Small Business and the COVID-19 Pandemic: The Role of Work from Home

Ting Zhang (✉ tzhang@ubalt.edu)

University of Baltimore

Dan Gerlowski

University of Baltimore

Zoltan Acs

George Mason University

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Ting Zhang, corresponding author, tzhang@ubalt.edu,

Associate Professor, Merrick School of Business,

Associate Director, Jacob France Institute

University of Baltimore, 1420 N. Charles Street, Baltimore, MD 21201

Dan Gerlowski,

Professor, Merrick School of Business,

University of Baltimore, 1420 N. Charles Street, Baltimore, MD 21201

and

Zoltan Acs,

Director, Center for Entrepreneurship and Public Policy;

University Professor, Schar School of Policy and Government,

George Mason University, 3351 Fairfax Dr., MS 3B1, Arlington, Virginia 22201

Abstract

Work from home (WFH) becomes the new norm in the COVID-19 pandemic. Whether the WFH norm will fade or accelerate after the stay-at-home mandate ends is unknown. The study builds a theoretical framework based on utility maximization theory subject to a “contagion” agglomeration parameter and argues that WFH is a rational choice for small businesses. We compiled an up-to-date real-time daily and weekly multifaceted data set tracking WFH propensity from March 20 through July 28. Our empirical analysis estimated a variety of fixed-effects panel data models, population-averaged generalized linear panel-data models with the generalized estimating equation (GEE) approach, and two-level mixed-effects panel-data models. After controlling for the local pandemic, economic, and demographic factors, we find

that, (1) after the stay-at-home order ended, WFH rate got higher; (2) small businesses in states with higher WFH rate are more likely to have higher increases in operating revenue, better cash flow and lower chances of temporary closure. Our robust empirics confirm our theory and hypotheses and demonstrate WFH as a potential force that expedited the “creative destruction” into a new efficient work paradigm.

Keyword

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Introduction

One disruption that the COVID crisis brought to our economy is working from home (WFH). Dingel & Neiman (2020) found that 37% of jobs in the United States can be performed entirely at home, with variation across cities and industries. Bartik, et al. (2020b) report that 45% of firms having at least some workers switch to teleworking during the COVID-19 pandemic and over 1/3 of those firms believe that WFH will remain more common at their companies after the COVID-19 crisis ends. Gallup Panel (2020) revealed that the percentage for Americans WFH doubled to over 60% between mid-March and early April 2020 and 59% U.S. workers who have been teleworking during the pandemic would prefer to continue WFH as much as possible, once public health restrictions are lifted, while only 41% would prefer to return to their workplace to work (Bremner 2020).

Will this COVID-induced WFH disruption emerge into a Schumpeterian (1934) “creative destruction” that help businesses grow better in the long run and will small businesses (with less than 500 employees and receipts of at least \$1,000) ride this WFH wave well? While small businesses employ almost 50% of American workers (Bartik, et al. 2020a), in economic crisis small businesses are vulnerable (Kolasa et al. 2010; Kennickell et al. 2017) and disproportionately negatively affected (Bartz & Winkler 2016). While a rising number of businesses adopt WFH and while prior literature discussed separately on WFH and on crisis impact on small businesses, whether WFH helps mitigate the crisis shock on small businesses is unknown.

This paper therefore focuses on examining (1) whether WFH rates continue to rise after singling out the pandemic severity and related stay-at-home mandate, and (2) how WFH helps small businesses do better in the pandemic. The exogenous pandemic shock could have expedited the WFH norm as the new Schumpeterian (1934) “creative destruction”: a norm that we were technically ready but hesitant to adopt. The future path of WFH will impact workplaces, life styles, and urban structure and planning.

The study builds a theoretical framework based on utility maximization theory subject to business costs, working hours, wages, and a contagion agglomeration parameter (Krugman 1996; Glaeser 1999), demonstrating conditions when

WFH is a rational choice for businesses. Then, we compiled an up-to-date real-time daily and weekly multifaceted data set tracking WFH propensity from March 20 through July 28. Relying on our theory and real-time data, our empirical analysis estimated a variety of fixed-effects panel data models, population-averaged generalized linear panel-data models with the generalized estimating equation (GEE) approach, and two-level mixed-effects panel-data models.

The next section focuses on our theoretical framework, followed by our two research hypotheses. Then in the methodology section, we describe our data and present our empirical findings with robustness check. After controlling for the local pandemic, economic, and demographic factors, we find (1) after the stay-at-home order (SHO) ended, WFH rates got higher; (2) small businesses in states with higher WFH rates are more likely to have an increase in operating revenue, a better cash flow situation, fewer temporary closures and fewer disruptions of supply chain.

Theoretical Framework

Our theoretical framework is cast in a cost benefit framework where workers and firms seek to be rational maximizing entities in a constrained environment comparing home and office workplaces. The four key factors of production for a firm include capital, labor, land, and technology and entrepreneurship (Bade and Parkin, 2018). Under certain technology conditions (X), it is business owners', or top managers', entrepreneurship that determines whether working in traditional brick-&-mortar offices or WFH. Based on the utility maximization theory, a rational choice is a choice that maximize one's utility. From the labor demand perspective, hiring decisions are based on the revenue and cost a marginal employee would bring.

Employers choose WFH versus brick-&-mortar office if WFH (H) brings more marginal net benefit than work in the traditional offices (O). Workers are endowed with certain skills and abilities (S) which are dependent on the level and use of technology available to the worker (X). Better technology will increase S and hence worker marginal productivity. Facing the pandemic, workers' working hours (T) is often affected by the pandemic conditions (P), no matter WFH or working in traditional offices. For employers, they hire employees based on employees' skills, $S(X)$, and potential working hours, $T(P)$, because $S(X)$ and $T(P)$ jointly determine potential revenue. Employers' cost spread to each employee include employees' wage (W), capital or equipment, office supply and utility costs (K), and land cost (L). In the traditional office settings, the marginal revenue of workers also benefits from an agglomeration parameter (A) (Krugman 1996; Glaeser 1999) with networking and knowledge spillovers (Saxenian 1994). In the pandemic, the location

based agglomeration effect is constrained also by the pandemic conditions (P) with social distancing needs. Therefore, employers would choose WFH versus working in traditional offices if the marginal revenue per unit of marginal costs of WFH is larger:

$$\frac{S(X)^H * T(P)^H}{W^H * K^H * L^H} \geq A(P) * \frac{S(X)^O * T(P)^O}{W^O * K^O * L^O} \quad (1)$$

(1) can be further transformed into

$$\frac{S(X)^H}{S(X)^O} * \frac{T(P)^H}{T(P)^O} * \frac{W^O}{W^H} * \frac{K^O}{K^H} * \frac{L^O}{L^H} * \frac{1}{A(P)} \geq 1 .$$

For employers, the labor search pool is enlarged beyond the local scope, resulting the employee skills out of location-unbounded web search, S^H , potentially better matched with the job than that out of local search only; for the same job, WFH would potentially require more technology savviness. Therefore, $S(X)^H > S(X)^O$, i. e., $\frac{S(X)^H}{S(X)^O} > 1$.

As for hours committed to work, many WFH workers feel the need to reciprocate the privilege of WFH with flexibility, autonomy, and saved commuting time by working longer hours and/or harder work (Gajendran & Harrison 2007), mirrored with empirical evidence on longer hours for WFH (Kelliher & Anderson 2010; Mariani 2000) or “hard to plug off work” in the survey (Buffer 2019). We therefore believe WFH workers work for longer hours than workers in traditional offices for a work day, i.e., $\frac{T^H}{T^O} > 1$. In the pandemic, working hours in traditional office could be even shorter to limit social distancing, i.e., $\frac{T(P)^H}{T(P)^O} > 1$.

With a wider labor pool to pick from, employers could potentially push the wage rate from WFH labor lower. As Mas & Pallais (2017) found, an average worker is willing to give up 8 percent of wages for WFH. This percentage could be much higher facing a pandemic health threat and high unemployment. Firms may regard WFH as a means to increase motivation and commitment (Caillier 2012; Eaton 2003). Bourdeau et al (2019) identify a flexibility stigma associated with WFH as a characteristic violating the work devotion schema that calls for intensive allegiance, dedication, and undivided attention to the workplace, which could push WFH wages lower. Therefore, wage rate for workers working in traditional offices, W^O , could be higher than wage rate for WFH employees for the same type of work, W^H . This means

$$\frac{W^O}{W^H} > 1.$$

For traditional office settings, business owners are obligated for capital or Administrative & General (A&G) costs like utilities, equipment, office furniture, supplies, and an office manager's salary to handle those administrative issues. In contrast, the home office setup cost for WFH case is often lower for employers: some employers might reimburse some home office supply and equipment costs and employers might need to pay for the technology to facilitate WFH, but typically not utility costs (e.g., electricity, gas, internet, telephone cost, insurance, etc.). For most small businesses, the potentially saved office costs could be even more important and the technology requirement for WFH might not have to be sophisticated or expensive with current advances in technology. Therefore, those office costs for workers working in the traditional office setting, K^O , is often larger than that for home offices for WFH, K^H , i.e., $\frac{K^O}{K^H} > 1$. However, the concerns about the ability of employers to manage WFH workers (Coenen and Kok 2014) may result in some management cost, or costs of organizational change and technological investments (see Aguilera, et al. 2016) which could offset the WFH capital cost advantage. However, in the COVID pandemic, the social distancing requirements (such as keeping space from each other for at least 6 feet), the cost for Personal Protective Equipment, makes the K^O larger, i.e., $\frac{K^O}{K^H} > 1$. From the employer perspective, WFH could become a more effective and cheaper way to achieve social distancing, reduce COVID spread, and lower the cost of losing key employees.

For traditional office settings, business owners are obligated for continuous, often monthly, land costs (L), either rent or mortgage (and tax) and insurance of the offices. For small businesses, this land costs are often a major operating costs. In contrast, the home office land cost for the WFH case is often not considered and not reimbursed by the employers. Therefore L^H is basically close to 0, except for essential offices. Matthews & Williams (2005) noted that WFH allowed companies to make *considerable* savings through lower real estate costs and productivity gains. Therefore, employers' land cost for workers working in the traditional office setting, L^O , is *considerably* larger than the almost 0 home offices land cost for WFH, L^H , i.e., $\frac{L^O}{L^H} \rightarrow +\infty$. With a close to 0 denominator, $\frac{L^O}{L^H}$ is reaching positive infinity.

Given the benefit of agglomeration, $A > 1$, for rational employers not to choose WFH versus from traditional offices in Inequation (1), A has to be a positive infinity to make $\frac{1}{A}$ off-set the joint effect from all the other vectors that is a product of a positive infinity vector ($\frac{L^O}{L^H}$) and other vectors that are larger than 1 (i.e.,

$\frac{S(X)^H}{S(X)^O}, \frac{W^O}{W^H}, \frac{K^O}{K^H}$, and $\frac{T(P)^H}{T(P)^O}$). Although A might enhance work efficiency to some extent, A cannot enhance work efficiency by positive infinity folds. Plus, with the growing technology conditions (X), the benefits of agglomeration ($A > 1$) may be

counter-balanced by the impact of technology and the likelihood of contagion for WFH workers as well, with even additional benefits such as recorded sessions, meeting transcripts, saved whiteboard images for needed review. Therefore, the probability for the agglomeration effect A to be larger than $\frac{S(X)^H}{S(X)^O} * \frac{W^O}{W^H} * \frac{K^O}{K^H} * \frac{T(P)^H}{T(P)^O} * \frac{L^O}{L^H}$ is impossible. As a result, a rational employer would most likely choose WFH over traditional office work. In the pandemic, the agglomeration effect A is further compromised by social distancing needs and therefore $A(P)$ is even smaller.

Currently WFH still face various barriers. Golden and Eddleston (2020) find empirical support in survey based research for some negative outcomes in promotions, raises, and career success for those pursuing flexible work arrangements including WFH. Firms that have not adopted WFH are likely to doubt productivity of WFH workers (see Aguilera, et al. 2016), though WFH were also found to be more productive than traditional office work (SHRM 2018) due to reasons such as less absenteeism. Any Schumpeterian “creative destruction” took a painful path to “disrupt” first before a newer and more productive or economically rational approach finally becomes a norm.

Hypotheses

When COVID-19 started to spread across the US, WFH started to dominate. This was pushed by the health concerns to limit the virus spread and correspondingly by the government SHO mandate. Although many businesses remained closed after the SHO was lifted, others reopened to partial or full business. One can easily argue that WFH would dramatically drop back to where it was before the COVID-19 started after the virus is contained or would be at least less popular after the SHO ends. However, based on our theoretical framework, since WFH seems a rational choice for businesses, we believe WFH would be gaining popularity and should not sharply drop because of the end of SHO.

In addition, out of this COVID pandemic, firms have now paid the fixed costs of learning how to make remote working functional (Bartik, et al., 2020b) and are more aware of the potential of WFH. Many firms did not adopt WFH before the pandemic either because of ignorance or coordination issues (Bartik, et al. 2020b). After this unexpected natural experiment and learning by doing experience of WFH in the pandemic, the paid fixed costs to facilitate WFH, the related work coordination, and the enhanced awareness of the WFH advantages may make WFH a real optimal for many businesses. Although some companies may return to traditional office setting, many firms may continue adopting WFH after the SHO ended or even after the pandemic is over. Both surveys in Bartik, et al. (2020b) show that 40% of both large and small firms expect that at least 40% of their workers who switched to remote work during the crisis will work

remotely after the crisis. Although the pandemic is unpleasant, it could have expedited our economy to utilize the new technological frontier better. We therefore hypothesize, the popularity of WFH would continue, *ceteris paribus*:

Hypothesis 1: After controlling for the local pandemic, economic, and demographic conditions, the WFH rate would not sharply drop after the SHO ended.

Although adopting WFH practices often requires organizational changes, such as surveillance and control or management of the psycho-sociological distance from the work environment (Belanger 1999; Taskin and Devos 2005; Wilton et al., 2011), WFH could save turnover cost from businesses because WFH increases employee well-being by reducing travel-related fatigue, providing a less stressful work environment (Ravi S. & David A. 2007; Redman et al., 2009) and a better balance between work and family life (Wheatley 2012), reducing the costs of commuting, pollution and urban congestion (Helminen and Ristimäki 2007; Mokhtarian et al. 2004), and even elevating productivity (Belanger 1999; SHRM 2018). Bailey and Kurland (2002) declare that in almost all empirical articles they examined, WFH was associated with higher productivity because of less absenteeism (Kitou and Horvath 2008).

A study by Belzunegui-Eraso and Erro-Garcés (2020) showed that WFH is being used by many companies to keep productivity up during the crisis, and that adopting WFH contributes to a reduced hit to GDP as a result of the crisis. Bartik, et al. (2020b) also noted that industries that are better suited to remote work also seemed to experience less productivity loss when switching to remote work. We therefore believe WFH can mitigate the negative economic impact from the COVID shock and help small businesses do better in the pandemic.

In a pandemic, it is often expected that a small business might temporarily close. Bartik, et al. (2020a) reported 43% of small businesses they surveyed did temporarily close and cited fragile financing with less than one month of cash on hand. On the other hand, Bartz & Winkler (2016), using German data for the 2009 crisis, identified relative growth advantages among small businesses due to flexibility. Temporary closures have important implications for the US workforce. The cash flow position often signals time-to-failure for small businesses. In addition, disruptions in the supply-chain exhibit challenges that other businesses are facing and have implications about the economy as a whole (Buffington, et al. 2020). Whether the operating revenue is increased is a direct indicator for business performance. Considering the potential impacts from financial assistance from the Paycheck Protection Program (PPP), we add those controls as well as aforementioned controls. Therefore we hypothesize:

Hypothesis 2: A higher (versus lower) WFH rate helps small businesses perform better in the pandemic with a lower probability of temporary closures, with more operating revenues, and with better cash flow positions, controlling for local pandemic, economic, demographic, and financial assistance program conditions.

Methodology

Our analysis demonstrates robustness across various specifications in three types of models: the fixed-effect cross-section time-series panel-data model, population-averaged generalized linear panel-data models with the generalized estimating equation (GEE) approach, and two-level mixed-effects panel-data model: Most of the independent variables adopted one-period lag to capture a sequential effect. In this section, we first explain our empirical models and variables. Then we present our data sources and variables measures.

Empirical Models and Variables

To test Hypothesis 1, we modeled the sensitivity of the end of SHO on WFH, controlling for local demographic, economic, and pandemic conditions. Our data is cross-sectional time-series data, assuming correlations over time for each state (or Washington D.C. (DC)) and independence between 50 states (and DC) in the United States. We started with the fixed-effect panel data modeling, fixed at the individual states:

$$WFH_{jt} = \beta_0 + \beta_1 AfterSHO_{jt} + \gamma_i \sum_{i=1}^4 COVID_{j(t-1)} + \eta_i \sum_{i=1}^3 ECON_{j(t-1)} + \theta_i \sum_{i=1}^4 Demographics_{j(t-1)} + v_j + \varepsilon_{jt}. \quad (1)$$

Our independent variable, $AfterSHO_{jt}$ is a binary variable labeling the data period after the SHO ended in each state j and time period t ; based on our theory and hypothesis, we expect $AfterSHO_{jt}$ to show a positive effect on WFH rates. $COVID_{jt}$ includes a set of four variables measuring the COVID pandemic severity. $ECON_{jt}$ captures three local macroeconomic condition measures. $Demographics_{jt}$ incorporates four demographic attributes. v_j is the state-specific error term; it differs between states, but for any particular state, its value is constant. ε_{jt} is the idiosyncratic error term.

Considering the fact that states' demographic attributes data do not capture weekly or even daily changes and WFH and the pandemic information was limited by March, fixed effects would be limited. We therefore also estimated population-averaged generalized linear panel-data models with the GEE approach described in Liang and Zeger (1986). This longitudinal data model do not require the data set to be balanced and allows among- and within-state covariates to be incorporated straightforwardly. Although the model incorporates an assumption of multivariate normality of a response vector conditional on covariates, with large samples, estimators of parameters in the models are consistent for the true values with a deduced approximate normal sampling distribution.

In addition, we also add in industry sector controls in our modeling. Dingel and Neiman (2020) demonstrated industry sector variations in WFH feasibility in the pandemic. Bartik, et al. (2020b) also noted industries that are better suited to remote work seem to experience less productivity loss when switching to remote work. We therefore first integrate industry sector fixed effects to the population-averaged generalized linear panel-data models with the GEE approach. Then we adopted the two-level (i.e., state and industry sector) mixed-effects model.

As our theoretical framework noted, WFH is subject to local labor market conditions as well as industry sectors. Individual businesses are interdependent not only in an area where knowledge, information, labor, and social networks flow and spillover easily, but also correlated in the same industry sector. In this case, fixed-effect logistic regression is limited, because the assumed independent and identical distribution between individual observations is violated (McCoach & Adelson 2010) and it does not allow for necessary random effects with an industry sector or a local areas. Multilevel modeling also enjoys the advantage of allowing for unbalanced sample size across local areas (Raudenbush 1993) shown in this study, compared to clustered standard errors. We want to observe not only variations across states (fixed state effects) but also random variations across industry sectors (random industry sector effects). In panel data, random effects are useful for modeling intra-industry sector; that is, states in the same industry sector are correlated because they share common industry sector level random effects. Mixed-effects modeling contains both fixed effects and random effects:

$$WFH_{jkt} = \beta_0 + \beta_1 AfterSHO_{jkt} + \gamma_i \sum_{i=1}^4 COVID_{jk(t-1)} + \eta_i \sum_{i=1}^3 ECON_{jk(t-1)} + \theta_i \sum_{i=1}^4 Demographics_{jk(t-1)} + Z_{jkt} \mu_{kt}. \quad (2)$$

In our two-level mixed-effects panel data model, states are conditional on a set of random effects μ_{kt} , for $k = 1, \dots, n$ industry sectors, with industry sector j consisting of $j = 1, \dots, m$ ($m \leq 51$) states' observations across time periods

(days or weeks) t . Vector Z_{jkt} is the covariate corresponding to the random effects. The random effects μ_{kt} are n realizations from a multivariate normal distribution, with mean 0 and variance δ . The random effects are not directly estimated as model parameters, but are instead summarized according to the unique elements of variance. Multilevel mixed-effects modeling have been used extensively in social science studies, such as Rabe-Hesketh and Skrondal (2012), which analyzes school data from Scotland.

To test Hypotheses 2, we adopted three similar models. In this case, our dependent variable is business performance, $Business_{jkt}$, which captures operating revenue, cash flow, temporary closure, or disruption of supply chain. Since financial assistance from Paycheck Protection Program (PPP) and other programs might impact firms' revenue, cash, and performance, we include $FIN_{j(t-1)}$ to capture nine financial assistance types. The base model, the fixed-effect panel-data model, is therefore:

$$Business_{jkt} = \beta_0 + \beta_1 WFH_{jk(t-1)} + \beta_2 AfterSHO_{jt} + \gamma_i \sum_{i=1}^4 COVID_{jk(t-1)} + \eta_i \sum_{i=1}^3 ECON_{jk(t-1)} + \theta_i \sum_{i=1}^4 Demographics_{jk(t-1)} + \epsilon_i \sum_{i=1}^9 FIN_{j(t-1)} + v_j + \varepsilon_{jt}. \quad (3)$$

The two-level mixed-effects model accordingly changes to

$$Business_{jkt} = \beta_0 + \beta_1 WFH_{jk(t-1)} + \beta_2 AfterSHO_{jt} + \gamma_i \sum_{i=1}^4 COVID_{jk(t-1)} + \eta_i \sum_{i=1}^3 ECON_{jk(t-1)} + \theta_i \sum_{i=1}^4 Demographics_{jk(t-1)} + \epsilon_i \sum_{i=1}^9 FIN_{j(t-1)} + Z_{jkt} \mu_{kt}. \quad (4)$$

Based on our theory and hypothesis, we expect our independent variable $WFH_{jk(t-1)}$ to show a positive effect on our measures of business performance, $Business_{jkt}$.

Data Sources and Variable Measures

Our main models to test Hypothesis 1 used daily data, starting from March 21, 2020 when the first state started the SHO till July 28, 2020, the last day we got our data. With one day lagged value for our independent variables, the daily data actually covers up to 130 days (depending on when a states starts the SHO) from March 20 to July 28, 2020 across all states (including DC) in the United States. Our data to test Hypothesis 2 are weekly data and include the small business data of April 26 through June 27, 2020. With one week lagged value for our dependent variables, the weekly data therefore covers 10 weeks from April 19 to June 27, 2020 over all states (including DC).

Our data comes from multiple data sources. Data for our key variable, WFH , are from the University of Maryland's Maryland Transportation Institute (MTI). WFH captures the daily percentage of workforce working from

home. It is calculated using daily mobile device¹ location based work trip information and US Department of Labor's unemployment claims information. According to Zhang, et al. (2020), MTI first integrated and cleaned location data from multiple sources representing person and vehicle movements to improve the quality of the mobile device location data panel and then clustered the location points into activity locations and identified home and work locations at the census block group level to protect privacy. If an anonymized individual in the sample did not make any trip longer than one-mile in distance, this anonymized individual was considered as staying at home. The data sources and computational algorithms have been validated based on a variety of independent datasets such as the National Household Travel Survey and American Community Survey (ACS), and peer reviewed by an external expert panel in a U.S. Department of Transportation Federal Highway Administration's Exploratory Advanced Research Program project².

The data for small business performance measures are from the US Census Bureau weekly Small Business Pulse Survey (SBPS). The survey targets toward all nonfarm, single-location employer operating businesses with 1-499 employees and receipts of \$1,000 or more in the 50 states, DC, and Puerto Rico. For those single-establishment small businesses, the decision to choose WFH often falls on business owners or top executives. The survey does not include businesses in agriculture, railroads, US Postal Service, Central Bank, Funds, Trusts, and other financial vehicles, religious grant operations and religious organizations, private households, public administration, or with unclassified legal form of organizations as tax-exempt or unknown.

As a survey conducted by the US Census Bureau, the survey represents the country's small businesses relatively well. As an online survey and with the sample restricted to businesses with e-mail addresses, the SBPS survey data comes with a potential selection issue, if businesses willing to participate in email-based surveys are systematically different from other businesses. However, since our study is on WFH, the online survey works better for businesses that could potentially allow WFH. The SBPS may be subject to non-response bias because of lack of response or because some may have already closed; however, according to Buffington et al. (2020), the estimates in the data have been re-weighted to adjust for non-response based on prior employment size. In addition, as Buffington et al. (2020) noted, although the businesses sampled in the SBPS tend to be larger than the average small business, they do not appear to differ substantially in terms of firm age.

¹ Daily feeds of more than 100 Million anonymized devices are used.

² Titled "Data analytics and modeling methods for tracking and predicting origin-destination travel trends based on mobile device data".

Our business performance measures include the percentages of small business that increased (or decreased) *operating revenues* and experienced (or not) *temporary closure, disruptions in supply chain, no cash flow* or *cash on hand* for *1-4 weeks, 1-2 months, or 3 months or more*. SBPS provides detailed information on the challenges that small businesses are facing during the COVID-19 pandemic as well as related financial assistance programs such as the PPP.

The main COVID-19 pandemic severity measures (COVID *new cases* and COVID *death rate*) are sourced from Johns Hopkins University (JHU) Center for Systems Science and Engineering (CSSE) Github data repository. The *COVID new cases* is measure by the number of COVID cases per 1000 people. *COVID death rate* is measured as the percentage of deaths among all COVID-19 cases. The CSSE repository is widely used since the start of pandemic. Funded by multiple agencies and prestigious institutions³, the CSSE data for the United States are from U.S. county and state health departments, multiple national government health departments, and data aggregating websites⁴ combining reports from local health departments and media reports (Dong et al. 2020).

Our data for *days of decreasing COVID cases* and *COVID exposure* are calculated by the MTI. *Days of decreasing COVID* cases is used because one federally recommended guideline to reopen is a decline in cases over 14-day period⁵. Since many states reopened and ended the SHO without meeting the federal guideline, we feel it necessary to include this measure in our model to better control the pandemic severity. It measures the number of days with decreasing COVID-19 cases. Since COVID caseload and death rates are subject to the test availability and people's behavior that differ across areas, to fully measure the pandemic severity, we also added a measure, *COVID exposure* which captures the number of residents already exposed per 1000 people.

The SHO data (*AfterSHO_{jt}*) are from the U.S. COVID-19 Hospital Needs and Death Projections data, compiled by the Institute for Health Metrics and Evaluation (IHME), University of Washington (IHME 2020). The earliest SHO started on March 21. Our data focus on the observations since the first SHO started. Therefore *AfterSHO_{jt}* has two values: 0 for when SHO was in effect and 1 for after the SHO ended.

For the economic background data, the *unemployment rates* are weekly from the US Department of Labor (USDOL). The *median household income* is again from the ACS. *Employment density* information is from the US Environmental Protection Agency (EPA)'s Smart Location Database (SLD). It captures jobs per acre on unprotected

³ e.g., the JHU, National Science Foundation, National Institute of Allergy and Infectious Diseases and National Aeronautics and Space Administration (NASA), Bloomberg Philanthropies, Stavros Niarchos Foundation.

⁴ Those websites Include 1point3acres, Worldometers.info, BNO, and the COVID Tracking Project.

⁵ See <https://www.whitehouse.gov/openingamerica/>.

land. According to EPA (2020), the Smart Location Database is a nationwide geographic data resource for measuring location efficiency for over 90 attributes summarizing characteristics (such as housing density, neighborhood design, destination accessibility, transit service, employment); most of them are available for every census block group.

The demographic data are from the ACS and include *percentages of men, African Americans, Hispanic Americans, older Americans aged 60 or above*. For the influence of financial assistance, in addition to the *PPP*, other controlled financial assistance programs in the models include assistance from the *Economic Injury Disaster Loans (EIDL)*, *SBA Loan Forgiveness*, *Other Federal Programs*, *State or Local Government*, *banks*, *self-fund*, *family*, *friends*, and *others*. Table 1 list the data source, type, time period, and measure for each variable.

<< Insert Table 1 about here >>

Findings

Since our data has two cuts: (1) daily data from March 20 to July 28, and (2) weekly from April 19 to June 27, 2020, we describe our findings using those two cuts separately. Although when adding industry sector information, the number of observations increased, the data attributes do not change substantially.

For the *daily* data, there are 4,551 observations across up to 130 days, 51 states (including Washington DC). Across states we see vast disparities. Over our observation period, averagely 27% of the US workforce since the start of states' SHO worked from home, ranging from the lowest rate in a state at only 5% to the highest at 56%; daily new COVID caseload was about 122 cases per 1 million people with the mean death rate at about 1.7%; about 12 out of 1000 people were exposed to the COVID-19; the average number of days of decreased caseload was less than 4 days. While the mean unemployment rate across all states during this period is 21.5%, it varies from the lowest at 8% to the highest at 44%. The median household income was around \$63,000, but the highest state almost doubled that of the lowest state's value. Similarly we see large racial distribution disparities across states.

<< Insert Table 2 about here >>

Appendix Table A presents the correlation matrix between those variables. We do not detect potential major concerns for multicollinearity.

Figure 1 shows related (either similar or opposite) trends between WFH, COVID new caseload, unemployment rate, and time (the start and end of the SHO). Since the start of SHO (starting on March 21, 2020 in some states), new COVID caseload and WFH were dropping and unemployment rate was rising until around the time when the SHO ended (starting on April 25, 2020 in some states). Soon after the SHO started to end, the unemployment rate started to tip down, and WFH and new COVID caseload started to tick up in June. Figure A in Appendix shows detailed variations across states.

<< Insert Figure 1 about here >>

The intuition from Figure 1 seem to show that the WFH rate change is almost a catching up following the COVID new caseload changes and unemployment rate. After controlling for the pandemic and unemployment changes, does the WFH rate change becomes irrelevant? Although the WFH rate has kept rising after the SHO ended, by the time we conducted this study it has not yet returned to the peak when SHO started, reflecting a very moderate negative correlation between WFH and the end of SHO (shown in Table A in Appendix), opposite to our Hypothesis 1 expectation.

We therefore estimated multivariate empirical models of this impact, controlling for the local pandemic, economic and demographic conditions, as shown in Table 3. Model (1) and (2) adopted the fixed-effect panel data models. Model (3) and (4) adopted the population-averaged generalized linear panel-data models with the GEE approach. Models (1) and (3) included the time variable, *Date*, to add the fixed time effect, in addition to the fixed state effects in Models (2) and (4). All the four models used the daily data and resulted in 4,551 observations.

Across all the four models, WFH demonstrated a consistently strong and higher rate after the SHO ended, controlling for the local pandemic, economic, and demographic conditions. Models (2) and (4) show that WFH rate is about 2 percentage points higher after versus before the SHO ended. Models (1) and (3) show an average 0.03 percentage point daily increase in WFH rate since the SHO started in addition to a 0.5 percentage point increase in WFH rate after the SHO ended.

<< Insert Table 3 about here >>

This effect is also presented in Figure 2. After the SHO ended, the policy requirement restricting workers to commute to work was lifted. However when holding local pandemic, economic, and demographic factors constant, this did not result in a drop in the WFH rate; instead, WFH rate continued to rise. This is consistent with our expectation in Hypothesis 1. All the four models also clearly evidenced the pandemic and economic impact on WFH rates.

<< Insert Figure 2 about here >>

For our weekly data, most variable summary statistics (shown in Appendix Table B) are similar to that of our *daily* data, except that the number of observation dropped to 687 overall and to 333 for small business measures. Among all the observing small businesses, only 2% of them reported no cash flow at all, 31% reported cash flow to last about 1-4 weeks, 29% reported cash flow to last 1-2 months, and 23% reported cash flow to last 3 months or longer. While all states have more small businesses reporting a decreasing versus increasing in operating revenue (shown in negative range), averagely across all states and observing period, 34 percentage of more businesses reported decreasing than increasing operating revenue. While some state in a certain week reported as high as 29% of small businesses experienced temporary closures, overall most small business did not experience temporary closure. The number of small businesses that did not report temporary closures in the survey is 46 percentage point higher than those that did. While some state reported as high as 8% of business experienced disruption of supply chain, the number of small businesses that did not report disruption of supply chain is 24 percentage points higher than those that did in the survey.

Considering the fact the WFH rate is much affected by the pandemic and economic conditions (as shown in Table 2), estimating the WFH effect on small business performance needs to control for local pandemic, economic, and demographic conditions. We first conducted four sets of empirical models with those controls, as well as industry sectors, to test Hypothesis 2. Appendix Table C Models (5) through (11) presents the estimates in seven two-level mixed-effects models, each on one business performance measure.

Considering the potential impact of PPP and other financial assistance programs, we also added the financial assistance control variables in our models in Table 1. The WFH effects on small business performance shown in Table 4 stayed highly similar to those shown in Appendix Table C.

<< Insert Table 4 about here >>

As Models (12) through (18) in Table 4, as well as Models (5) through (11) in Appendix Table C, show, a higher WFH rate is associated with a better performance for small businesses when controlling for local pandemic, economic and demographic conditions: one percentage point increase in the WFH rate is associated with a small businesses' share increase for (1) a cash flow lasting 1 week to 3 month or more, (2) increasing operating revenue, (3) no temporary closures, and (4) no disruptions in supply chain. Our models also show that the pandemic has negative impacts on small business performances, consistent with previous literature (see Bartik, et al. 2020a). Although the COVID pandemic itself naturally bring economic shock to small businesses (such as a decrease in operating revenue, temporary closures, and disruption in supply chain as shown in Table 4), WFH helped offset small businesses some of those negative shocks, as expected in Hypothesis 2.

As Models (12) through (15) shows, while a higher WFH rate does not increase the percentage of small businesses that have no cash flow reserved at all, it is associated with a higher share of small businesses with cash flow reserve for 1-4 weeks, 1-2 months, or 3 or more months respectively by 0.14, 0.45, and 0.35 percentage points, when holding local pandemic, economic, demographic, and financial assistance conditions constant. Figure 3 partially illustrates those effects for observations with the WFH rates for 99.3% of the observation without the two extreme tails.⁶ Noting that the impact is stronger for cash flow reserves longer than one month. Since businesses that have longer cash flow reserves were probably slightly larger, this is consistent with the finding from the literature (see Aguilera, et al. 2016) that larger businesses are more likely to adopt WFH.

<<Insert Figure 3 about here>>

Model (16) demonstrates the WFH effect on small businesses' operating revenue increase. When controlling for local pandemic, economic, and demographic conditions, each one percentage point increase in a state's WFH rate is associated with a 0.6 percentage point net increase in the small businesses' operating revenue a week later. This positive WFH effect is reflected in Figure 4 with 95% confidence interval. The left panel of Figure 4 presents the WFH effect for the 99.3% of the observation without the two extreme tails; the right panel is for all observations.

<<Insert Figure 4 about here >>

⁶ Figures 3 partially illustrates those effects. Figure 3 omitted observations for WFH rate below 3% and above 50% (i.e., omitting the two extreme tails at 3% and 50-56%) because those observation only represent 0.7% of the observation, but have a much larger and more dramatic effect from WFH rates. Presenting those in the graph will visually inflate the WFH effects.

As shown in Model (17), *ceteris paribus*, a percentage point increase in states' WFH rates resulted in 0.8 percentage point decrease in the small businesses' probability of temporarily closures. The left panel of Figure 5 presents the WFH effect without the two tiny tails; the right panel is for all observations.

<< Insert Figure 5 about here >>

Model (11) shows that each one percentage point increase in states' WFH rates resulted in 0.4 percentage point decrease in small businesses' probability of supply chain disruptions, *ceteris paribus*. The left panel of Figure 6 presents the effect without the tiny tails; the right is for all observations.

<< Insert Figure 6 about here >>

The financial assistance from PPP (shown in Table 4) has a positive effect on small business cash flow, temporary closures, and disruptions in supply chain. This reflects the importance of PPP. However, PPP show a negative effect on small businesses' increase in operating revenue, reflecting the fact that businesses receiving assistance from PPP tended to have lower operating revenue.

This positive WFH rate effect on small business performance in Models (5)-(18)⁷ and Hypothesis 2 further confirms our theory and Hypothesis 1. This positive effect confirms WFH as a business rational option and is a driving force for the rising WFH rates even after SHO ended.

Robustness Check

To gauge the robustness of our empirical form, we not only ran three types of models, we also added different variables to check whether the effects are consistent. As mentioned above, adding time effects in Models (1) and (3) in Table 3 or adding controls for financial assistance programs in Models (12)-(18) in Table 4, our findings are consistent and highly similar respectively to Models (2) and (4) in Table 3 or Models (5)-(11) in Appendix Table C.

⁷ Models (12) through (18) are in Table 4 and Models (5) through (11) are in Appendix Table C.

We also estimated alternative models. For Hypothesis 1, we further estimated Models (19)-(22) in Appendix Table D using weekly, instead of daily, data, including fixed industry sector effects, and with the three aforementioned types of models. All those models show the same strong rising WFH trends after the SHO ended, consistent with Models (1) through (4) using daily data presented in Table 3,

For Hypothesis 2, to check the robustness of our two-level mixed-effects models [Models (5) through (18)] that tested Hypothesis 2, again we estimated a set of fixed-effects panel data models [Models (23) -(29) in Appendix Table E], population-averaged generalized linear panel-data models with the GEE approach [Models (30)- (36) in Appendix Table F], and population-averaged generalized linear panel-data models with the GEE approach with fixed industry sector effects [Models (37)-(43) in Appendix Table G]. The positive business effects we found in our two-level mixed-effects models [Models (5) through (18)]⁸ are basically the same as the population-averaged generalized linear panel-data models with the GEE approach and fixed industry sector effects [Models (37) through (43) in Appendix Table G] and not inconsistent with the other models as well.

The highly consistent effects across the 43 models indicate the robustness of our models. Also, among the fixed-effects models, those testing Hypothesis 1 explained 33% to 43% of variability of WFH; those testing Hypothesis 2 explained lower variability (up to 12%) for small business performance measures because the relatively limited number of observations with the weekly data. All those models have a statistically significant F statistics. The chi-square tests are statistically significant for all the population-averaged generalized panel-data models with the GEE approach and two-level mixed-effects models. The latter also have high log likelihoods and show significant difference from linear models via the likelihood ratio tests, indicating the advantage of controlling both state and industry sector level variations.

Discussion

Following Schumpeter (1934)'s "creative destruction" argument, although COVID-19 resulted a human health and economic disaster, this destruction may result in some new creations, innovations, and creative ways to better utilize our advances in high-tech communication platforms. This "creative destruction", expedited by the painful COVID-crisis, may have sped up our learning curve for using and accepting high-tech communication platforms as a norm; this could set a more efficient and more cost-effective new course of production in the long run. The forced new WFH norm may have

⁸ Models (12) through (18) are in Table 4 and Models (5) through (11) are in Appendix Table C.

not only expedited WFH-ready firms to implement WFH practice more fully, but may also push other firms to creatively find new solutions to utilizing the modern communication technology in any possible creative ways. Out of this disruption, not only our health care system can be reborn mending many exposed weaknesses, the potential of WFH could be more fully realized. A disruption from the traditional brick-&-mortar offices might result in a new hybrid or a WFH-dominant new workplace setting. If the new WFH norm really emerges soon, our current human resource practice, real estate industry, urban sprawling patterns, urban planning, racial segregation, city externalities would all await to be transformed. This would have huge public policy implications.

More importantly and sadly, the rising WFH popularity would deepen the digital divide and widen the wealth gap. Dingel & Neiman (2020) noted lower-income economies have a lower share of WFH jobs. Those who have and have-nots would be increasingly different, unless more and more jobs can be done via WFH. Otherwise the world would be more polarized, like what education has divided us in the long human history: on the one hand, high skilled workers who master digital skills are not only enjoy better pay, better work-life balance (Mas & Pallais 2017) and better control of their schedules, but also better health with limited exposure to virus or bacteria; on the other hand, workers without digital skills or digital access often conduct relatively low-paid jobs, remain a life demanded by their bosses' schedules, and more importantly, always at the front line to be exposed to any transmutable disease, virus, germs. Dingel & Neiman (2020)'s contribution on teleworkable jobs offered the timely and critical contribution in the pandemic. When WFH really becomes the new norm, we hope certain innovation can penetrate WFH better to currently non-teleworkable jobs eventually. This requires entrepreneurship from often the nimble and creative small businesses.

The internet and globalization are double edged swords: they on the one hand reached out better to the poor with a larger market, on the other hand made it easier for the large firms to sell and profit more. WFH would further make the internet and globalization a necessity.

WFH itself is a double-edged sword as well. It not only brings the flexibility and a better work-family balance to workers [c.f. Gajendran, et al (2007)], but also often blurs the boundaries between work and family (Riggoti et al. 2020). There is also general managerial concern on control and surveillance for WFH workers (Coenen and Kok 2014), or a career path concerns with limited in-person presence (Golden and Eddleston 2020), both related to an appropriate psychosociological distance (Belanger, 1999; Taskin and Devos 2005; Wilton et al., 2011). Best practice human resources policies need to be further discussed for a healthy and sustaining labor relations.

This paper used small business data because small business are often the most vulnerable in the crisis. It is not our intention to compare the WFH effects for small businesses to that for larger businesses. Small businesses often do not have as much resources as larger businesses to build robust WFH infrastructure (Vilhelmson and Thulin 2016), including costs of organizational change and technological investments (Aguilera, et al. 2016). This could have limited some of our evidence. Since we found positive productive role of WFH in small business performance, the impacts for larger businesses could be even larger. Although we do not have data on business owners or decision making process, for the timeliness and limitation of the data availability, this paper relies on the best available data that is publicly available and well-represented to empirically test the WFH effects.

In this COVID-19 pandemic, social distancing is critical. Whether a small business can adjust its goods and service to pickup/carry-out/delivery as their only means to serve customers shows how nimble and adaptive to change a small business is. This could also be related WFH. We initially planned to also model WFH effects on this. However, it is unclear what types of impact can be expected. Further analysis on this will need to be considered. In addition, fear factor could affect economic recovery in the pandemic and its aftermath. Before the effective vaccine is found and prevalent, this fear factor could affect the WFH trajectory. Further research is needed on that.

Conclusion

The study first builds a theoretical framework based on utility maximization theory subject to a “contagion” agglomeration parameter and argues that WFH is a rational choice for small businesses. We then compiled an up-to-date real-time daily and weekly multifaceted data set tracking WFH propensity from March 20 through July 28. Using this data set, we estimated a variety of fixed-effects panel data models, population-averaged generalized linear panel-data models with the GEE approach, and two-level mixed-effects panel-data models.

Our empirical findings are consistent with our initial expectation and also support the hypotheses drawn from our theoretical framework. First, WFH has potential attractiveness for employers. In the pandemic, although WFH rate is dramatically increased due to the COVID pandemic and the SHO mandate, after the SHO ended, WFH rate did not drop and instead rose, after controlling for local pandemic, economic, and demographic conditions. This paper empirically supports the idea that WFH could be the new norm.

With various economic and health advantages, WFH has been shown in this study to positively associate with small business' operating revenue increases, stronger cash flow positions, and reductions in temporary closure and in supply chain disruption. These help mitigate the negative pandemic shock and suggest that a policy response include provisions to promote teleworkable jobs and WFH.

More importantly, if this pandemic brings in major economic structure disruption, WFH could be the opportunity for Schumpeterian “creative” innovation out of this disruption. As nimble and creative as small businesses have always been, riding or even leading this WFH wave well would not only help small businesses survive better in the pandemic, it might make them the vanguard of a new work paradigm. With public policy facilitating WFH with technology and institution, this new potential may really happen.

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Tables and Figures

Table 1. Data Sources, Types, Time Periods, Measures for all Variables

Variable Name	Description	Source	Time Period	Data Type
WFH: Work From Home				
WFH	Percentage of workforce working from home based on UMD models. Calculated by MTI based on changes in work trips and unemployment claims.	MTI	3/21-7/28, daily	Continuous (%)
AfterSHO: After Stay-Home Order Ended				
afterSHO	The date is later than the state's stay-home order end date	IHME	3/21-7/28, daily	Dummy
Business: Business Performance Measures				
Opr Rev	Percentage of businesses reported "increased" (+) or "decrease" (-) to the question "In the last week, did this business experience a change in operating revenues?"	SBPS	4/26-6/27, weekly	Continuous (%)
Tenp Closure	Percentage of businesses reported "yes" (+) or "no" (-) to the question "In the last week, did this business temporarily close any of its locations for at least one day?"	SBPS	4/26-6/27, weekly	Continuous (%)
Disrpt. Sup Chn	Percentage of businesses reported "yes" (+) or "no" (-) to the question "In the last week, did this business have disruptions in its supply chain?"	SBPS	4/26-6/27, weekly	Continuous (%)
cashFlow0	Percentage of businesses reported "No cash available for business operations" to the question "How would you describe the current availability of cash on hand for this business?"	SBPS	4/26-6/27, weekly	Continuous (%)
cashFlow4w	Percentage of businesses reported "1-4 weeks of business operations" to the question "How would you describe the current availability of cash on hand for this business?"	SBPS	4/26-6/27, weekly	Continuous (%)
cashFlow2m	Percentage of businesses reported "1-2 months of business operations" to the question "How would you describe the current availability of cash on hand for this business?"	SBPS	4/26-6/27, weekly	Continuous (%)
cashFlow3m+	Percentage of businesses reported "3 or more months of business operations" to the question "How would you describe the current availability of cash on hand for this business?"	SBPS	4/26-6/27, weekly	Continuous (%)
COVID: COVID-19 Pandemic Severity				
New Case / 1k	Number of COVID-19 daily new cases per 1000 people (three-day moving average).	CSSE	3/20-7/28, daily	Continuous (0/000)
Death Rt	% deaths among all COVID-19 cases. Calculated by MTI based on number of deaths and estimated total COVID cases including confirmed and untested cases.	CSSE	3/20-7/28, daily	Continuous (%)
exposure / 1k	Number of residents already exposed to coronavirus per 1000 people. Calculated by MTI.	MTI	3/20-7/28, daily	Continuous (0/000)
Days Decr.	Number of days with decreasing COVID-19 cases. Calculated by MTI based on weekly pattern of new daily cases.	MTI	3/20-7/28, daily	Continuous
ECON: Economic Background				
Unemploy Rt	Unemployment rate updated weekly.	USDOL	3/15-7/28, weekly	Continuous (%)

Median Inc.	Median household income from the US Census Bureau	ACS	2018, yearly	Continuous
Emp Density	Gross employment density (jobs per acre) on unprotected land.	EPA SLD	2013, one time	Continuous (%)
DEMO: Demographics				
% 60+	Percent of population above the age of 60.	ACS	2018, yearly	Continuous (%)
% African Am.	Percentage of African Americans.	ACS	2018, yearly	Continuous (%)
% Hispanic Am.	Percentage of Hispanic Americans.	ACS	2018, yearly	Continuous (%)
% male	Percentage of male.	ACS	2018, yearly	Continuous (%)
FIN: Business Financial Assistance				
Fin_PPP	Percentage of businesses reported "Paycheck Protection Program (PPP)" to the question "Since March 13,2020, has this business requested financial assistance from any of the following sources??"	SBPS	4/26-6/27, weekly	Continuous (%)
Fin_EIDL	Percentage of businesses reported "Economic Injury Disaster Loans (EIDL)" to the question "Since March 13,2020, has this business requested financial assistance from any of the following sources??"	SBPS	4/26-6/27, weekly	Continuous (%)
Fin_SBAlnForg	Percentage of businesses reported "SBA Loan Forgiveness" to the question "Since March 13,2020, has this business requested financial assistance from any of the following sources??"	SBPS	4/26-6/27, weekly	Continuous (%)
Fin_OtherFed	Percentage of businesses reported "Other Federal Programs" to the question "Since March 13,2020, has this business requested financial assistance from any of the following sources??"	SBPS	4/26-6/27, weekly	Continuous (%)
Fin_StLocGov	Percentage of businesses reported "State or Local Government" to the question "Since March 13,2020, has this business requested financial assistance from any of the following sources??"	SBPS	4/26-6/27, weekly	Continuous (%)
Fin_Banks	Percentage of businesses reported "Banks" to the question "Since March 13,2020, has this business requested financial assistance from any of the following sources??"	SBPS	4/26-6/27, weekly	Continuous (%)
Fin_Self	Percentage of businesses reported "Self" to the question "Since March 13,2020, has this business requested financial assistance from any of the following sources??"	SBPS	4/26-6/27, weekly	Continuous (%)
Fin_FamFriend	Percentage of businesses reported "Family or Friends" to the question "Since March 13,2020, has this business requested financial assistance from any of the following sources??"	SBPS	4/26-6/27, weekly	Continuous (%)
Fin_Other	Percentage of businesses reported "Other" to the question "Since March 13,2020, has this business requested financial assistance from any of the following sources??"	SBPS	4/26-6/27, weekly	Continuous (%)

Table 2. Descriptive Statistics for *Daily Data*

Variable	Obs	Mean	Std. Dev.	Min	Max
WFH					
WFH	4,551	0.26674	0.09349	0.048	0.557
Date					
Date	4,551	22062.9	35.6531	21995	22124
afterSHO	4,552	0.56305	0.49606	0	1
COVID					
New Case / 1k (t-1)	4,551	0.1216	0.16573	0	1.007
Death Rt (t-1)	4,551	0.01737	0.00817	0.0032	0.0458
Exposure / 1k (t-1)	4,551	11.5198	12.1186	0.48	52.03
Days Decr. (t-1)	4,551	3.57064	6.49126	0	44
ECON					
Unemploy Rt (t-1)	4,551	0.21547	0.07449	0.081	0.444
Median Inc. (t-1)	4,551	62176.3	10649.5	44445	84342
Emp Density (t-1)	4,551	511.443	2569.62	1	16044
Demographics					
% 60+ (t-1)	4,551	0.22194	0.02325	0.17	0.27
% African Am. (t-1)	4,551	0.12306	0.11018	0.004	0.461
% Hispanic Am. (t-1)	4,551	0.10943	0.08692	0.015	0.392
% male (t-1)	4,551	0.49291	0.00803	0.4746	0.5221

Figure 1. Trend of WFH, COVID severity, Unemployment, March 21-July 28, 2020

Table 3. Empirical Models for the End of SHO Effect on WFH Rates

Model (1)				Model (2)			Model (3)			Model (4)		
Dependent Variable: WFH Rates	Fixed-effects Panel Data Model			Fixed-effects Panel Data Model			GEE Population-averaged Generalized Linear Panel Data Model			GEE Population-averaged Generalized Linear Panel Data Model		
	Coef.	Std. Err.		Coef.	Std. Err.		Coef.	Std. Err.		Coef.	Std. Err.	
Independent Variable												
afterSHO (t-1)	0.0054	0.0012	***	0.0176	0.0009	***	0.0054	0.0012	***	0.0176	0.0009	***
Control Variable: Time Effects												
Date	0.0003	0.0000	***				0.0003	0.0000	***			
Control Variables: COVID: COVID-19 Pandemic Severity												
New Case / 1k (t-1)	0.0217	0.0036	***	0.0252	0.0037	***	0.0223	0.0036	***	0.0259	0.0037	***
Death Rt (t-1)	-0.7573	0.0965	***	-0.5998	0.0982	***	-0.7231	0.0949	***	-0.5645	0.0967	***
exposure / 1k (t-1)	-0.0001	0.0001	*	0.0004	0.0000	***	-0.0001	0.0001	**	0.0004	0.0001	***
Days Decr. (t-1)	-0.0001	0.0001		-0.0002	0.0000	***	-0.0001	0.0001		-0.0002	0.0001	***
Control Variables: ECON: Economic Background												
Unemploy Rt (t-1)	-0.8093	0.0079	***	-0.7948	0.0080	***	-0.8102	0.0077	***	-0.7959	0.0079	***
Median Inc. (t-1)	(omitted)			(omitted)			0.0000	0.0000	***	0.0000	0.0000	***
Emp Density (t-1)	(omitted)			(omitted)			0.0000	0.0000	***	0.0000	0.0000	***
Industry												
Control Variables: DEMO: Demographics												
% 60+ (t-1)	(omitted)			(omitted)			0.0236	0.4785		0.0720	0.4651	
% African Am. (t-1)	(omitted)			(omitted)			-0.0819	0.1227		-0.0942	0.1193	
% Hispanic Am. (t-1)	(omitted)			(omitted)			0.2746	0.0853	***	0.2580	0.0829	***
% male (t-1)	(omitted)			(omitted)			-4.0208	1.5873	**	-3.7291	1.5430	**
Constant, Random Error, or Random Effect												
Constant	-6.2795	0.4603	***	0.4314	0.0018	***	-4.4465	0.9833	***	2.0800	0.8533	**
Random Error or Random Effects	sigma_u	0.0710		sigma_u	0.0685							
	sigma_e	0.0212		sigma_e	0.0217							
	rho	0.9184		rho	0.9092							
Diagnostics												
F test that all u_i=0:	F(36, 4507)	838.97	***	(36, 4508)	795.73							
# of Obs	# obs	4551		# obs	4551		# obs	4551		# obs	4551	
# of Groups	# groups	37		# groups	37		# groups	37		# groups	37	
R-Squared	Within	0.8521		Within	0.8451		Link:	identity		Link:	identity	
	B/w	0.1657		B/w	0.2121		Family:	Gaussian		Family:	Gaussian	
	Overall	0.3938		Overall	0.4274		Corr	exchangeable		Corr:	exchangeable	
F or Wald Chi2	F(7,4507)	3708	***	F(6,4508)	4099	***	Wald chi2(13)	26828	***	Wald chi2(12)	25326	***
Other Stat	corr(u_i, Xb)	-0.082		corr(u_i, Xb)	-0.036		Scale Param.:	0.0020		Scale Param.:	0.0020	

Figure 2. Marginal Effect of the End of SHO on WFH based on Model (4)

Table 4. WFH Effects on Small Business Performance with Financial Assistance, Multilevel Mixed-effects Models (12)-(18)

	No Cash FLOW			Cash Flow foe 1-4 Weeks			Cash Flow for 1-2 Months			Cash Flow for 3+ Months			Increase Operating Revenue			Temporary Closure			Disruptino in Supply Chain		
	Model (12)			Model (13)			Model (14)			Model (15)			Model (16)			Model (17)			Model (18)		
	Coef	St. Er.		Coef	St. Er.		Coef	St. Er.		Coef	St. Er.		Coef	St. Er.		Coef	St. Er.		Coef	St. Er.	
WFH: Work From Home																					
WFH (t-1)	-0.01	0.01		0.14	0.06	**	0.45	0.09	***	0.35	0.08	***	0.61	0.15	***	-0.75	0.18	***	-0.39	0.18	**
Time Effects																					
afterSHO (t-1)	0.00	0.00	*	-	0.03	0.00	0.00	0.01		0.01	0.01	**	0.23	0.01	*	-	0.24	0.01	-	0.10	0.0
COVID: COVID-19 Pandemic Severity																					
New Case / 1k (t-1)	0.03	0.00	**	0.06	0.04		-	0.12	0.06	*	0.09	0.06	-	0.45	0.11	*	0.43	0.13	0.29	0.1	3
Death Rt (t-1)	0.06	0.04		0.79	0.37	**	0.91	0.55	*	1.09	0.50	**	9.72	0.97	*	8.64	1.14	*	4.86	1.1	**
exposure / 1k (t-1)	0.00	0.00	**	0.00	0.00	*	0.00	0.00	*	0.00	0.00	*	0.01	0.00	*	0.00	0.00	**	0.00	0.0	0.0
Days Decr. (t-1)	0.00	0.00		0.00	0.00	*	0.00	0.00	*	0.00	0.00	*	0.00	0.00	*	0.00	0.00	*	0.00	0.0	0.0
ECON: Economic Background																					
Unemploy Rt (t-1)	-	0.01	**	0.02	0.06		0.39	0.09	*	0.44	0.08	*	1.46	0.16	*	-	0.93	0.19	-	0.1	9
Median Inc. (t-1)	0.00	0.00	*	0.00	0.00		0.00	0.00		0.00	0.00	**	0.00	0.00	**	0.00	0.00	**	0.00	0.0	0.0
Emp Density (t-1)	0.00	0.00		0.00	0.00	*	0.00	0.00	*	0.00	0.00	*	0.00	0.00	*	0.00	0.00	*	0.00	0.0	0.0
DEMO: Demographics																					
% 60+ (t-1)	0.02	0.02		0.43	0.13	*	1.29	0.20	*	1.11	0.18	*	0.84	0.35	**	1.49	0.41	*	0.51	0.4	2
% African Am. (t-1)	-	0.00		-	0.11	0.04	0.19	0.06	*	0.29	0.06	*	0.32	0.11	*	0.39	0.12	*	0.26	0.1	3
% Hispanic Am. (t-1)	0.00	0.00		0.19	0.03	*	0.19	0.04	*	0.16	0.04	*	0.75	0.07	*	0.60	0.09	*	0.23	0.0	9
% male (t-1)	0.06	0.08		-	4.15	0.72	6.94	1.06	*	-	6.00	0.98	3.81	1.88	**	-	2.38	2.20	4.37	2.2	2
FIN: Business Financial Assistance																					
Fin_PPP	0.00	0.00		0.01	0.01		0.06	0.01	*	0.06	0.01	*	-	0.14	0.02	*	-	0.12	-	0.0	2

Fin_EIDL	0.00	0.00		0.13	0.01	**	0.31	0.02	**	0.14	0.02	**	-		**	0.02	0.04	-	0.0
			**			**													0.1
Fin_SBAInForg	0.02	0.01	*	0.43	0.05	*	0.08	0.07		0.02	0.06		0.30	0.12	**	0.16	0.14	0.10	4
	-																	-	0.8
Fin_OtherFed	0.05	0.03		0.16	0.28		0.13	0.42		0.18	0.39		0.53	0.75		0.05	0.87	0.64	8
			**				-			-			-					-	0.1
Fin_StLocGov	0.02	0.01	*	0.02	0.06		0.09	0.09		0.12	0.08		0.04	0.15		0.43	0.18	**	8
			**			**				-			-				**		0.1
Fin_Banks	0.03	0.01	*	0.48	0.06	*	0.13	0.09		0.13	0.08		0.13	0.16		0.54	0.19	*	9
						**											**		0.1
Fin_Self	0.01	0.00	**	0.33	0.04	*	0.14	0.06	**	0.11	0.05	**	0.15	0.10		0.34	0.12	*	2
			**				-			-			-						0.6
Fin_FamFriend	0.33	0.02	*	0.22	0.22		0.60	0.32	*	0.73	0.29	**	0.05	0.57		0.47	0.66	0.09	7
	-			-						-			-			-		-	0.7
Fin_Other	0.02	0.03		0.02	0.23		0.02	0.35		0.37	0.32		0.02	0.62		0.28	0.72	0.15	3
Constant & Model Diagnostics																			
Constant	-					**			**			**	-		**	-		-	1.1
	0.03	0.04		2.14	0.37	*	3.54	0.55	*	2.99	0.51	*	2.55	0.98	*	1.92	1.15	*	5
Random-effects Parameters		St.			St.			St.			St.			St.			St.		**
NAICS	Est.	Er.		Est.	Er.		Est.	Er.		Est.	Er.		Est.	Er.		Est.	Er.		
							Identity												
sd(_cons)	0.00	0.00	**	0.04	**	##	0.07	0.01	**	0.08	0.02	**	0.06	0.01	**	0.28	0.05	**	0.0
																			5
sd(Residual)	0.01	0.00	**	0.09	**	##	0.13	0.00	**	0.12	0.00	**	0.24	0.00	**	0.28	0.00	**	0.0
LR test vs. linear			**			**			**			**			**			**	**
model:chibar2(01)	9		*	424		*	570		*	901		*	122		*	1371		*	*
Number of obs	2909			2909			2909			2909			2909			2909			
Number of groups	17			17			17			17			17			17			
Obs per Group, min	5			5			5			5			5			5			
Obs per Group, ave	171			171			171			171			171			171			
Obs per Group, max	285			285			285			285			285			285			
				151			104						115			105			
Wald chi2(12)	488	***	0	8	***	0	9	***	0	617	***	0	7	***	0	7	***	0	171
Log likelihood	9147			2837			1694			1929			25			-441			-465

Figure 3 WFH Rate Effects on Small Business' Cash Flow, Based on Models (12)-(15)

Note: This graph omitted observations for WFH rate below 3% and above 50% (i.e., omitting two tails at 2% and 51-56%) because those observation only represent 0.7% of the observations, but have a much larger and more dramatic effect from WFH rates. Presenting those in the graph will visually inflate the WFH effects.

Figure 4. WFH Effects on Small Business' Operating Revenue Increase, Based on Model (16)

For WFH Rate between 3-50% (99.3% of observation)

For All WFH Rates (2-56%)

Figure 5 WFH Rate Effects on Small Business' Temporary Closure, Based on Model (17)

For WFH Rate between 3-50% (99.3% of observation)

For All WFH Rates (2-56%)

Figure 6 WFH Rate Effects on Small Business' Disruption in Supply Chain, Based on Model (18)

For WFH Rate between 3-50% (99.3% of observation)

For All WFH Rates (2-56%)

Appendix

Table A. Correlation Matrix for the Daily Data

		1	2	3	4	5	6	7	8	9	10	11	12	13	14
1	WFH	1.00													
2	Date	0.06	1.00												
3	afterSHO	-0.06	0.79	1.00											
4	New Case / 1k (t-1)	0.35	0.37	0.21	1.00										
5	Death Rt (t-1)	0.01	0.10	0.04	-0.24	1.00									
6	exposure / 1k (t-1)	0.37	0.55	0.35	0.62	0.29	1.00								
7	Days Decr. (t-1)	-0.10	0.11	0.10	-0.07	0.28	0.27	1.00							
8	Unemploy Rt (t-1)	-0.65	0.10	0.14	-0.30	0.44	-0.04	0.24	1.00						
9	Median Inc. (t-1)	0.35	-0.02	-0.15	-0.07	0.10	0.17	0.09	0.00	1.00					
10	Emp Density (t-1)	0.48	0.00	-0.03	0.05	0.06	0.19	-0.04	-0.07	0.33	1.00				
11	% 60+ (t-1)	-0.21	0.00	-0.06	-0.11	0.03	-0.16	0.10	0.02	-0.35	-0.37	1.00			
12	% African Am. (t-1)	0.26	0.02	0.04	0.26	0.12	0.34	-0.07	-0.01	-0.01	0.51	-0.35	1.00		
13	% Hispanic Am. (t-1)	0.22	0.00	0.00	0.14	-0.03	0.21	0.03	0.08	0.18	0.01	-0.35	-0.09	1	
14	% male (t-1)	-0.37	-0.01	0.04	-0.17	-0.26	-0.39	-0.04	0.10	0.10	-0.39	-0.17	-0.70	0.13	1

Figure A. Trend of WFH, COVID severity, Unemployment by Date and State

Table B. Summary Statistics of the Weekly Data

Variable	Obs	Mean	Std. Dev.	Min	Max
WFH: Work From Home					
WFH	687	0.270	0.092	0.048	0.557
WFH (t-1)	687	0.268	0.092	0.048	0.557
Business: Business Performance Measures					
cashFlow0	333	0.021	0.027	0.000	0.119
cashFlow4w	333	0.312	0.087	0.000	0.526
cashFlow2m	333	0.291	0.041	0.143	0.426
cashFlow3m+	333	0.228	0.054	0.000	0.415
Opr Rev	333	-0.400	0.180	-0.811	-0.052
Tenp Closure	333	-0.464	0.219	-0.863	0.290
Disrpt. Sup Chn	333	-0.239	0.120	-0.624	0.078
Time Effects					
afterSHO	687	0.568	0.495	0.000	1.000
COVID: COVID-19 Pandemic Severity					
New Case / 1k (t-1)	687	0.115	0.158	0.000	1.007
Death Rt (t-1)	687	0.017	0.008	0.004	0.045
Exposure / 1k (t-1)	687	10.66	11.71	0.480	52.03
Days Decr. (t-1)	687	3.267	6.120	0.000	44.000
ECON: Economic Background					
Unemploy Rt (t-1)	687	0.211	0.074	0.081	0.444
Median Inc. (t-1)	687	62171	10659	44445	84342
Emp Density (t-1)	687	506	2553	1	16044
DEMO: Demographics					
% 60+ (t-1)	687	0.222	0.023	0.170	0.270
% African Am. (t-1)	687	0.123	0.110	0.004	0.461
% Hispanic Am. (t-1)	687	0.109	0.087	0.015	0.392
% male (t-1)	687	0.493	0.008	0.475	0.522
FIN: Business Financial Assistance					
Fin_PPP	333	0.743	0.047	0.551	0.879
Fin_EIDL	333	0.276	0.047	0.125	0.424
Fin_SBAlnForg	333	0.087	0.042	0.000	0.203
Fin_OtherFed	333	0.009	0.013	0.000	0.047
Fin_StLocGov	333	0.045	0.061	0.000	0.317
Fin_Banks	333	0.063	0.038	0.000	0.158
Fin_Self	333	0.096	0.042	0.000	0.193
Fin_FamFriend	333	0.022	0.023	0.000	0.143
Fin_Other	333	0.020	0.021	0.000	0.104

Table C. WFH Effects on Small Business Performance, Multilevel Mixed-effects Models

Dependent Variables:				No Cash Flow			Cash Flow foe 1-4 Weeks			Cash Flow for 1-2 Months			Cash Flow for 3+ Months			Increase Operating Revenue			Temporary Closure			Disruption in Supply Chain		
Model (5)				Model (6)			Model (7)			Model 8)			Model (9)			Model (10)			Model (11)					
St.		Coef.		St.		Coef.		St.		Coef.		St.		Coef.		St.		Coef.		St.				
Independent Variable: WFH: Work From Home																								
WFH (t-1)	-0.01	0.01		0.18	0.06	***	0.54	0.09	***	0.38	0.08	***	0.59	0.16	***	-0.94	0.18	***	-0.50	0.18	***			
Control Variable: Time Effects																								
afterSHO (t-1)	0.00	0.00	***	-0.04	0.00	***	-0.01	0.01	**	0.00	0.01		0.23	0.01	***	-0.23	0.01	***	-0.10	0.01	***			
Control Variables: COVID: COVID-19 Pandemic Severity																								
New Case / 1k (t-1)	0.02	0.00	***	0.06	0.05		-0.16	0.06	**	0.02	0.06		-0.26	0.11	**	0.22	0.13	*	0.17	0.13				
Death Rt (t-1)	0.09	0.05	*	1.93	0.42	***	2.03	0.59	***	1.74	0.53	***	10.32	1.01	***	10.45	1.18	***	5.20	1.17	***			
exposure / 1k (t-1)	0.00	0.00	***	0.00	0.00	***	0.00	0.00	***	0.00	0.00	***	0.01	0.00	***	0.00	0.00	***	0.00	0.00				
Days Decr. (t-1)	0.00	0.00		0.00	0.00	***	0.00	0.00	***	0.00	0.00	***	0.00	0.00	***	0.00	0.00	*	0.00	0.00				
Control Variables: ECON: Economic Background																								
Unemploy Rt (t-1)	-0.01	0.01	*	0.04	0.07		0.43	0.10	***	0.46	0.09	***	1.50	0.17	***	-1.17	0.19	***	-1.14	0.19	***			
Median Inc. (t-1)	0.00	0.00		0.00	0.00		0.00	0.00	*	0.00	0.00	***	0.00	0.00	***	0.00	0.00	***	0.00	0.00				
Emp Density (t-1)	0.00	0.00		0.00	0.00	***	0.00	0.00	***	0.00	0.00	***	0.00	0.00	***	0.00	0.00	***	0.00	0.00				
Control Variables: DEMO: Demographics																								
% 60+ (t-1)	0.01	0.02		-0.69	0.15	***	-1.58	0.21	***	-1.33	0.18	***	0.81	0.35	**	1.88	0.41	***	0.76	0.41	*			
% African Am. (t-1)	-0.01	0.00		-0.19	0.04	***	-0.26	0.06	***	-0.34	0.06	***	-0.31	0.11	***	0.42	0.13	***	0.32	0.12	**			
% Hispanic Am. (t-1)	0.01	0.00	***	0.42	0.03	***	0.42	0.04	***	0.27	0.04	***	-0.81	0.07	***	0.77	0.09	***	0.24	0.09	***			
% male (t-1)	-0.04	0.09		-7.25	0.78	***	10.30	1.11	***	-7.98	0.99	***	4.77	1.89	**	2.09	2.20		5.64	2.19	***			
Constant & Model Diagnostics																								
Constant	0.02	0.04		3.68	0.40	***	5.23	0.58	***	4.02	0.51	***	-3.10	0.98	***	-1.95	1.14	*	-3.00	1.14	***			
Random-effects Parameters:	Est.	St. Er.		Est.	St. Er.		Est.	St. Er.		Est.	St. Er.		Est.	St. Er.		Est.	St. Er.		Est.	St. Er.				
NAICS industry	Identity																							

sd(_cons)	0.00	0.00	**	0.07	0.01	**	0.10	0.02	**	0.08	0.02	**	0.06	0.02	**	0.28	0.05	**	0.28	0.05	**
sd(Residual)	0.01	0.00	**	0.10	0.00	**	0.14	0.00	**	0.13	0.00	**	0.24	0.00	**	0.28	0.00	**	0.28	0.00	**
LR test vs. linear model:chibar2(01)	27.27		***	694.63		***	779.48		***	802.1		***	118.48		***	1404.83		***	2043.56		***
Number of obs	2909			2909			2909			2909			2909			2909			2909		
Number of groups	17			17			17			17			17			17			17		
Obs per Group, min	5			5			5			5			5			5			5		
Obs per Group, ave	171			171			171			171			171			171			171		
Obs per Group, max	285			285			285			285			285			285			285		
Wald chi2(12)	124	***	0	726	***	0	597	***	0	441	***	0	1014	***	0	933	***	0	155	***	0
Log likelihood	8983			2548			1515			1854			-27			-487			-473		

Table D. Alternative Models for the End of SHO Effect on WFH

Model (19)				Model (20)			Model (21)			Model (22)					
Fixed-effects Panel Data Model				GEE Population-averaged Generalized Linear Panel Data Model			GEE Population-averaged Generalized Linear Panel Data Model			Multilevel Mixed-effects Model					
Coef.		Std. Err.		Coef.		Std. Err.		Coef.		Std. Err.		Coef.		Std. Err.	
Time Effects															
Date afterSHO (t-1)	0.030 0.004 ***			0.030 0.004 ***			0.007 0.001 ***			0.023 0.001 ***					
COVID: COVID-19 Pandemic Severity															
New Case / 1k (t-1)	0.025 0.014 *			0.034 0.014 **			0.060 0.011 ***			0.048 0.013 ***					
Death Rt (t-1)	-1.089 0.370 ***			-0.607 0.354 *			0.613 0.165 ***			4.154 0.093 ***					
exposure / 1k (t-1)	0.001 0.000 **			0.001 0.000 **			0.002 0.000 ***			-0.001 0.000 ***					
Days Decr. (t-1)	0.000 0.000 *			0.000 0.000 *			0.000 0.000 ***			0.000 0.000 **					
ECON: Economic Background															
Unemploy Rt (t-1)	-0.702 0.031 ***			-0.717 0.031 ***			-0.743 0.021 ***			-0.875 0.012 ***					
Median Inc. (t-1)	(omitted)			0.000 0.000 ***			0.000 0.000 ***			0.000 0.000 ***					
Emp Density (t-1)	(omitted)			0.000 0.000 ***			0.000 0.000 ***			0.000 0.000 ***					
Industry							Yes								
DEMO: Demographics															
% 60+ (t-1)	(omitted)			0.026 0.466			0.142 0.125			0.083 0.043 *					
% African Am. (t-1)	(omitted)			-0.123 0.120			-0.038 0.035			-0.021 0.013					
% Hispanic Am. (t-1)	(omitted)			0.247 0.083 ***			0.211 0.020 ***			0.289 0.007 ***					
% male (t-1)	(omitted)			-4.044 1.555 ***			-0.480 0.564			-1.686 0.227 ***					
Constant, Error Terms, or Random Effect															
Constant, Error Terms, or Random Effect	0.411 0.006 ***			2.225 0.859 ***			0.459 0.298			0.960 0.117 ***					
Random Errors or Random Effects	sigma_u	0.070								Random-effects Param.			Estimate	Std. Err.	
	sigma_e	0.032								NAICS:			Identity		
	rho	0.828								sd(cons)			0.001	0.001 **	
										sd(Resi.1)			0.030	0.000 **	
Diagnostics															

F test that all $u_i=0$:	F(36, 644)	58	***							LR test vs. linear model:	chi2(01)	0.070
# of Obs	# obs	687		# obs	687	# obs	2909	# obs	2909			
# of Groups	# groups	37		# groups	37	# groups	414	# groups	17			
	R2 Within	0.68		Link:	identity	Link:	identity	Obs per Group, min	5			
R-Squared	B/w	0.16		Family:	Gaussian	Family:	Gaussian	Obs per Group, ave	171			
	R2 Overall	0.33		Corr:	exchangeable	Corr:	exchangeable	Obs per Group, max	285			
F or Wald Chi2	F(6,644)	226	***	Wald chi2(28)	1479	***	Wald chi2(28)	2297	***	Wald chi2(12)	13545	***
Other Stat	corr(u_i , Xb)	0.057		Scale Param.:	0.002		Scale Param.:	0.001		Log likelih.	6111	

Models (19) and (20) followed the design of Models (2) and (4), i.e., using respectively fixed-effects models and population-averaged generalized linear panel-data models with the GEE approach. Model (21) followed Model (20), but added the industry sector fixed effects in. Model (22) adopted the two-level mixed-effects model controlling correlations at the both the state and industry sector levels.

Table E. WFH Effects on Small Business Performance, Fixed-effect Panel Data Models

No Cash Flow				Cash Flow foe 1-4 Weeks			Cash Flow for 1-2 Months			Cash Flow for 3+ Months			Increase Operating Revenue			Temporary Closure			Disruption in Supply Chain				
Model (23)				Model (24)			Model (25)			Model (26)			Model (27)			Model (28)			Model (29)				
Coef.		St. Er.		Coef.		St. Er.		Coef.		St. Er.		Coef.		St. Er.		Coef.		St. Er.		Coef.		St. Er.	
WFH: Work From Home																							
WFH (t-1)	-0.01	0.05		0.07	0.16		-0.13	0.10		0.03	0.11		0.54	0.23	**	-0.47	0.27	*	-0.24	0.23			
Time Effects																							
afterSHO (t-1)	-0.01	0.00	***	-0.02	0.01	**	0.00	0.01		0.02	0.01	***	0.09	0.01	***	-0.08	0.02	***	-0.04	0.01	**		
COVID: COVID-19 Pandemic Severity																							
New Case / 1k (t-1) Death Rt (t-1) exposure / 1k (t-1) Days Decr. (t-1)	0.01	0.02		0.13	0.07	*	-0.04	0.05		0.02	0.05		0.19	0.11	*	-0.33	0.12	***	0.02	0.11			
	-0.63	0.45		-0.04	1.43		1.33	0.93		-1.55	0.97		4.55	2.08	**	-5.42	2.38	**	-0.21	2.08			
	0.00	0.00		0.00	0.00		0.00	0.00		0.00	0.00	**	0.01	0.00	***	-0.01	0.00	***	-0.01	0.00	***		
	0.00	0.00		0.00	0.00	**	0.00	0.00	**	0.00	0.00		0.00	0.00		0.00	0.00		0.00	0.00			
ECON: Economic Background																							
Unemploy Rt (t-1)	-0.31	0.07	***	-0.99	0.21	***	0.37	0.13	***	0.88	0.14	***	4.01	0.30	***	-3.99	0.34	***	-2.24	0.30	***		
Median Inc. (t-1)	(omitted)			(omitted)			(omitted)			(omitted)			(omitted)			(omitted)			(omitted)				
Emp Density (t-1)	(omitted)			(omitted)			(omitted)			(omitted)			(omitted)			(omitted)			(omitted)				
DEMO: Demographics																							
% 60+ (t-1)	(omitted)			(omitted)			(omitted)			(omitted)			(omitted)			(omitted)			(omitted)				
% African Am. (t-1)	(omitted)			(omitted)			(omitted)			(omitted)			(omitted)			(omitted)			(omitted)				
% Hispanic Am. (t-1)	(omitted)			(omitted)			(omitted)			(omitted)			(omitted)			(omitted)			(omitted)				
% male (t-1)	(omitted)			(omitted)			(omitted)			(omitted)			(omitted)			(omitted)			(omitted)				
Constant & Model Diagnostics																							
Constant	0.12	0.03	***	0.55	0.08	***	0.20	0.05	***	0.00	0.06		-	0.12	***	0.90	0.14	***	0.46	0.12	***		
	0.03			0.08			0.04			0.06			0.29			0.36			0.15				
sigma_u																							

sigma _e	0.02		0.05		0.03		0.04		0.08		0.09		0.08	
rho	0.72		0.69		0.57		0.71		0.93		0.94		0.78	
F test that all u _i =0: F(36, 289)	6.2	***	9.02	***	3.13	***	6.07	***	10.38	***	19.7	***	5.14	***
Number of obs	333		333		333		333		333		333		333	
Number of groups	37		37		37		37		37		37		37	
R-Sq Within	0.41		0.37		0.21		0.52		0.82		0.76		0.58	
R-Sq Bwtween	0.04		0.01		0.04		0.03		0.31		0.42		0.01	
R-Sq Overall	0.04		0.08		0.01		0.12		0.08		0.00		0.12	
F(7,4507) corr(u _i , Xb)	29	***	24	***	11	***	45	***	183	***	133	***	58	***
	-0.64		-0.56		-0.80		-0.73		-0.83		-0.82		-0.81	

Table F. WFH Effects on Small Business Performa, population-averaged generalized linear panel-data models with the GEE approach

	No Cash Flow			Cash Flow foe 1-4 Weeks			Cash Flow for 1-2 Months			Cash Flow for 3+ Months			Increase Operating Revenue			Temporary Closure			Disruption in Supply Chain		
	Model (30)			Model (31)			Model (32)			Model (33)			Model (34)			Model (35)			Model (36)		
	Coef.	St. Er.		Coef.	St. Er.		Coef.	St. Er.		Coef.	St. Er.		Coef.	St. Er.		Coef.	St. Er.		Coef.	St. Er.	
WFH: Work From Home																					
WFH (t-1)	0.02	0.04		0.08	0.12		0.01	0.07		0.22	0.08	**	0.50	0.22	**	-0.39	0.26		-0.36	0.20	*
Time Effects																					
afterSHO (t-1)	-0.02	0.00	***	-0.04	0.01	***	0.02	0.01	***	0.05	0.01	***	0.10	0.01	***	-0.10	0.02	***	-0.08	0.01	***
COVID: COVID-19 Pandemic Severity																					
New Case / 1k (t-1)	0.03	0.02		0.11	0.07		-0.09	0.04	**	-0.03	0.05		0.14	0.11		-0.26	0.12	**	0.14	0.10	
Death Rt (t-1)	0.77	0.26	***	1.56	0.89	*	0.36	0.50		-1.89	0.62	***	2.33	1.94		-2.59	2.23		3.91	1.53	***

exposure / 1k (t-1)	0.00	0.00		0.00	0.00		0.00	0.00		0.00	0.00		0.01	0.00	***	-0.01	0.00	***	0.00	0.00	**
Days Decr. (t-1)	0.00	0.00	*	0.00	0.00	***	0.00	0.00	***	0.00	0.00	*	0.00	0.00		0.00	0.00		0.00	0.00	
ECON: Economic Background																					
Unemploy Rt (t-1)	-0.11	0.04	***	-0.54	0.14	***	0.14	0.08	*	0.62	0.10	***	3.72	0.28	***	-3.68	0.33	***	-1.56	0.23	***
Median Inc. (t-1)	0.00	0.00		0.00	0.00	***	0.00	0.00	**	0.00	0.00		0.00	0.00	*	0.00	0.00	**	0.00	0.00	
Emp Density (t-1)	0.00	0.00	***	0.00	0.00	***	0.00	0.00		0.00	0.00		0.00	0.00		0.00	0.00		0.00	0.00	
DEMO: Demographics																					
% 60+ (t-1)	0.11	0.11		0.01	0.46		-0.21	0.20		-0.60	0.32	*	-3.34	2.75		4.75	3.32		1.08	0.96	
% African Am. (t-1)	0.08	0.03	***	0.19	0.11	*	-0.08	0.05		-0.25	0.08	***	-1.05	0.70		1.09	0.85		0.36	0.24	
% Hispanic Am. (t-1)	0.10	0.02	***	0.05	0.09		0.04	0.04		-0.14	0.06	**	-0.90	0.49	*	1.01	0.59	*	0.16	0.17	
% male (t-1)	0.54	0.45		0.56	1.78		-0.89	0.80		-1.79	1.24		-5.05	9.46		3.34	11.40		2.08	3.63	
Constant & Model Diagnostics																					
Constant	-0.29	0.24		0.28	0.96		0.68	0.43		1.05	0.67		2.28	5.20		-2.92	6.27		-1.13	1.96	
Number of obs	333			333			333			333			333			333			333		
Number of groups	37			37			37			37			37			37			37		
Link:	identity			identity			identity			identity			identity			identity			identity		
Family:	Gaussian			Gaussian			Gaussian			Gaussian			Gaussian			Gaussian			Gaussian		
Correlation:	exchangeable			exchangeable			exchangeable			exchangeable			exchangeable			exchangeable			exchangeable		
Wald chi2(13)	254	***	0	221	***	0	57	***	0	256	***	0	1254	***	0	906	***	0	321	***	0
Scale parameter:	0.00			0.00			0.00			0.00			0.06			0.08			0.01		

Table G. WFH Effects on Small Business Performa, population-averaged generalized linear panel-data models with the GEE approach, with Industry Sector Fixed Effects

No Cash Flow				Cash Flow foe 1-4 Weeks			Cash Flow for 1-2 Months			Cash Flow for 3+ Months			Increase Operating Revenue			Temporary Closure			Disruption in Supply Chain				
Model (37)				Model (38)			Model (39)			Model (40)			Model (41)			Model (42)			Model (43)				
St. Coef.		St. Er.		St. Coef.		St. Er.		St. Coef.		St. Er.		St. Coef.		St. Er.		St. Coef.		St. Er.		St. Coef.		St. Er.	
WFH: Work From Home																							
WFH (t-1)	0.00	0.01		0.11	0.07	*	0.34	0.10	***	0.20	0.09	**	0.63	0.17	***	-1.04	0.20	***	-0.55	0.19	***		
Time Effects																							
afterSHO (t-1)	0.00	0.00	***	-0.03	0.00	***	0.00	0.01		0.02	0.01	***	0.21	0.01	***	-0.22	0.01	***	-0.10	0.01	***		
COVID: COVID-19 Pandemic Severity																							
New Case / 1k (t-1)	0.02	0.01	***	0.13	0.04	***	-0.12	0.06	**	0.08	0.05		-0.25	0.11	**	0.26	0.13	**	0.22	0.13	*		
Death Rt (t-1)	0.11	0.05	**	2.21	0.49	***	2.15	0.70	***	1.34	0.63	**	13.17	1.17	***	11.92	1.34	***	5.73	1.24	***		
exposure / 1k (t-1)	0.00	0.00	**	0.00	0.00	***	0.00	0.00	***	0.00	0.00	***	0.01	0.00	***	0.00	0.00		0.00	0.00			
Days Decr. (t-1)	0.00	0.00	**	0.00	0.00	***	0.00	0.00		0.00	0.00	***	0.00	0.00	**	0.00	0.00		0.00	0.00			
ECON: Economic Background																							
Unemploy Rt (t-1)	-0.02	0.01	**	-0.11	0.08		0.34	0.11	***	0.55	0.10	***	2.01	0.19	***	-1.69	0.22	***	-1.27	0.20	***		
Median Inc. (t-1)	0.00	0.00		0.00	0.00		0.00	0.00		0.00	0.00	***	0.00	0.00	***	0.00	0.00	***	0.00	0.00			
Emp Density (t-1)	0.00	0.00		0.00	0.00	***	0.00	0.00	***	0.00	0.00	**	0.00	0.00	**	0.00	0.00	***	0.00	0.00			
Industry	Yes			Yes			Yes			Yes			Yes			Yes			Yes				
DEMO: Demographics																							
% 60+ (t-1)	0.02	0.02		-0.55	0.27	**	-1.59	0.37	***	-1.47	0.33	***	0.61	0.53		2.57	0.58	***	0.80	0.47	*		
% African Am. (t-1)	-0.01	0.01		-0.14	0.08	*	-0.25	0.10	**	-0.40	0.09	***	-0.38	0.15	**	0.56	0.17	***	0.32	0.14	**		
% Hispanic Am. (t-1)	0.01	0.00	**	0.41	0.05	***	0.44	0.06	***	0.25	0.06	***	-0.95	0.10	***	0.85	0.11	***	0.27	0.09	***		
% male (t-1)	-0.01	0.11		-5.55	1.31	***	-8.89	1.79	***	-7.90	1.60	***	5.04	2.66	*	4.18	2.93		5.33	2.45	**		

Constant & Model Diagnostics																					
Constant	0.00	0.05		2.74	0.68	***	4.42	0.93	***	4.11	0.84	***	-3.37	1.39	**	-3.14	1.53	**	-3.09	1.27	**
Number of obs	2909			2909			2909			2909			2909			2909			2909		
Number of groups	414			414			414			414			414			414			414		
Link:	identity			identity			identity			identity			identity			identity			identity		
Family:	Gaussian			Gaussian			Gaussian			Gaussian			Gaussian			Gaussian			Gaussian		
Correlation:	exchangeable			exchangeable			exchangeable			exchangeable			exchangeable			exchangeable			exchangeable		
Wald chi2(13)	142	***	0	461	***	0	394	***	0	428	***	0	1241	***	0	1819	***	0	2603	***	0
Scale parameter:	0.00			0.01			0.02			0.02			0.06			0.08			0.08		

Figures

Figure 1

Trend of WFH, COVID severity, Unemployment, March 21-July 28, 2020

Figure 2

Marginal Effect of the End of SHO on WFH based on Model (4)

Note: This graph omitted observations for WFH rate below 3% and above 50% (i.e., omitting two tails at 2% and 51-56%) because those observation only represent 0.7% of the observations, but have a much larger and more dramatic effect from WFH rates. Presenting those in the graph will visually inflate the WFH effects.

Figure 3

WFH Rate Effects on Small Business' Cash Flow, Based on Models (12)-(15)

For WFH Rate between 3-50% (99.3% of observation)

For All WFH Rates (2-56%)

Figure 4

WFH Effects on Small Business' Operating Revenue Increase, Based on Model (16)

For WFH Rate between 3-50% (99.3% of observation)

For All WFH Rates (2-56%)

Figure 5

WFH Rate Effects on Small Business' Temporary Closure, Based on Model (17)

For WFH Rate between 3-50% (99.3% of observation)

For All WFH Rates (2-56%)

Figure 6

WFH Rate Effects on Small Business' Disruption in Supply Chain, Based on Model (18)