the COVID exposure, firms are more likely to redeploy mobile employees to do additional work that emerges from COVID-related layoffs and absenteeism. Mobile employees tend to possess more general (rather than specific) skills (e.g., Wasmer 2006; Donangelo 2014). As a result, firms can redeploy these employees at lower labor cost due to the lower pay for general skills (e.g., Neal 1995; Parent 2000; Wasmer 2006; Poletaev and Robinson 2008), which could in turn reduce labor disruption and achieve cost efficiency and hence help firms stay resilient. Second, as firms are exposed to the COVID-19 pandemic, they are more likely to redeploy mobile employees to do alternative work as they adjust product/service portfolio, due

[4] Campello, Murillo, and Kankanhalli (2021) show that firms scale back their hiring during the pandemic – firms start to cut their new job postings in the ninth week of 2020; there is an abrupt decline in job ads starting in the first week of March 2020; active job postings in May through December 2020 are about half of job postings over the same period in 2017 through 2019. Similarly, Wall Street Journal (2020a) mentioned "lockdowns and travel restrictions because of the coronavirus pandemic created one set of hiring hurdles this year."

to these employees' broader expertise (e.g., Wasmer 2006; Donangelo 2014), which could allow these firms to stay resilient. Third, as firms are exposed to the COVID-19 pandemic, they face a new working environment; mobile employees can better adapt to this environment, due to their various experiences at different jobs (e.g., Donangelo 2014), which helps their firms to stay resilient. Given that mobile labor can be redeployed to do additional work at a lower cost, to do alternative work more easily, and can better adapt to the new environment, we predict that firms with mobile labor are more resilient to the COVID exposure.

While this prediction is plausible, it is possible that mobile employees impair their firms' resilience to the COVID exposure for several reasons. First, despite the fewer outside opportunities during the pandemic, mobile employees still have more flexibility to move to other jobs (Donangelo 2014), which can potentially hurt firm performance in the presence of the COVID exposure. The reason is that firms may need to offer higher pay to retain mobile employees (e.g., Leung, Mazouz, Chen, and Wood 2018), or incur labor adjustment cost and face labor disruptions when mobile employees move to other jobs (e.g., Kuehn, Simutin, and Wang 2017). Second, labor mobility might discourage firms from investing in human capital; such underinvestment can be more serious in the presence of the COVID exposure, due to the performance decline and potential financial constraint in this case, thereby leading to lower productivity and worse performance for firms with the COVID exposure. Therefore, it is ultimately an empirical question how mobile labor influences firm resilience to the COVID exposure.

To test our prediction that firms with more mobile labor stay more resilient to the COVID exposure, we follow Ding, Levine, Lin, and Xie (2021) to measure firm resilience using the weekly stock return. We also follow Ding et al. (2021) to measure a firm's COVID exposure using the weekly growth rate of the number of confirmed COVID-19 cases in a county where a firm's headquarter is located. To measure labor mobility, we first follow Donangelo (2014) to construct industry-level labor mobility measure based on the average occupation dispersion of employed workers in an industry. Then we apply Kim and Kung (2017)'s approach to map industry-level labor mobility to firm-level labor mobility based on a firm's sales in various industries to which each business segment belongs. That is, firm-level labor mobility is the weighted average of industry-level labor mobility across a firm's business segments, where the weight is the proportion of sales from each business segment relative to a firm's total sales.

Given that the main endogeneity concern in our study lies in labor mobility and comes from correlated omitted variables, we follow Ding et al. (2021) to control for a set of firm features and firm and industry-week fixed effects. With these control variables and fixed effects, we condition out (a) all time-invariant firm features and major time-varying firm features, such as differences in size and leverage, and (b) all time-varying and time-invariant industry features, such as differences in the intensity of required in-person contact with co-workers that might influence stock price reactions to the COVID exposure. We also lag the labor mobility variable relative to firm resilience to the COVID exposure, which should alleviate the concern for reverse causality. Conditioning on a set of control variables and fixed effects and lagging the labor mobility variable allow us to better isolate the differential impact of the COVID exposure on stock prices as a function of firms' labor mobility.

Using a sample of U.S. public firms for the period between January 20, 2020 and June 26, 2020, we conduct empirical analyses and provide findings as follow. First, we examine the relation between labor mobility and stock price reactions to the COVID exposure; we find that a firm's negative stock price reaction to the COVID exposure is significantly alleviated by its labor mobility. This result is robust to the inclusion of firm and industry-week fixed effects and controls for various firm characteristics interacted with the COVID exposure. This result is also robust to alternative measures of the COVID exposure, alternative measures of firm resilience, alternative specifications of labor mobility, alternative sample periods, and alternative industry compositions. Overall, these results suggest that firms with more mobile labor are more resilient to the COVID exposure than firms with less mobile labor, consistent with our prediction.

Next, we conduct multiple additional tests to further address the endogeneity concern. First, we use state-level variation in the enforcement of non-compete agreements as an exogenous shock to labor mobility. We find that the adverse impact of COVID exposure on firm resilience is more severe for firms located in states with more stringent enforcement of non-compete agreements – firms with low labor mobility. Second, we apply propensity score matching and find that firms with high labor mobility would be less resilient to the COVID exposure if they had not had high labor mobility. Lastly, we employ an instrumental variable (IV) approach developed by Lewbel (2012) and find that our baseline results continue to hold. These tests help corroborate our causal inference that mobile labor enhances firm resilience to the COVID exposure. Nonetheless, we acknowledge that it is impossible to completely rule out the concern for corelated omitted variables. Therefore, we follow prior studies (e.g., Frank, 2000; Larcker and Rusticus, 2010) and conduct an analysis of the impact threshold for a confounding variable to overturn our results. The results show that an omitted confounding variable would need to be at least 2.67 times larger than the most impactful interaction term in order to overturn the effect of labor mobility on firm resilience to the COVID exposure, which seems unlikely given our inclusion of firm and industry-week fixed effects as well as commonly used control variables.

We also conduct several additional analyses to address alternative explanations. First, to address the concern that our results are driven by corporate governance or ownership structure, which has been shown to influence firm resilience to COVID exposure (Ding et al. 2021), we control for the effect of corporate governance and management ownership. We find our results continue to hold. Second, to alleviate the concern that our results are driven by county-level factors such as demographics and/or economic situations, which may influence firm resilience to the COVID exposure, we use two approaches. One approach is to conduct an event study to examine the relation between labor mobility and short-window stock price reaction to the first COVID-19 case in a firm's headquarter county. We find that firms with more mobile labor force experience less negative stock price reactions to the first COVID-19 case in their county. The other approach is to perform a time-series analysis by comparing the effect of labor mobility on stock returns before and during the pandemic. We find that firms with more mobile labor experience less negative stock return during the pandemic relative to the pre-pandemic period than firms with less mobile labor. In summary, our results are robust to a number of additional tests and consistently suggest that mobile employees improve their firms' resilience to the COVID exposure.

In light of the beneficial effect of labor mobility documented above, we next conduct additional analyses to better understand the underlying channels through which mobile labor increases firm resilience to the COVID exposure. If firms with mobile employees stay resilient to the COVID exposure because they can redeploy these employees to do additional work that emerges from COVID-related layoffs (i.e., the first channel), we expect that the impact of labor mobility on firm resilience to the COVID exposure (i.e., our baseline relation) will be more pronounced for firms that lay off more employees during the pandemic. Using monthly change in unemployment rate to capture employee layoffs, we find results consistent with this prediction. The first channel also implies that firms with more mobile employees operate more efficiently in response to the COVID exposure than firms with less mobile employees. Indeed, we find that in response to the COVID exposure, firms with less mobile employees incur higher operating expenses per sales dollar and per employee, while firms with more mobile employees incur a smaller increase in operating expenses per sales dollar and per employee.

If firms with mobile employees stay resilient to the COVID exposure because they can redeploy these employees to do alternative work more easily as they adjust their product/service portfolio, we expect that our baseline relation will be more pronounced for firms that have more redeployable assets and more related business segments before the pandemic. Using asset redeployability measure constructed following Kim and Kung (2017) and segment relatedness measure constructed following Chen et al. (2018), we find results consistent with this prediction. The evidence confirms the contention that the pandemic is a reallocation shock (Wall Street Journal 2020, 2021).[5] If firms with mobile employees stay resilient to the COVID exposure because these employees can better adapt to the new working environment in the presence of the COVID exposure, we expect that our baseline relation will be more pronounced for firms that are more exposed to such new working environment during the pandemic. Given that one distinct feature of the new environment is remote work, we test whether the baseline relation is more pronounced for firms with a higher likelihood of switching to remote work during the pandemic. Using work-from-home feasibility measure from Dingel and Neiman (2020), we find that our baseline relation is stronger in the subsample with high work-from-home feasibility.

Our study makes several contributions. First, we contribute to the emerging research on firm resilience during the COVID crisis, a public health crisis that is distinct from prior crises. Li, Liu, Mai, and Zhang (2021) show that a strong corporate culture helps firms stay resilient to the

[5] As Wall Street Journal (2020b) mentioned recently, "The coronavirus pandemic is forcing the fastest reallocation of labor since World War II, with companies and governments mobilizing an army of idled workers into new activities that are urgently needed."

COVID exposure. Ding et al. (2021) provide international evidence that firm resilience to COVID is associated with financial conditions, international exposure to COVID, CSR activities, management entrenchment, and ownership structure. However, prior research has paid little attention to the role of employees, who have become increasingly important in a modern corporation (Zingales 2000) but have been substantially and adversely affected by the COVID pandemic, in influencing firm resilience to the COVID exposure. To our knowledge, this study is the first to show that *rank-and-file* employees, particularly mobile employees, play an important role in helping firms stay resilient to the COVID exposure.

Second, we contribute to the growing body of research that examines the impact of labor, particularly mobile labor, on corporate activities and outcomes. Extant literature has long viewed labor mobility as being costly to a firm, as mobile employees have the flexibility to walk away from the current employer in response to better opportunities (e.g., Donangelo 2014; Leung, Mazouz, Chen, and Wood 2018). For instance, Donangelo (2014) shows that greater labor mobility generates a form of labor-induced operating leverage, thereby increasing a firm's cost of equity. However, several recent studies document that labor mobility does not always have an adverse effect on a firm (e.g., Hass, Hribar, and Kalogirou 2018; Hass, Omer, and Vergauwe 2019). For example, Hass, Hribar, and Kalogirou (2018) show that greater labor mobility disciplines firms from making myopic operating decisions. Our study adds to the ongoing debate on the implications of labor mobility by examining its role in influencing firm resilience to the COVID exposure. Given that the COVID exposure is exogenous to a firm's fundamentals, this setting allows us to establish the causal impact of bad times on the labor mobility-firm value link.

Third, our study is timely and has implications for regulators and practitioners. Our findings should inform regulators that economic policies focusing on alleviating the effect of

COVID-19 should consider labor force characteristics. Moreover, practitioners have been exploring ways to stay resilient and recover from the COVID crisis, as numerous companies experienced serious losses in revenue and the number of companies that defaulted or filed for bankruptcy increased during this crisis. Our findings should inform practitioners that enhancing labor redeployability (e.g., by increasing reliance on general human capital) and adaptability (e.g., by hiring and encouraging employees to have various experiences at different jobs) could increase firm resilience to the COVID exposure.

The remainder of the paper is organized as follows. Section 2 discusses the related literature and develops the testable hypothesis. Section 3 describes the sample, variable construction, and the empirical model. Section 4 reports and discusses the main results. Section 5 presents robustness checks and additional analyses, and Section 6 concludes the paper.

2. Related Literature and Hypothesis Development

2.1 Labor mobility

The literature has long viewed labor mobility as being costly to the firm, as mobile employees have the flexibility to leave the current employer in response to better opportunities elsewhere. For instance, Donangelo (2014) shows that greater labor mobility generates a form of labor-induced operating leverage, which in turn increases a firm's cost of equity. Leung, Mazouz, Chen, and Wood (2018) suggest that greater labor mobility could render an organization's capital investment risker from the shareholder's perspective. The mobility of skilled labor can be especially important to firm activities and outcomes. Indeed, Shen (2018) finds that skilled labor mobility negatively affects firm value by increasing labor adjustment costs and reducing long-term investments. Relatedly, Sanati (2018) shows that an increase in worker mobility adversely influences leverage and investment, but only in firms that rely on highly skilled workers, as these workers are more likely to receive valuable outside job offers more frequently.

Several recent studies, however, document that labor mobility does not always have an adverse effect on a firm. Hass, Hribar, and Kalogirou (2018) show that greater labor mobility disciplines firms from making myopic operating decisions (i.e., real activity management) to reassure employees about firms' future prospects and avoid labor adjustment costs stemming from labor turnover. Hass, Omer, and Vergauwe (2019) find that higher labor mobility is associated with higher cash effective tax rates and lower volatility of cash effective tax rates, suggesting that firms with more mobile employees engage in less tax avoidance due to these employees' stronger ability and incentive to demand lower levels of tax avoidance. Overall, there is mixed evidence on the role of labor mobility. Accordingly, the impact of labor mobility on firm activities and outcomes remains to be under intense debate.

2.2 Hypothesis development

We examine whether and how labor mobility influences firm resilience to the COVID exposure; we expect that mobile labor could increase firm resilience to the COVID exposure through three channels. First, as firms are exposed to the COVID-19 pandemic, they are more likely to redeploy mobile employees to do additional work that emerges from COVID-related layoffs and absenteeism, due to the lower labor cost of these employees, which could in turn help these firms stay resilient. Mobile employees tend to possess more general (rather than specific) skills (e.g., Wasmer 2006; Donangelo 2014). For instance, workers in the wholesale trade industry are more mobile than those in the healthcare industry; and those in the former (e.g., operations managers and computer analysts) have more general skills than those in the latter (e.g., medical doctors and nurses). Such more general skills are paid at a lower rate than specific skills (e.g., Neal

1995; Parent 2000; Wasmer 2006; Poletaev and Robinson 2008). Due to the lower pay for mobile employees' general skills, firms with high exposure to COVID are therefore more likely to redeploy mobile employees to do additional work that emerges from COVID-related layoffs and absenteeism and hence avoid labor disruption and achieve cost efficiency.[6]

Second, as firms are exposed to the COVID-19 pandemic, they are more likely to redeploy mobile employees to do alternative work as they adjust product/service portfolio, due to these employees' broader expertise, which could allow these firms to stay resilient. In response to the decline and change in customer demand associated with the COVID exposure, firms may adjust their product/service portfolio to fit the changing customer preference and the new customer demand. In the adjustment process, firms may redeploy employees to perform alternative work in different product/service lines. This is consistent with prior studies that document that economic shocks lead to job reallocation (e.g., Wasmer 2006). In particular, Levy and Haber (1986, page 299) point out that "in the face of an unanticipated change in demand conditions or technology, firms often react by transferring employees to different product lines." For example, General Motors (GM) relocated workers from its Tennessee plant, where it faced a weaker demand for the models produced there; it also transferred workers from other factories/divisions to the Missouri plant to meet stronger-than-expected demand for the models built there (Wall Street Journal 2020).[7] Given mobile employees' more general skills (e.g., Wasmer 2006; Donangelo 2014), they

[6] As firms are exposed to the COVID-19 pandemic, they may lay off employees due to the demand change or the financial constraints they face, or employees may take leaves due to their own health issue or family/childcare responsibilities (Wall Street Journal 2020). For instance, Intercom laid off 6% of its staff of about 650 in May 2020. Employee absenteeism is especially serious at manufacturers, particularly automakers and suppliers (NPR 2020). As a result, firms that experience absenteeism issue may rely on existing employees to stay late, arrive early and pick up extra shifts to continue operations. At several automakers, such as Honda, they even ask office workers to take on production roles due to high level of absenteeism of assembly line workers (NPR 2020).

[7] As another example, in the early seventies U.S. automobile manufacturers transferred engineers who were designing larger cars to the development of smaller, more fuel-efficient cars, when they recognized a shift in demand toward smaller cars (Levy and Haber 1986).

can more easily pick up alternative work and hence are more reallocateable (Gervais, Livshits, and Meh 2008), because such skills are applicable across different jobs. Consequently, in response to the COVID exposure, firms are more likely to redeploy mobile employees to alternative work in different product/service lines, which could help these firms stay resilient.

Third, as firms are exposed to the COVID-19 pandemic, they face a new working environment; mobile employees can better adapt to this change in working environment, due to their various experiences at different jobs, which helps their firms stay resilient. Karaevli and Hall (2006) develop a theory on how individual adaptability develops from career variety. Specifically, they argue that individuals who have a variety of career experiences in different functional areas (e.g., production, sales, finance, and law) and institutional contexts (e.g., firm, industry, country) develop certain behavioral competencies such as dealing with unique and uncertain work situations, learning technologies and procedures, demonstrating inter-personal adaptability. Such competencies help individuals to adapt to various circumstances and new environment without lengthy training or socialization. Based on Karaevli and Hall (2006)'s theory, mobile employees are likely to have developed adaptability to the new environment associated with the COVID exposure that features various uncertainties, remote/digital work, and social distancing. This is because mobile employees may have changed jobs in the past (e.g., Donangelo 2014); their experiences at different jobs in different institutional contexts (e.g., industries) could help them develop behavioral competencies and better adapt to the new environment. As a result, such adaptability of mobile employees could improve their firms' resilience to the COVID exposure.

In summary, the above discussions lead us to predict that firms with mobile labor forces are more resilient to the COVID exposure, because these labor forces can be redeployed to do additional work at a lower cost, to do alternative work more easily, and can better adapt to the new environment. Therefore, we propose the following hypothesis, stated in the alternative form:

Hypothesis: *Labor mobility is positively associated with firm resilience to the COVID exposure.*

On the other side, it is possible that mobile employees impair their firms' resilience to the COVID exposure for several reasons. First, despite the fewer outside opportunities during the pandemic, mobile employees may still have more flexibility to move to outside jobs (Donangelo 2014), which could potentially hurt firm performance in the presence of the COVID exposure. To retain mobile employees, firms may need to offer higher pay (e.g., Leung, Mazouz, Chen, and Wood 2018), creating additional burden for firms with COVID exposure. Moreover, if mobile employees do move to other job opportunities, such labor turnover can create labor disruptions, given the challenges in job transition and hiring in the COVID environment, and can increase labor adjustment cost associated with hiring and training new employees (e.g., Kuehn, Simutin, and Wang 2017),[8] thereby lowering performance for firms with COVID exposure.

Second, labor mobility might discourage firms from investing in human capital; such underinvestment can be more serious in the presence of the COVID exposure due to the performance decline and potential financial constraint, which could in turn lead to lower productivity and worse performance for firms with the COVID exposure. Garmaise (2011) show that as labor mobility restrictions are imposed through noncompetition agreements, firms are more willing to invest in their managers' human capital. If a similar practice exists for rank-and-file employees, then labor mobility might discourage firms from investing in these employees' human

[8] Kuehn, Simutin, and Wang (2017, page 2131) state that "according to the U.S. Department of Labor, the cost of replacing a worker amounts to one-third of a new hire's annual salary. Direct costs include advertising, sign-on bonuses, headhunter fees, and overtime. Indirect costs include recruitment, selection, training, and decreased productivity while current employees pick up the slack." Blatter, Muehlemann, and Schenker (2012) offer similar evidence.

capital. The COVID exposure can exacerbate such underinvestment due to the performance decline and potential financial constraint, thereby leading to lower productivity and worse performance for these firms with mobile employees.[9] Therefore, the impact of labor mobility on firm resilience to the COVID exposure is ultimately an empirical question.

3. Sample and Research Design

3.1 Sample and data

We obtain data on COVID-19 cases in the U.S. as of each day from the Coronavirus COVID-19 Global Cases Database managed by the Center for Systems Science and Engineering at Johns Hopkins University (JHU CSSE).[10] Our sample consists of firms at the intersection of the COVID-19 data from JHU CSSE, data to construct labor mobility measure from the Occupational Employment Statistics (OES) program of the Bureau of Labor Statistics, stock return data from the Center for Research in Security Prices (CRSP), and financial data from Compustat. As the first COVID-19 case in the U.S. appeared on January 20, 2020, our sample period ranges from January 20, 2020 to June 26, 2020. We exclude firm-year observations with missing data for any of the variables in the baseline regression analysis. To mitigate the effects of outliers, we winsorize all continuous variables at the top and bottom 0.5 percentiles of their distributions. Our final sample comprises 75,274 firm-week observations for 3,339 unique firms.

3.2 Measurement of COVID exposure

Following prior studies (e.g., Ding et al. 2021), we measure a firm's COVID exposure (*COVID*) using the weekly growth rate of the cumulative number of confirmed COVID-19 cases in the county where a firm is headquartered. To match with the weekly stock return data, we

[9] Relatedly, prior studies document that firms underinvest in the labor force with respect to the reporting process, as firms tradeoff investment in accounting human capital and investment in non-accounting human capital. This tradeoff is especially pronounced when firms face resource constraints (e.g., Bernard et al. 2020; Lee and Yu 2021).
[10] The data can be downloaded from https://github.com/CSSEGISandData/COVID-19.

construct *COVID* using confirmed COVID-19 cases from Saturday of the previous week to Friday of the current week. Specifically, for each county c in week w, $COVID_{c,w}$ is calculated as ln(1+ $Cumulative\ Cases_{c,w}$) − ln(1+$Cumulative\ Cases_{c,w-1}$), where $Cumulative\ Cases_{c,w}$ is the cumulative number of confirmed cases in county *c* as of Friday in week *w*.

3.3 Measurement of labor mobility

We construct the firm-level labor mobility measure based on Donangelo (2014) and Kim and Kung (2017). Specifically, we first follow Donangelo's (2014) two-stage procedure to calculate an industry-level labor mobility measure. In the first stage, we capture (the inverse of) the intrinsic flexibility of workers in each occupation to switch industries by calculating the concentration of workers in a particular occupation among industries as follows:[11]

$$Concentration_{j,t} = \left(\frac{Employ_{i,j,t}}{\sum_i Employ_{i,j,t}} \right)^2 \tag{1}$$

where $Employ_{i,j,t}$ is the number of workers in occupation *j* who are employed in industry *i* in year *t*. High values of $Concentration_{j,t}$ indicate that workers in occupation *j* has lower flexibility to move across industries in year *t*.

In the second stage, we aggregate the occupation-level concentration measure by industry, weighting by the proportion of wages paid to workers in a particular occupation. Using wages in this stage gives a higher weight to occupations that pay higher wages, because these occupations have a bigger impact on cash flows. To make interpretation easier, we then take the inverse of this

[11] Consistent with the data source, Occupational Employment Statistics (OES) program of the Bureau of Labor Statistics, we define industries by the four-digit NAICS code and occupations by the five-digit SOC code. We exclude industries denoted as "Not Elsewhere Classified" or "Miscellaneous" (NAICS xxx9) from the sample as firms in these industries are unlikely to share a common workforce (Donangelo 2014).

wage-weighted average of the occupation concentration measures across occupations in an industry to derive the industry-level labor mobility measure:

$$LM\_IND_{i,t} = \left(\sum_j Concentration_{j,t} \times \frac{Employ_{i,j,t} \times Wage_{i,j,t}}{\sum_j Employ_{i,j,t} \times Wage_{i,j,t}} \right)^{-1} \tag{2}$$

where $Wage_{i,j,t}$ is the average annual wage paid to workers in industry i and occupation j in year t. To simplify interpretation of the results, *LM_IND* is standardized so that it has a mean of zero and standard deviation of one.

Finally, employing the approach that Kim and Kung (2017) use to construct the firm-level asset redeployability measure, we build on industry-level labor mobility to construct firm-level labor mobility (*LM*). Specifically, we calculate firm-level labor mobility as the weighted average of industry-level labor mobility measures across a firm's business segments, where the weight is the proportion of a firm's total sales that is contributed by each business segment.[12,13]

$$LM_{h,t} = \left(\sum_k LM\_IND_{k,t} \times \frac{Sale_{h,k,t}}{\sum_k Sale_{h,k,t}} \right) \tag{3}$$

where $Sale_{h,k,t}$ is the sale of business segment k at firm h in year t; $LM\_IND_{k,t}$ is the industry-level labor mobility for the industry which business segment k corresponds to. High values of $LM_{h,t}$ indicate that workers in firm h are more mobile (i.e., higher flexibility to change jobs) in year t.

3.4 Measurement of firm resilience

To measure a firm' resilience to the COVID exposure, we follow prior studies (e.g., Ding et al. 2021) and use weekly stock return. We obtain stock return data for the U.S. publicly listed

[12] When segment data is not available for a firm-year observation in the Compustat segment files, we use industry-level labor mobility identified based on the firm's primary industry classification as firm-level labor mobility measure.
[13] For single-segment firms, firm-level labor mobility is equal to industry-level labor mobility. Approximately 19% of firms in our sample are single-segment firms.

firms from January 20, 2020 to June 26, 2020 from CRSP. We construct the weekly stock return measure, *RET*, based on the closing stock prices of the firms on the last trading day of the week.

3.5 Empirical model

To empirically test our hypothesis that labor mobility is positively associated with firm resilience to the COVID exposure, we estimate the following model using ordinary least squares (OLS) regressions:

$$\begin{aligned} RET_{h,w} = {} & \alpha COVID_{c,w} + \beta_1 LM_h * COVID_{c,w} + \beta_2 SIZE_h * COVID_{c,w} + \beta_3 LEV_h * COVID_{c,w} \\ & + \beta_4 ROA_h * COVID_{c,w} + \beta_5 CASH_h * COVID_{c,w} + \beta_6 MTB_h * COVID_{c,w} \\ & + \beta_7 BETA_h * COVID_{c,w} + Firm\ FE + Industry\_Week\ FE \\ & + \varepsilon \end{aligned} \tag{4}$$

where *h* and *w* index firm and week. $RET_{h,w}$ is the stock return for firm h from Saturday in week *w*-1 to the last trading day in week w. $COVID_{c,w}$ is the growth rate of the cumulative number of confirmed COVID-19 cases in county c where a firm is headquartered during week w. LM_h is labor mobility for firm h in the fiscal year 2019. Our variable of interest is the interaction between $COVID_{c,w}$ and LM_h. Given that our hypothesis predicts a positive association between labor mobility and firm resilience to COVID exposure, we expect β_1 to be positive.

We include firm and industry-week fixed effects to control for time-invariant firm factors and time-varying industry factors that may influence stock returns. Similar to prior studies (e.g., Ding et al. 2021; Li et al. 2021), we also include the interactions between *COVID* and a set of firm characteristics as control variables. Specifically, we include firm size (*SIZE*), leverage (*LEV*), profitability (*ROA*) and cash holdings (*CASH*), because a firm's financial conditions are shown to influence its resilience to COVID exposure (Ding et al. 2021). We include market-to-book ratio (*MTB*) and market beta (*BETA*), since growth opportunities and systematic risk have been shown to influence stock return during the COVID-19 pandemic (e.g., Ding et al. 2021; Li et al. 2021). Note that the main effects of firm-level variables are not included, because these firm-level variables are not time-varying during our sample period, and they will be dropped out from the estimation when we include firm fixed effects in the regression model. To alleviate the concern for potential within-firm correlations in the data, we report t-statistics using Huber-White standard errors corrected for firm clustering (Petersen 2009).

4. Main Empirical Results

4.1 Descriptive statistics

Table 1 presents the descriptive statistics for the variables used in the baseline analyses. The mean and median value of *COVID* is 0.293 and 0.084 across all county-weeks, respectively. We plot the time trend of *COVID* for our sample period in Figure 1. It shows that the weekly growth rate of COVID-19 cases experiences a spike in March 2020 and then slows down in April and thereafter.

The mean (median) value of weekly stock return (*RET*) is -0.2% (-0.6%), consistent with an overall pessimistic market outlook due to the COVID-19 pandemic. The standard deviation of *RET* is 13.5%, indicating large variations in stock returns across firms and across time. Figure 2 plots the cumulative stock returns since the spread of the COVID-19 case and shows a pattern similar to the statistics of *RET*. Cumulative stock returns are overall negative and plumet in March 2020 and gradually recover afterwards.

Our labor mobility measure (*LM*) has a mean value of 0.038, with a standard deviation of 0.894, suggesting substantial cross-firm variation in labor mobility. For control variables such as firm size (*SIZE*), leverage (*LEV*), and profitability (*ROA*), the firm-level mean values are 6.982, 0.290, and -0.121, respectively.

<<Insert Table 1 here>>

4.2 Baseline Results

Figure 3 presents the relation between the growth rate of COVID-19 cases and stock returns. The x-axis is the weekly growth of COVID-19 cases, and the y-axis represents average weekly stock returns. We divide the x-axis into 100 bins and compute the average weekly stock return within each bin. This figure shows that the growth rate of COVID-19 cases is negatively related to stock returns, suggesting that the COVID exposure contributes to poor firm performance.

Figure 4 plots the relation between the growth rate of COVID-19 cases and stock returns conditional on labor mobility. The x-axis and y-axis represent the same variables as those in Figure 3. We split the full sample into high vs. low labor mobility firms based on the median of labor mobility. While we observe a downward-sloping trend line for both firms with high labor mobility and those with low labor mobility, the slope of the trend line is less negative for firms with high labor mobility. This figure provides some graphical evidence that mobile employees help their firms fare better and stay resilient to the COVID exposure.

Next, we perform multivariate regression analyses and report the results of estimating equation (4) in Table 2. In column 1, we only include *COVID* and its interaction with *LM* together with firm fixed effects and industry-week fixed effects, without including firm-level control variables to avoid biases arising from potential measurement errors in the control variables (Jennings, Kim, Lee, and Taylor 2020). The coefficient on *COVID* is negative and significant at 1% level, suggesting that a firm's COVID exposure has an adverse effect on its stock returns. More importantly, the coefficient on our variable of interest, $LM \times COVID$, is positive and significant at 1% level, suggesting that the adverse impact of COVID exposure on firm resilience is alleviated by labor mobility.

Since no control variables other than fixed effects are included in column 1, it is possible that the estimated coefficients in this column are confounded by these omitted variables. In column 2, we add a set of interactions between *COVID* and firm characteristics, where firm characteristics include size, leverage, profitability, cash holdings, market-to-book ratio, and market beta. We continue to find that the coefficient on *COVID* is negative and significant at 1% level, while the coefficient on *LM*×*COVID* is positive and significant at 1% level. These results again suggest that mobile labor alleviates the adverse impact of COVID exposure on stock return. In terms of economic significance, a one standard deviation increase in a firm's labor mobility alleviates the adverse impact of an average COVID exposure on stock return by 0.14% (=0.004×0.895×0.385). Overall, the results in Table 2 suggest that mobile labor helps firms fare better when they are exposed to the COVID and accordingly firms with more mobile labor are more resilient to the COVID exposure than firms with less mobile labor, supporting our hypothesis.

<<Insert Table 2 here>>

4.3 Underlying channels

Our results thus far suggest that labor mobility is associated with higher firm resilience to COVID exposure. In this section, we explore the underlying channels through which this effect takes place. As discussed in Section 2, there are three potential channels: First, mobile labor can be redeployed to do additional work at a lower cost, as employers experience labor shortage due to employee layoffs or absenteeism associated with the COVID exposure. Second, mobile labor can be redeployed to do alternative work more easily when a firm changes its product and/or services portfolio in response to the COVID exposure. Third, mobile labor can better adapt to the new working environment in the presence of the COVID exposure, which may involve switching to remote work, using digital tools, social distancing, etc.

We use two sets of empirical analyses to test these channels. One examines the cross-sectional variation in the relation between labor mobility and firm resilience to COVID exposure, while the other looks at firm outcomes that mobile labor will directly influence.

4.3.1 Cross-Sectional Analyses

In this subsection, we explore the three potential channels by examining the cross-sectional variation in the relation between labor mobility and firm resilience to COVID exposure. As the first channel implies that mobile labor can be redeployed to do additional work at a lower cost when employers experience labor shortage due to the COVID exposure, we expect that the relation between labor mobility and firm resilience to COVID exposure will be more pronounced when firms experience high layoffs during the pandemic. We measure employee layoffs using the monthly change in unemployment rate in each county where the firm is headquartered (*UMEMP_CH*). We then partition our sample into high versus low layoff groups based on the median of *UMEMP_CH* and re-estimate equation (4) separately for the two subsamples. Table 3 presents the results. The coefficient on *LM*×*COVID* is positive and significant in the high layoff subsample (column 2), but not significant in the low layoff subsample (column 1). A directional F-test indicates that the coefficient on *LM*×*COVID* in the high layoff group is significantly higher than that in the low layoff group. These results indicate that mobile labor play a more important role in improving firm resilience to the COVID exposure when firms experience high employee layoffs during the pandemic. The evidence is in line with the argument that mobile labor can be redeployed to do additional work that emerges from COVID-related layoffs at a lower cost, which could in turn avoid labor disruption and help firms stay resilient, supporting the first channel.

<<Insert Table 3 here>>

The second channel implies that mobile labor can be redeployed to do alternative work more easily when a firm changes its product and/or services portfolio in response to the COVID exposure; hence, we expect that the relation between labor mobility and firm resilience to COVID exposure will be more pronounced when firms have more redeployable assets or more related business segments before the pandemic. The rationale is that firms are more likely to adjust their product and/or service portfolio when they have more redeployable assets or more related business segments. We construct asset redeployability measure (*AT_REDEPLOY*) following Kim and Kung (2017) and segment relatedness measure (*SEG_RELATED*) following Chen, Martin, Roychowdhury, Wang and Billett (2018). Appendix A provides these variable definitions. We then partition the sample based on the median of *AT_REDEPLOY* and *SEG_RELATED*, respectively, and re-estimate equation (4) for each subsample. As shown in columns 3 and 4 (5 and 6) of Table 3, the coefficient on *LM×COVID* is positive and significant in the high asset redeployability (segment relatedness) subsample but insignificant in the low asset redeployability (segment relatedness) subsample. A directional F-test indicates that the coefficient on *LM×COVID* in the high asset redeployability (segment relatedness) subsample is significantly higher than that in the low asset redeployability (segment relatedness) subsample. These results suggest that mobile labor plays a more valuable role in enhancing firm resilience to COVID exposure – mobile employees can be redeployed to do alternative work more easily, when firms are more likely to adjust product/service portfolio in response to COVID exposure, supporting the second channel.

The third channel implies that mobile labor can better adapt to the new working environment in the presence of the COVID exposure; thus, we expect that the relation between labor mobility and firm resilience to COVID exposure will be more pronounced when firms are more likely to shift to remote work during the pandemic. The rationale is that remote work is a distinct feature of the new working environment that is common in the presence of COVID exposure,[14] and it typically involves social distancing, digital work, and uncertainty, which increases the importance of employee adaptability. We follow Dingel and Neiman (2020) and measure a firm's likelihood of switching to remote work (*WFH*) using the shares of jobs that can be performed from home for the industry group that it belongs to. As shown in columns 7 and 8 of Table 3, the coefficient on *LM×COVID* is positive and significant in the high *WFH* subsample, but not significant in the low *WFH* subsample. A directional F-test indicates that the coefficient on *LM×COVID* in the high *WFH* subsample is significantly larger than that in the low *WFH* subsample. These results are consistent with the argument that mobile labor has a more positive effect on firm resilience to COVID exposure when there are significant changes to working environment in response to COVID exposure, because mobile employees can better adapt to the new working environment, supporting the third channel.

Lastly, we examine the cross-sectional variation in the relation between labor mobility and firm resilience to COVID exposure conditional on asset intangibility. If mobile labor plays a valuable role in improving firm resilience to COVID exposure, we expect that the baseline relation between labor mobility and firm resilience to COVID exposure will be more pronounced when asset intangibility is high. The rationale is that human capital is more important when asset intangibility is high because firms rely more on human capital rather than tangible assets in this situation (e.g., Bowen, DuCharme, and Shores 1995). Similar to Bowen et al. (1995), Gao, Zhang, and Zhang (2018), and Matsumoto (2002), we measure asset intangibility (*AT_INTANGIBLE*) by one minus gross property, plant and equipment scaled by total assets. We then partition our sample into high versus low asset intangibility groups based on the median of *AT_INTANGIBLE* and re-

[14] Bloom (2020, page 1) state that "Forty-two percent U.S. workers are now working from home full time, accounting for more than two-thirds of economic activity."

estimate equation (4) separately for the two subsamples. As shown in Columns 9 and 10 of Table 3, the coefficient on *LM×COVID* is positive and significant for the high asset intangibility subsample, but insignificant for the low asset intangibility subsample. A directional F-test indicates that the coefficient on *LM×COVID* in the high *AT_INTANGIBLE* subsample is significantly larger than that in the low *AT_INTANGIBLE* subsample. These results suggest that mobile labor plays a more important role in helping firms stay resilient to the COVID exposure when firms rely more on human capital, providing additional support for the underlying channels.

Overall, our cross-sectional analyses provide support for the underlying channels through which mobile labor improves firm resilience to COVID exposure – mobile labor can be redeployed to do additional work at a lower cost, to do alternative work more easily, and can better adapt to the new environment in response to COVID exposure.

4.3.2 Operating Efficiency Analyses

To further shed light on the first channel through which mobile labor improves firm resilience to COVID exposure, we analyze operating efficiency and examine the role of labor mobility in affecting this firm outcome. Given that the first channel implies that mobile labor can be redeployed to do additional work at a lower cost in response to the COVID exposure, we expect that mobile labor will help improve a firm's operating efficiency as it is exposed to COVID. We capture operating efficiency using two measures: quarterly operating expenses per sales dollar (*OPEXP_SALE*) and quarterly operating expense per employee (*OPEXP_EMP*). We then regress operating efficiency measure (one at a time) on all explanatory variables included in the baseline model in equation (4). In these analyses, we replace industry-week fixed effects with industry-quarter fixed effects since these analyses use quarterly financial data for the first two quarters of 2020 and exclude firm fixed effects due to the small within-firm variation.

Table 4 presents the regression results. Column 1 uses *OPEXP_SALE* to measure operating efficiency, while column 2 uses *OPEXP_EMP*. In column 1, the coefficient on *COVID* is positive and significant, suggesting that operating expense per sales dollar increases with the COVID exposure. More important, the coefficient on *LM×COVID* is negative and significant, suggesting that the COVID-related increases in operating expenses are significantly smaller for firms with more mobile labor than for firms with less mobile labor. In column 2, we similarly find a negative and significant coefficient on *LM×COVID*, indicating that firms with more mobile labor experience smaller increases in operating expenses per employee. Together, these results in Table 4 show that mobile labor mitigates the loss in operating efficiency as a firm is exposed to the COVID-19 pandemic. Hence, the evidence provides additional support for the first channel that mobile labor can be redeployed to do additional work at a lower cost as employers experience labor shortage in response to the COVID exposure.

<<Insert Table 4 here>>

5. Robustness Checks and Additional Analyses

In this section, we check the robustness of our baseline results to alternative measures of COVID exposure, alternative specifications of labor mobility, alternative measures of firm resilience, and alternative samples. We also conduct additional analyses to address alternative explanations and potential endogeneity concerns.

5.1 Alternative measures of COVID exposure

We construct two alternative measures of COVID exposure. First, since death cases may be less relevant for measuring a firm's ongoing exposure to COVID, we construct an alternative measure for COVID exposure that excludes death cases (*COVID_ACTIVE*).[15] This measure

[15] Ding et al. (2021) exclude both death and recovery cases from confirmed cases to calculate their alternative measure of COVID exposure at the country level. Our analysis, however, is at the county level, and data on recovery cases are

reflects the growth rate of the number of active COVID-19 cases. For each county c in week w, $COVID\_ACTIVE_{c,w}$ is calculated as ln(1+ $Active\ Cases_{c,w}$) – ln(1+$Active\ Cases_{c,w-1}$), where $Active\ Cases_{c,w}$ is the cumulative number of confirmed cases minus death cases in county c as of Friday in week w. Second, to account for the possibility that a firm's COVID exposure is not limited to the county where its headquarter is located, because the firm has subsidiaries and/or stakeholders such as suppliers and customers in other regions, we alternatively measure a firm's COVID exposure at the national level (*COVID_NATION*). *COVID_NATION* is defined as the growth rate of the cumulative number of confirmed COVID-19 cases across the country in a given week. We then re-estimate equation (4) after replacing our main measure of COVID exposure (*COVID*) with one alternative measure at a time.

Panel A of Table 5 presents the regression results. Column 1 uses *COVID_ACTIVE* as an alternative measure for COVID exposure, while column 2 uses *COVID_NATION*. Regardless of the alternative measures for COVID exposure, we consistently find a positive and significant coefficient on the interaction term between *LM* and COVID exposure. Thus, our baseline results are insensitive to alternative measures of COVID exposure.

<<Insert Table 5 here>>

5.2 Alternative specifications of labor mobility

In this subsection, we check the robustness of our results to alternative specifications of labor mobility. The first alternative specification is the industry-level labor mobility measure (*LM_IND*) as described in section 3. As we convert the industry-level labor mobility measure into the firm-level labor mobility measure, measurement error may arise; hence, we use the industry-level labor mobility measure to alleviate this concern. The second alternative specification is the

not available at the county level. Therefore, we only exclude death cases to construct the alternative measure of COVID exposure at the county level.

decile rank of firm-level labor mobility measure (*LM_RANK*). This specification can account for potential nonlinearity in the relation between labor mobility and firm resilience to COVID exposure and outliers in the firm-level labor mobility measure (*LM*). We then re-estimate equation (4) after replacing our main measure of labor mobility (*LM*) with one alternative specification at a time.

Panel B of Table 5 presents the regression results. Column 1 uses *LM_IND* as an alternative specification for labor mobility, while column 2 uses *LM_RANK*. For both alternative specifications of labor mobility, we consistently find a positive and significant coefficient on the interaction term between labor mobility and COVID exposure. Thus, our baseline results are robust to alternative specifications of labor mobility.

5.3 Alternative measures of firm resilience

Next, we run sensitivity tests to check whether our baseline results are robust to alternative measures of firm resilience. In the baseline analyses, we use weekly raw returns as the measure for firm resilience and control for market beta to address the concern that weekly raw returns are affected by risk factors. To further alleviate this concern about risk factors, we construct two measures of weekly abnormal returns that adjust for risk factors: *ARET_CAPM* and *ARET_FF3*. *ARET_CAPM* is the weekly abnormal return adjusted for market beta based on the CAPM model. *ARET_FF3* is the weekly abnormal return adjusted for the Fama and French 3 Factors. We then re-estimate equation (4) after replacing *RET* with these alternative return measures one at a time.

Panel C of Table 5 presents the regression results. Whether using *ARET_CAPM* (column 1) or *ARET_FF3* (column 2) as the dependent variable, we consistently find a positive and significant coefficient on *LM*×*COVID*. These results suggest that it is unlikely that our baseline results, a positive association between labor mobility and firm resilience to COVID exposure, are driven by risk factors rather than future cashflow expectations.

To further check robustness and address the concern that stock returns simply reflect market perception about future firm performance and hence may be a noisy measure for actual firm resilience, we construct an alternative measure for firm resilience using an accounting-based performance variable. Specifically, we calculate operating profit using operating income divided by total assets (*OPPROFIT*). Then, we re-estimate our baseline model with *OPPROFIT* as the dependent variable. As shown in Panel D of Table 5, the coefficient on *LM×COVID* continues to be positive and significant. Overall, these results in Panels C and D of Table 5 suggest that our baseline results are insensitive to alternative measures of firm resilience.

5.4 Alternative samples

In this subsection, we assess the robustness of our main results to alternative samples. First, one concern is that major government bailouts starting from late March 2020 increase investor optimism and hence reduce the validity of stock returns as a measure for firm resilience. For instance, the Federal Reserve Board (Fed) announced two facilities to provide large corporations credit on March 23, 2020, and the U.S. government approved a $2 trillion relief bill on March 27, 2020. It is ex ante unclear whether firms with more mobile labor benefit more or less from the government bailouts. Moreover, this concern should have been alleviated by our control of market beta, which could capture the effect of a firm's exposure to market-wide factors, such as government bailouts, on its stock return, and by our use of alternative measures of firm resilience. To further address this concern, we only use the sample from January 20, 2020 to March 27, 2020. As shown in column 1 of Table 6, the coefficient on *LM×COVID* continues to be significantly positive. Second, since the number of COVID-19 cases in the U.S. is quite limited in January and

February of 2020, we alternatively limit the sample period to be from March 2, 2020 to June 26, 2020. As shown in column 2 of Table 6, the coefficient on *LM×COVID* continues to hold.

Third, we follow Ding et al. (2021) and exclude firms in the energy sector since these firms have been heavily affected by the price war between Russia and Saudi Arabia during early 2020. Column 3 of Table 6 reports the regression results based on this reduced sample and shows that the coefficient on *LM×COVID* remains significantly positive. Fourth, like Hassan et al. (2020), we exclude firms in the pharmaceutical and healthcare sector as these firms have been affected by the pandemic differently relative to firms in other sectors. Column 4 of Table 6 reports the regression results using this reduced sample and shows that the coefficient on *LM×COVID* remains positive and significant. Lastly, we exclude firms in the airline industry as these firms have received substantial government subsidy during the pandemic. Column 5 of Table 6 reports the results based on this reduced sample and shows that the coefficient on *LM×COVID* remains significantly positive. In summary, Table 6 suggests that our results are robust to the use of alternative samples that eliminate either the early or later sample period, exclude firms in the energy sector, firms in the healthcare and pharmaceutical industry, or firms in the airline industry.

<<Insert Table 6 here>>

5.5 Alternative explanations

5.5.1 Are the results driven by corporate governance or management ownership?

Ding et al. (2021) show that corporate governance and ownership structure are related to stock return reactions to the COVID exposure. Thus, one may argue that our results are driven by corporate governance or ownership structure. Prior studies have not examined the relation between corporate governance (ownership structure) and labor mobility; hence, it is uncertain whether corporate governance or ownership structure are alternative explanations for our results of a positive association between labor mobility and firm resilience to COVID exposure. To address this concern, we control for the effect of corporate governance and that of management ownership. We capture corporate governance using two alternative measures: board size (*BOARD_SIZE*) and board independence (*BOARD_IND*). We capture management ownership using the total percentage of management shareholding (*MGMT_OWN*). Appendix A defines these variables.

Table 7 presents the regression results. In columns 1 through 3, we separately control for the effect of board size, board independence, and management ownership, while in column 4 we control for the effect of all three variables.[16] Across the four columns, the coefficient on *LM×COVID* is consistently positive and significant. These results suggest that it is unlikely that our results are driven by corporate governance or management ownership.

<<Insert Table 7 here>>

5.5.2 Are the results driven by county-level factors?

Given that we measure a firm's COVID exposure using the weekly growth rate of the COVID-19 cases in the county where the firm is headquartered, another concern is that our results are driven by various county-level factors, such as demographics and economic situations. For example, counties with more minority groups or poor economic conditions might be less resilient to COVID exposure and meanwhile have lower labor mobility. To address this concern, we use two approaches.

First, we conduct an event study using the first COVID-19 case in each county as the event. Since an event study can better identify causal relations and the first COVID-19 case in each county would induce the strongest stock price reaction, we expect that the stock price reactions to

[16] We only include the respective interaction of these additional control variables with *COVID* and do not include their main effects, because these firm-level control variables are for the fiscal year 2019 only and do not have within-firm variation and therefore will drop out from the estimation when we include firm fixed effects in the regression model.

the first COVID-19 case would better identify the effect of COVID exposure on firm resilience and will be less likely to be driven by county-level factors such as demographics or economic situations. Specifically, we construct three measures of short-window stock returns within [-1, +1] days around the first COVID-19 case in the county where the firm is headquartered, including *CR* [-1, +1], *CAR_CAPM* [-1, +1], *CAR_FF3* [-1, +1]. *CR* [-1, +1] is a firm's cumulative returns within [-1, +1] days around the first COVID-19 case in the firm's headquarter county. *CAR_CAPM* [-1, +1] is a firm's cumulative abnormal returns adjusted for market beta based on CAPM model within [-1, +1] days around the first COVID-19 case in the firm's headquarter county, while *CAR_FF3* [-1, +1] is cumulative abnormal returns adjusted for the Fama and French 3 Factors. We then use these measures to conduct univariate analyses and multivariate analyses of the relation between labor mobility and firm resilience to COVID exposure.

Table 8 presents the results. Panel A and B report the results of the univariate analyses by comparing the mean and median of short-window stock returns, respectively, while Panel C reports the results of multivariate analyses. Whether comparing the mean or the median, we consistently find that firms with more mobile labor experience less negative stock price reactions to the first COVID-19 case in their respective county than firms with less mobile labor. After adding the explanatory variables in our baseline model and industry-week fixed effects, we find similar results. In summary, the results in Table 8 suggest that county-level factors are unlikely to drive our baseline results.

<<Insert Table 8 here>>

Second, we conduct a time-series analysis by testing the impact of labor mobility on stock returns before vs. during the pandemic. The advantage of this approach is that we identify the effect of COVID exposure by leveraging the exogenous time-series variation in COVID exposure from the pre-pandemic period to the pandemic period. Hence, the effect of COVID exposure on stock returns is less likely to be attributed to county-level factors, such as demographics or economic situations. Specifically, we construct an indicator variable *DURING*, which takes the value one for the observations during the pandemic (January 20, 2020 to June 26, 2020), and zero for the observations during the corresponding period before the pandemic (January 24, 2019 to June 30, 2019). We then re-estimate equation (4) after replacing *COVID* with *DURING* and adding the main effects of the control variables.[17]

Table 9 presents the results of the analysis. The coefficient on *DURING* is negative and significant, suggesting that stock returns perform worse during the pandemic than before the pandemic. The coefficient on our variable of interest *LM×DURING* is positive and significant, suggesting that labor mobility alleviates the worse stock returns during the pandemic relative to the pre-pandemic period. Overall, the evidence in Table 9 provides additional support that our baseline results are unlikely to be attributable to county-level factors.

<<Insert Table 9 here>>

5.6 Endogeneity concerns

The main endogeneity concern in our study lies in labor mobility and stems from correlated omitted variables. That is, labor mobility could increase due to some unidentified factors that might also affect firm resilience to the COVID exposure. Another potential endogeneity concern is that firms with high resilience to the COVID exposure are more likely to hire mobile employees (i.e., reverse causality), which is less likely given the significant cost of employing mobile labor (e.g.,

[17] Here we can include the main effects of the control variables because we now use data for control variables over two fiscal years, 2019 and 2020, and these variables have within-firm variation after we include firm fixed effects. But given that the within-firm variation for the control variables may be small in this case, we alternatively exclude firm fixed effects from the analyses in Table 9. We find results similar to those reported in this table (untabulated for brevity).

Donangelo 2014; Leung et al. 2018). Our baseline empirical specifications should alleviate these endogeneity concerns, as we follow Ding et al. (2021) to control for a set of firm features and firm and industry-week fixed effects and lag the labor mobility variable relative to firm resilience to the COVID exposure. With these control variables and fixed effects, we condition out (a) all time-invariant firm features and major time-varying firm features, such as differences in size and leverage, and (b) all time-varying and time-invariant industry features, such as differences in the intensity of required in-person contact with co-workers that might influence stock price reactions to the COVID exposure. Lagging the labor mobility variable should alleviate the concern for reverse causality. Our additional analyses – the analyses using alternative samples and those that further control for corporate governance and management ownership – should also mitigate the endogeneity concerns in labor mobility.

To further address such endogeneity concerns, we perform four additional analyses as discussed below: (1) a natural experiment analysis that leverages the enforcement of non-compete agreements; (2) a propensity score-matched sample analysis; (3) an instrumental variable approach; and (4) an impact threshold analysis of a confounding variable.

5.6.1 A natural experiment with non-compete agreements

Following prior studies (e.g., Tang, Wang, and Zhou 2020; Kini, Williams, and Yin 2020; Bai et al. 2020), we use state-level variation in the enforcement of non-compete agreements as an exogenous shock to labor mobility. Non-compete agreements restrict employees from joining or forming competing firms after leaving their previous employment and therefore reduce labor mobility. Moreover, the enforcement of non-compete agreements depends on state jurisdictions that are exogeneous to the actions of individual firms, and therefore alleviates the concern about correlated omitted variables (e.g., Tang et al. 2020). Specifically, we measure state-wide enforcement intensity of non-compete agreements with an enforceability index from Bai et al. (2020) (*NC*). Higher values of *NC* indicate more stringent enforcement of non-compete agreements in a state and lower labor mobility for firms in the state. We then replace *LM* with *NC* and re-estimate equation (4). Table 10 presents the results. We find a negative and significant coefficient on *NC*×*COVID*, indicating that the adverse impact of COVID exposure on firm resilience is more pronounced for firms located in states with more stringent enforcement of non-compete agreements – firms with low labor mobility. These results provide further support that mobile employees help their firms stay resilient to the COVID exposure.

<<Insert Table 10 here>>

5.6.2 Propensity score matching

Next, we apply propensity score matching (PSM) to determine whether firms with high labor mobility would be less resilient to the COVID exposure had they not had high labor mobility. This approach involves matching the treatment and control observations based on the likelihood that an observation would be a high labor mobility firm conditional on observables (Rosenbaum and Rubin 1983; 1984). Specifically, we first define an indicator variable *HIGH_LM*, which takes one if a firm's labor mobility is above the sample median, zero otherwise. We then use a probit model to estimate the probabilities of being a high labor mobility firm (i.e., propensity score) by regressing *HIGH_LM* on all firm-level control variables in equation (4) (i.e., *SIZE*, *LEV*, *ROA*, *CASH*, *MTB*, and *BETA*) and industry fixed effects.[18] Next, we use nearest-neighbor matching to match each treatment observation (i.e., *HIGH_LM*=1) with a control observation (i.e.,

[18] We do not include firm fixed effects or week-related fixed effects because the probit model only uses firm-level variables for the fiscal year 2019 and these variables do not have within-firm variation or variation at the week level.

HIGH_LM=0) that has the closest propensity score within a predefined caliper of 0.01.[19] After creating the matched sample, we perform regression analyses.

Table 11 presents the results of these analyses. In Columns 1 and 2, we regress *RET* on *COVID* for the high *LM* and low *LM* subsamples separately and then compare the two coefficients using a directional F-test. We find negative and significant coefficients on *COVID* in both subsamples, and the coefficient on *COVID* is significantly less negative for the high *LM* subsample than for the low *LM* subsample. These results suggest that the adverse impact of COVID exposure on firm resilience is less severe for firms with high labor mobility than for firms with low labor mobility. In Column 3, we use the full matched sample and replace the continuous variable *LM* with the indicator variable *HIGH_LM* to re-estimate the baseline model in equation (4). We find a negative and significant coefficient on *HIGH_LM×COVID*, providing further support for our hypothesis. In Column 4, we use the full matched sample and re-estimate equation (4). The coefficient on *LM×COVID* is positive and significant, consistent with our main result. Put together, the results in Table 11 further support the hypothesis that mobile employees help their firms stay resilient to the COVID exposure.

<<Insert Table 11 here>>

5.6.3 Instrumental variable approach

The third approach to address the endogeneity concern is an instrumental variable (IV) approach developed by Lewbel (2012). The ideal instrument in our setting should affect labor mobility but not firm resilience to COVID exposure except through labor mobility. Such an instrument is very difficult to identify, as firm resilience to COVID exposure is affected by a myriad of factors. Given this limitation, we follow recent studies (e.g., Mayberry, Park, and Xu

---

[19] Applying a predefined caliper improves covariance balance. However, it results in a smaller matched sample because some treatment observations cannot be matched with a control observation within the caliper.

2021; Anderson and Core 2018; Marvis et al. 2020) and employ the heteroskedasticity-based instrumentation method developed by Lewbel (2012). This approach constructs heteroskedasticity-based instruments as functions of the model's control variables and therefore can be applied to settings where no external instruments are available. Using Lewbel (2012)'s approach, we instrument *LM* and *LM×COVID* based on all control variables and industry-week fixed effects in equation (4) in the first-stage analysis and then use the generated instruments in the second-stage analysis.[20]

Table 12 presents the results of Lewbel (2012)'s IV approach. In the first-stage regressions for *LM* and *LM×COVID* (untabulated), we find that the Lewbel estimated instruments are strong predictors for *LM* and *LM×COVID*. The Kleibergen-Paap rk Wald F statistic for the week identification test is 55.84, which is above the critical value in Stock and Yogo (2002) and rejects the null hypothesis of weak identification. Moreover, the Hansen J statistic for the overidentification test is 16.81 with a p-value of 0.157, indicating that we cannot reject the null hypothesis of exogenous instruments. In the second-stage regression, we use the instrumented *LM* and *LM×COVID* (*Predicted LM* and *Predicted LM×COVID*). We find a positive and significant coefficient on *Predicted LM×COVID*, consistent with our main result. Overall, Table 12 provide additional support that mobile labor improves firm resilience to the COVID exposure.

<<Insert Table 12 here>>

5.6.4 Impact threshold of a confounding variable

Although we have used various approaches to address the concern for potential endogeneity as described above, we acknowledge that it is impossible to completely rule out the

[20] We do not include firm fixed effects in the IV regressions because our endogenous variable *LM* does not have multiple time series – we have only one-year data for *LM*. Inclusion of firm fixed effects will subsume the within-firm variation in *LM* and cause the regressions to be unestimatable. Due to the exclusion of firm fixed effects, we are able to include the main effects of the control variables in the IV regressions.

concern for correlated omitted variables. Therefore, to assess the sensitivity of our results to possible correlated omitted variables, we now conduct an analysis of the impact threshold for a confounding variable following prior studies (Frank 2000; Larcker and Rusticus 2010; Chapman, Miller, and White 2019). This approach computes the minimum amount an omitted variable must be to overturn the main results (i.e., the impact threshold). The larger the impact threshold for a confounding variable, the less likely the main results will be affected by the omitted confounding variables. In practice, the impact threshold of a confounding variable is usually benchmarked against that of the most impactful control variable.

Table 13 presents the results of the impact threshold analysis. We first present the impact of each control variable on the coefficient for *LM×COVID*, our variable of interest. It is calculated following Frank (2000) as the partial correlation between each control variable and the dependent variable multiplied by the partial correlation between each control variable and *LM×COVID*. The row labelled "Largest impact" identifies the control variable in the model that has the largest impact on the coefficient for *LM×COVID*. The row labelled "Largest impact of interaction term" identifies the most impactful control variable in the interaction form. The row labelled "Impact threshold of the confounding variable" identifies the minimum magnitude an omitted confounding variable needs to be to overturn the main result on *LM×COVID* and is calculated following Frank (2000). A comparison among the three rows suggests that an omitted confounding variable would need to be at least 2.67 times larger than the most impactful interaction term in order to overturn the coefficient on *LM×COVID*, which seems unlikely given our inclusion of firm and industry-week fixed effects as well as commonly used control variables in the regression. Overall, while these results cannot rule out omitted confounding variables, they indicate that such variables are unlikely to drive the main results in Table 2.

<<Insert Table 13 here>>

Overall, we employ a number of approaches to address the endogeneity concern. While each approach has its own strengths and weaknesses, collectively, the consistent inferences across multiple approaches lend confidence to our main result on the beneficial effect of labor mobility on firm resilience to the COVID exposure. Nevertheless, we acknowledge that it is challenging to completely rule out the endogeneity concern and the potential for correlated omitted variables.

6. Conclusion

The COVID-19 pandemic has triggered a global health crisis and caused unprecedented challenges for firms around the world. Thus, it is pressing to understand factors and forces that help companies stay resilient to the COVID exposure. In this paper, we examine whether and how mobile labor helps firms stay resilient to the COVID exposure. We focus on mobile labor because, as a critical resource for a modern corporation, labor have been directly affected by the COVID-19 pandemic, and their mobility, in particular, has been seriously constrained.

Using a sample of U.S. firms during the first two quarters of 2020, we find that mobile labor helps their firms stay resilient to the COVID exposure. Specially, we find that while a firm's stock price generally reacts negatively to its COVID exposure, this negative stock price reaction is significantly alleviated by labor mobility. This result is robust to the inclusion of firm and industry-week fixed effects and controls for various firm characteristics interacted with the COVID exposure. This result is also robust to alternative measures of the COVID exposure, alternative measures of firm resilience, alternative specifications of labor mobility, alternative sample periods, and alternative industry compositions.

In light of the beneficial effect of labor mobility discussed above, we next conduct additional analyses to better understand the underlying channels through which mobile labor force increases firm resilience to the COVID exposure. If firms with mobile employees stay resilient to the COVID exposure because they can redeploy these employees to do additional work that emerges from the COVID-related layoffs at a lower cost, we expect that the impact of labor mobility on firm resilience to the COVID exposure will be more pronounced for firms that lay off more employees during the pandemic. Using the monthly change in unemployment rate to capture employee layoffs, we find results consistent with this prediction.

If firms with mobile employees stay resilient to the COVID exposure because they can redeploy these employees to do alternative work more easily as they adjust product/service portfolio in response to the COVID exposure, we expect that our baseline relation will be more pronounced for firms with more redeployable assets and more related business segments before the pandemic. Using asset redeployability measure constructed following Kim and Kung (2017) and segment relatedness measure constructed following Chen et al. (2018), we find results consistent with this prediction. If firms with mobile employees stay resilient to the COVID exposure because these employees can better adapt to the new working environment in the presence of the COVID exposure, we expect that our baseline relation will be more pronounced for firms that are more exposed to such new working environment during the pandemic. Given that one distinct feature of the new environment is remote work, we test whether our baseline relation is stronger for firms that are more likely to switch to remote work during the pandemic. Using work-from-home feasibility measure from Dingel and Neiman (2020); we find results consistent with this prediction.

Overall, our evidence suggests that mobile labor plays a valuable role in helping their firms fare well and stay resilient to the COVID exposure. The evidence should have implications to regulators and practitioners who have been exploring ways for firms to stay resilient to the COVID exposure. Our study extends the emerging research on firm resilience during the COVID crisis and that on the impact of labor, particularly mobile labor, on corporate activities and outcomes. Interpreting our results in conjunction with those from prior studies (e.g., e.g., Donangelo 2014; Leung et al. 2018; Shen 2018) suggests that while mobile employees are costly to their firms during the *normal* times due to their flexibility to move, they are valuable in helping their firms stay resilient during the *abnormal* COVID pandemic, when their mobility is constrained.

References

Anderson, J.D., Core, J.E., 2018. Managerial Incentives to Increase Risk Provided by Debt, Stock, and Options. *Management Science* 64(9), 4408-4432.

Bai, J., Eldemire-Poindexter, A., Serfling, M., Growing Pains: The Effect of Labor Mobility on Corporate Investment over the Business Cycle (June 14, 2021). Available at SSRN: https://ssrn.com/abstract=3721708.

Bernard, D., Ge, W., Matsumoto, D. and Toynbee, S., 2020. Implied Tradeoffs of Chief Financial Officer Accounting Expertise: Evidence from Firm-Manager Matching. Management Science.

Blatter, M., Muehlemann, S., Schenker, S., 2012. The Costs of Hiring Skilled Workers. *European Economic Review* 56, 20-35.

Bowen, R.M., DuCharme, L. and Shores, D., 1995. Stakeholders' implicit claims and accounting method choice. *Journal of accounting and economics*, *20*(3), pp.255-295.

Campello, M., Kankanhalli, G., Muthukrishnan, P., 2020. Corporate Hiring under COVID-19: Labor Market Concentration, Downskilling, and Income Inequality. NBER Working Papers 27208, National Bureau of Economic Research, Inc.

Chapman, K., Miller, G.S., White, H.D., 2018. Investor Relations and Information Assimilation. *The Accounting Review* 94, 105-131.

Cheema-Fox, A., LaPerla, B.R., Serafeim, G., Wang, H., 2020. Corporate Resilience and Response During COVID-19. Harvard Business School Accounting & Management Unit Working Paper No. 20-108.

Chen, C., Martin, X., Roychowdhury, S., Wang, X. and Billett, M.T., 2018. Clarity begins at home: Internal information asymmetry and external communication quality. *The Accounting Review*, *93*(1), pp.71-101.

Ding, W., Levine, R., Lin, C., Xie, W., 2021. Corporate Immunity to the COVID-19 Pandemic. *Journal of Financial Economics*, forthcoming.

Dingel, J.I., Neiman, B., 2020. How Many Jobs Can be Done at Home? *Journal of Public Economics* 189, 104235.

Donangelo, A., 2014. Labor Mobility: Implications for Asset Pricing. *The Journal of Finance* 69, 1321-1346.

Frank, K.A., 2000. Impact of a Confounding Variable on a Regression Coefficient. *Sociological Methods & Research* 29, 147-194.

Gao, H., Zhang, H. and Zhang, J., 2018. Employee turnover likelihood and earnings management: evidence from the inevitable disclosure doctrine. *Review of Accounting Studies*, *23*(4), pp.1424-1470.

Garmaise, M.J., 2011. Ties that truly bind: Noncompetition agreements, executive compensation, and firm investment. *The Journal of Law, Economics, and Organization*, *27*(2), pp.376-425.

Gervais, M., Livshits, I., Meh, C., 2008. Uncertainty and the Specificity of Human Capital. *Journal of Economic Theory* 143, 469-498.

Hart, O., Moore, J., 1990. Property Rights and the Nature of the Firm. *Journal of Political Economy* 98, 1119-1158.

Harvard Business Review 2020. A guide to building a more resilient business. https://hbr.org/2020/07/a-guide-to-building-a-more-resilient-business.

Hass, L.H., Hribar, P., Kalogirou, F., 2018. The Disciplining Effect of Labor Mobility on Managerial Myopia. Working paper.

Hass, L.H., Omer, T.C., Vergauwe, S., 2019. Do Employees Matter for Firms' Tax Planning Decisions? Evidence from Labor Mobility. Working paper.

Hassan, T.A., Hollander, S., Van Lent, L., Schwedeler, M. and Tahoun, A., 2020. Firm-level exposure to epidemic diseases: Covid-19, SARS, and H1N1 (No. w26971). National Bureau of Economic Research.

Hertzberg, F., 1959. The Motivation to Work. J. Wiley & Sons, New York.

Jeffers, J., 2019. The impact of restricting labor mobility on corporate investment and entrepreneurship. *Available at SSRN 3040393*.

Jennings, J., Kim, J.M., Lee, J., Taylor, D., 2020. Measurement Error and Bias in Causal Models in Accounting Research. *Available at SSRN* https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3731197

Karaevli, A., Tim Hall, D.T., 2006. How Career Variety Promotes the Adaptability of Managers: A Theoretical Model. *Journal of Vocational Behavior* 69, 359-373.

Kim, H., and H. Kung. 2017. The asset redeployability channel: How uncertainty affects corporate investment. *Review of Financial Studies, 30*(1): 245–280.

Kuehn, L.A., Simutin, M., Wang, J.J., 2017. A Labor Capital Asset Pricing Model. *The Journal of Finance* 72, 2131-2178.

Krueger, A.B., and E.A. Posner, 2018, A Proposal for Protecting Low-Income Workers from Monopsony and Collusion, Brookings Institute-Hamilton Project, Policy Proposal.

Larcker, D.F., Rusticus, T.O., 2010. On the Use of Instrumental Variables in Accounting Research. *Journal of Accounting and Economics* 49, 186-205.

Lee, Ruby and Yu, Gwen, Investment in Human Capital and External Reporting Quality (May 14, 2021). Available at SSRN: https://ssrn.com/abstract=3846394.

Leung, W.S., Mazouz, K., Chen, J., Wood, G., 2018. Organization Capital, Labor Market Flexibility, and Stock Returns around the World. *Journal of Banking & Finance* 89, 150-168.

Levy, D.T., Haber, L.J., 1986. An Advantage of the Multiproduct Firm: The Transferability of Firm-specific Capital. *Journal of Economic Behavior & Organization* 7, 291-302.

Lewbel, A., 2012. Using Heteroscedasticity to Identify and Estimate Mismeasured and Endogenous Regressor Models. *Journal of Business & Economic Statistics* 30(1), 67-80.

Li, K., Liu, X., Mai, F., Zhang, T., 2021. The Role of Corporate Culture in Bad Times: Evidence from the COVID-19 Pandemic. European Corporate Governance Institute – Finance Working Paper No. 726/2021.

Matsumoto, D.A., 2002. Management's incentives to avoid negative earnings surprises. *The accounting review*, *77*(3), pp.483-514.

Mayberry, M., Park, H.J., Xu, T., 2021. Risk-Taking Incentives and Earnings Management: New Evidence. *Contemporary Accounting Research*. Forthcoming.

Marvis, C.P., McNamee, N.P., Petmezas, D., Travlos, N.G., 2020. Selling to buy: Asset Sales and Acquisitions. *Journal of Corporate Finance* 62, 101587.

Maslow, A.H., 1943. A theory of human motivation. *Psychological review*, *50*(4), p.370.

McGregor, D., 1960. The Human Side of Enterprise. McGraw-Hill, New York.

Neal, D., 1995. Industry-specific human capital: Evidence from displaced workers. *Journal of labor Economics*, *13*(4), pp.653-677.

NPR 2020. White collar workers put on assembly line as COVID-19 shrinks worker population. https://www.npr.org/2020/08/01/898099517/white-collar-workers-put-on-assembly-line-as-covid-19-shrinks-worker-population.

Parent, D., 2000. Industry-Specific Capital and the Wage Profile: Evidence from the National Longitudinal Survey of Youth and the Panel Study of Income Dynamics. *Journal of Labor Economics* 18, 306-323.

Petersen, M.A., 2009. Estimating standard errors in finance panel data sets: Comparing approaches. The Review of financial studies, 22(1), pp.435-480.

Petrosky-Nadeau, N., 2016, Job-to-job transitions in an evolving labor market, FRBSF Economic Letter 34, 1–5.

Poletaev,M., Robinson, C., 2008. Human Capital Specificity: Evidence from the Dictionary of Occupational Titles and Displaced Worker Surveys, 1984–2000. *Journal of Labor Economics* 26, 387-420.

Rosenbaum, P.R. and Rubin, D.B., 1983. The central role of the propensity score in observational studies for causal effects. *Biometrika*, *70*(1), pp.41-55.

Rosenbaum, P.R. and Rubin, D.B., 1984. Reducing bias in observational studies using subclassification on the propensity score. *Journal of the American statistical Association*, *79*(387), pp.516-524.

Sanati, A., 2018. How Does Labor Mobility Affect Corporate Leverage and Investment? Working paper.

Statista Research Department, 2021. Impact of COVID-19 on the Global Financial Markets – Statistics & Facts. https://www.statista.com/topics/6170/impact-of-covid-19-on-the-global-financial-markets/#dossierKeyfigures.

Shen, M., 2018. Skilled Labor Mobility and Firm Value: Evidence from a Natural Experiment. Dissertation, Georgia State University, https://scholarworks.gsu.edu/finance_diss/33.

Stock, J.H., Yogo, M., 2002. Testing for Weak Instruments in Linear IV Regression. National Bureau of Economic Research Working paper.
The Wall Street Journal 2020. GM uses salaried employees to fill vacancies at Missouri pickup-truck plant. https://www.proquest.com/newspapers/gm-uses-salaried-employees-fill-vacancies-at/docview/2436910724/se-2?accountid=14784.

The Wall Street Journal 2020a. Business recovery hampered for some by foreign-worker visa bans; ski resorts see trouble ahead after struggling to fill summer amusement park jobs. https://www.proquest.com/newspapers/business-recovery-hampered-some-foreign-worker/docview/2440362339/se-2?accountid=14784.

The Wall Street Journal 2020b. Coronavirus pandemic compels historic labor shift. https://www.proquest.com/newspapers/coronavirus-pandemic-compels-historic-labor-shift/docview/2383906000/se-2?accountid=14784.

The Wall Street Journal 2021. A pandemic may be a risky time for a higher minimum wage. https://www.proquest.com/newspapers/pandemic-may-be-risky-time-higher-minimum-wage/docview/2495485890/se-2?accountid=14784.

Wasmer, E., 2006. General versus specific skills in labor markets with search frictions and firing costs. *American Economic Review*, *96*(3), pp.811-831.

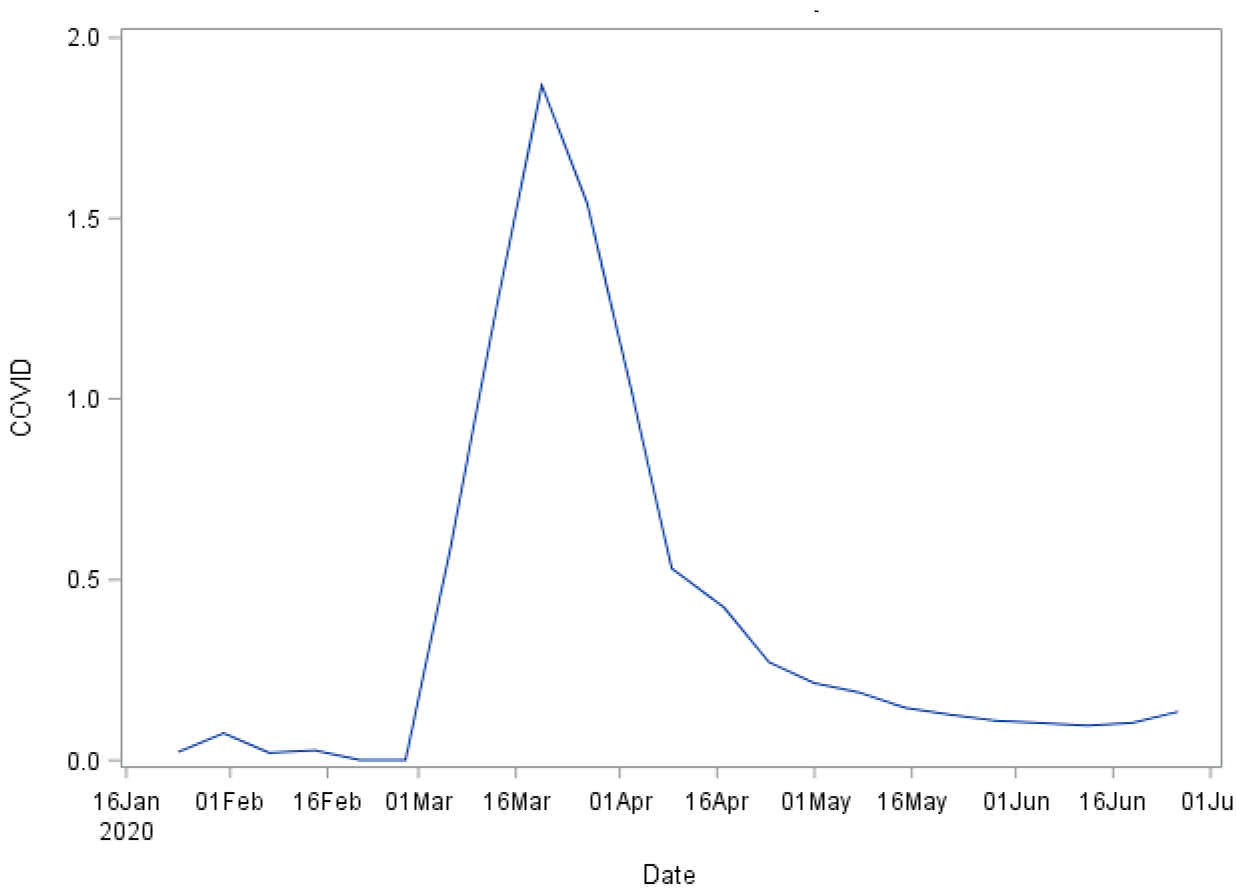
Zingales, L., 2000. In Search of New Foundations. *The Journal of Finance* 55, 1623-1653.

Appendix A: Variable Definitions and Data Sources

Variable	Definition	Data Source
Return Variables		
RET	The weekly stock return based on dividend-adjusted closing prices on the last trading day of the week	CRSP
ARET_CAPM	The weekly abnormal return adjusted for market beta based on CAPM model	CRSP
ARET_FF3	The weekly abnormal return adjusted for Fama and French 3 Factors	CRSP; Kenneth French Data Library
Labor Mobility Variables		
LM_IND	The industry-level labor mobility measure. First, we specify an occupation's concentration score based on the proportion of the occupation's employees in each industry. Second, we take the inverse of the value-weighted average of the occupation concentration scores across all occupations in each industry to generate an industry-level labor mobility score. The weight is each industry's wages paid to employees in a particular occupation divided by its total wages.	OES data from the U.S. Bureau of Labor Statistics
LM	The firm-level labor mobility measure. We construct the firm-level labor mobility measure as the average industry-level labor mobility score across the business segments in which the firm operates, weighted by the share of each business segment's sales in the firm's total sales. If segment data is missing for a firm-year in the Compustat segment files, we set the firm-level labor mobility measure to be equal to the industry-level labor mobility measure based on the firm's industry classification in Compustat.	Compustat Segment; OES data from the U.S. Bureau of Labor Statistics
LM_RANK	The decile rank of the firm-level labor mobility measure. We obtain the decile rank of the sample firms based on their *LM* levels and scale the ranks to be in the interval [0,1].	Compustat Segment; OES data
COVID Variables		
COVID	The growth rate of the cumulative number of confirmed COVID-19 cases in the county where a firm is headquartered during a given week. For each county in week w, *COVID* = ln(1+#cumulative cases in week w) – ln(1+#cumulative cases in week w-1), where #cumulative cases in week w is the cumulative number of confirmed cases in the county as of Friday in week w.	Center for Systems Science and Engineering at Johns Hopkins University (JHU CSSE)
COVID_ACTIVE	The growth rate of the cumulative number of active COVID-19 cases in the county where a firm is headquartered during a given week. For each county in week w, *COVID_ACTIVE* = ln(1+#active cases in week w) – ln(1+#active cases in week w-1), where #active cases = # cumulative cases – # death cases.	JHU CSSE
COVID_NATION	The growth rate of the cumulative number of confirmed COVID-19 cases across the country in a given week.	JHU CSSE
Control Variables		
SIZE	The natural logarithm of total assets	Compustat
LEV	The ratio of total debt divided by total assets.	Compustat
ROA	Income before extraordinary items divided by total assets	Compustat
CASH	Cash and short-term investments divided by total assets	Compustat
MTB	Market value of equity divided by book value of equity	Compustat
BETA	Market Beta, estimated from the market model using weekly returns in the past 60 months	CRSP
Partitioning/Channel Variables		
UNEMP_CH	The monthly change in unemployment rate in each county where the firm is headquartered	U.S. Bureau of Labor Statistics
AT_REDEPLOY	The firm-level asset redeployability measure. Following Kim and Kung (2017), we first specify a capital asset's redeployability score as the sum of the weights of industries that use the asset. Industry weight is calculated using the market	Compustat Segment; BEA data from the

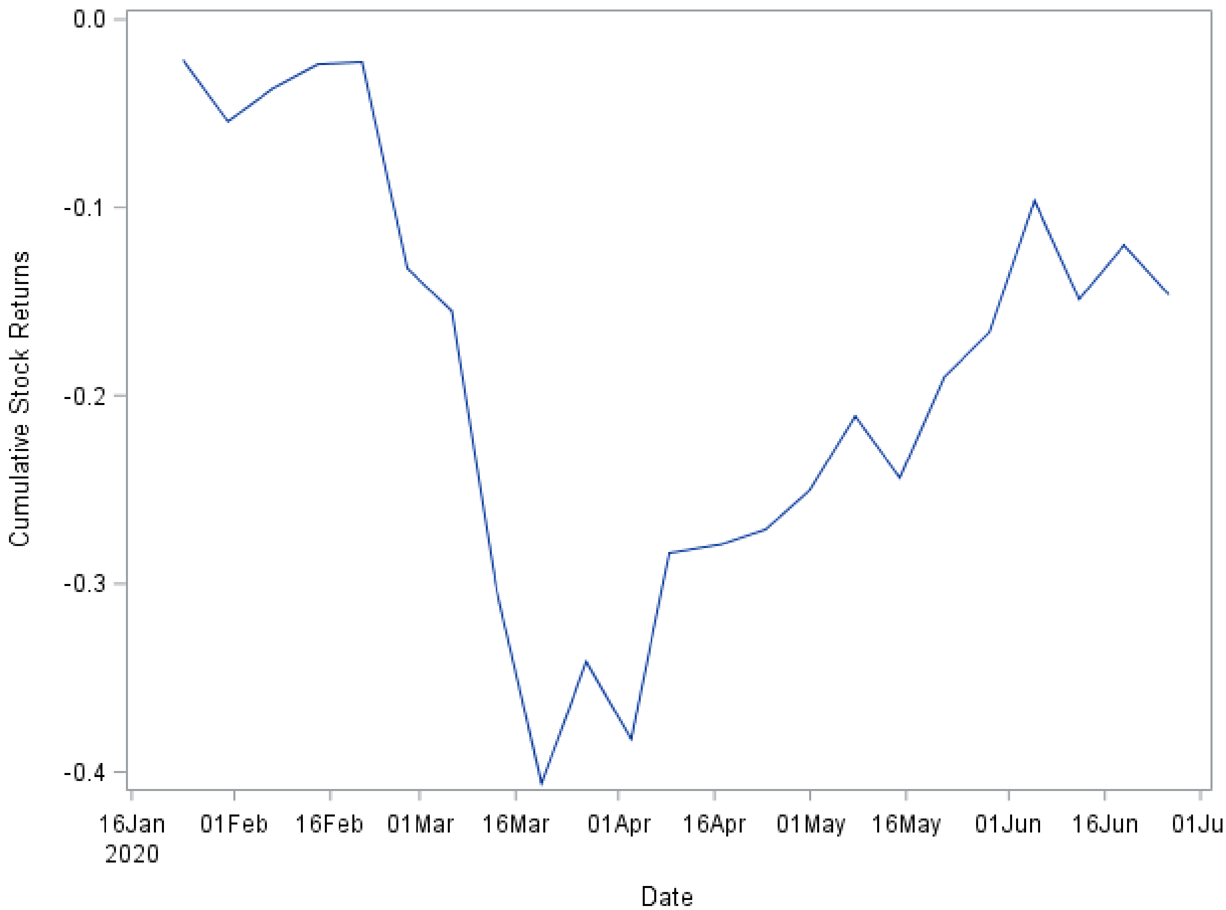
	capitalization of Compustat firms in each industry. Second, we take the value-weighted average of the asset-level redeployability scores across the capital assets in the BEA table to generate an industry-level capital redeployability index. The weight is each industry's expenditure on a particular capital asset divided by its total capital expenditure. Last, we construct the firm-level capital redeployability score as the average industry-level capital redeployability index across the business segments in which the firm operates, weighted by the share of each business segment's sales in the firm's total sales. If segment data is missing for a firm-year in the Compustat segment files, we set the firm-level capital redeployability score to be equal to the industry-level capital redeployability index based on the firm's industry classification in Compustat.	U.S. Bureau of Labor Statistics
SEG_RELATED	Segment relatedness, defined as the number of related business segments divided by the total number of business segments, where the number of related business segments is calculated as the difference between the total number of business segments and the number of segments with different main two-digit SIC code.	Compustat Segment
WFH	Work from home measure from Dingel and Neiman (2020), i.e., the shares of jobs in an industry that can be performed from home, derived from O*NET survey data from the U.S. Department of Labor.	Dingel and Neiman (2020)
AT_INTANGIBLE	Asset intangibility, calculated as one minus gross property, plant, and equipment scaled by total assets.	Compustat
OPEXP_SALE	The firm's quarterly operating expense, calculated as the sum of cost of goods sold and SG&A expense, divided by sales for the quarter	Compustat
OPEXP_EMP	The firm's quarterly operating expense divided by the number of employees for the year 2020	Compustat
Other Variables		
OPPROFIT	The firm's quarterly operating income before depreciation divided by total assets for the quarter	Compustat
BOARD_SIZE	The firm's total number of board members	RiskMetrics
BOARD_IND	The percentage of independent board members on a firm's board.	RiskMetrics
MGMT_OWN	The percentage of shares that management hold in their firm.	Compustat

Figure 1: Growth Rate of Covid-19 Cases



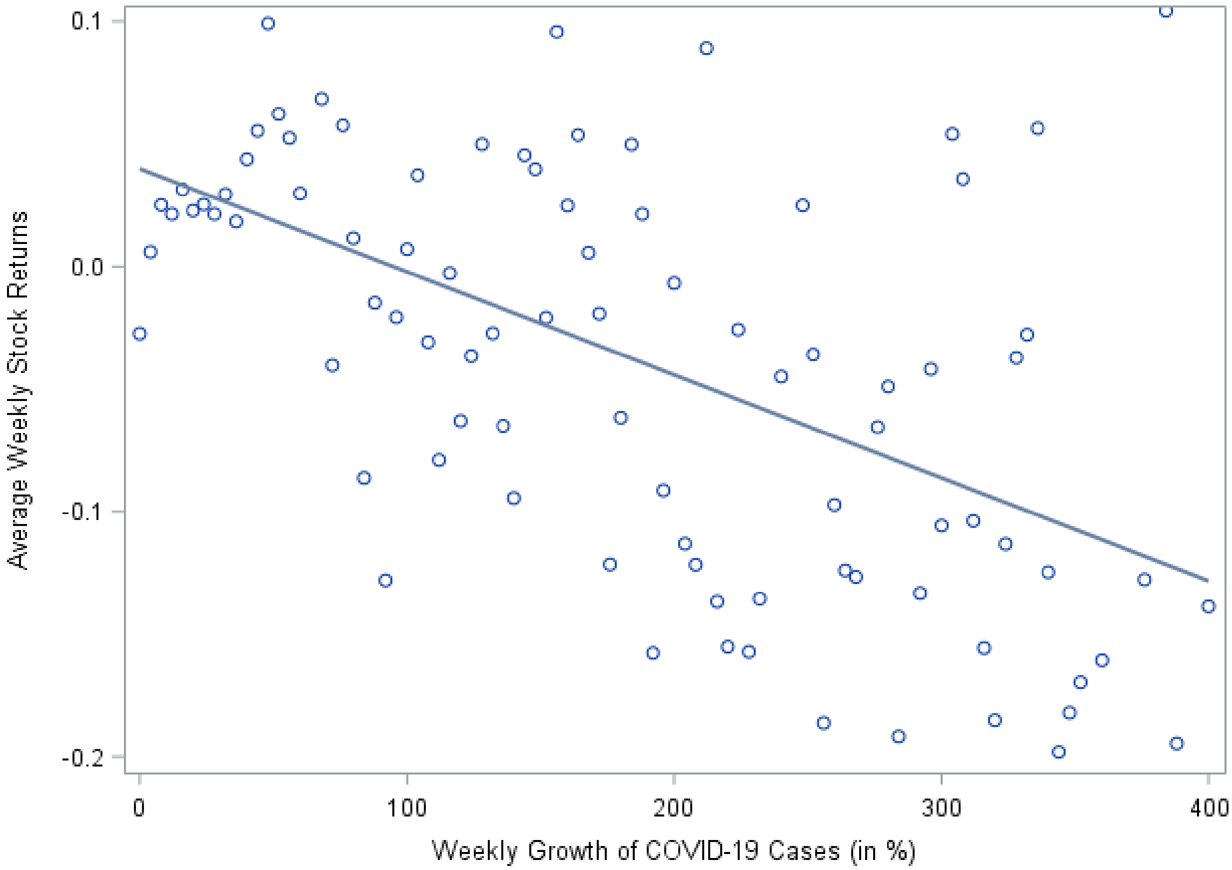
This figure depicts the time trend of the weekly growth rate of COVID-19 cases during the weeks from January 20, 2020 to June 26, 2020. The x-axis denotes the calendar date, and the y-axis represents the growth rate of cumulative number of confirmed COVID-19 cases in a county in a given week (*COVID*).

Figure 2: Cumulative Stock Returns since the Spread of Covid-19



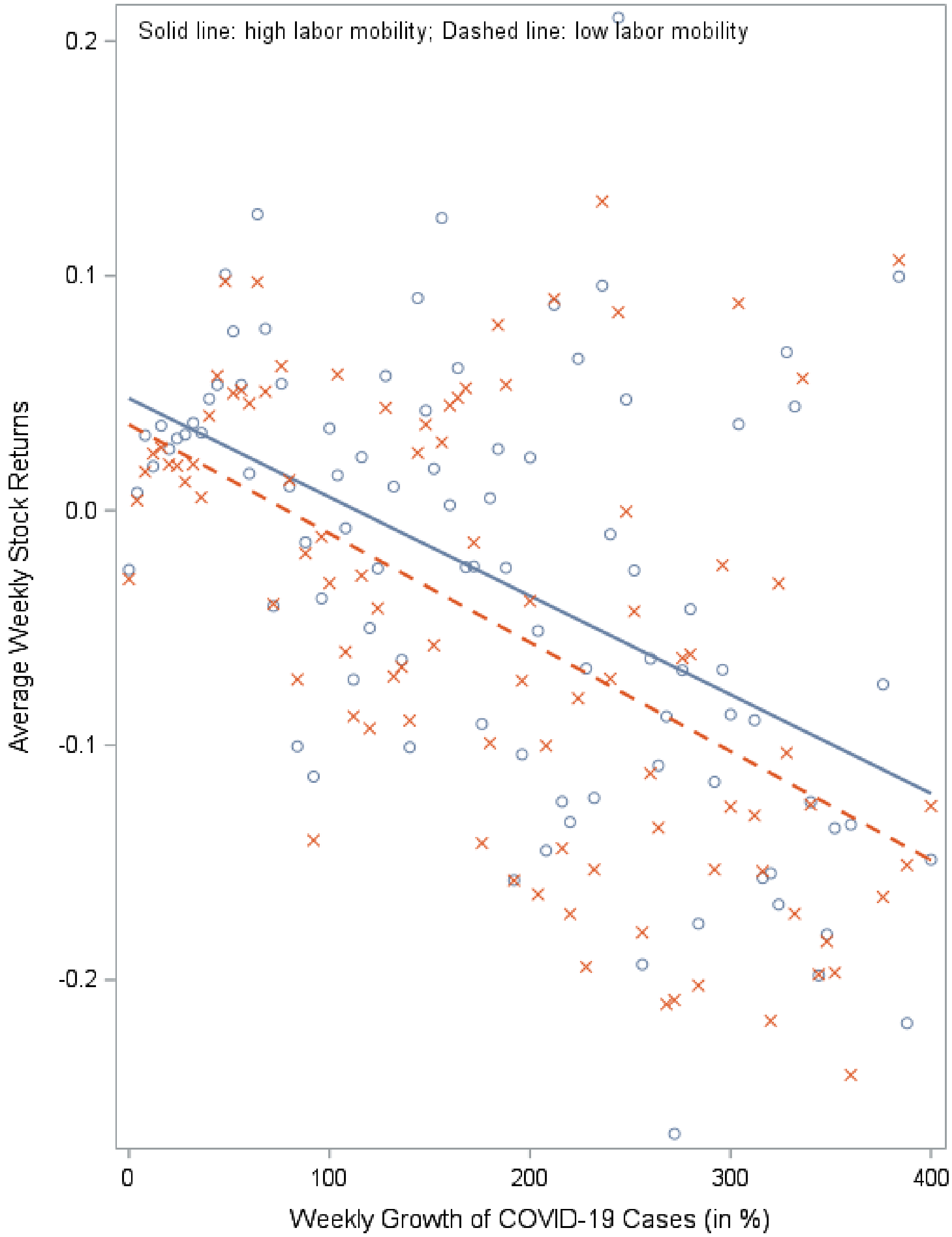
This figure plots the cumulative stock market returns during the weeks from January 20, 2020 to June 26, 2020 for the U.S publicly listed firms. Cumulative stock returns are calculated as the average of cumulative weekly stock returns for all firms in the sample.

Figure 3: COVID-19 Cases and Stock Returns



This figure presents the relation between the growth rate of COVID-19 cases and stock returns during the weeks from January 20, 2020 to June 26, 2020. The x-axis denotes the weekly growth of COVID-19 cases, and the y-axis represents average weekly stock returns, calculated as the average of the weekly stock returns for all firms in our sample. We divide the x-axis into 100 bins, where each bin has an equal "width", so that the first bin includes observations with weekly growth of COVID-19 cases in the interval (0%, 4%], bin two has observations with weekly case growth in the interval (4%, 8%], and the 100th bin has observations with weekly case growth in the interval (396%, 400%]. There is not an equal number of observations in each bin. Each dot represents the average weekly stock return across observations within each bin. The dashed line is the linear fitted line.

Figure 4: COVID-19 Cases and Stock Returns conditional on Labor Mobility



This figure presents the relation between the growth rate of COVID-19 cases and stock returns conditional on labor mobility during the weeks from January 20, 2020 to June 26, 2020. The x-axis denotes the weekly growth of COVID-19 cases, and the y-axis represents weekly stock returns. We divide the x-axis into 100 bins, where each bin has an equal "width", so that the first bin includes observations with weekly growth of COVID-19 cases in the interval (0%, 4%], bin two has observations with weekly case growth in the interval (4%, 8%], and the 100th bin has observations with weekly case growth in the interval (396%, 400%]. There is not an equal number of observations in each bin. Each dot represents the average weekly stock return across observations within each bin. The dashed line is the linear fitted line - the solid line is for firms with high labor mobility and the dashed line is for firms with low labor mobility, where high (low) labor mobility firms correspond to firms with *LM* above (below) the sample median.

Table 1: Descriptive Statistics

Variable	N	Mean	Std. Dev.	P10	P25	Median	P75	P90
RET	75,274	-0.002	0.135	-0.147	-0.071	-0.006	0.054	0.144
COVID	75,274	0.385	0.635	0.000	0.000	0.128	0.409	1.261
COVID (County-week level)	11,426	0.293	0.519	0.000	0.000	0.084	0/308	0.956
Firm characteristics at the firm-week level								
LM	75,274	0.035	0.895	-1.126	-0.849	0.291	0.629	1.153
SIZE	75,274	6.998	2.317	3.687	5.424	7.196	8.587	9.851
LEV	75,274	0.291	0.256	0.015	0.076	0.248	0.443	0.618
ROA	75,274	-0.118	0.410	-0.491	-0.083	0.011	0.046	0.093
CASH	75,274	0.208	0.262	0.010	0.028	0.084	0.284	0.672
MTB	75,274	3.594	11.565	0.531	1.120	1.932	3.928	8.813
BETA	75,274	1.127	0.873	0.358	0.732	1.096	1.520	2.003
Firm characteristics at the firm level								
LM	3,339	0.038	0.894	-1.126	-0.816	0.291	0.629	1.153
SIZE	3,339	6.982	2.314	3.685	5.409	7.172	8.574	9.842
LEV	3,339	0.290	0.257	0.014	0.074	0.246	0.442	0.617
ROA	3,339	-0.121	0.411	-0.497	-0.090	0.011	0.046	0.093
CASH	3,339	0.211	0.266	0.010	0.028	0.085	0.289	0.691
MTB	3,339	3.595	11.512	0.529	1.121	1.948	3.964	8.892
BETA	3,339	1.037	0.828	0.123	0.521	1.001	1.486	2.044

This table presents the descriptive statistics of the variables used in our baseline analyses. In the column headings, N designates the number of non-missing observations for the variable, Mean and Std. Dev. provide the average and standard deviation across these observations for the variable, and P10, P25, Median, P75, and P90 give the value of the variable at the 10th, 25th, 50th, 75th, and 90th percentile of the distribution of the variable. All variables are defined in Appendix A. All continuous variables are winsorized at the top and bottom 0.5 percentile. The sample includes 75,274 firm-week observations for 3,339 unique firms. The sample period is from January 20, 2020 to June 26, 2020.

Table 2: Impact of Labor Mobility on Firm Resilience to COVID Exposure

	(1)	(2)
VARIABLES	*RET*	*RET*
COVID	-0.005***	-0.013***
	(-3.89)	(-3.42)
LM×COVID	**0.004*** **	**0.004*** **
	(3.56)	**(3.48)**
SIZE×COVID		0.001**
		(2.50)
LEV×COVID		-0.017***
		(-4.80)
ROA×COVID		-0.001
		(-0.25)
CASH×COVID		0.006
		(1.52)
MTB×COVID		0.000
		(0.47)
BETA×COVID		0.005**
		(2.56)
Firm FE	Yes	Yes
Industry-Week FE	Yes	Yes
Observations	75,274	75,274
Adj. R-squared	0.413	0.415

This table presents the regression results for the impact of labor mobility on firm resilience to COVID exposure. The sample period is from January 20, 2020 to June 26, 2020. All variables are defined in Appendix A. All continuous variables are winsorized at the top and bottom 0.5 percentile. We include firm and industry-week fixed effects in our regression analysis. The t-statistics are reported in parentheses and based on standard errors for the coefficient estimates that are heteroskedasticity-robust and clustered by firm. Significance levels are based on two-tailed tests: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 3: Cross-Sectional Analyses

	UNEMP_CH		*AT_REDEPLOY*		*SEG_RELATED*		*WFH*		*AT_INTANGIBLE*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
DEP=RET	Low	High	Low	High	Low	High	Low	High	Low	High
COVID	-0.017**	-0.007*	-0.015**	-0.014***	-0.022**	-0.028***	-0.017***	-0.011***	-0.011**	-0.019***
	(-2.34)	(-1.74)	(-2.41)	(-3.37)	(-2.51)	(-3.14)	(-3.12)	(-2.83)	(-2.03)	(-4.76)
LM×COVID	**-0.000**	**0.005*** **	**0.002**	**0.007*** **	**0.000**	**0.008*** **	**-0.000**	**0.005*** **	**0.001**	**0.005*** **
	(-0.18)	**(3.37)**	**(1.30)**	**(4.59)**	**(0.17)**	**(3.03)**	**(-0.11)**	**(3.68)**	**(0.74)**	**(4.05)**
SIZE×COVID	-0.001	0.001	0.001*	0.001**	0.001	0.002**	0.002***	0.001*	0.001	0.001***
	(-1.44)	(1.35)	(1.70)	(2.17)	(0.87)	(2.10)	(2.59)	(1.87)	(1.09)	(3.28)
LEV×COVID	-0.006	-0.023***	-0.009	-0.019***	-0.013	-0.029***	-0.011**	-0.020***	-0.015***	-0.020***
	(-0.86)	(-6.26)	(-1.60)	(-5.59)	(-1.42)	(-3.55)	(-2.02)	(-5.36)	(-3.02)	(-6.00)
ROA×COVID	-0.003	-0.003	-0.006	0.002	0.015**	0.034**	0.000	-0.006**	-0.001	-0.002
	(-0.43)	(-1.19)	(-1.25)	(1.06)	(2.57)	(2.49)	(0.14)	(-1.99)	(-0.38)	(-0.73)
CASH×COVID	-0.008	0.005	0.015*	-0.002	0.018**	0.017*	0.009*	0.011*	0.017**	0.003
	(-1.07)	(1.09)	(1.71)	(-0.43)	(2.13)	(1.76)	(1.80)	(1.91)	(2.40)	(0.83)
MTB×COVID	0.000	-0.000	-0.000	0.000	-0.000	-0.000	0.000	0.000	-0.000	0.000
	(1.07)	(-0.78)	(-0.71)	(0.69)	(-0.45)	(-1.13)	(0.22)	(0.08)	(-0.03)	(0.59)
BETA×COVID	0.022***	0.004***	0.003*	0.009***	0.013***	0.014***	0.004**	0.005***	-0.040***	-0.036***
	(7.31)	(6.84)	(1.93)	(9.16)	(5.10)	(3.96)	(2.48)	(5.13)	(-17.42)	(-15.31)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Week FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	37,675	37,547	31,102	34,053	14,457	14,534	36,126	35,172	33,489	41,785
Adj. R-squared	0.367	0.434	0.420	0.414	0.403	0.417	0.404	0.442	0.400	0.437
Subsample Diff.	P-value = 0.066*		P-value = 0.058*		P-value = 0.072*		P-value = 0.038**		P-value = 0.065*	

This table presents the regression results of the cross-sectional analyses for the impact of labor mobility on firm resilience to COVID exposure. The sample period is from January 20, 2020 to June 26, 2020. All variables are defined in Appendix A. All continuous variables are winsorized at the top and bottom 0.5 percentile. We include firm and industry-week fixed effects in our regression analysis. The t-statistics are reported in parentheses and based on standard errors for the coefficient estimates that are heteroskedasticity-robust and clustered by firm. Significance levels are based on two-tailed tests except the subsample comparison: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. For comparison of coefficients across subsamples, the p-values are based on one-tailed tests.

Table 4: The Impact of Labor Mobility on Operating Efficiency

	(1)	(2)
VARIABLES	*OPEXP_SALE*	*OPEXP_EMP*
COVID	0.070**	2.831
	(2.30)	(0.75)
LM×COVID	**-0.020*** **	**-6.688*** **
	(-3.67)	**(-6.49)**
SIZE×COVID	-0.010***	0.370
	(-2.76)	(0.95)
LEV×COVID	0.006	-8.795
	(0.26)	(-1.40)
ROA×COVID	-0.024	-3.185
	(-1.42)	(-0.79)
CASH×COVID	-0.113*	0.233
	(-1.92)	(0.05)
MTB×COVID	-0.000	-0.013*
	(-0.22)	(-1.75)
BETA×COVID	0.042**	0.728
	(2.48)	(0.30)
LM	-0.048	17.886**
	(-1.40)	(2.47)
SIZE	-0.099***	-0.067
	(-6.47)	(-0.02)
LEV	0.270	217.435***
	(1.55)	(5.26)
ROA	-0.039**	-23.762
	(-2.21)	(-1.07)
CASH	2.015***	178.844***
	(5.17)	(5.76)
MTB	-0.000	0.074**
	(-0.50)	(2.20)
BETA	0.170**	4.519
	(2.35)	(0.40)
Industry-Quarter FE	Yes	Yes
Observations	8,369	7,564
Adj. R-squared	0.152	0.156

This table presents the regression results for the impact of labor mobility on the relation between COVID exposure and operating efficiency. The sample period is the first two fiscal quarters of 2020. All variables are defined in Appendix A. All continuous variables are winsorized at the top and bottom 0.5 percentile. We include industry-quarter fixed effects in our regression analysis. The t-statistics are reported in parentheses and based on standard errors for the coefficient estimates that are heteroskedasticity-robust and clustered by firm. Significance levels are based on two-tailed tests: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 5: Alternative Measures

Panel A: Alternative Measures of COVID Exposure

	(1)	(2)
	COVID_ALT=COVID_ACTIVE	*COVID_ALT=COVID_NATION*
VARIABLES	*RET*	*RET*
COVID_ALT	-0.013***	-0.037***
	(-3.50)	(-8.14)
LM× COVID_ALT	**0.004*** **	**0.002** **
	(3.46)	**(2.09)**
SIZE× COVID_ALT	0.001**	0.001***
	(2.53)	(3.72)
LEV× COVID_ ALT	-0.017***	-0.023***
	(-4.79)	(-7.94)
ROA× COVID_ ALT	-0.001	0.004*
	(-0.25)	(1.87)
CASH× COVID_ ALT	0.006	-0.001
	(1.55)	(-0.33)
MTB× COVID_ ALT	0.000	0.000***
	(0.46)	(2.91)
BETA× COVID_ ALT	0.005**	0.003***
	(2.55)	(3.73)
Firm FE	Yes	Yes
Industry-Week FE	Yes	Yes
Observations	75,274	75,274
Adj. R-squared	0.415	0.415

Panel B: Alternative Specifications of Labor Mobility

	(1)	(2)
VARIABLES	*RET*	*RET*
COVID	-0.013***	-0.017***
	(-3.42)	(-4.03)
LM_IND×COVID	**0.004*** **	
	(3.37)	
LM_RANK×COVID		**0.009*** **
		(2.94)
SIZE×COVID	0.001**	0.001**
	(2.48)	(2.43)
LEV×COVID	-0.017***	-0.017***
	(-4.78)	(-4.82)
ROA×COVID	-0.001	-0.001
	(-0.24)	(-0.27)
CASH×COVID	0.006	0.007*
	(1.55)	(1.75)
MTB×COVID	0.000	0.000
	(0.48)	(0.52)
BETA×COVID	0.005**	0.005**
	(2.56)	(2.55)
Firm FE	Yes	Yes
Industry-Week FE	Yes	Yes
Observations	75,274	75,274
Adj. R-squared	0.415	0.415

Panel C: Alternative Return Measures

VARIABLES	(1) *ARET_CAPM*	(2) *ARET_FF3*
COVID	-0.018***	-0.015***
	(-4.59)	(-3.51)
LM×COVID	**0.002***	**0.003****
	(1.66)	**(2.47)**
SIZE×COVID	0.002***	0.002***
	(4.67)	(4.01)
LEV×COVID	-0.011***	-0.013***
	(-2.84)	(-2.96)
ROA×COVID	0.000	0.000
	(0.12)	(0.02)
CASH×COVID	0.019***	0.018***
	(4.16)	(3.38)
MTB×COVID	0.000	-0.000
	(0.12)	(-1.45)
Firm FE	Yes	Yes
Industry-Week FE	Yes	Yes
Observations	75,274	75,274
Adj. R-squared	0.136	0.0443

Panel D: Alternative Firm Resilience Measures

	(1)
VARIABLES	*OPPROFIT*
COVID	-0.003**
	(-2.22)
LM×COVID	**0.001****
	(2.32)
SIZE×COVID	0.001***
	(3.02)
LEV×COVID	-0.002
	(-0.92)
ROA×COVID	-0.006***
	(-2.90)
CASH×COVID	0.000
	(0.04)
MTB×COVID	0.000
	(1.11)
BETA×COVID	-0.002***
	(-2.89)
LM	0.006*
	(1.76)
SIZE	0.002**
	(1.96)
LEV	0.004
	(0.18)
ROA	0.128***
	(214.79)
CASH	-0.057***
	(-5.00)
MTB	-0.000**
	(-1.99)
BETA	-0.001
	(-0.51)
Industry-Quarter FE	Yes
Observations	9,472
Adj. R-squared	0.698

This table presents the regression results for the effect of labor mobility on firm resilience to COVID exposure using alternative measures. Panel A presents the results using alternative measures of COVID exposure. Panel B presents the results using alternative specifications of labor mobility. Panel C presents the results using alternative return measures. Panel D presents the results using alternative firm resilience measures based on quarterly financials. The sample period is from January 20, 2020 to June 26, 2020 for Panels A through C, and the first two fiscal quarters of 2020 for Panel D. All variables are defined in Appendix A. All continuous variables are winsorized at the top and bottom 0.5 percentile. We include firm and industry-week fixed effects in Panels A through C, and industry-quarter fixed effects in Panel D. The t-statistics are reported in parentheses and based on standard errors for the coefficient estimates that are heteroskedasticity-robust and clustered by firm. Significance levels are based on two-tailed tests: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 6: Alternative Samples

	Jan. 20, 2020 – Mar. 27, 2020	*Mar. 2, 2020 – Jun. 26, 2020*	*Excluding Energy Sector*	*Excluding Pharmaceutical & Healthcare*	*Excluding Airline Industry*
DEP=RET	(1)	(2)	(3)	(4)	(5)
COVID	-0.012***	-0.014***	-0.013***	-0.014***	-0.013***
	(-2.66)	(-3.04)	(-3.33)	(-3.46)	(-3.45)
LM×COVID	**0.003****	**0.005*****	**0.004*****	**0.003*****	**0.004*****
	(2.37)	**(3.31)**	**(3.57)**	**(3.12)**	**(3.22)**
SIZE×COVID	0.000	0.001**	0.001***	0.001**	0.001**
	(0.13)	(2.57)	(2.60)	(2.52)	(2.57)
LEV×COVID	-0.011***	-0.025***	-0.017***	-0.017***	-0.017***
	(-2.86)	(-5.73)	(-4.89)	(-4.56)	(-4.83)
ROA×COVID	-0.006*	0.002	-0.001	-0.000	-0.001
	(-1.86)	(0.66)	(-0.36)	(-0.08)	(-0.26)
CASH×COVID	0.002	0.005	0.005	0.008**	0.006
	(0.49)	(1.07)	(1.32)	(2.02)	(1.57)
MTB×COVID	-0.000	0.000	0.000	0.000	0.000
	(-0.09)	(0.59)	(0.47)	(0.72)	(0.44)
BETA×COVID	0.009**	0.004*	0.005**	0.005**	0.005**
	(2.56)	(1.84)	(2.55)	(2.38)	(2.56)
Firm FE	Yes	Yes	Yes	Yes	Yes
Industry-Week FE	Yes	Yes	Yes	Yes	Yes
Observations	32,661	52,433	72,891	71,497	74,884
Adj. R-squared	0.431	0.421	0.415	0.422	0.414

This table presents the regression results for the effect of labor mobility on firm resilience to COVID exposure using alternative samples. All variables are defined in Appendix A. All continuous variables are winsorized at the top and bottom 0.5 percentile. We include firm and industry-week fixed effects in our regression analyses. The t-statistics are reported in parentheses and based on standard errors for the coefficient estimates that are heteroskedasticity-robust and clustered by firm. Significance levels are based on two-tailed tests: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 7: Controlling for Corporate Governance and Management Ownership

	(1)	(2)	(3)	(4)
VARIABLES	*RET*	*RET*	*RET*	*RET*
COVID	-0.021***	-0.020**	-0.017**	-0.012
	(-3.18)	(-2.30)	(-2.47)	(-1.27)
LM×COVID	**0.004****	**0.004****	**0.004****	**0.004****
	(2.44)	**(2.42)**	**(2.46)**	**(2.52)**
SIZE×COVID	0.001	0.001**	0.001	0.001
	(1.43)	(2.07)	(1.63)	(1.18)
LEV×COVID	-0.030***	-0.030***	-0.031***	-0.031***
	(-5.41)	(-5.42)	(-5.63)	(-5.56)
ROA×COVID	0.032**	0.032**	0.032**	0.032**
	(2.32)	(2.31)	(2.35)	(2.37)
CASH×COVID	0.022***	0.022***	0.023***	0.023***
	(2.92)	(2.91)	(3.01)	(3.03)
MTB×COVID	-0.000	0.000	-0.000	-0.000
	(-0.01)	(0.01)	(-0.12)	(-0.12)
BETA×COVID	0.010***	0.010***	0.010***	0.010***
	(5.74)	(5.79)	(5.83)	(5.78)
BOARD_SIZE×COVID	0.000			0.000
	(0.72)			(0.64)
BOARD_IND×COVID		-0.001		-0.008
		(-0.09)		(-0.84)
MGMT_OWN×COVID			-0.043**	-0.047**
			(-2.33)	(-2.40)
Firm FE	Yes	Yes	Yes	Yes
Industry-Week FE	Yes	Yes	Yes	Yes
Observations	26,277	26,277	26,277	26,277
Adj. R-squared	0.552	0.552	0.552	0.552

This table presents the regression results for the effect of labor mobility on firm resilience to COVID exposure after controlling for corporate governance and management ownership. The sample period is from January 20, 2020 to June 26, 2020. All variables are defined in Appendix A. All continuous variables are winsorized at the top and bottom 0.5 percentile. We include firm and industry-week fixed effects in our regression analyses. The t-statistics are reported in parentheses and based on standard errors for the coefficient estimates that are heteroskedasticity-robust and clustered by firm. Significance levels are based on two-tailed tests: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 8: Event Study

Panel A: Univariate Analyses - Comparing the mean

Mean Comparison	Low *LM*	High *LM*	Difference (High - Low)	P-Value
CR [-1, +1]	-0.070	-0.057	0.013	0.0101 **
CAR_CAPM [-1, +1]	-0.032	-0.013	0.019	0.0013 ***
CAR_FF3 [-1, +1]	-0.018	-0.004	0.014	0.0197 **

Panel B: Univariate Analyses - Comparing the median

Median Comparison	Low *LM*	High *LM*	Difference (High - Low)	P-Value
CR [-1, +1]	-0.059	-0.050	0.009	0.0340 **
CAR_CAPM [-1, +1]	-0.026	-0.010	0.016	<0.0001 ***
CAR_FF3 [-1, +1]	-0.015	-0.005	0.010	0.0004 ***

Panel C: Multivariate Analyses

	(1)	(2)	(3)
VARIABLES	*CR* [-1, +1]	*CAR_CAPM* [-1, +1]	*CAR_FF3* [-1, +1]
LM	**0.008****	**0.010****	**0.010****
	(2.02)	**(2.52)**	**(2.29)**
SIZE	0.003**	0.007***	0.007***
	(2.08)	(4.43)	(4.23)
LEV	-0.036***	-0.029*	-0.023
	(-2.79)	(-1.95)	(-1.52)
ROA	-0.011	-0.030*	-0.036**
	(-0.86)	(-1.91)	(-2.28)
CASH	0.025	0.015	0.002
	(1.53)	(0.75)	(0.07)
MTB	0.000	-0.000	-0.000
	(0.11)	(-0.81)	(-1.44)
CONSTANT	-0.040*	-0.037*	-0.038*
	(-1.69)	(-1.70)	(-1.82)
Industry-Week FE	Yes	Yes	Yes
Observations	3,365	3,365	3,365
Adj. R-squared	0.0207	0.00992	0.0108

This table presents the results of the event study using the first COVID-19 case in each county as the event. Panel A reports the results from the univariate analyses, while Panel B reports the results from the multivariate analyses. The sample period is from January 20, 2020 to June 26, 2020. *CR* [-1, +1], *CAR_CAPM* [-1, +1], *CAR_FF3* [-1, +1] are a firm's cumulative returns, cumulative abnormal returns adjusted for market beta based on CAPM model, and cumulative abnormal returns adjusted for Fama and French 3 Factors, respectively, within [-1, +1] days around the first COVID-19 case in the county where the firm is headquartered. All other variables are defined in Appendix A. All continuous variables are winsorized at the top and bottom 0.5 percentile. We include industry-week fixed effects in our regression analysis. The t-statistics are reported in parentheses and based on standard errors for the coefficient estimates that are heteroskedasticity-robust and clustered by firm. Significance levels are based on two-tailed tests: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 9: Impact of Labor Mobility on Stock Returns pre. vs. during the COVID-19 Pandemic

	(1)
VARIABLES	*RET*
DURING	-0.008**
	(-2.30)
LM×DURING	**0.002****
	(2.35)
SIZE×DURING	-0.001***
	(-6.18)
LEV×DURING	0.001
	(0.44)
ROA×DURING	-0.007***
	(-3.41)
CASH×DURING	0.002
	(0.58)
MTB×DURNG	-0.000
	(-0.50)
BETA×DURING	0.008***
	(7.73)
LM	0.002
	(1.15)
SIZE	-0.004**
	(-2.10)
LEV	-0.001
	(-0.15)
ROA	-0.000
	(-0.15)
CASH	-0.010*
	(-1.65)
MTB	0.000
	(0.19)
BETA	-0.001
	(-1.49)
Firm FE	Yes
Industry-Week FE	Yes
Observations	153,143
Adj. R-squared	0.363

This table presents the regression results for the impact of labor mobility on stock returns pre. vs. during the COVID-19 pandemic. The sample period includes the period from January 21, 2019 to June 28, 2019 and the period from January 20, 2020 to June 26, 2020. *DURING* is an indicator variable that equals 1 if the observation is during the pandemic (January 20, 2020 to June 26, 2020), and 0 for the corresponding period before the pandemic (January 21, 2019 to June 28, 2019). All other variables are defined in Appendix A. All continuous variables are winsorized at the top and bottom 0.5 percentile. We include firm and industry-week fixed effects in our regression analysis. The t-statistics are reported in parentheses and based on standard errors for the coefficient estimates that are heteroskedasticity-robust and clustered by firm. Significance levels are based on two-tailed tests: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 10: Natural Experiment with Non-compete Agreements

	(1)
VARIABLES	*RET*
COVID	-0.008**
	(-2.10)
NC×COVID	**-0.001****
	(-2.32)
SIZE×COVID	0.001*
	(1.88)
LEV×COVID	-0.017***
	(-4.73)
ROA×COVID	-0.000
	(-0.17)
CASH×COVID	0.008**
	(1.99)
MTB×COVID	0.000
	(0.69)
BETA×COVID	0.005**
	(2.55)
Firm Fixed	Yes
Industry-Week Fixed	Yes
Observations	75,274
Adj. R-squared	0.446

This table presents the regression result for the impact of labor mobility on firm resilience to COVID exposure using a natural experiment based on state-level enforcement of non-compete agreements. The sample period is from January 20, 2020 to June 26, 2020. *NC* captures the state-wide enforcement intensity of non-compete agreements and is the enforceability index from Bai et al. (2020). Higher values of *NC* indicate more stringent enforcement of non-compete agreements in a state and hence imply lower labor mobility for firms in the state. All other variables are defined in Appendix A. All continuous variables are winsorized at the top and bottom 0.5 percentile. We include firm and industry-week fixed effects in our regression analysis. The t-statistics are reported in parentheses and based on standard errors for the coefficient estimates that are heteroskedasticity-robust and clustered by firm. Significance levels are based on two-tailed tests: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 11: Propensity-score Matched (PSM) Sample Analyses

VARIABLES	(1) High *LM* Subsample *RET*	(2) Low *LM* Subsample *RET*	(3) Full PSM Sample *RET*	(4) Full PSM Sample *RET*
COVID	**-0.025***** **(-11.38)**	**-0.031***** **(-13.68)**	-0.058*** (-6.89)	-0.057*** (-6.81)
HIGH_LM×COVID			**0.007**** **(1.97)**	
LM×COVID				**0.005**** **(2.48)**
SIZE×COVID			0.003*** (2.95)	0.003*** (3.03)
LEV×COVID			-0.033*** (-3.40)	-0.032*** (-3.27)
ROA×COVID			-0.006 (-0.79)	-0.006 (-0.76)
CASH×COVID			0.022* (1.95)	0.022* (1.91)
MTB×COVID			-0.000 (-1.53)	-0.000 (-1.56)
BETA×COVID			0.015*** (3.81)	0.015*** (3.80)
Subsample Difference	P-value=0.034**			
Firm FE	Yes	Yes	Yes	Yes
Industry-Week FE	Yes	Yes	Yes	Yes
Observations	9,064	9,064	18,128	18,128
Adj. R-squared	0.105	0.071	0.090	0.091

This table presents the regression results for the impact of labor mobility on firm resilience to COVID exposure using a propensity-score matched sample. The sample period is from January 20, 2020 to June 26, 2020. All variables are defined in Appendix A. All continuous variables are winsorized at the top and bottom 0.5 percentile. We include firm and industry-week fixed effects in our regression analysis. The t-statistics are reported in parentheses and based on standard errors for the coefficient estimates that are heteroskedasticity-robust and clustered by firm. Significance levels are based on two-tailed tests except the subsample comparison: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. For comparison of coefficients across subsamples, the p-values are based on one-tailed tests.

Table 12: Instrumental Variable Approach

	Second Stage
	RET
Predicted LM	**-0.003**
	(-1.33)
Predicted LM×COVID	**0.004*** **
	(3.72)
SIZE	-0.001***
	(-4.97)
LEV	0.010***
	(5.21)
ROA	-0.003*
	(-1.84)
CASH	0.009***
	(3.19)
MTB	0.000
	(1.03)
BETA	0.002***
	(4.00)
COVID	-0.012***
	(-4.06)
SIZE×COVID	0.001***
	(3.63)
LEV×COVID	-0.017***
	(-6.71)
ROA×COVID	-0.001
	(-0.36)
CASH×COVID	0.006*
	(1.94)
MTB×COVID	0.000
	(0.38)
BETA×COVID	0.002***
	(3.64)
CONSTANT	-0.000
	(-0.13)
Industry-Week Fixed Effect	Yes
Observations	75,274
R-squared	0.426

This table presents the regression results for the impact of labor mobility on firm resilience to COVID exposure using an instrumental variable approach developed by Lewbel (2012). The sample period is from January 20, 2020 to June 26, 2020. All variables are defined in Appendix A. All continuous variables are winsorized at the top and bottom 0.5 percentile. We include industry-week fixed effects in our regression analysis. The t-statistics are reported in parentheses and based on standard errors for the coefficient estimates that are heteroskedasticity-robust and clustered by firm. Significance levels are based on two-tailed tests: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 13: Impact Threshold of Confounding Variables

	(1)
VARIABLES	*RET*
COVID	0.0045
SIZE× COVID	0.0005
LEV× COVID	0.0006
ROA× COVID	0.0002
CASH× COVID	0.0021
MTB× COVID	0.0002
BETA× COVID	0.0002
Largest impact	0.0045
Largest impact of an interaction term	0.0021
Impact threshold of the confounding variable	0.0056
Minimum magnitude of the confounding variable relative to largest impact of an interaction term required to overturn LM×COVID	2.67

This table presents the results of an analysis of the impact threshold of confounding variable (ITCV) for each of the main results. The sample period is from January 20, 2020 to June 26, 2020. Each row represents the impact on the coefficient for *LM×COVID* of each additional independent variable, which is calculated as the partial correlation between that variable and the dependent variable times the partial correlation between that variable and the independent variable of interest, *LM×COVID*. These partial correlations are not presented for parsimony. The row labeled "Largest impact" identifies the most impactful explanatory variable included in the model. The row labeled "Largest impact of an interaction term" identifies the most impactful interaction term included in the model. The row labeled "Impact threshold of the confounding variable" is calculated following Frank (2000). The last row describes the minimum magnitude of the confounding variable relative to largest impact of an interaction term required to overturn *LM×COVID*, which is calculated as the impact threshold of confounding variable divided by the largest impact of an interaction term.