



Working from home: small business performance and the COVID-19 pandemic

Ting Zhang · Dan Gerlowski · Zoltan Acs

Accepted: 6 April 2021 / Published online: 25 April 2021

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Abstract During the COVID-19 pandemic, many firms began operating in a working-from-home environment (WFH). This study focuses on the relationship between WFH and small business performance during the pandemic. We built a theoretical framework based on firm profit maximization, compiled an up-to-date (March through November) real-time daily and weekly multifaceted data set, and empirically estimated fixed-effect panel data, fractional logit, and multilevel mixed effects models to test our hypotheses. We find that in states with higher WFH rates, small businesses performed better overall with industry variations, controlling for the local pandemic, economic, demographic, and policy factors. We also find that WFH rates increased even after stay-at-home orders (SHOs) were rescinded. With the ready technology and practice of WFH in the pandemic, our robust empirics confirm our theory and hypotheses and demonstrate WFH as a potential force that may expedite “creative destruction” instance and permanently impact industrial structure and peoples’ work lives.

Plain English summary The Rise of Working from Home (WFH) as a Silver Lining and “Creative Destruction” in the Pandemic: WFH Helps Small Businesses Perform Better with Industry Variations and Continues to Shine after Stay-at-Home Orders Ended. This study focuses on the role of working from home (WFH) for small business performance during the COVID-19 pandemic. We built a theoretical framework based on firm profit maximization and identified WFH as a rational business choice. We then compiled a real-time multifaceted data set, estimated panel fixed-effect, fractional logit, and multilevel mixed effects models, and find that (1) small businesses in states with higher WFH rates performed better with industry variations, controlling for local pandemic and socioeconomic factors; and (2) WFH rates increased after stay-at-home orders were rescinded. Our study demonstrates WFH as a potential “creative destruction” force that may expedite our technologically ready WFH adoption and permanently impact industrial structure and peoples’ work lives.

T. Zhang (✉)
Merrick School of Business, University of Baltimore, 1420 N.
Charles Street, Baltimore, MD 21201, USA
e-mail: tzhang@ubalt.edu

D. Gerlowski
Merrick School of Business, University of Baltimore, 1420 N.
Charles Street, Baltimore, MD 21201, USA

Z. Acs
Center for Entrepreneurship and Public Policy, Schar School of
Policy and Government, George Mason University, 3351 Fairfax
Dr., MS 3B1, Arlington, VA 22201, USA

Keywords Work from home · COVID-19 · Small business · Stay-at-home order

JEL classifications O33 · L25 · L16 · M54 · L26

1 Introduction

One disruption that the COVID crisis brought to our economy is a much more widespread acceptance and use of the working-from-home environment (WFH).

Dingel and Neiman (2020) found that 37% of jobs in the United States can be performed entirely at home, with variation across cities and industries. Bartik, Cullen, et al. (2020b) report that 45% of firms have at least some workers 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 pandemic. Gallup Panel (2020) revealed that the percentage for WFH American workers doubled to over 60% between mid-March and early April 2020, and 59% US workers who have been teleworking during the pandemic would prefer to continue WFH as much as possible, once public health restrictions are lifted (Bremner, 2020).

While a rising number of businesses adopt WFH, the WFH's impact on small businesses is unknown. While small businesses employ almost 50% of American workers (Bartik, Bertrand, et al., 2020), in economic crises small businesses are typically more vulnerable than larger firms (Kennickell et al., 2017; Kolasa et al., 2010) and disproportionately negatively affected despite a relative growth advantages due to flexibility (Bartz & Winkler, 2016). Using a survey at the beginning of the COVID Pandemic, Bartik, Cullen, et al. (2020c) demonstrated the financial fragility of small businesses and this fragility may be a barrier if WFH is costly to firms. This could partially explain Aguilerra's (2016) finding that teleworking is more frequent in larger companies. Small businesses often do not have as much resources as larger businesses to build robust WFH infrastructure (Vilhelmson & Thulin, 2016). If WFH could help small businesses, it would help larger business even more. With the most current data available from the Small Business Pulse Survey, we are able to examine the WFH's impact on small businesses.

This paper therefore focuses on examining (1) whether the WFH environment helps small businesses perform better during the pandemic with expected industry variation and (2) whether WFH rates remain rising after stay-at-home mandates are removed, as a testable implication of (1). If both are true, the COVID-19 pandemic may expedite the WFH environment as a new norm that we were technically ready but hesitant to adopt. It could be an example of a Schumpeterian (1934) "creative destruction". The long run implications are numerous for workplaces, lifestyles, and urban planning.

While many studies on WFH have emerged recently, this study is the first that builds a theoretical framework and empirically tests hypotheses with real-time data

addressing WFH as an opportunity to improve small business performance in the COVID crisis. Based on firm profit maximization, the study builds a theoretical framework subject to variable business costs, working hours, wages, and a contagion agglomeration parameter, and demonstrates conditions when WFH is a rational choice for businesses. A date set is compiled with up-to-date real-time daily and weekly multifaceted data elements from March 20, 2020, through November 9, 2020. Using the data, we empirically test our hypotheses through fixed-effects panel data (FEP) models, fractional logit models (FLMs), and multilevel mixed effect (MLM) models with various specifications.

The next section focuses on our theoretical framework, followed by a statement of our hypotheses. Then we describe our empirical methodology, data sources, and present our findings. After controlling for the local pandemic, economic, demographic, and policy factors, we find that (1) small businesses in states with higher WFH rates are less likely to have declines in operating revenue, disruptions of supply chain, and worse cash flow positions overall across all industries; (2) the higher WFH rates during the pandemic are associated with less declines in operating revenue for small businesses in *Professional Services*, *Wholesale*, and *Retail Trade*, but more closures in *Construction* and *Health Services*, and more supply chain disruptions in *Accommodation and Food Service*; and (3) after the stay-at-home orders (SHOs) ended, WFH rates continue to rise.

2 Theoretical framework

Our theoretical approach is cast in a basic firm revenue–expense accounting framework where firms are assumed to be profit-maximizing entities. The approach is consistent with a firm choosing to continue operations during the pandemic, migrating from a traditional office (O) setting to a WFH (H) setting as an unconstrained decision. Considering the four key factors of production for a firm—labor (L), capital (K), land (G), and entrepreneurship (E) (Bade & Parkin, 2018), under a given technological condition (X), a firm's output is the revenue produced, represented by $R(L, K, G, E, X)$.

We include a geographically agglomeration impact similar to that of Krugman (1996) and Glaeser (1999) and with networking and knowledge spillovers (Acs et al., 2009), affected by the pandemic severity (P). The agglomeration effect for the office setting $A(P)^O$ is

decreasing with the pandemic severity as required social distancing and other protective policies and practices diminish the traditional physical proximity based agglomeration impacts. The agglomeration impact for WFH is different than the office setting, and $A(P)^H$ relies on physical proximity, pandemic severity, and residential economic and demographic conditions. A firm’s total revenue in a WFH setting is thus $A(P)^H * R^H(L^H, K^H, G^H, E^H, X^H)$ and in the office setting is $A(P)^O * R^O(L^O, K^O, G^O, E^O, X^O)$.

Considering that most of firms’ fixed costs are already paid, comparing to revenue, the home and office scenarios’ variable costs of $L, K,$ and $G,$ represented respectively as wage (W), capital (K), and rent (G), are of primary importance. We designate entrepreneurship (E) as the decision making process and the control of the firm. We assume that under either the WFH or the office scenarios the entrepreneurship contribution would be the same, that $E^H = E^O = E$. We also factor the contribution of technology (X) into labor (L) through enhancing workers’ intellectual capital, human capital, or skills (I). Therefore, the marginal labor productivity depends on $IX,$ i.e., $I(X)$. We specify a firm’s variable revenue as a product of labor hours (T) and marginal productivity, $I(X)$, per hour: $I(X)*T$.

A profit maximizing firm would then choose WFH if the ratio of variable revenue to variable cost is larger for the WFH setting (H) than that for the traditional office setting (O), i.e.,

$$A(P)^H \frac{I(X)^H * T^H}{W^H * K^H * G^H} \geq A(P)^O * \frac{I(X)^O * T^O}{W^O * K^O * G^O} \tag{1}$$

Inequation (1) can be further transformed into

$$\frac{I(X)^H}{I(X)^O} * \frac{T^H}{T^O} * \frac{W^O}{W^H} * \frac{K^O}{K^H} * \frac{G^O}{G^H} * \frac{A(P)^H}{A(P)^O} \geq 1 \tag{2}$$

Each of the ratios can offer a theoretical perspective comparing WFH (H) to the traditional office (O) setting. Compared to the traditional office setting, employers of WFH jobs are likely to find a larger labor search pool and a potentially better intellectual capital match since it is not as geographically constrained, enabling selection of higher productivity workers and implying $I(X)^H > I(X)^O,$ or $\frac{I(X)^H}{I(X)^O} > 1$. This echoes a 13% employee productivity increase from WFH noted by Bloom et al. (2015), due in part to fewer breaks and sick days. Consistent with 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 & Horvath, 2008).

As for hours committed to work, many WFH workers may feel the need to reciprocate the privilege of WFH in flexibility, autonomy, and saved commuting time by working longer hours and/or harder work (Gajendran & Harrison, 2007). This mirrors longer reported working hours for WFH workers found by Kelliher and Anderson (2010) and Mariani (2000) or situation of “hard to plug off work” identified in a e 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., $\frac{T(P)^H}{T(P)^O} > \frac{T^H}{T^O} > 1$. Barrero et al. (2020) found that during the first 7 months of the COVID pandemic, the shift to WFH saved 60 million hours of commuting time per day, of which 25% went to more time spent at their primary jobs. DeFillipis et al. (2020) find that WFH workers’ behavior changed in terms of collaboration, with more but shorter meetings, and small but significant increases in the workday (8.2% or 48.5 min) before and after the lockdowns.

With a wider labor pool to pick from, employers could potentially push the wage rate from WFH labor lower. As Mas and Pallais (2017) found, an average worker is willing to give up 8% of wages for WFH. This percentage could be much higher facing a pandemic health threat and high unemployment. 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 $\frac{w(P)^O}{w(P)^H} > \frac{w^O}{w^H} > 1$.

For traditional office settings, business owners are obligated for capital, Administrative and 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 is often lower for employers: some employers might reimburse some home office supply and equipment costs (including the technology cost to facilitate WFH), but typically not utility costs (e.g., electricity, gas, internet, telephone, and insurance) or time spent managing those costs. For most small businesses, the potentially saved A&G costs could be even more

important and the technology requirement for WFH might not have to be expensive with current advances in technology. Therefore, those capital and A&G costs (K) 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 & Kok, 2014) may result in some cost of organizational change and technological investments (see Aguilera et al., 2016) which could somewhat offset the WFH A&G cost advantage. However, in the COVID pandemic, the social distancing requirements (for at least 6 ft), the cost for Personal Protective Equipment, makes the $K(P)^O$ larger, i.e., $\frac{K(P)^O}{K(P)^H} > 1$. 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 (G), either rents or mortgages (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 is often not reimbursed by the employers. Therefore G^H is basically close to 0, except for essential or headquarter offices. Matthews and 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, G^O , is *considerably* larger than the almost-0 home offices land cost for WFH, G^H . With a close to 0 denominator, $\frac{G^O}{G^H}$ is reaching positive infinity, i.e., $\frac{G^O}{G^H} \rightarrow +\infty$.

Given the benefit of agglomeration effect in office (versus home) settings with more business network and resources close, we believe $\frac{A(P)^H}{A(P)^O} < 1$. With the growing technology conditions (X), the advantage of $A(P)^O$ over $A(P)^H$ may decline; the likelihood of contagion for WFH workers could be enhanced by web meeting benefits such as recorded sessions, meeting transcripts, saved whiteboard images for needed review. In the pandemic, social distancing dramatically compromises $A(P)^O$.

For the above six ratios, four of them, $\frac{I(X)^H}{I(X)^O}$, $\frac{T^H}{T^O}$, $\frac{W^O}{W^H}$, $\frac{K^O}{K^H}$, are larger than 1; one, $\frac{G^O}{G^H}$, approaches positive infinity; and only one, $\frac{A(P)^H}{A(P)^O}$, is potentially less than 1.

The product of the six ratios is then most likely larger than 1, i.e., $\frac{I(X)^H}{I(X)^O} * \frac{T^H}{T^O} * \frac{W^O}{W^H} * \frac{K^O}{K^H} * \frac{G^O}{G^H} * \frac{A(P)^H}{A(P)^O} > 1$. As a result, a rational employer would most likely choose WFH over traditional office work.

3 Hypotheses

In a pandemic, it is often expected that a small business might close. Bartik, Bertrand, et al. (2020) reported 43% of small businesses they surveyed did temporarily close and cited fragile financing with less than one month of cash on hand. A study by Belzunegui-Eraso and Erro-Garcés (2020) showed that WFH is being adopted by many companies to keep productivity up during the crisis, contributing to a lessened decline to GDP as a result of the crisis. This mirrors earlier findings of a higher productivity from WFH (see Bailey & Kurland, 2002; SHRM, 2018) due to less absenteeism (Kitou & Horvath, 2008), saved turnover cost from less commute and stress (Redman et al., 2009) and better work-life balance (Wheatley, 2012). We believe WFH can mitigate some of the negative economic impact from the COVID shock and help small businesses performance during the pandemic.

The performance of small businesses may be measured in several ways. We adopt four measures: changes in operating revenues, disruptions in the supply chain, temporary closures, and cash flow positions. Closures have important implications for the US workforce; cash flow positions often signal time-to-failure for small businesses; operating revenue directly measure business income; disruptions in supply-chain is a sign of challenges posed by issues at other businesses and have implications about the economy as a whole (Buffington et al., 2020).

Recent research has also indicated that the impact of the WFH varies by industry sectors. Dingel and Neiman (2020) demonstrated industry sector variations in WFH propensities: jobs in sectors such as *Educational Services* and *Professional Services* are most likely to be done at home, while jobs in nonagricultural sectors such as *Accommodation and Food Services*, *Retail Trade*, and *Construction* are least likely to be done at home. Bartik, Cullen, et al. (2020b) also noted industries that are better suited to remote work seem to experience less productivity loss when switching to remote work in the pandemic.

Based on prior research we argue that the performance of small businesses during the pandemic will be enhanced by adoption of a WFH environment, but that industry variations will be present. Formally, we hypothesize the following:

Hypothesis 1: A higher (versus lower) WFH rate is associated with better small business performance, with variations by industry sectors. Better performance refers to a lower probability of closures, disruption in supply chain, or reduction in operating revenues, but better cash flow positions, controlling for local pandemic, economic, demographic, and policy conditions.

Many firms did not adopt WFH before the pandemic either because of ignorance or coordination issues (Bartik, Cullen, 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 (Bartik et al., 2020b), the related work coordination, and the enhanced awareness of the WFH advantages explained above may make WFH a real optimal for many businesses without having to readapt to daily face-to-face work. Following our theoretical framework and Hypothesis 1, businesses will eventually recognize cost efficiencies and productivity gains possible in a WFH environment and choose that environment for the future. Given the ongoing pandemic we cannot consider a long run outcome; however we can, in the context of the ongoing pandemic specify a testable implication of our Hypothesis 1:

Hypothesis 2: The WFH rate would not drop after the stay-at-home order (SHO) ended after controlling for the local pandemic, economic, and demographic conditions.

Empirical support for Hypothesis 2 could reflect a potential work paradigm change even beyond the pandemic. It is possible that the exogenous shock from the pandemic would invoke a Schumpeterian creative destruction scenario moving the world to a potential new post-COVID WFH-dominated work norm.

4 Methodology

To test our hypotheses, our empirical models include three types: the fixed-effect cross-section time-series

panel-data (FEP) model, fractional logit regression models (FLMs), and multilevel-mixed effects (MLM) models. Our variables reflect some key measures in our theoretical framework. Our data covers from March 21 through November 9, 2020, including daily and weekly data depending on availability and data cuts.

4.1 Empirical models and variables

To test Hypothesis 1, we modeled the sensitivity of states' WFH rates on small business performance overall and by 2-digit industry sectors, controlling for local demographic, economic, pandemic, and policy conditions. Our dependent variable is business performance, $Business_{jt}$, which is measured in four different ways: changes in operating revenue, disruption of supply chain, business closures, and cash flows. Those four measures reflect business output R in our theoretical framework. With cross-sectional time-series data, we first estimated our base model, the FEP model. Considering the fact that states' demographic and some local socioeconomic conditions do not vary by days or weeks, fixed effects models could be limited.

Since our dependent variable measures of $Business_{jt}$ are proportions ranging from 0 to 1, we estimated FLMs, following Wooldridge (2011) who applied a FLM methodology to analyze the proportion of employees that participate in a company's pension plan. Our FLM is shown below:

$$\begin{aligned} \text{logit}(Business_{jt}) = & \beta_0 + \beta_1 WFH_{j(t-1)} + \beta_2 AfterSHO_{jt} \\ & + \gamma_i \sum_{i=1}^4 COVID_{j(t-1)} + \eta_i \sum_{i=1}^3 ECON_{j(t-1)} \quad (3) \\ & + \theta_i \sum_{i=1}^4 Demographics_{j(t-1)} + \delta_i \sum_{i=1}^4 FIN_{j(t-1)} \\ & + \omega_i + \nu_j + \varepsilon_{jt} \end{aligned}$$

$WFH_{j(t-1)}$ denotes WFH rate in the immediately prior period and is the independent variable, corresponding to the scenario represented by superscript H in our theoretical framework. A higher $WFH_{j(t-1)}$ is expected to associate with better performance. ω_i and ν_j , respectively capture other unobserved location and time fixed effects changing through time or across states. The fixed time effect also helps capture the unobserved global effect that does not vary in individual states. ε_{jt} is the idiosyncratic error term.

Our control variables also reflect our theoretical model parameters. $AfterSHO_{jt}$ is a binary policy variable labeling the ending of the SHO mandate in each state j and during time period t and $COVID_{j(t-1)}$ contains 4

measures of pandemic severity; both control for pandemic conditions (P) and are related to the agglomeration effect (A) mentioned in our theoretical framework. The ending of SHO allows for greater proximity and increasing agglomeration (A) impacts, while an increase in pandemic severity will encourage people to remain more isolated. The agglomeration effect (A) is captured by control variables $ECON_{jt}$ and $Demographics_{jt}$. $ECON_{jt}$ captures three local macroeconomic condition measures and $Demographics_{jt}$ incorporates four demographic attributes; both controls for the business ecosystem for agglomeration (A). We assume agglomeration (A) reflect individuals' response to sociodemographic environment and pandemic severity.

To test for variations by industry sectors, the second part of Hypothesis 1, we apply the FLM to each 2-digit-NAICS-coded industry sector and observe the varying estimates of β_1 . Considering that fact that our business data can be broken down by industry sectors, this allows for hierarchical data structure (by state, industry, as well as time). We also estimated MLM models that allow for unbalanced panels and random effects with across industry sectors following Raudenbush (1993) and Zhang and Acs (2018). As our theoretical framework noted, WFH is subject to agglomeration effects under local labor market and industry sector conditions. 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 model 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. MLM models contain variations both across states (fixed state effects) and across industry sectors (random industry sector effects):

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

In our MLM models, states are conditional on a set of random effects μ_{kt} , for $k = 1, \dots, n$ industry sectors, with industry sector k 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.

To test Hypotheses 2, we adopted the similar models, but changed the dependent variable into the WFH_{jt} in each state and changed the independent variable into $AfterSHO_{jt}$. The corresponding FLM and MLM models are respectively

$$\begin{aligned} \text{logit}(WFH_{jt}) = & \beta_0 + \beta_1 AfterSHO_{jt} \\ & + \gamma_i \sum_{i=1}^4 COVID_{j(t-1)} \\ & + \eta_i \sum_{i=1}^3 ECON_{j(t-1)} \\ & + \theta_i \sum_{i=1}^4 Demographics_{jt} + \omega_t \\ & + v_j + \varepsilon_{jt} \end{aligned} \quad (5)$$

$$\begin{aligned} WFH_{jkt} = & \beta_0 + \beta_1 AfterSHO_{jkt} \\ & + \gamma_i \sum_{i=1}^4 COVID_{jk(t-1)} \\ & + \eta_i \sum_{i=1}^3 ECON_{jk(t-1)} \\ & + \theta_i \sum_{i=1}^4 Demographics_{jkt} + Z_{jkt} \mu_{kt} \end{aligned} \quad (6)$$

In Eqs. (5) and (6), we expect the coefficient β_1 will be nonnegative. Since business and industry sector data only exist in weekly data, Eqs. (3), (4), and (6) only apply to weekly data; Eq. (5) use both daily and weekly data. For robustness check, in addition to running three types of models with model diagnostics, we also estimated models with different variable specifications and with daily versus weekly data.

4.2 Data sources and variable measures

Since business data are only offered at weekly level, our models to test Hypothesis 1 used weekly data by state for 18 weeks during the pandemic: April 26 through June 27 (Wave 1) and August 9 through October 12, 2020 (Wave 2). To test Hypothesis 2, we used daily and weekly data from March 21 when the first state started the SHO till November 9, 2020. Our data comes from multiple data sources, but all details are aggregated at the state level. Most of the data are expressed as proportions in each state. Different data sets are matched by state and date (or week).

The data for small business performance measures are from the US Census Bureau weekly Small Business Pulse Survey (SBPS). All the business performance measures are in proportions of surveyed small businesses in a specific states during a specific week. The survey targets toward all nonfarm, single-location employer operating small businesses with 1–499 employees and receipts of \$1000 or more in the 50 states, DC, and Puerto Rico. Those businesses are tracked and surveyed weekly throughout the observing period. For those single-establishment small businesses, the decision to choose WFH often falls on business owners or top executives, consistent with this survey design. 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 longitudinal 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 has a potential selection issue, if businesses willing to participate in email-based surveys are systematically different from other businesses. The SBPS may be subject to nonresponse 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 reweighted to adjust for nonresponse 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. The set of businesses in the SBPS target population of the survey were approximately 1.7 million firms with between 1 and 499 employees of the over 6 million single-establishment employer businesses from the respondents to the 2017 Economic Census that utilized an all-electronic data collection strategy. Eligible respondents to the Economic Census went through authentication process with a valid email address. The number of active, in-scope businesses with valid email addresses totaled about 940,500 businesses.

Our business performance measures, $Business_{jkt}$, include the percentages of small business that experienced or did not experience reduction in (1) *operating revenues*, (2) *closures*, (3) *disruptions in supply chain*, or

had (4) *no cash flow* or *cash* on hand for 1–4 weeks, 1–2 months, or 3 months *or more* during the pandemic.

Data for our key variable, WFH_{jkt} , 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. 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 (Zhang et al., 2020). 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 US Department of Transportation Federal Highway Administration's Exploratory Advanced Research Program project².

For the four pandemic severity measures, $\sum_{i=1}^4 COVID_{j(t-1)}$, two of them, *COVID new cases* and *COVID death rate*, are from widely used Johns Hopkins University (JHU) Center for Systems Science and Engineering (CSSE). Table 1 explains the detailed measures. Data for the other two, *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 period³. 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. 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 *COVID exposure* measure.

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"

³ See <https://www.whitehouse.gov/openingamerica/>

For the economic and demographic data, $\sum_{i=1}^3 ECON_{j(t-1)}$ and $\sum_{i=1}^4 Demographics_{jkt}$ respectively, the *unemployment rates* are weekly from the US Department of Labor (USDOL). The *median household income* and all demographic data are from the ACS. *Employment density* information is from the US Environmental Protection Agency (EPA)'s Smart Location Database (SLD). It captures jobs per thousand acre on unprotected land. To be consistent with other measures, those COVID, economic, and demographic measures are also in proportions for each state. Table 1 lists the data source, type, time periods, and measure for each variable.

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

5 Findings

Although most of our data, except for the business data, has two cuts: (1) daily data from March 20 to November 9, and (2) weekly from April 19 to October 12; the data attributes do not change substantially. For the *daily* data, there are 8399 observations with vast disparities across states, 76% of which are after the SHO ended. Over our observation period, averagely 25% 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%; Although this WFH rate is lower than some recent studies' estimate, this WFH rate is among the US *workforce*, not *workers*, for *March through November*, and it is from location based *mobile device records compounded with administrative records* instead of *opinion surveys*⁴. Only 2% small business reported no cash flow, but three quarters reported cash flow, almost evenly distributed to last 1–4 weeks, 1–2 months, or 3 or more months. In total, 73% of those businesses reported requesting financial assistance from the Paycheck Protection Program (PPP). Table 2 presents the summary statistics. Appendix Table 6 presents

the correlation matrix between those variables. We do not detect concerns for multicollinearity.

Table 3 presents our FLM estimates for the WFH rate effect on small business performance based on Eq. (3), testing the first half of Hypothesis 1. A higher WFH rate in a state is associated with a lower percentage of small businesses to have reduced operating revenue or disruption in supply chain and a higher percentage of small businesses with cash flow lasting for a longer period. This FLM finding is similar to the FEP and MLM model findings, as shown in the Appendix Tables 7 and 8, respectively. This is expected in Hypothesis 1. Specifically, based on the FLMs, one percentage point increase in a state's WFH rate lowers the log of odds for reduced operating revenue by 1.38, for disruption in supply chain by 0.85, and raises the log of odds for cash flow lasting 1–4 weeks, 1–2 months, and 3 or more months respectively by 0.79, 0.52, and 0.83, when controlling for local pandemic, economic, demographic and policy conditions. However, the WFH effects on business closures is statistically insignificant. This could be related to the fact that the SBPS questions changed for business closure measure from Wave 1 Survey to the Wave 2 Survey.

Those WFH effects are visualized in Fig. 1. The vertical height shows the marginal WFH effect on each business performance measure by percentage point of WFH rate, based on the FLM estimates. The band width shows the 95% confidence interval with the mean marginal WFH effect shown in the middle of the band.

Table 4 compares the WFH effects, β_1 in Eq. (3), across each 2-digit-NAICS-coded industry sector⁵, testing the latter half of Hypothesis 1. On the one hand, for sectors with a high WFH propensity according to Dingel and Neiman (2020), such as *Professional Services* (54⁶) and even *Wholesale Trade* (42), a higher WFH rate reduces the odds of declined operating revenue and elevates the odds with cash flow; on the other hand, for sectors with low WFH propensity, a higher WFH rate is associated with a higher odds of supply chain disruptions in *Accommodation* (72) and a higher odds of closures in *Construction* (23) and *Health Services* (62). This supports the latter half of Hypothesis 1. There are much more nuances in each industry sector. In *Retail Trade* (44–45) that has a relatively low WFH

⁴ Also it is an *arithmetic average* across states, not a *weighted mean* across states or across all surveyed individuals

⁵ The details for the models across each individual industry sectors are available from corresponding authors upon requested

⁶ The number in the parenthesis is the 2-digit NAICS code

Table 1 Data sources, types, time periods, and 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	3/21–11/9, daily	Continuous (%)
AfterSHO: stay-home order mandate				
afterSHO	=1 if after a state's stay-home order end date	IHME	3/21–11/9, daily	Dummy
Business: business performance measures				
Reduced Operating Revenue	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; 8/9–10/12, weekly	Continuous (%)
Closures	Percentage of businesses reported "yes" (+) or "no" (-) to the question "In the last week, did this business temporarily or permanently close any of its locations for at least one day?"	SBPS	4/26–6/27; 8/9–10/12, weekly	Continuous (%)
Disruption in Supply Chain	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; 8/9–10/12, weekly	Continuous (%)
No Cash Flow	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; 8/9–10/12, weekly	Continuous (%)
Cash Flow for 1–4 Weeks	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; 8/9–10/12, weekly	Continuous (%)
Cash Flow for 1–2 Months	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; 8/9–10/12, weekly	Continuous (%)
Cash Flow for 3+ Months	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; 8/9–10/12, 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	3/20–11/9, 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	3/20–11/9, daily	Continuous (%)
exposure/1k	Number of residents already exposed to coronavirus per 1000 people. Calculated by MTI.	MTI	3/20–11/9, 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	3/20–11/9, daily	Continuous
ECON: economic background				
Unemploy Rt	Unemployment rate updated weekly.	USDOL	3/15–11/9, weekly	Continuous (%)
Median Inc.	Median household income (\$000) from the US Census Bureau	ACS	2018, yearly	Continuous
Emp Density	Gross employment density (jobs per 1k 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	

Table 1 (continued)

Variable name	Description	Source	Time period	Data type
				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; 8/9–10/12, 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; 8/9–10/12, weekly	Continuous (%)
Fin_SBAInForg	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; 8/9–10/12, 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; 8/9–10/12, weekly	Continuous (%)

Table 2 Descriptive statistics: variables included in all models

Variable	Data type	Obs	Mean	Std. dev.	Min	Max
WFH (t-1)	Daily	8399	0.25	0.09	0.05	0.56
afterSHO (t-1)	Daily	8399	0.76	0.43	0.00	1.00
COVID New Case/1k (t-1)	Daily	8399	0.25	0.26	0.00	1.12
COVID Death Rt (t-1)	Daily	8399	0.02	0.02	0.00	0.09
COVID Exposure/1k (t-1)	Daily	8399	15.61	11.37	0.48	52.03
COVID Days Decr. (t-1)	Daily	8399	2.05	5.16	0.00	44.00
Unemploy Rt (t-1)	Daily	8399	0.17	0.08	0.06	0.44
Median Inc.	Daily	8399	62,124	10,655	44,445	84,342
Emp Density	Daily	8399	514	2579	1	16,044
% 60+	Daily	8399	0.22	0.02	0.17	0.27
% African Am.	Daily	8399	0.12	0.11	0.00	0.46
% Hispanic Am.	Daily	8399	0.11	0.09	0.02	0.39
% male	Daily	8399	0.49	0.01	0.47	0.52
No Cash Flow	Weekly	666	0.02	0.02	0.00	0.14
Cash Flow for 1–4 Weeks	Weekly	666	0.28	0.08	0.00	0.53
Cash Flow for 1–2 Months	Weekly	666	0.28	0.04	0.00	0.43
Cash Flow for 3+ Months	Weekly	666	0.25	0.06	0.00	0.49
Reduced Operating Revenue	Weekly	666	0.42	0.15	0.18	0.81
Closures	Weekly	421	0.22	0.14	0.01	0.65
Disruption in Supply Chain	Weekly	666	0.38	0.06	0.18	0.64
Fin_PPP	Weekly	592	0.73	0.05	0.55	0.88
Fin_EIDL	Weekly	592	0.24	0.06	0.00	0.42
Fin_SBAInForg	Weekly	592	0.08	0.04	0.00	0.20
Fin_OtherFed	Weekly	592	0.02	0.02	0.00	0.10

Table 3 Fractional logit models for WFH effects on small business performance

	Decrease operating revenue, Model (1)	Disruption in supply chain, Model (2)	Temporary closures, Model (3)	No cash flow, Model (4)	Cash flow for 1–4 weeks, Model (5)	Cash flow for 1–2 months, Model (6)	Cash flow for 3+ months, Model (7)
WFH (t-1)	-1.382 (0.236)	*** -0.851 (0.173)	*** -0.078 (0.341)	0.625 (1.459)	0.790 (0.3)	*** 0.516 (0.172)	*** 0.827 (0.21)
afterSHO (t-1)	-0.326 (0.039)	*** -0.161 (0.026)	*** -0.089 (0.039)	** -1.019 (0.139)	*** -0.117 (0.04)	*** 0.023 (0.025)	*** 0.156 (0.033)
COVID New Case/1k (t-1)	-0.012 (0.068)	0.074 (0.051)	-0.480 (0.168)	*** 0.369 (0.265)	0.140 (0.075)	* -0.081 (0.043)	* -0.082 (0.059)
COVID Death Rt (t-1)	1.162 (0.87)	1.825 (0.655)	*** 2.703 (1.64)	* 7.989 (2.923)	*** 2.633 (0.966)	*** -3.028 (0.567)	*** -4.235 (0.722)
COVID Exposure/1k (t-1)	0.000 (0.002)	0.002 (0.001)	0.015 (0.002)	*** -0.011 (0.006)	* -0.005 (0.002)	** -0.001 (0.001)	0.000 (0.001)
COVID Days Decr. (t-1)	0.000 (0.002)	-0.001 (0.002)	-0.002 (0.003)	0.020 (0.009)	** 0.007 (0.003)	** -0.002 (0.001)	-0.004 (0.002)
Fin_PPP	0.305 (0.242)	-0.405 (0.21)	* -0.681 (0.394)	* -0.977 (1.474)	1.141 (0.423)	*** -0.372 (0.219)	* -0.234 (0.24)
Fin_EIDL	0.638 (0.332)	* -0.232 (0.243)	1.332 (0.392)	*** 1.804 (1.668)	-0.420 (0.423)	-0.290 (0.244)	-0.393 (0.271)
Fin_SBAInForg	0.228 (0.366)	0.380 (0.276)	0.321 (0.474)	6.689 (2.169)	*** 1.549 (0.588)	*** 0.448 (0.273)	-0.392 (0.342)
Fin_OtherFed	1.244 (0.672)	* 1.255 (0.496)	** 2.479 (1.208)	** 11.404 (2.25)	*** 2.125 (0.614)	*** 0.084 (0.393)	1.184 (0.56)
Unemploy Rt (t-1)	-0.910 (0.274)	*** -1.698 (0.185)	*** 1.613 (0.367)	*** -1.917 (1.152)	* -0.921 (0.307)	*** 0.663 (0.187)	*** 1.281 (0.237)
Median Inc.	0.005 (0.002)	*** -0.001 (0.001)	0.011 (0.002)	*** 0.015 (0.007)	** -0.011 (0.002)	*** 0.002 (0.001)	** 0.004 (0.001)
Emp Density	0.019 (0.006)	*** -0.002 (0.006)	0.044 (0.008)	*** -0.092 (0.066)	-0.087 (0.016)	*** -0.004 (0.005)	0.017 (0.007)
% 60+	1.449 (0.797)	* 1.216 (0.522)	** 3.595 (1.11)	*** 3.291 (2.95)	-0.231 (0.931)	-0.540 (0.597)	-1.380 (0.657)
% African Am.	0.439 (0.231)	* -0.032 (0.164)	-0.009 (0.295)	2.701 (0.954)	*** 0.634 (0.318)	** -0.134 (0.166)	-0.914 (0.198)
% Hispanic Am.	0.688 (0.145)	*** -0.343 (0.106)	*** -0.006 (0.197)	3.497 (0.523)	*** 0.070 (0.172)	-0.025 (0.111)	-0.296 (0.123)
% male	3.588 (3.605)	4.166 (2.492)	* -0.651 (5.262)	8.019 (16.469)	0.511 (5.402)	-1.155 (2.829)	-3.793 (3.264)
Time FE (Weeks)	-0.064 (0.004)	*** -0.021 (0.002)	*** -0.161 (0.007)	*** 0.013 (0.016)	-0.022 (0.004)	*** -0.001 (0.003)	0.024 (0.003)
State FE	0.000 (0.001)	0.000 (0.001)	-0.001 (0.001)	0.002 (0.004)	0.002 (0.001)	*** 0.000 (0.001)	-0.001 (0.001)
_cons	198.7 (11.757)	*** 64.4 (7.459)	*** 502.9 (22.489)	*** -50.1 (51.763)	68.2 (12.474)	*** 2.6 (8.092)	*** -74.2 (9.997)
Number of obs	592	592	372	592	592	592	592
Wald Chi2	2655	*** 414	*** 2698	*** 446	*** 387	*** 218	*** 414
Pseudo R2	0.047	0.004	0.099	0.059	0.015	0.002	0.006
Log pseudolikelihood	-381	-390	-171	-53	-345	-350	-335

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Robust standard errors clustered at project level in parentheses

Other control variables that are less significant in the models include COVID New Case/1k (t-1), COVID Days Decr. (t-1), Fin_EIDL, Fin_SBAInForg, Fin_OtherFed, and % male

propensity, we actually observe WFH associate with better operating revenue and cash flow positions. This could be related to the fact that during this COVID pandemic, many retail businesses adapted to WFH by changing their business delivery, which along with the vast adoption of e-commerce could have stimulated or sustained the demand from the WFH workers. While Dingel and Neiman (2020) also mentioned *Education Services (61)* is expected to benefit from WFH, we do not observe a significant effect in our data. One reason is that many states did not report data in this sector and we ended up with limited number of observations (43–126).

Table 5 shows the estimates to test Hypothesis 2 with all the three types of empirical models and two different data cuts. Across all the five models, WFH rates rose after the SHO ended, controlling for the local pandemic, economic, and demographic conditions. After the SHO ended, the WFH rate is about 1–3 percentage points higher in Models (8), (10), and (12) or with a higher log of odds by 0.12–0.19 in Models (9) and (11). This is consistent with Hypothesis 2.

Figure 2 presents this FLM effect of the SHO effect with 95% confidence interval band. After the SHO ended, the policy requirement restricting workers to commute to work was lifted. However when holding local pandemic, economic, and demographic conditions constant, this did not result in a drop in the WFH rate; instead, WFH rate continued to rise, displaying an upward sloping trend of the WFH rate after SHO end (when *AfterSHO*=1) in Fig. 2. This finding echoes the aforementioned benefit of WFH in business performance, illustrated in Table 4 and Fig. 1.

As mentioned above, our findings are similar across the FEP, FLM, and MLM models. As shown in Table 5, our daily and weekly data also generate highly similar model estimates. In fact, when we conducted FEP models (Models (8) and (10)) and FLMs (Models (9) and (11)), the data used do not have the industry sector breakdown and are not hierarchical; when we used the data with an additional level—industry sector breakdown, we ran MLM models (e.g., Model (12)). Our weekly and daily data are two separate data cuts and are not nested, but our findings are similar. This demonstrate our empirical robustness, as well as avoid data correlation noises.

In addition to using daily versus weekly data and estimating different types of models (FEP, FLM, and MLM models), for further robustness check, we also run additional FLMs removing the SHO mandate effect

(*afterSHO*) or COVID exposure measure (*COVID Exposure*). Those additional models, presented in the Appendix Table 9, have the similar findings as the FLMs in Table 3. The consistent findings across various models reflects the robustness of our models, so do the highly significant F or chi-square statistics across all models.

6 Discussion

Our empirical analysis showed that WFH is associated with overall better small business performance and is on the rise even after the SHO mandate ended, consistent with our hypotheses. This is consistent with prior studies identifying a higher productivity when adopting WFH (Bailey & Kurland, 2002; Belzunegui-Eraso & Erro-Garcés, 2020; SHRM, 2018) due to less absenteeism (Kitou & Horvath, 2008), saved turnover cost from less commute and stress (Redman et al., 2009), better work-life balance (Wheatley, 2012), and reduced the costs of pollution and urban congestion (Helminen & Ristimäki, 2007). However, adopting WFH practices often requires organizational changes, such as surveillance and control or management of the psycho-sociological distance from the work environment (Wilton et al., 2011), considering limited promotions, raises, and career success often associated with WFH (Golden & Eddleston, 2020). Otherwise, the benefit of WFH could be compromised or even lost.

Our data showed 25% of US workers worked from home during the pandemic, which is still less than the 37% jobs that can be conducted entirely from home as Dingel and Neiman (2020) noted. This is consistent with our findings that WFH is still on the rise even after SHO ended. This means WFH still has a potential room to further grow if more firms are ready for the change. The sustainability of WFH and even its further growth will call for firm human resource management (HRM) innovations to address the current concerns on managers' control and surveillance needs (Coenen & Kok, 2014), employees' career path (Golden & Eddleston, 2020), and psycho-sociological distance (Taskin & Devos, 2005; Wilton et al., 2011). Accordingly, other public policy measures related to urban planning may need to adjust. 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. (2014)], but also often blurs the boundaries between work and family (Rigotti et al., 2020).

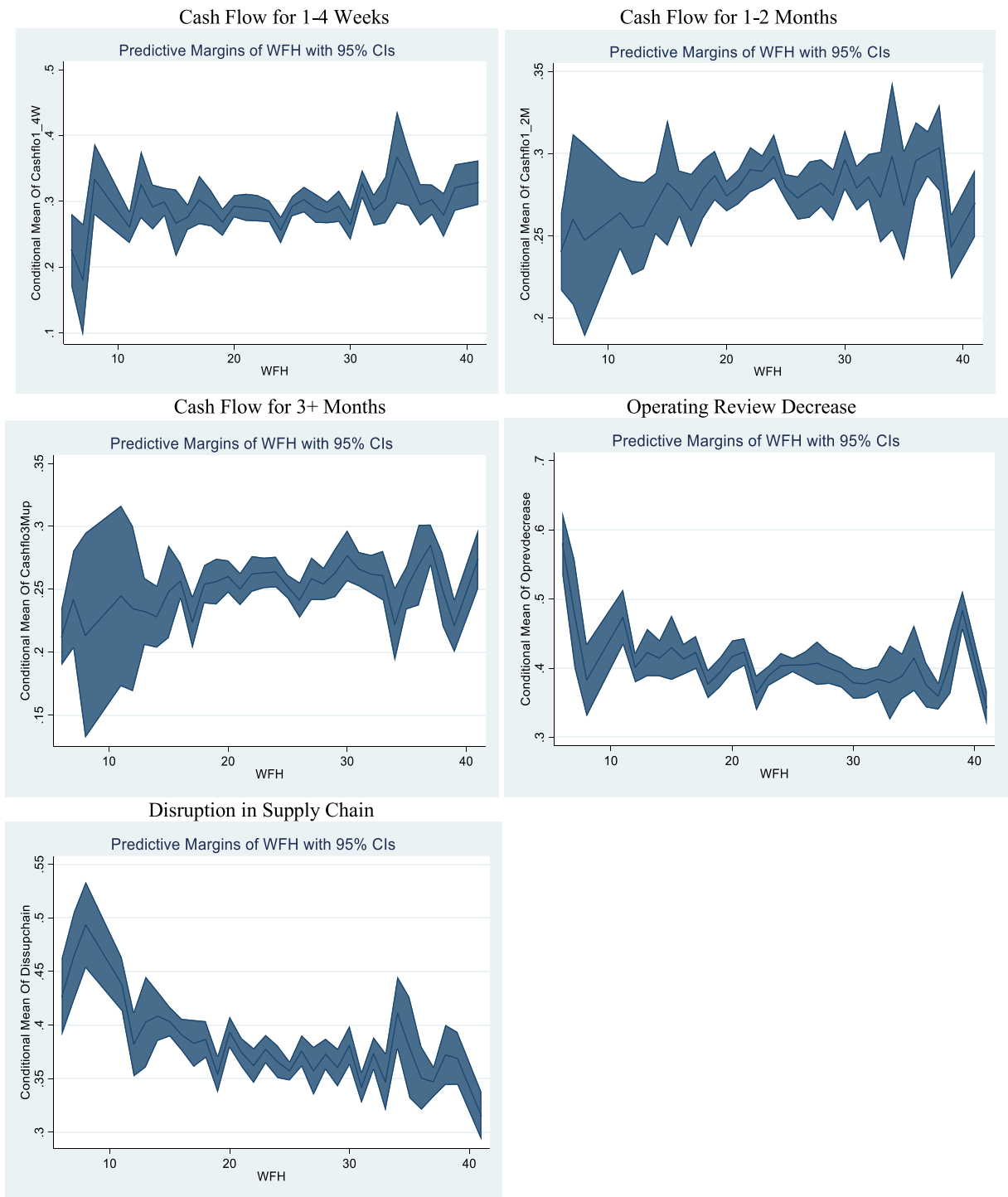


Fig. 1 WFH rate effects on small business’ performance. Note: This graph covers 98% of the observations for WFH rate of 5% 46%, omitting the extreme tails

Following Schumpeter’s (1934) “creative destruction” argument, although COVID-19 resulted in a

human health and economic disaster, this destruction may result in some new adaptation, innovations, and

Table 4 WFH effects only on small business performance by industry sectors (NAICS), fractional logit model estimates

NAICS	Reduced operating revenue	Disruption in supply chain	Temporary closures	No cash flow	Cash flow for 1–4 weeks	Cash flow for 1–2 months	Cash flow for 3+ months	Obs
23	−0.987	0.657	5.342 ***		6.898 ***	6.855 ***	7.810 ***	219–427
Construction	(0.822)	(0.66)	(1.679)		(2.21)	(1.68)	(2.014)	
31	−0.057	−0.621	0.539		4.397 ***	5.207 ***	4.681 ***	233–481
Manufacturing	(0.578)	(0.539)	(1.117)		(1.544)	(1.333)	(1.428)	
42	−2.278 ***	−0.539	0.275	3.251	7.632 ***	6.463 ***	6.504 ***	243–493
Wholesale trade	(0.45)	(0.39)	(0.936)	(14.134)	(1.229)	(0.921)	(1.184)	
44	−2.269 ***	−0.076	1.183		7.895 ***	3.183 **	7.098 ***	242–503
Retail trade	(0.554)	(0.562)	(1.069)		(2.019)	(1.365)	(1.514)	
48	−1.057	−0.263	2.568		6.941	−4.365	3.108	136–308
Trans./wareh.	(0.968)	(0.932)	(1.829)		(6.81)	(5.519)	(6.429)	
51	0.332	3.549 *	−3.448				−0.031	58–172
Information	(1.73)	(2.003)	(2.616)				(10.573)	
52	−1.561	−0.216	1.468		−12.030	7.534 ***	6.165 ***	174–373
Fin. and insur.	(1.113)	(1.036)	(1.412)		(9.581)	(2.598)	(1.744)	
53	0.274	0.890	2.015			−8.992 **	0.812	116–286
Real estate	(1.49)	(1.12)	(2.503)			(4.016)	(3.535)	
54	−1.806 ***	−0.258	0.398		6.246 ***	6.105 ***	5.856 ***	270–555
Prof. sci. tech. serv	(0.515)	(0.481)	(0.951)		(1.441)	(0.902)	(1.004)	
56	0.540	1.929 **	2.852 *		0.050	4.321	1.933	179–374
Admin. support	(0.994)	(0.823)	(1.494)		(6.379)	(2.668)	(4.075)	
61	3.500	−0.080	−4.318			6.869		43–126
Educational serv.	(2.26)	(2.066)	(6.652)			(15.078)	(0)	
62	−0.384	−0.729	2.550 ***		6.841 ***	3.961 ***	6.361 ***	238–502
Health care	(0.597)	(0.459)	(0.901)		(1.481)	(1.031)	(1.241)	
71	2.573	2.741 *	−3.843			13.502 *	−7.103	84–250
Arts, enter., rec.	(1.793)	(1.613)	(2.958)			(7.677)	(5.69)	
72	−1.157	1.265 **	−1.858 *	−14.397 **	−10.880 **	2.934	5.666 **	180–417
Accom. food serv.	(0.744)	(0.611)	(1.07)	(7.197)	(5.089)	(2.136)	(2.375)	
81	−2.877 ***	0.109	−1.229		4.132 *	9.918 ***	1.810	202–410
Other service	(0.573)	(0.593)	(1.132)		(2.402)	(1.717)	(2.748)	

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Robust Standard errors clustered at project level in parentheses. For a full listing of NAICS industry names, see <https://www.naics.com/search/>

creative ways to better utilize technology and the very nature of work. A disruption from the traditional brick-and-mortar offices might result in a new hybrid or a WFH-dominant workplace setting. If the new WFH norm really emerges soon, our current HRM practice, real estate industry, urban sprawling patterns, urban planning, racial segregation, city externalities would all await to be

transformed. This would have important public policy implications.

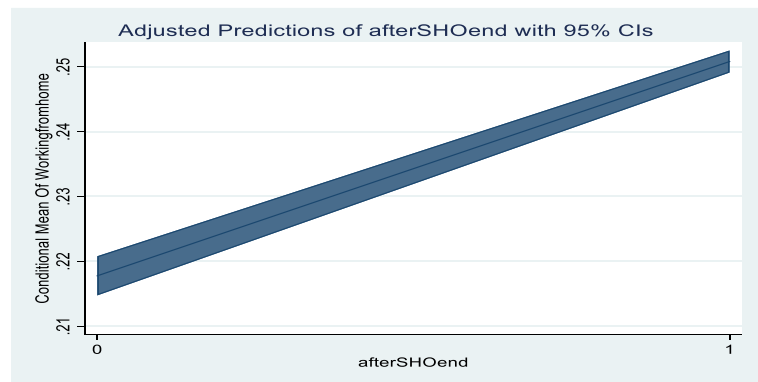
More importantly and sadly, the rising WFH popularity may deepen the digital divide and widen the wealth gap. Our study identified industry sectoral variations in the WFH effects on small business performance; this is largely consistent with sectoral variations in WFH propensities observed by Dingel

Table 5 Empirical models for the end of SHO effect on WFH rates

	Daily data				Weekly data					
	FEP, Model (8)		FLM, Model (9)		FEP, Model (10)		FLM, Model (11)		MLM, Model (12)	
afterSHO (t-1)	0.032	***	0.185	***	0.013	***	0.117	***	0.033	***
	(0.001)		(0.011)		(0.003)		(0.04)		(0.008)	
COVID New Case/1k (t-1)	-0.055	***	0.026		-0.050	***	0.167	***	0.032	**
	(0.002)		(0.019)		(0.007)		(0.074)		(0.014)	
COVID Death Rt (t-1)	-2.257	***	0.613	**	-1.222	***	4.095	***	-0.413	
	(0.05)		(0.282)		(0.174)		(1.122)		(0.292)	
COVID Exposure/1k (t-1)	0.001	***	0.004	***	0.000		-0.002		-0.001	
	(0)		(0)		(0)		(0.002)		(0.0004)	
COVID Days Decr. (t-1)	0.000	***	0.004	***	0.000		0.005	*	0.001	**
	(0)		(0.001)		(0)		(0.003)		(0.0004)	
Unemploy Rt (t-1)	-0.560	***	-3.474	***	-0.493	***	-4.113	***	-0.732	***
	(0.007)		(0.067)		(0.024)		(0.261)		(0.048)	
Median Inc.	(Omitted)		0.011	***	(Omitted)		0.011	***	0.001	**
			(0)				(0.001)		(0.0004)	
Emp Density	(Omitted)		0.047	***	(Omitted)		0.051	***	0.016	***
			(0.001)				(0.004)		(0.001)	
% 60+	(Omitted)		0.974	***	(Omitted)		0.974		0.620	**
			(0.236)				(0.794)		(0.259)	
% African Am.	(Omitted)		-0.389	***	(Omitted)		-0.348		0.008	
			(0.068)				(0.253)		(0.064)	
% Hispanic Am.	(Omitted)		1.488	***	(Omitted)		1.786	***	0.368	***
			(0.043)				(0.157)		(0.054)	
% male	(Omitted)		-18.221	***	(Omitted)		-19.361	***	-2.558	***
			(1.038)				(4.016)		(0.819)	
Time FE (Weeks)	0.000	***	-0.005	***	-0.003	***	-0.042	***	-0.001	***
	(0)		(0)		(0)		(0.004)		(0.0001)	
State FE	(Omitted)		0.001	***	(Omitted)		0.001	*	0.00003	
			(0)				(0.001)		(0.0003)	
_cons	10.997	***	111.724	***	9.037	***	138.520	***	19.810	***
	(0.277)		(2.423)		(1.043)		(11.577)		(2.166)	
Number of obs	8399		8399		592		592		416	
Number of groups	37				37				17	
within	0.575				0.4484					
between	0.003				0.0205					
overall	0.078				0.0557					
F test	1612	***			63.65	***				
F test that all u _i =0	960	***			960	***				
Wald Chi2			20190	***			1548	***	3784	***
Pseudo R2			0.022				0.024			
Log pseudolikelihood			-4605				-309		717	
Random Est: NAICS sd(_cons)									0.009	**
sd(Residual)									0.043	**
LR test vs. linear model: chibar2(01)									3.31	**

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Robust standard errors clustered at project level in parentheses

Fig. 2 Marginal effect of the end of SHO on WFH based on Model (11)



and Neiman (2020). Industry sectors with lower WFH propensities are also noted with lower income (Dingel & Neiman, 2020). At the one end, high-skilled workers who master digital skills 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. At the other end, workers without digital skills or digital access often hold relatively low-paid jobs, face difficult, inflexible schedules, and more importantly, always have the most exposure to any transmittable diseases or virus. Dingel and Neiman's (2020) work on WFH propensity offered the timely and critical contribution in the pandemic. Should WFH become the new norm, we hope innovation and training can penetrate at least some barriers, and improve conditions and pay for currently nonteleworkable jobs.

This paper used small business data because small business are often the most vulnerable in the crisis. However, small businesses in this study have a broad definition and include businesses with up to 500 employees, which may be classified as large businesses in other studies. 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 & Thulin, 2016), including costs of organizational change and technological investments (Aguilera et al., 2016). Since we found positive productive role of WFH in small business

performance, the impacts for larger businesses could be even larger.

7 Conclusion, limitation of the study, and future research

This is the first study building theoretical rationale and relying on real-time data to empirically examine the role of WFH in small business performance during the pandemic. With the widespread public health threat and the sudden skyrocketing urgency for adopting WFH, people are facing enormous uncertainty and stress. However, this study shows a potential silver lining of the pandemic—WFH and its potential of a “creative destruction” for a new work norm.

The study first built a theoretical framework based on the profit maximization theory including a “contagion” agglomeration parameter and argued that WFH is a rational choice for small businesses overall. We then compiled an up-to-date real-time daily and weekly multifaceted data set tracking WFH propensity from March 20 through November 9, 2020. Using this data set, we estimated a variety of FEP, FLM, and MLM models.

Our empirical findings are consistent with our initial expectation and support the hypotheses drawn from our theoretical framework. WFH has potential attractiveness for small businesses with lower odds of reduced operating revenue, supply chain disruption, and a better cash flow condition. These help mitigate the negative pandemic shock and suggest

that a policy response include provisions to promote teleworkable jobs and WFH. This positive WFH effect on small business performance, however, varies across industry sectors. While *Professional Services*, *Wholesale Trade*, and *Retail Trade* small businesses benefited from a higher WFH rate, *Construction*, *Health Service*, and *Accommodation and Food Service* small businesses suffered. After the SHO ended, WFH rate did not drop and instead rose, after controlling for local pandemic, economic, and demographic conditions. This reflects various economic and health advantages of WFH.

During the pandemic, much of the cost of learning and adapting to WFH is already paid, the awareness of WFH is much elevated, and creative approaches utilizing WFH have been adopted. After the vaccines take effect and after the pandemic is over, shall we really go back to the traditional office work norm and totally abandon what we learned about and created with WFH? Do we really want to go through the painful experience to relearn the WFH when we need it again?

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, institution, and HRM innovations, particularly for nimble but vulnerable small business, this new potential may really happen.

As the first study addressing the role of WFH in small business performance in the pandemic, the study has limitations. First, the data is ongoing real-time data. With further data come up, some statistics is subject to change. Second, considering the fact that the SBPS survey is delivered to businesses via email, there is a potential sample selection bias for the survey. Since the SBPS data is aggregated at the state level and each state report proportions of the business performance measures,

conducting the Heckman (1976) selection test did not work without censored observations. However, as a national small business survey conducted by the US Census, the selection bias is relatively limited particularly after applying the sampling weights, as well as reweighting to adjust nonresponse bias. While the particular sample used in this survey was not drawn using traditional probabilistic methods, sampling weights (considering both with and without email addresses) were employed to ensure that the particular sample represented the entire in-scope population, as Buffington et al. (2020) noted. However, if an alternative dataset comes up, we would like to verify our findings.

In addition, we have a few related future research plans to continue this study. Small businesses are defined in the data as businesses with less than 500 employees. However, there remains disparities among the broad definition of “small” businesses. Our future study would focus on the different size categories of those businesses. This study analyzed industry sector variations at the 2-digit-NAICS-code level. One possible future plan is to focus on representative 3-digit-NAICS sectors for further nuances. In addition, as the pandemic effect diffuse spatially even in the digital age, another future study plan is to analyze the spatial pattern of the WFH effect.

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 to WFH. We initially planned to also model WFH effects on the delivery change. However, the second wave of the SBPS data did not collect data on this and resulted in a limited number of observations on this topic. Further analysis on this can be considered if more data is available. In addition, fear factor could affect economic recovery in the pandemic and its aftermath. Before the effective vaccine is prevalent, this fear factor could affect the WFH trajectory. Further research is needed on that.

Appendix

References

Table 6 Correlation matrices

(1) Correlation matrix for the daily data

Obs=8399	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1 WFH (t-1)	1														
2 afterSHO (t-1)	-0.16	1													
3 COVID New Case/1k (t-1)	-0.06	0.35	1												
4 COVID Death Rt (t-1)	0.09	0.25	-0.04	1											
5 COVID Exposure / 1k (t-1)	0.11	0.44	0.58	0.21	1										
6 COVID Days Decr. (t-1)	-0.01	-0.09	-0.19	-0.07	0.09	1									
7 Unemploy Rt (t-1)	-0.26	-0.26	-0.45	-0.18	-0.28	0.36	1								
8 Median Inc.	0.33	-0.09	-0.11	0.19	-0.03	0.05	0.06	1							
9 Emp Density	0.49	-0.02	-0.06	0.12	0.10	-0.03	-0.03	0.34	1						
10 % 60+	-0.18	-0.04	-0.14	0.03	-0.20	0.07	-0.03	-0.35	-0.37	1					
11 % African Am.	0.29	0.03	-0.02	0.17	0.33	-0.04	-0.02	-0.01	0.51	-0.35	1				
12 % Hispanic Am.	0.24	0.002	0.02	0.07	0.20	0.01	0.09	0.18	0.01	-0.35	-0.09	1			
13 % male	-0.39	0.03	0.15	-0.35	-0.26	-0.04	0.11	0.10	-0.39	-0.17	-0.70	0.13	1		
14 Time (Days)	-0.18	0.71	0.52	0.43	0.51	-0.24	-0.55	-0.01	0.002	-0.002	0.01	0.001	-0.01	1	
15 State	-0.02	-0.04	-0.12	0.07	-0.11	0.02	-0.04	-0.10	-0.19	0.24	-0.16	-0.13	-0.11	-0.002	1

(2) Correlation matrix for the weekly data

Obs=372	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1 No Cash Flow	1														
2 Cash Flow for 1-4 Weeks	0.11	1													
3 Cash Flow for 1-2 Months	-0.25	-0.38	1												
4 Cash Flow for 3+ Months	-0.19	-0.57	0.15	1											
5 Decrease Operating Revenue	0.09	0.18	0.12	-0.52	1										
6 Temporary Closure	0.07	0.09	0.16	-0.41	0.88	1									
7 Disruption in Supply Chain	0.14	0.29	-0.10	-0.48	0.49	0.41	1								
8 WFH (t-1)	0.21	-0.01	0.04	0.10	-0.01	0.13	-0.08	1							
9 afterSHO (t-1)	-0.26	-0.17	-0.06	0.33	-0.61	-0.61	-0.41	-0.09	1						
10 COVID New Case / 1k (t-1)	0.26	-0.05	-0.22	0.15	-0.40	-0.41	-0.05	0.15	0.13	1					
11 COVID Death Rt (t-1)	0.36	0.04	-0.28	0.01	-0.32	-0.29	-0.09	0.23	0.09	0.25	1				
12 COVID Exposure / 1k (t-1)	0.33	-0.15	-0.17	0.15	-0.27	-0.10	-0.19	0.34	0.09	0.47	0.41	1			

Table 6 (continued)

(1) Correlation matrix for the daily data

Obs=8399	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
13 COVID Days Decr. (t-1)	0.07	0.07	-0.02	-0.09	0.16	0.30	-0.03	0.05	-0.13	-0.19	-0.02	0.23	1		
14 Fin_PPP	-0.01	0.20	-0.08	-0.14	0.11	0.07	-0.04	-0.04	-0.11	0.04	0.03	0.12	0.02	1	
15 Fin_EIDL	0.07	-0.16	0.08	-0.10	0.46	0.54	0.02	-0.07	-0.33	-0.35	-0.12	-0.04	0.22	0.05	1
16 Fin_SBAInForg	0.21	0.28	0.02	-0.11	0.07	0.02	0.02	-0.07	-0.07	0.00	0.13	0.09	0.05	0.27	0.08
17 Fin_OtherFed	0.42	0.03	-0.20	0.23	-0.45	-0.45	-0.01	0.23	0.10	0.61	0.45	0.46	-0.10	-0.04	-0.33
18 Unemploy Rt (t-1)	-0.28	-0.08	0.26	-0.09	0.40	0.50	-0.10	-0.47	-0.16	-0.48	-0.30	-0.21	0.26	0.17	0.50
19 Median Inc.	0.33	-0.39	0.06	0.25	0.04	0.15	-0.16	0.32	-0.19	0.12	0.22	0.30	0.11	-0.14	0.33
20 Emp Density	-0.03	-0.39	0.05	0.17	0.10	0.27	-0.15	0.52	-0.08	0.05	0.01	0.22	0.01	0.00	0.14
21 % 60+	-0.04	0.17	-0.10	-0.18	0.00	0.00	0.20	-0.24	-0.10	-0.15	0.02	-0.18	0.08	-0.04	0.04
22 % African Am.	0.02	0.01	-0.08	-0.10	0.05	0.12	-0.08	0.30	0.03	0.14	0.10	0.35	-0.04	0.32	-0.01
23 % Hispanic Am.	0.33	-0.08	0.03	0.16	-0.11	-0.14	-0.23	0.24	0.10	0.18	0.14	0.33	-0.07	-0.12	0.04
24 % male	-0.11	-0.12	0.16	0.14	-0.02	-0.11	0.00	-0.43	0.10	-0.15	-0.29	-0.46	-0.05	-0.34	0.09
25 Time (Weeks)	0.25	-0.23	-0.27	0.42	-0.80	-0.81	-0.31	0.02	0.44	0.59	0.50	0.42	-0.22	-0.11	-0.38
26 State	0.02	0.18	-0.07	-0.01	-0.04	-0.06	0.12	-0.04	-0.07	-0.08	0.10	-0.03	-0.03	0.05	-0.06
16	17	18	19	20	21	22	23	24	25	26					
16 Fin_SBAInForg	1														
17 Fin_OtherFed	0.12	1													
18 Unemploy Rt (t-1)	0.11	-0.57	1												
19 Median Inc.	-0.02	0.18	-0.09	1											
20 Emp Density	-0.33	-0.10	-0.03	0.30	1										
21 % 60+	0.09	-0.08	0.06	-0.31	-0.32	1									
22 % African Am.	-0.01	0.01	0.00	-0.04	0.50	-0.31	1								
23 % Hispanic Am.	0.13	0.34	-0.15	0.15	-0.01	-0.37	-0.07	1							
24 % male	-0.10	-0.11	0.14	0.10	-0.38	-0.18	-0.71	0.11	1						
25 Time (Weeks)	-0.01	0.68	-0.57	0.16	-0.06	-0.02	-0.04	0.25	-0.02	1					
26 State	0.10	0.19	-0.06	-0.08	-0.18	0.11	-0.15	-0.07	-0.10	0.06	1				

Table 7 Fixed-effect panel data (FEP) model estimates on small business performance

WFH (t-1)	No cash flow	Cash flow for 1–4 weeks	Cash flow for 1–2 months	Cash flow for 3+ months	Decrease operating revenue	Temporary closure	Disruption in supply chain
	-0.054	-0.049	0.063	0.134 *	-0.222 **	-0.087	-0.491 ***
	(0.034)	(0.109)	(0.078)	(0.08)	(0.109)	(0.113)	(0.08)
afterSHO (t-1)	-0.014 ***	-0.029 ***	0.010	0.035 ***	-0.081 ***	-0.039 ***	-0.026 ***
	(0.003)	(0.008)	(0.006)	(0.006)	(0.008)	(0.007)	(0.006)
COVID New Case / 1k (t-1)	-0.006	-0.010	-0.011	0.003	-0.001	-0.004	0.017
	(0.006)	(0.018)	(0.013)	(0.013)	(0.018)	(0.022)	(0.013)
COVID Death Rt (t-1)	-0.469 ***	-0.920 **	0.149	0.248	-1.809 ***	-3.160 ***	-1.554 ***
	(0.144)	(0.465)	(0.333)	(0.342)	(0.463)	(0.494)	(0.341)
COVID Exposure / 1k (t-1)	0.000	-0.002 ***	0.001 *	0.001 ***	-0.002 ***	0.000	-0.001
	(0.0002)	(0.001)	(0.0004)	(0.0004)	(0.001)	(0.001)	(0.0004)
COVID Days Decr. (t-1)	0.000	0.001 **	0.000	-0.001 **	0.000	0.000	0.000
	(0.0002)	(0.0005)	(0.0004)	(0.0004)	(0.0005)	(0.0004)	(0.0004)
Fin_PPP (t-1)	-0.040 *	-0.003	-0.002	0.008	-0.070	-0.077	-0.029
	(0.021)	(0.066)	(0.047)	(0.049)	(0.066)	(0.07)	(0.049)
Fin_EIDL (t-1)	0.017	-0.018	-0.056	-0.081	0.023	0.035	-0.134 ***
	(0.022)	(0.069)	(0.05)	(0.051)	(0.069)	(0.079)	(0.051)
Fin_SBAlnForg (t-1)	0.018	0.069	0.087 *	-0.138 ***	0.141 *	0.074	0.133 **
	(0.022)	(0.072)	(0.052)	(0.053)	(0.072)	(0.078)	(0.053)
Fin_OtherFed (t-1)	0.044	0.202	-0.107	0.044	0.350 **	0.207	0.371 ***
	(0.045)	(0.145)	(0.104)	(0.107)	(0.145)	(0.222)	(0.107)
Unemploy Rt (t-1)	-0.156 ***	-0.201 **	0.160 ***	0.341 ***	-0.506 ***	-0.475 ***	-0.730 ***
	(0.026)	(0.083)	(0.059)	(0.061)	(0.083)	(0.077)	(0.061)
Time FE (Weeks)	0.000	-0.002 **	-0.001 *	0.003 ***	-0.015 ***	-0.017 ***	-0.006 ***
	(0.0003)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
_cons	1.398	6.350 **	3.777 *	-10.752 ***	48.834 ***	54.218 ***	20.839 ***
	(0.894)	(2.877)	(2.062)	(2.115)	(2.871)	(3.228)	(2.115)
Number of obs	592	592	592	592	592	372	592
Number of groups	37	37	37	37	37	37	37
R-Sq: within	0.177	0.257	0.174	0.387	0.857	0.891	0.392
R-Sq: between	0.153	0.008	0.049	0.006	0.089	0.004	0.302
R-Sq: overall	0.001	0.105	0.095	0.209	0.699	0.503	0.251
F Test	10 ***	16 ***	10 ***	29 ***	271 ***	221 ***	29 ***
F test that all u _i =0	7.52 ***	9.51 ***	1.36 *	5.18 ***	5.8 ***	8.78 ***	8.78 ***

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Robust standard errors clustered at project level in parentheses

Table 8 Multilevel mixed-effects (MLM) model estimates on small business performance

	Decrease operating revenue	Temporary closure	Disruption in supply chain	No cash flow	Cash flow for 1–4 weeks	Cash flow for 1–2 months	Cash flow for 3+ months
WFH (t-1)	-0.275 (0.036)	*** -0.034 (0.045)	0.010 (0.032)	0.002 (0.004)	0.150 (0.027)	*** 0.398 (0.039)	*** 0.342 (0.04)
afterSHO (t-1)	-0.079 (0.004)	*** -0.045 (0.005)	*** -0.048 (0.004)	*** -0.003 (0.0005)	*** -0.027 (0.004)	*** -0.007 (0.005)	-0.003 (0.005)
COVID New Case / 1k (t-1)	0.007 (0.009)	0.076 (0.026)	*** 0.030 (0.008)	*** 0.001 (0.001)	0.059 (0.007)	*** 0.063 (0.01)	*** 0.065 (0.01)
COVID Death Rt (t-1)	0.367 (0.118)	*** 2.003 (0.231)	*** 0.397 (0.102)	*** 0.044 (0.012)	*** 0.424 (0.09)	*** -0.228 (0.131)	* 0.086 (0.136)
COVID Exposure / 1k (t-1)	0.0002 (0.0002)	0.002 (0.0003)	*** 0.00001 (0.0002)	0.0001 (0.00002)	*** -0.001 (0.0002)	*** -0.002 (0.0003)	*** -0.002 (0.0003)
COVID Days Decr. (t-1)	-0.00005 (0.0003)	0.001 (0.0003)	** 0.0003 (0.0003)	-0.00001 (0.00003)	0.001 (0.0002)	*** 0.001 (0.0003)	*** 0.002 (0.0004)
Fin_PPP (t-1)	-0.037 (0.011)	*** -0.009 (0.009)	0.032 (0.007)	*** -0.001 (0.001)	0.006 (0.005)	0.061 (0.007)	*** 0.079 (0.008)
Fin_EIDL (t-1)	-0.051 (0.012)	*** 0.032 (0.013)	** 0.005 (0.011)	-0.00001 (0.001)	0.160 (0.009)	*** 0.333 (0.013)	*** 0.184 (0.014)
Fin_SBAInForg (t-1)	0.087 (0.032)	*** 0.074 (0.039)	* 0.010 (0.032)	0.043 (0.004)	*** 0.621 (0.03)	*** 0.108 (0.043)	** 0.010 (0.045)
Fin_OtherFed (t-1)	-0.256 (0.062)	*** 0.385 (0.204)	* -0.213 (0.06)	*** 0.034 (0.008)	*** 0.156 (0.055)	*** 0.135 (0.081)	* 0.158 (0.084)
Unemploy Rt (t-1)	-0.323 (0.035)	*** 0.043 (0.045)	-0.348 (0.031)	*** -0.007 (0.004)	* 0.0001 (0.026)	0.265 (0.038)	*** 0.249 (0.039)
Median Inc.	0.001 (0.0002)	*** 0.001 (0.0003)	*** -0.001 (0.0002)	*** 0.00004 (0.00002)	** -0.001 (0.0001)	*** -0.001 (0.0002)	*** -0.0001 (0.0002)
Emp Density	0.003 (0.001)	** 0.009 (0.002)	*** -0.004 (0.001)	*** -0.0005 (0.0001)	*** -0.009 (0.001)	*** -0.010 (0.001)	*** 0.001 (0.002)
% 60+	0.331 (0.103)	*** 0.752 (0.128)	*** 0.317 (0.093)	*** 0.017 (0.011)	-0.138 (0.081)	* -0.750 (0.117)	*** -0.454 (0.122)
% African Am.	0.226 (0.034)	*** 0.084 (0.04)	** 0.035 (0.03)	0.001 (0.003)	-0.017 (0.024)	-0.087 (0.036)	** -0.117 (0.037)
% Hispanic Am.	0.087 (0.02)	*** 0.130 (0.024)	*** 0.026 (0.018)	0.012 (0.002)	*** 0.212 (0.016)	*** 0.189 (0.023)	*** 0.225 (0.024)
% male	2.325 (0.559)	*** 1.177 (0.69)	* 1.468 (0.488)	*** -0.086 (0.054)	-2.623 (0.393)	*** -3.945 (0.574)	*** -2.466 (0.596)
Time FE (Weeks)	-0.016 (0.0005)	*** -0.023 (0.001)	*** -0.003 (0.0004)	*** -0.0001 (0.00005)	** -0.001 (0.0003)	** 0.003 (0.001)	*** 0.006 (0.001)
State FE	-0.0002 (0.0001)	** 0.001 (0.0001)	*** 0.0002 (0.0001)	** 0.00001 (0.00001)	0.001 (0.00008)	*** 0.001 (0.0001)	*** 0.001 (0.0001)
_cons	49.152 (1.413)	*** 70.357 (2.366)	*** 10.495 (1.234)	*** 0.385 (0.147)	*** 3.560 (1.065)	*** -6.085 (1.554)	*** -16.669 (1.615)
Rand.Eff. Para.: NAICS: Identity							
sd(_cons)	0.053 (0.009)	** 0.123 (0.021)	** 0.133 (0.023)	** 0.004 (0.001)	** 0.057 (0.01)	** 0.070 (0.012)	** 0.085 (0.015)

Table 8 (continued)

	Decrease operating revenue		Temporary closure		Disruption in supply chain		No cash flow		Cash flow for 1–4 weeks		Cash flow for 1–2 months		Cash flow for 3+ months	
sd(Residual)	0.088	**	0.089	**	0.090	**	0.012	**	0.083	**	0.122	**	0.127	**
	(0.001)		(0.001)		(0.001)		(0)		(0.001)		(0.001)		(0.001)	
Number of obs	4,111		3,058		5,531		6,290		6,290		6,290		6,290	
Number of groups	17		18		18		18		18		18		18	
Wald chi2(19)	7770	***	3134	***	602	***	493	***	2734	***	2110	***	1380	***
Log likelihood	4145		3016		5436		19116		6654		4278		4035	
LR test vs. linear model	790	***	1873	***	4816	***	690	***	1801	***	1313	***	2079	***

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Robust standard errors clustered at project level in parentheses

Table 9 Fractional logit model (FLM) estimates on small business performance(1) FLM without *afterSHO*

	Decrease operating revenue	Temporary closure	Disruption in supply chain	No cash flow	Cash flow for 1–4 weeks	Cash flow for 1–2 months	Cash flow for 3+ months
WFH (t-1)	-1.659 *** (0.22)	-0.278 (0.326)	-1.027 *** (0.16)	0.234 (1.456)	0.635 ** (0.268)	0.605 *** (0.153)	0.791 *** (0.187)
COVID New Case / 1k (t-1)	0.050 (0.047)	-0.147 (0.18)	0.154 *** (0.036)	0.498 ** (0.232)	0.069 (0.067)	-0.031 (0.037)	-0.043 (0.041)
COVID Death Rt (t-1)	0.944 (0.806)	3.717 ** (1.456)	1.692 *** (0.604)	4.243 (2.688)	2.216 *** (0.776)	-2.229 *** (0.485)	-2.864 *** (0.627)
COVID Exposure / 1k (t-1)	-0.001 (0.002)	0.010 *** (0.002)	-0.001 (0.001)	-0.012 * (0.006)	-0.006 *** (0.002)	-0.001 (0.001)	-0.0000005 (0.001)
COVID Days Decr. (t-1)	-0.0001 (0.002)	0.001 (0.002)	-0.001 (0.001)	0.014 (0.009)	0.007 *** (0.002)	-0.002 * (0.001)	-0.002 (0.002)
Fin_PPP (t-1)	0.192 (0.21)	-0.687 ** (0.333)	-0.625 *** (0.181)	-0.941 (1.27)	0.779 ** (0.324)	-0.238 (0.188)	-0.019 (0.21)
Fin_EIDL(t-1)	0.664 ** (0.261)	1.146 *** (0.382)	0.382 * (0.211)	4.105 *** (1.318)	-0.283 (0.347)	-0.140 (0.19)	-0.351 (0.246)
Fin_SBAInForg (t-1)	0.394 (0.289)	0.325 (0.402)	0.219 (0.224)	4.811 *** (1.821)	1.446 *** (0.453)	0.187 (0.222)	-0.572 ** (0.278)
Fin_OtherFed (t-1)	1.937 *** (0.507)	2.598 ** (1.073)	1.877 *** (0.36)	14.287 *** (2.212)	2.893 *** (0.507)	-0.158 (0.311)	0.854 ** (0.415)
Unemploy Rt (t-1)	-1.175 *** (0.215)	1.605 *** (0.325)	-1.486 *** (0.154)	-1.256 (1.174)	-0.724 *** (0.269)	0.811 *** (0.16)	1.301 *** (0.193)
Median Inc (\$000)	0.007 *** (0.001)	0.014 *** (0.002)	0.0003 (0.001)	0.018 ** (0.007)	-0.010 *** (0.001)	0.002 ** (0.001)	0.004 *** (0.001)
Emp Density/1kAcr	0.023 *** (0.006)	0.051 *** (0.008)	-0.008 (0.006)	-0.104 (0.068)	-0.094 *** (0.015)	-0.009 * (0.005)	0.017 *** (0.006)
% 60+	1.968 *** (0.572)	4.243 *** (0.817)	0.625 (0.425)	0.819 (3.06)	-3.275 *** (0.67)	-0.355 (0.394)	-0.298 (0.501)
% African Am.	0.317 * (0.185)	-0.082 (0.227)	-0.201 (0.133)	1.267 (0.824)	-0.275 (0.23)	-0.017 (0.123)	-0.576 *** (0.159)
% Hispanic Am.	0.696 *** (0.114)	0.631 *** (0.164)	-0.178 ** (0.081)	2.788 *** (0.6)	-0.341 ** (0.144)	0.020 (0.093)	-0.081 (0.103)
% male	-1.618 (2.68)	-3.576 (3.779)	-4.393 ** (1.917)	-27.939 ** (14.222)	-13.911 *** (3.924)	-0.718 (1.994)	0.223 (2.331)
Time FE (Weeks)	-0.075 *** (0.003)	-0.170 *** (0.005)	-0.020 *** (0.002)	-0.010 (0.014)	-0.023 *** (0.003)	0.001 (0.002)	0.027 *** (0.002)
State FE	-0.0001 (0.001)	0.0002 (0.001)	-0.001 (0.0005)	0.003 (0.003)	0.0005 (0.001)	-0.0001 (0.001)	-0.001 (0.001)
_cons	235.300 *** (8.877)	532.467 *** (15.899)	66.167 *** (6.187)	38.454 *** (44.679)	78.175 *** (9.956)	-2.868 (6.277)	-84.973 *** (7.369)
Number of obs	816	497	816	816	816	816	816
Wald Chi2	3125 ***	2962 ***	279 ***	442 ***	466 ***	227 ***	420 ***
Pseudo R2	0.045	0.090	0.002	0.054	0.014	0.001	0.005
Log pseudolikelihood	-526	-229	-537	-69	-476	-482	-461

Table 9 (continued)(1) FLM without *afterSHO*(2). FLM without *afterSHO* and *COVID Exposure*

WFH (t-1)	-1.665	***	-0.088	-1.033	***	0.027	0.612	**	0.598	***	0.791	***		
	(0.221)		(0.337)	(0.161)		(1.496)	(0.27)		(0.153)		(0.187)			
COVID New Case / 1k (t-1)	0.029		0.093	0.123	***	0.254	-0.059		-0.057	*	-0.043			
	(0.038)		(0.171)	(0.028)		(0.179)	(0.054)		(0.032)		(0.032)			
COVID Death Rt (t-1)	0.956		4.775	***	1.707	***	4.744	*	2.285	***	-2.217	***	-2.864	***
	(0.804)		(1.507)		(0.605)		(2.702)		(0.788)		(0.487)		(0.626)	
COVID Days Decr. (t-1)	-0.001		0.005	**	-0.002	*	0.006		0.004	**	-0.003	***	-0.002	*
	(0.002)		(0.002)		(0.001)		(0.007)		(0.002)		(0.001)		(0.001)	
Fin_PPP (t-1)	0.182		-0.557		-0.639	***	-1.116		0.714	**	-0.251		-0.019	
	(0.21)		(0.345)		(0.181)		(1.267)		(0.33)		(0.187)		(0.21)	
Fin_EIDL(t-1)	0.667	**	1.090	***	0.386	*	4.062	***	-0.266		-0.137		-0.351	
	(0.261)		(0.398)		(0.21)		(1.309)		(0.349)		(0.19)		(0.246)	
Fin_SBAInForg (t-1)	0.405		0.146		0.232		4.875	***	1.493	***	0.199		-0.572	**
	(0.288)		(0.407)		(0.224)		(1.824)		(0.465)		(0.221)		(0.277)	
Fin_OtherFed (t-1)	1.974	***	1.925	*	1.930	***	14.479	***	3.136	***	-0.112		0.854	**
	(0.51)		(1.035)		(0.362)		(2.231)		(0.502)		(0.309)		(0.414)	
Unemploy Rt (t-1)	-1.179	***	1.808	***	-1.488	***	-1.407		-0.733	***	0.808	***	1.301	***
	(0.216)		(0.325)		(0.155)		(1.188)		(0.274)		(0.16)		(0.193)	
Median Inc.	0.007	***	0.016	***	0.0002		0.017	**	-0.011	***	0.002	**	0.004	***
	(0.001)		(0.002)		(0.001)		(0.007)		(0.001)		(0.001)		(0.001)	
Emp Density	0.024	***	0.045	***	-0.007		-0.097		-0.091	***	-0.008		0.017	***
	(0.006)		(0.008)		(0.006)		(0.07)		(0.016)		(0.005)		(0.006)	
% 60+	2.007	***	3.691	***	0.681		1.090		-3.053	***	-0.306		-0.298	
	(0.579)		(0.822)		(0.431)		(3.119)		(0.686)		(0.399)		(0.502)	
% African Am.	0.302	*	-0.149		-0.225	*	1.250		-0.374	*	-0.037		-0.576	***
	(0.184)		(0.229)		(0.131)		(0.812)		(0.226)		(0.121)		(0.157)	
% Hispanic Am.	0.682	***	0.701	***	-0.201	**	2.601	***	-0.439	***	0.001		-0.081	
	(0.111)		(0.163)		(0.08)		(0.578)		(0.138)		(0.091)		(0.1)	
% male	-1.237		-8.726	**	-3.872	**	-20.802		-11.629	***	-0.256		0.223	
	(2.617)		(3.582)		(1.899)		(13.917)		(4.073)		(1.979)		(2.273)	
Time FE (Weeks)	-0.075	***	-0.165	***	-0.021	***	-0.017		-0.026	***	0.0002		0.027	***
	(0.003)		(0.005)		(0.002)		(0.014)		(0.003)		(0.002)		(0.002)	
State FE	-0.0001		0.001		-0.001		0.003		0.0004		-0.0001		-0.001	
	(0.001)		(0.001)		(0.0005)		(0.003)		(0.001)		(0.001)		(0.001)	
_cons	236.552	***	519.283	***	67.872	***	55.480		85.965	***	-1.362		-84.973	***
	(8.703)		(15.569)		(5.879)		(46.164)		(9.542)		(6.079)		(7.164)	
Number of obs	816		497		816		816		816		816		816	
Wald Chi2	3119	***	2714	***	278	***	458	***	449	***	222	***	420	***
Pseudo R2	0.045		0.090		0.002		0.053		0.014		0.001		0.005	
Log pseudolikelihood	-526		-229		-537		-69		-476		-482		-461	

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Robust standard errors clustered at project level in parentheses

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