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REGULAR ARTICLE

Who innovates during a crisis? Evidence from small businesses in the COVID-19 pandemic

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Abstract
The first months of the COVID-19 crisis offer the possibility to observe patterns of innovation in response to a large, unanticipated shock, simultaneously creating severe adversity and new opportunities. Using new survey data on 22,102 small businesses, we study the amounts, types, and determinants of innovation, particularly firm age, size, factor adjustment, and prior capabilities. Results imply high rates of innovation during the pandemic, including new products, processes, and modes of delivery. Regressions show that rates are higher for younger and larger firms, where younger firms show a greater propensity for product innovations and larger firms for process innovations. Innovation is higher for firms that adjust factors (employment) less. Firms with either extensive or zero pre-pandemic capabilities to accommodate social distancing innovated the least in directions that would expand this capability, while firms with some prior capability innovated the most to expand upon process innovations related to social distancing. Young firms are more likely to increase E-sales, while large firms are more likely to adjust the share of teleworkers.

Keywords Innovation · Patterns of innovation · Small business · COVID-19

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1 Introduction

How much and in what ways have different types of firms innovated during the COVID-19 pandemic? Most businesses experienced large negative shocks, forcing many to shut down temporarily or permanently, and many continued to operate only at a lower scale, while only very few experienced growth (Bartik et al., 2020; Cajner et al., 2020; Coibion et al., 2020; Fairlie, 2020). At the same time, large shifts in both demand and supply for many products and factors of production have generated opportunities for creative types of innovation (Breier et al., 2021; Ebersberger and Kuckertz, 2021; Kraus et al., 2020; Kuckertz et al., 2020; Manolova et al., 2020). Anecdotal evidence also suggests many firms changed the goods or services they offered or the characteristics of their products, others pivoted across types of customers, some others changed the ways they deliver products, and many adopted teleworking practices (Bai et al., 2021; Dingel and Neiman, 2020). If the anecdotal evidence holds in the aggregate, it implies a seismic shift in production processes and routines over a relatively short period of time. Additionally, there is emergent evidence that also suggests increased innovative activity during the COVID-19 pandemic (Breier et al., 2021; Dinlersoz et al., 2021; Ebersberger and Kuckertz, 2021; Kraus et al., 2020; Kuckertz et al., 2020; Manolova et al., 2020).

In this paper, we document the amount and types of innovation that small businesses engaged in during the first few months of the COVID-19 pandemic. We focus on firm characteristics associated with these patterns of innovation, including firm age, size, prior capabilities, and employment adjustment. We adopt a standard definition of innovation used in much of the literature and in many innovation surveys, derived from the Oslo Manual (OECD, Eurostat, 2018).[1] Our choice of firm characteristics is motivated by theories about the sources of innovation, yet we test them under the unique circumstances of the first few months of the COVID-19 pandemic. These theories are difficult to test under normal circumstances in a relatively stable world where relative prices change only incrementally, where innovation is part of long-run firm strategies, and where it is difficult to measure innovation activities as distinct from the shocks that generate them.

Our premise in this paper is that the abrupt changes associated with the COVID pandemic provides large-scale identifying variation from a largely unanticipated shock that may prompt very different responses from firms with different characteristics. Some health experts had been warning for years about the possibility of a pandemic, but it seems fair to say that the rapid spread and large-scale dislocation caused by COVID-19 caught most firms by surprise. Until early March, most - perhaps nearly all - managers, workers, and customers took little heed of what suddenly became an

[1] The OECD defines innovation as “the implementation of a new or significantly improved product (good or service), or process, a new marketing method, or a new organizational method in business practices, workplace organization or external relations” (OECD, Eurostat, 2018). This focus on innovation activities implies we do not study patents, data for which are not yet available in any case and which are largely irrelevant in many industries and smaller firm size categories.

unprecedented crisis[2]. By April, already over 40 percent of small businesses nationally were temporarily closed citing demand loss and health concerns as primary reasons for closure (Bartik et al., 2020). Given the large impact on business operations in a very short period, we argue that the COVID-19 pandemic was a largely unanticipated shock for firms.

The theoretical perspectives that motivate our empirical analysis are discussed in further detail below, and here we summarize them briefly. One hypothesis, stemming from Schumpeter (1911, 1942) and often referred to as "Mark I," is that greater innovation would be found in young firms, recent entrants who can more readily pivot toward new opportunities in disrupted markets. Another, later Schumpeterian "Mark II" hypothesis implies that innovation is largely a product of the R&D departments of large organizations and is enabled by rent accumulation in large, profitable firms during times of increasing rents when they have greater resources to channel towards higher risk activities such as R&D (Breschi et al., 2000; Freeman et al., 1982; Patel and Pavitt, 1994; Winter and Nelson, 1982; Schumpeter, 1939).

The pandemic created a large negative shock, so these theories suggest we may expect young firms to have innovated most during the pandemic. However, another hypothesis suggests that frictions to adjustment in response to a sudden demand loss may lower a firm's opportunity cost to innovate in certain directions such that even larger firms may find reason to innovate during a crisis. This "trapped-factors" model (Bloom et al., 2013) opens up the possibility that the nature of the demand shock may offer lower costs to innovate in directions where trapped resources may be repurposed. Indeed, some of the anecdotal stories of how businesses accommodated social distancing, increased teleworking options, expanded in their online sales, or pivoted their production, seem to fit this theory. To the extent that trapped factors are more prevalent in larger firms, because of their larger capital-labor ratios, higher complexity of production and division of labor, and greater reliance on firm-specific skills and assets, firm size may be positively related to innovation. However, this relationship is opposite to that implied by the Mark II hypothesis which suggests a negative shock that decreases resources should reduce innovation, while the trapped factors hypothesis implies an increase in innovation.

A final theoretical perspective concerns capabilities arising from previous experience that facilitate innovation. Specifically, Winter and Nelson (1982) posited that innovation is a path-dependent process that "unfolds" new knowledge from prior knowledge, but the innovative behavior of firms is also tied to their capability to redeploy their resource base in adaptation of a changing environment (Teece et al., 1997). The pandemic again offers a valuable context for investigating the capabilities hypothesis, as there are specific types of experience and practices that make some innovation easier in this context. For instance, the ability to implement social distancing and already having digital capabilities for online sales or teleworking.

We examine the predictions of these theories in the context of the pandemic, when firms face sudden and unanticipated shocks. Our contribution is thus not only in measuring the amount of innovation of different types during a crisis, but also in

[2] More details about COVID crisis is available in the following link. https://www.cdc.gov/museum/timeline/covid19.html

examining the patterns of innovation by firm characteristics and the degree to which these patterns accord with the theories.

We focus on innovation patterns of small firms during the early pandemic period, when the possibility for distinguishing shock from response is greatest, relying on a large sample of firms that we surveyed in August 2020. The rapid responses covering the first few months of the pandemic do not lend themselves to measurement through patenting, nor do the wide variety of industries we consider. Instead, we use standard questions from innovation surveys, based on OECD, Eurostat (2018), particularly the US Annual Survey of Entrepreneurs (ASE) in 2014, which contained a module of innovation questions.[3] Together with some pandemic-specific questions we have added, these questions enable us to measure different types of innovation activities during the early pandemic. Among the measures are; developing completely new products, adding a new product for the particular business, adding a new feature to a product, improving a technique or process, changing the type of customer, changing the mode of delivery, retraining workers for new products or processes, and changing processes to achieve social distancing.

We relate these types of behavior, and some aggregations based on them, to measures of firm characteristics and resources, including access to government programs, while controlling for the size of the original revenue shock, firm industry, and other variables. We also relate the observed innovation outcomes to a firm's change in employment in the first months of the pandemic as an inverse proxy for the extent of trapped factors: firms facing demand loss that did not immediately reduce employment had the most factors trapped, which could then be repurposed toward innovation.

Our survey data that form the basis for this analysis include responses from 22,201 businesses in California. The sample list was obtained through Small Business Development Centers (SBDCs), based on their contacts in the small business community. The data include detailed information on firm characteristics, the initial impact of the COVID-19 shock on business sales, factors affecting business operations, business access to government assistance and other financing sources, and prior capabilities that favored continued operations during the pandemic such as teleworking, e-sales, and the ability to accommodate social distancing.

Our findings reveal novel insights on firm-level innovation during crises. We demonstrate that innovation occurs not only in good times and among large and high-growth firms, but is also the response of most small firms to a crisis, even for types of firms that might otherwise be considered non-innovative. Although both younger and larger firms demonstrate greater propensities to innovate during a crisis, these propensities favor larger firms in process innovations, but younger firms in product innovations. The data thus support the Schumpeter Mark I hypothesis, but they are inconsistent with Mark II: the reduction in rents associated with the crisis should have reduced, not increased innovation. However, we also find empirical evidence in support of the trapped-factors model, as firms reducing employment less tend to innovate more than those engaged in large employment cuts. Finally, we find an inverted U-shaped relationship between a firm's propensity to innovate and its prior capabilities. Particu-

[3] Brown et al. (2020) use the ASE data to study innovation differences between immigrant- and native-owned firms in the high-tech sector.

larly, firms with some prior experience in e-sales and teleworking practices expanded on these advantages, while those with no prior experience, and those already fully expanded upon these capabilities, were the least likely to expand on these capabilities. Similarly, in a more direct fashion, firms that implemented social distancing practices were those that reported having the most capacity to recapture most lost demand by adopting social distancing.

In the following section, we further develop our research hypotheses, including necessary background on previous literature and our motivation for studying each. Next, we provide a detailed description of our data and methods. The presentation of results begins with documenting the amounts of various types of innovations and adaptations during the early pandemic and then goes on to analyze how these types of behavior vary systematically across firms with respect to their characteristics, resources, and access to government support. The final section contains a brief conclusion.

2 Research questions, context, and motivations

Our over-arching research question concerns the amount and types of innovation during the pandemic and how these patterns relate to firm-level characteristics. Besides firm age and size, we also consider how prior capabilities influence the decision to innovate, and provide evidence on the "trapped factors" model of innovation (Bloom et al., 2013).

Previous research on innovation during crises tends to focus on variation with the business cycle, typically finding it to be pro-cyclical, with lower levels during financial crises, with some exception for new firms and those who were already highly innovative before the crisis (Archibugi et al., 2013; Guellec and Wunsch-Vincent, 2009; Kanerva and Hollanders, 2009; Paunov, 2012). Following these expectations, the pandemic may also reflect a period of depressed innovative activity compared to 'normal times' and where only a few innovate.

Yet, the COVID-19 pandemic was different from a cyclical downturn that is usually interpreted as affecting all actors relatively homogeneously across industries, reflecting aggregate fluctuations, while the impact may vary geographically. By contrast, the impact of the pandemic varied less geographically, but with pronounced differences across industries. Sharp declines occurred in some sectors, especially those where workers or customers come into close proximity, such as restaurants, accommodation, travel, and personal services, and there were apparent gains in others, such as non-store retailers, online services, and groceries (Bartik et al., 2020; Fairlie and Fossen, 2021).

The factors impacting business operations were both direct results of the pandemic, such as the health risks posed to workers and customers, and indirect results of the pandemic, such as changes in market conditions, supply chain disruptions, or the government ordered lockdowns. As such, the question of who innovates during a pandemic reduces to a firm-level decision on the expected returns to innovation given the constraints each firm faces with regards to their available resources and capabilities just prior to the shock (Evangelista and Vezzani, 2010; Frenz and Lambert, 2009; Latham, 2009; Kitching et al., 2009; March, 1991; Pisano and Teece, 1994; Teece et al., 1997). The canonical distinction in the literature reflecting these propensities to innovate is one of firm size and firm age (Acs and Audretsch, 1988; Alvarez et al., 2010; Antonelli et al., 2012; Audretsch and Acs, 1991; Filippetti and Archibugi, 2011; Kanerva and Hollanders, 2009; Paunov, 2012).

A first theoretical perspective that we examine suggests that younger firms would be more innovative during the pandemic as they are better poised to exploit opportunities in a disrupted market (Tushman and Anderson, 1986; Henderson and Clark, 1990; Simonetti, 1996; Freeman and Louçã, 2001; Perez, 2003, 2009). In what Freeman et al. (1982) labeled as Schumpeter's "Mark I" perspective on 'creative destruction', startups have fewer sunk costs, including organizational routines as well as physical and human capital that impede innovation, particularly in novel directions, such as the creation of new products (Levinthal and March, 1993; Leonard-Barton, 1992; Henderson and Clark, 1990; Schumpeter, 1911). Some evidence of a sudden reallocation of entrepreneurial effort towards new business registrations during the pandemic has been documented in the Business Formation Statistics (BFS) and detailed by Dinlersoz et al. (2021).

Yet the later works of Schumpeter accommodate the possibility for greater innovation by well-established firms (Schumpeter, 1942). According to this Schumpeter "Mark II" perspective, larger firms operating in imperfectly competitive environments use their rents to innovate to stay competitive and discourage entry by newcomers (Fabrizio and Tsolmon, 2014; Barlevy, 2007; Comin and Gertler, 2006; Fatas, 2000; Geroski and Walters, 1995). According to this view, innovation during normal times, especially incremental and process innovations rather than completely new products, should be positively related to firm size (Bell and Pavitt, 1993; Malerba and Orsenigo, 1995; Pavitt, 1999). During a crisis that reduces rents, however, large firm innovation may decline disproportionately.

In the context of the pandemic, the Mark I hypothesis would suggest that newer firms would be more agile than older firms in finding opportunities to innovate (Freeman and Louçã, 2001; Louçã and Mendonça, 2002; Perez, 2003, 2009; Simonetti, 1996). Examples of these innovators would include new startups with solutions for the tracking, testing, and treatment of COVID-19 (Farrugia and Plutowski, 2020), and even software apps that help find availability of essential goods at different stores during the early shortages (Guillen, 2020). On the other hand, the Mark II hypothesis would suggest lower innovative activity by larger firms which in the face of declining rents would defer any planned innovation activities and focus instead on cost reductions (Latham and Le Bas, 2006).

A more recent theory emphasizes a role for "trapped factors," inputs with high adjustment costs and/or asset specificity, that can be reallocated towards innovation activities during times of low demand (Bloom et al., 2013). This hypothesis makes allowances for larger firms to innovate in certain directions where the opportunity cost is lower. For instance, Bloom et al. (2016) find that European manufacturing firms most negatively impacted by the competitive shock from China joining the WTO were the most likely to increase patenting and productivity. The trapped factors model interpretation is that firms pivoted their now slack resources towards innovation and adoption of new technologies. This theory is especially appropriate to our setting of a large, unanticipated shock, which could lead firms to suddenly have more inputs than those necessary to meet current demand. Like the Mark II perspective, it also seems more apt with reference to incremental and process innovations, rather than completely new products, although the previous literature on trapped factors has not distinguished different types of innovation.

Furthermore, the importance of trapped factors is likely to increase with firm size. Larger firms face higher adjustment costs and asset specificities, associated with higher capital-labor ratios, greater division of labor, and more complex production technologies. For instance, it is a well documented fact that larger firms pay higher wages, provide more fringe benefits, and have lower labor turnover compared to smaller firms (Even and Macpherson, 1996; Oi and Idson, 1999). Their higher investments in labor and firm-specific capital in turn advantage larger firms with a more productive workforce and a denser accumulation of skills and capabilities (Idson and Oi, 1999). These organizational resources reduce the opportunity costs to innovate along certain pathways that would otherwise be too expensive for smaller, newer firms (Antonelli, 1997; Dosi, 1984; Winter and Nelson, 1982). Besides firm size, we also use the extent of employment adjustment as a proxy for the extent of trapped factors within the firm.

The relationship between firm size and product and process innovations has received some attention in the literature. Early work by (Pavitt et al., 1987) found the share of process R&D to be increasing with the number of employees in a sample of British firms. Scherer (1991), similarly found a positive relation between firm size, as measured by sales, and the share of process R&D of the firm using a database of Fortune 1000 firms. Cohen and Klepper (1996) extended Scherer's analysis using the same dataset but at the level of the business unit and also find the share of process R&D to rise with unit size as measures by sales. More recently, (Fritsch and Meschede, 2001) examining a survey or German manufacturers present evidence that process R&D increases proportionally faster with the size of the firm than product innovation. Huergo and Jaumandreu (2004) examine a large cohort of 2,300 Spanish firms over their lifecycle and find a strong positive link between firm size and innovation, with process innovation increasing at a greater rate the product innovation with size. Within the context of crises, Archibugi et al. (2013) find that product innovations are more common with firms that persist in their innovations during cyclical downturns. Continuous process innovations on the other hand are rare during downturns (Roper and Hewitt-Dundas, 2008). Given this evidence, we would expect that larger firms are better able to leverage their resources towards process innovations.

The relationship between firm age and product and process innovation in the literature is more nuanced. This is because innovation over a firm's lifecycle is a function of the firm's innovation strategy designed by its managers. Here, Cucculelli (2018) finds new ventures and new CEO's to be determinants of new product innovations. Huergo and Jaumandreu (2004) also find a negative relationship between firm age and product innovations. Similarly, other studies also examining innovation over a firm's lifecycle find that firms are least innovative before they exit, but for surviving firms the impact of age on the probability of innovative activity is highly non-linear with greater average frequencies of process over product innovations (Huergo and Jaumandreu, 2004). Accordingly, we may expect to see a clearer relationship between product innovations and young firms, whereas the evidence may not be clear for older firms.

Beyond firm age and firm size, another influential factor in a firm's decision to innovate during the pandemic is whether its prior capabilities and resources align well with new opportunities (Teece et al., 1997). This notion is partly implicit in the Mark II hypothesis but investigating this mechanism further can shed important light on when and how innovative capacity may be baked into a firm's capabilities (Raymond et al., 2010). For instance, we may expect that businesses in innovative sectors, such as high-tech businesses, may also be more innovative during the pandemic compared to low-tech businesses. Yet, low-tech businesses may be more directly impacted due to the nature of the pandemic and faced greater pressures to adapt.

Some firms may have had a technical advantage during the pandemic, based on previous experience with either e-commerce activities or remote working. The nature of the pandemic shock was such that businesses with e-commerce and teleworking capabilities were able to build on them further during the pandemic. Evidence suggests that the adoption of these practices improved firm outcomes over the pandemic and many firms continued to expand upon their teleworking options even after the government ordered lockdowns were removed (Zhang et al., 2021). The interesting question is whether such firms find more, or less, reason to innovate during a crisis.

For instance, did e-commerce businesses with all their sales conducted online prior to the pandemic innovate more, or less? It is likely they had little incentive to change how they sold their products or services, yet they may have found opportunities to allocate their resources towards building on other competitive opportunities. Similarly, remote work businesses with most of their employees teleworking prior to the pandemic likely had little need for adopting social distancing practices but may have found themselves in an advantageous position to undertake other innovations.

Adopting social distancing practices is also an innovative activity as it requires learning and implementing new processes and developing new organizational routines. Not all businesses were able to adopt social distancing as effectively to regain lost revenues. Many restaurants were able to accommodate safe social distancing practices for their staff, enabling them to resume take-out and delivery services. Some restaurants were additionally able to accommodate outdoor seating and safe practices for their customers to dine-in, and consequently regain a greater portion of their lost revenues. At the same time, many small business saw revenues collapse at the start of the crisis, limiting their capital resources to dedicate towards innovation (Kim et al., 2020). From an innovation perspective, it would be useful to know if having prior advantage during a crisis increases or reduces the incentive to innovate.

The Mark I, Mark II, trapped-factors, and prior capability perspectives are not necessarily at odds with each other. Each of these may play a role in explaining why firms pursue different amounts and types of innovations, also taking into account other factors such as access to capital, which may also have changed dramatically in a short period at the start of the pandemic (Hall, 2005; Roper and Hewitt-Dundas, 2008).

Our findings, detailed in the results section, support the Schumpeter Mark I, trapped factors, and prior capabilities hypotheses. Innovation levels during the early pandemic are dramatically higher compared with beforehand, and they are higher in younger firms, larger firms, those adjusting employment less, and those with prior capabilities. The results appear to be inconsistent with Mark II, which would imply lower innovation, especially in larger firms. Instead, most surviving firms engage in some kind of innovation, either to exploit new opportunities or in an effort to re-purpose slack resources to survive. Firms with prior capabilities that aligned with opportunities during the crisis show greater propensities to innovate in these directions. We discuss these results in more detail in the latter sections, but in the next section we first discuss the data and methods applied in this analysis.

3 Data and methods

3.1 Data

The primary data used in this study come from the Survey of Businesses in the Time of COVID (SBTC), an extensive survey of California Small Business Development Center (SBDC) past and present clients.[4] The SBDCs are non-profit organizations supported by the Small Business Administration (SBA) to assist small firms with operations and finance.[5] The survey was conducted across California in July 2020.[6] The surveys were distributed to all California SBDC clients by email through the regional SBDC networks. The response rate is about 8 percent, and the final sample size is 22,102.

Information in the survey are linked to business-owner and firm characteristics in the SBDC's administrative database, which is updated by SBDC counselors from each contact with the firm, and with comprehensive business data from the 2019 Your Economy Time Series (YTS) to provide other firm-level baseline variables such as geographic location and industry of operation. In December 2020, the SBA released data on all recipients of the Payment Protection Program (PPP) and the Economic Injury and Disaster Loan (EIDL) under the Freedom of Information Act (FOIA). We link these data on loan recipients with our survey to validate and fill in missing loan information in the survey responses.

3.1.1 Survey sample

The SBDC client survey sample provides unique advantages for our study, focusing on small businesses. The SBDCs have traditionally been the primary vehicle for disaster loan assistance to small businesses and thus played an out-sized role during the COVID crisis in connecting and advising distressed businesses on government assistance.[7] Therefore, the sample captures businesses that were more likely to seek government

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[4] For details about the SBTC and descriptive statistics, please see Dani et al. (2021).

[5] The Small Business Development Center (SBDC) Program is an extensive national network of close to 1,000 small business service centers leading the charge in providing no-cost tools and guidance needed to help entrepreneurs and small businesses realize their full potential. The California SBDCs include five regional networks covering the state, devoted to helping all industries and all levels of small businesses with accessing capital, human resources, marketing/social media, e-commerce, accounting, disaster resources and pivoting strategies and any other business needs.

[6] A pilot survey covering the period of January through April was disseminated to clients only in the Los Angeles and San Diego SBDC regional networks in April 2020.

[7] In the first months of 2020, California's SBDCs had counseled more than 44,000 small business clients over 172,000 hours, supported over $1.27 billion dollars in small business funding, including COVID assistance, and helped 938 entrepreneurs establish new startups during the crisis. Between March and April alone, CA SBDCs client engagement increased by over 191 percent.

assistance during the pandemic, and also the types of small businesses that receive little attention in most studies of innovation, those in non-high-technology and non-high-growth sectors, and non-employer type establishments.

To understand the difference between our survey sample and the population of firms in California, we compare the distributions of basic firm characteristics between SBTC and the Business Dynamics Statistics (BDS) for California, from the U.S. Census Bureau.[8] The BDS enables us to compare the share of employer establishments in California not only by industry and firm size but also by firm age.

We provide the distributions of firm age, size, and industry composition for all firms in the SBTC, SBTC employers, and BDS employers (the BDS includes only employers) in Appendix Tables 6, 7, and 8. Compared to the BDS, the SBTC employer sample has a similar share of firms less than 11 years old, although the youngest category (0 to 2 years) is smaller in our survey sample. The share of small firms with less than 10 employees is also similar in the SBTC employer sample to the BDS. Compared to the share of firms in BDS, SBTC shares are slightly higher in Retail trade and Other services, but lower in Health care and social assistance. Except for these industries, the distribution of firms across industries is quite similar.

Overall, compared to the BDS our survey sample skews in favor of younger and smaller firms with relatively more respondents concentrated in the retail trade and in other services.

3.1.2 Innovation measures

Our main variables measuring innovation activities come from the SBTC, which are similar to other standard innovation surveys.[9] For our study, these product and process innovation measures are more appropriate than other innovation measures, such as patents or research and development (R&D) investment. This is because our study focuses on innovation activities that occurred in a relatively short time frame during the early months of the pandemic, and it takes much longer to prepare a patent application and receive a patent right (at least one year). Additionally, our study sample focuses on small businesses, and R&D as a separate exploratory innovative activity is rarely conducted in these small businesses. Therefore, by using product and process innovation measures rather than patent and/or R&D measures, our study captures small businesses' innovation activities in the early pandemic period.

In Table 1, we provide definitions of the innovation measures. The SBTC includes very detailed information about innovation activities during the pandemic. Specifically,

[8] Based on the Longitudinal Business Database (LBD) covering all U.S. private sector employers, the BDS provides aggregate-level information on the number of firms, establishments, and employment as well as dynamics including entry, exit, job creation, and job destruction.

[9] Mairesse and Mohnen (2010) reviewed qualitative questions on product and process innovations in innovation surveys, including the Community Innovation Surveys (CIS) in Europe and the Business Research and Development and Innovation Survey (BRDIS) in the U.S. More recently, the 2014 Annual Survey of Entrepreneurs by the U.S. Census Bureau provided similar product and process innovation measures, which were studied in the context of immigrant entrepreneurs (Brown et al., 2020) and black entrepreneurs (Lee et al., 2022).

respondents were asked if they engaged in any of the following types of activities; (1) Sold a new good or service that no business has ever offered before; (2) Sold a new good or service that your business has never offered before; (3) Sold to different types of customers (e.g., consumers rather than businesses); (4) Added a new feature to a product or service; (5) Changed the way a product or service was distributed or delivered; (6) Made a significant improvement in a technique or process by upgrading a technique, software, or automation; (7) Retrained workers for new products or processes; (8) Changed work processes significantly to achieve social distancing; (9) No change.

The first four innovation measures (i.e., (1) to (4)) capture product innovation and the second four innovation measures (i.e., (5) to (8)) reflect process innovation. We create a dummy variable for each innovation measure, treating as missing the firms that did not provide response to this question. We also construct three aggregate measures: any innovation, product innovation, and process innovation. Any innovation is defined as one if a firm conducted any of the eight activities, and zero otherwise. Product and process innovations are defined as one if a firm conducted one of the four product or process innovations, respectively.

To examine pandemic-related innovations, we analyze e-sales and teleworking. We create a binary variable that is equal to one if the proportion of e-sales in total sales increases between January and July, and zero otherwise. Similarly, we create another binary variable to measure the increase in the proportion of teleworkers.

3.1.3 Independent variables

In addition to innovation measures, the linked SBTC data also provides detailed firm characteristics before and during the pandemic. Detailed definitions of these variables are provided in the Appendix Table 5.

Our main variables of interest are firm age, size, employment adjustment, and prior capabilities. Using the information on the year of establishment, we construct binary variables for the five firm age categories of 0-2, 3-5, 6-10, 11-15, and 16 or more years in operation. Given that the firms with 10 or less years in operation are young firms in an entrepreneurial period, the firm age variables reflect the innovation dynamics in the analysis.

The survey asks for detailed information about the workers used in the business at the end of January (before the COVID), April, and July 2020. To avoid the pandemic effects on firm sizes, we use the number of employees in January 2020 to create categorical variables for the seven firm size categories: 1, 2-4, 5-9, 10-19, 20-49, 50-99, and 100 or more employees. For non-employers, we impute one employee (the owner). Also, the SBTC sample does not have many large businesses, and we aggregate large businesses into one category for 100 or more employees.

Besides firm size, we also analyze employment adjustment as a proxy variable for the extent of trapped factors. This variable is defined as the absolute value of the change in the number of employees from January to July 2020 as a ratio to the January level.

Table 1 Definitions of Innovation Measures

Variable	Definition
Aggregated Innovation Measures	
Any Innovation	Introduced any product innovation in the first 6 months of pandemic
Number of Innovations	Number of innovations that firm introduced in the first 6 months of pandemic
Product Innovation	Implemented any product innovation in the first 6 months of pandemic
Process Innovation	Implemented any process innovation in the first 6 months of pandemic
Product Innovation Measures	
New Product to Market	Sold a new good or service that no business has ever offered before in the first 6 months of pandemic
New Product to This Business	Sold a new good or service that your business has never offered before in the first 6 months of pandemic
Different Customer	Sold to different types of customers in the first 6 months of pandemic
New Feature to Product	Added a new feature to a product or service in the first 6 months of pandemic
Process Innovation Measures	
Changed Delivery	Changed the way a product or service was distributed or delivered in the first 6 months of pandemic
Improved Process	Made a significant improvement in a technique or process by upgrading a technique, software, or automation in the first 6 months of pandemic
Retrained Workers	Retrained workers for new products or processes in the first 6 months of pandemic
Changed Process for Social Distance	Changed work processes significantly to achieve social distancing in the first 6 months of pandemic
E-sales and Teleworker Measures	
Increased the share of E-sales	Increased the share of E-sales in total sales between January and July, 2020
Increased the share of teleworkers	Increased the share of teleworkers in total labor between January and July, 2020

The table provides the definitions of innovation measures used in the analysis. Except for the number of innovations, which is continuous, all innovation measures are dummy variables equal to 1 if a firm implemented that innovation and 0 otherwise

As a measure of firm capabilities, we use answers to a question about the amount of demand the could be met under social distancing. Respondents were asked the following question: “if your workplace were to adopt social distancing, about what percentage of your previous (pre-Covid) demand do you estimate your business could meet?” We construct a set of categorical variables for the percentage of demand met, including 0% (none of your previous demand), 1-25%, 26-50%, 51-75%, 76-99%, and 100% (All of your previous demand).

Control variables include the size of the sales shock, factors affecting operations during the crisis, measures of finance, and industry. The sales shock is measured between January and April 2020 in the following categories: 100% decline (no sales in April), 76%-99% decline, 51%-75% decline, 26%-50% decline, 1%-25% decline, 0% (no change), 1%-50% increase, and 51% or more increase in sales. In addition to the sales shock, we also control factors that affect business operations. In the survey, respondents with a change in operating status during the period of the survey were also asked about the different factors affecting their operation. The eight options presented to them on a scale of “Not Important”; “Somewhat Important”; and, “Very Important” included; (1) Worker safety, (2) Customer safety, (3) Reduced demand or cash flow unrelated to safety concerns, (4) Problems accessing private bank credit, (5) Problems getting credit from suppliers, (6) Difficulties getting supplies or inputs, (7) Difficulties with transportation, storage, or warehousing, and (8) Government ordered lockdown. In the analysis, we group these eight factors into categories of direct and indirect factors. The direct factors refer to the immediate health impact of the pandemic on business operations due to concerns of maintaining worker or customer safety. The indirect factors refer to the secondary impact of the pandemic which reflect changes in market conditions, supply chain interruptions, and the government lockdown brought about by the crisis. In the analysis, these factors were coded as indicators equal to 1 if the respondent answered “Very Important” for the corresponding factor and 0 otherwise.

Access to finance is an important consideration for a business to be able to adapt or innovate. For this reason, we construct a set of dummy variables for the following financial sources that firms received during the pandemic; (1) Main Street Lending Program; (2) Other federal programs (not PPP, EIDL, or Main Street Lending); (3) State and local programs; (4) Commercial bank loans; (5) Owner financing; (6) Friends and Family; and (7) Venture Capital. Finally, because the COVID shock was heterogeneous across industries, we create industry dummy variables, that are narrowly defined at the 3-digit NAICS level.[10]

3.2 Methods

We start by documenting innovation activities during the pandemic. Specifically, we first compare innovations that happened during the first months of the pandemic with those before the pandemic.[11] Then, we examine the differences in innovations between high- and low-tech sectors, and discuss if the different types of innovation measures are correlated with each other.

[10] The descriptive statistics of variables are provided in the Appendix Tables 6, 7, 8, 9, 10, 11, 12, 13, and 14.

[11] The SBTC measures innovations during the first six months of the pandemic while the ASE measures innovations in the last three years at the time of the interview. In order to compare these for the same length of time period, we computed the innovation rate for a six month period in the ASE as follows: $Innovation_{6months} = 1 - (1 - Innovation_{36months})^{1/6}$.

To investigate which firm characteristics influence firm-level innovation during the pandemic, we estimate regressions of innovation measures on firm age, size, and capabilities. Our regressions were specified as follows.

$$y_i = \alpha + \sum_g \delta^g \cdot Age_i^g + \sum_h \gamma^h \cdot Size_i^h + \sum_j \theta^j \cdot Demand_i^j + \mathbf{X}_i \eta + \epsilon_i \qquad (1)$$

where y_i is an innovation outcome during the pandemic for a firm i. Innovation outcomes include any innovation, new products or services to the market, new products or services to this business, new customer, new feature to products or services, changing delivery process, retraining workers, and changing process to achieve social distancing. AGE_i^g is the set of the firm age categories (i.e., 0-2, 3-5, 6-10, 11-15, and 16+), $SIZE_i^h$ is a vector of size group categories of total number of workers (i.e., 1, 2-4, 5-9, 10-19, 20-49, 50-99, and 100+), and $Demand_i^j$ is a set of the shares of demand met under social distancing (i.e., 0%, 1%-25%, 25%-50%, 51%-75%, 76%-99%, and 100%). X_i is the set of controlling variables including a set of factors (i.e., direct and indirect factors (Very Important)), finance sources (i.e., PPP, EIDL, other federal support, other local support, bank, owner, family, and venture capital), sales shock (e.g., sales changes between January and April 2021), and industries (i.g., NAICS 3-digit codes).

Firm characteristics are measured pre-pandemic, so they are not affected by the shock while our innovation measures capture the changes during the first few months of the pandemic, through July 2020. We of course cannot separate innovation due to the pandemic from innovation activities that would have occurred in the absence of COVID-19. However, as we show, the measured rate of innovation activity in these few months is much larger than the comparable measures of U.S. firms during normal times, which suggests a large role for innovation activities in response to the pandemic.

Our empirical specification includes multiple sets of control variables. First, to control for different sizes of shocks the specification includes the sales change between January and April, when the shock was sudden and unexpected. The specification also includes direct and indirect factors that affected businesses during the pandemic as well as different types of finance that businesses received in the same period. Finally, because the magnitudes of the COVID shock were heterogeneous across the industries, we include industry effects defined at the 3-digit NAICS level. Altogether, the specification allows us to understand the relationship between firm characteristics and innovation activities while controlling for the heterogeneity of the COVID shock.

Following Angrist and Pischke (2009), we estimate the specifications with linear probability models and calculate robust standard errors. We assume that the linear probability model provides conditional expected values of our binary innovation measures. Because our dependent variables are binary, we also estimate Probit regressions as a robustness check and provide average marginal effects, with an assumption that the errors are normally distributed.[12] Overall, the magnitudes and patterns are qualitatively similar between linear probability models and Probit regressions. Similar patterns are

[12] The average marginal effects from Probit regressions are provided in the Appendix Tables 18, 19, and 20.

consistent even when the incidence of innovation is low, such as for bringing a new product to market or finding a new customer.

To study the trapped factor model, we also estimate the relationship of innovation with employment adjustment. The model examines if a firm's adjustment to its employment levels (reflecting trapped factors) is related to it's innovation activities. We use the following specification.

$$y_i = \lambda + \beta \cdot \left|\frac{(E^{Jul} - E^{Jan})}{E^{Jan}}\right| + \sum_g \mu^g \cdot Age_i^g + \sum_h \mu^h \cdot Size_i^h + \sum_j \mu^j \cdot Demand_i^j + \mathbf{X}_i \gamma + u_i \tag{2}$$

where $|\frac{(E^{Jul}-E^{Jan})}{E^{Jan}}|$ is the absolute value of the proportionate change in employment from January to July for firm i. In this specification, the sample is restricted to firms that experience 0 (no change) or negative employment changes, excluding the small number of firms with positive employment change. Therefore, the absolute proportionate change in employment varies from 0 to 1, increasing in the extent of trapped factors, and the trapped factor model would imply a negative coefficient (β) on $|\frac{(E^{Jul}-E^{Jan})}{E^{Jan}}|$.

Finally, in addition to innovation measures, we also examine potential digital adjustment channels due to decreased social interactions during the pandemic. Using equation (1), we estimate the regressions of changes in the shares of E-sales and teleworkers between January and July, 2020 on firm age, size, and prior capability, while controlling for other characteristics. In these specifications, instead of $Demand_i^j$, we directly control for $Esales_i^j$ and $Teleworker_i^j$ that captures the set of shares of E-sales in total sales in January (i.e., 0%, 1%-25%, 25%-50%, 51%-75%, 76%-99%, and 100%) and the set of shares of teleworkers in total employees in January 2021 (i.e., 0%, 1%-25%, 25%-50%, 51%-75%, 76%-99%, and 100%), respectively.

4 Results

4.1 Innovation during the pandemic

To understand innovation activities by small businesses during the pandemic, we start by examining the magnitudes of the different types of innovation measured in the survey.

Table 2 reports the rates of innovative activity by type for respondents to our survey compared to public tabulations from the 2014 Annual Survey of Entrepreneurs (ASE).[13] In the comparison between SBTC and ASE, we find higher rates of innovation and adjustments during the first months of the pandemic as compared to "normal" times. The ASE estimates are shown only where the categories are directly comparable across the questionnaires. With the exception of, "Sold a new good or service that no business has ever offered before", the SBTC respondents report higher rates than

[13] Brown et al. (2020) and Lee et al. (2022) used micro level ASE data to study innovation activities by immigrant and African-Amerian owned businesses, respectively.

Table 2 Innovation: SBTC vs. ASE

	SBTC (All)	SBTC (Employer)	ASE 2014
Any Innovation	0.69	0.74	N.A.
Number of Innovations	1.62	1.85	N.A.
Product Innovation	0.36	0.38	N.A.
Process Innovation	0.59	0.66	N.A.
New Product to Market	0.04	0.05	0.02
New Product to This Business	0.19	0.20	0.03
Different Customer	0.10	0.10	N.A.
New Feature to Product	0.24	0.26	0.04
Changed Delivery	0.33	0.38	0.04
Improved Process	0.18	0.20	0.03
Retrained Workers	0.12	0.18	N.A.
Changed Process for Social Distance	0.41	0.48	N.A.
Increased the share of E-sales in total sales	0.20	0.21	N.A.
Increased the share of teleworkers in total labor	0.07	0.13	N.A.

Note: The data is from the SBTC survey. The ASE data is from public tabulation. The SBTC sample includes both non-employers and employers, while the ASE 2014 sample includes only employers with at least one paid employee. The averages for SBTC employer sample is provided for comparison between SBTC and ASE 2014. The reference period for the SBTC innovation questions is six months, while it is three years in the ASE 2014, so for comparability the latter is rescaled to 6 months using the relationship $Innovation_{6months} = 1 - (1 - Innovation_{36months})^{1/6}$. SBTC = the Survey of Businesses in the Time of COVID; ASE = Annual Survey of Entrepreneurs

the ASE. Given that the SBTC is based on a shorter reference period and includes non-employer businesses, these results imply massive innovation activities during the pandemic.

Notably, nearly 70 percent of our sample reported engaging in some innovation during the crisis. Considering only employer-type businesses, the share of innovators is even higher, at 74 percent. The most common type of innovation involved "Changing work processes significantly to achieve social distancing" accounting for 41 percent of all respondents and 48 percent of employers. The second most common innovation involved "Changing the way a product or service was distributed or delivered." This activity is directly comparable to the ASE, where we see about 20 percent of businesses updating how delivery or distribution channels within six months, yet in the crisis these rates are close to doubling for employers at 38 percent and 33 percent across the entire SBTC sample.

The least common innovation refers to "Sold a new good or service that no business has ever offered before" across both the SBTC and the ASE. The ASE estimates indicate that within six months about 2 percent of businesses innovate a completely new product to market in normal times, whereas in the SBTC these rates double, at 4 percent for the entire sample and 5 percent for employers.

We also find high rates of innovation during the pandemic for both high-tech and low-tech firms, breaking with the conventional expectation that innovation is primarily

Table 3 Innovation by High-tech

	High-tech	Low-tech
Any Innovation	0.66	0.69
Number of Innovations	1.49	1.63
Product Innovation	0.36	0.36
Process Innovation	0.56	0.60
New Product to Market	0.05	0.04
New Product to This Business	0.16	0.19
Different Customer	0.09	0.10
New Feature to Product	0.24	0.24
Changed Delivery	0.24	0.34
Improved Process	0.22	0.18
Retrained Workers	0.12	0.12
Changed Process for Social Distance	0.37	0.42
Increased the share of E-sales in total sales	0.17	0.20
Increased the share of teleworkers in total labor	0.11	0.07
Share	0.03	0.97

Note: The table reports the share of innovation activities by high-tech or low-tech industry

a high-tech activity. Table 3 provides a comparison of that share of innovation by high-tech vs. low-tech firms in the SBTC sample. High-tech firms make up about 3 percent of our sample or some 642 firms, while the low-tech sample covers the remaining 97 percent. The most striking results from Table 3 are the high but comparable rates of innovation between both high and low-tech firms, with the former having a slightly greater propensity for product innovations, while the later having greater rates of process innovation.

With evidence of such high rates of innovation across all the different categories, we also examine how the innovation measures are related to each other. In Table 4, we provide the pairwise correlation matrix between our innovation measures.[14] Columns (1) to (8) show the correlations between each innovation measure. The highest correlation is 0.36 between "New Feature to Product" and "New Product to Market" and the lowest is 0.03 between "Increased the Share of Teleworkers" and "New Product to Market". The last two rows show the correlations with "Increased the Share of E-Sales" and "Increased the Share of Teleworkers". "Increased the Share of E-Sales" is most associated with "Changed Delivery" while "Increased the Share of Teleworkers" is most associated with "Retrained workers," both of which seem natural. Nonetheless, although the correlations are positive and statistically significant, the coefficients are relatively low and less than 0.3 in most cases. The low degrees of correlation suggest a fair amount of independence between our innovation variables.[15]

[14] Aggregated innovation measures (e.g., any, product, or process innovation) are excluded from this analysis because they are highly correlated with each innovation measure by construction.

[15] Despite the low correlations, we also estimate using seemingly unrelated regression methods as robustness checks to see if the correlations among innovation measures affect the main findings.

Table 4 Pairwise Correlation Matrix of Innovation Measures

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
New Product to Market	1.000									
New Product to This Business	0.224	1.000								
Different Customer	0.211	0.315	1.000							
New Feature to Product	0.180	0.363	0.253	1.000						
Changed Delivery	0.088	0.240	0.190	0.321	1.000					
Improved Process	0.134	0.198	0.184	0.326	0.287	1.000				
Retrained Workers	0.118	0.184	0.124	0.249	0.255	0.274	1.000			
Changed Process for Social Distance	0.034	0.087	0.066	0.150	0.276	0.184	0.249	1.000		
Increased the Share of E-Sales	0.045	0.200	0.118	0.147	0.273	0.115	0.088	0.098	1.000	
Increased the Share of Teleworkers	0.028	0.077	0.052	0.091	0.096	0.106	0.136	0.121	0.100	1.000

Note: Correlation matrix is provided across innovation measures, the share of E-Sales, and the share of teleworkers. All pairwise correlations are statistically significant at the 1% level

4.2 Firm age

In this section, we provide the coefficient plots with 95% confidence intervals for different types of innovation measures, focusing on the firm characteristics of age, size, and capability. These coefficient plots allow us to visually compare how the relationship between innovation and firm characteristics changes across different types of innovations. For detailed information, the full regression results are also provided in the Appendix.

In Fig. 1, we examine the relationship between innovation and firm age, controlling for all the other factors in equation (1) with 16 years and older as the reference group. The results show younger firms are more likely to engage in innovation activities than older are firms. Compared to firms aged 16 years or more, firms younger than 11 years have a more than 5 percentage point higher propensity for any innovation. Coefficients are statistically significant at the 5 percent significance level or better. Although magnitudes differ, these patterns are fairly consistent across all types and measures of innovation, except for social distancing, where there is no difference across the age groups.

Another notable pattern is that the age relationship is much stronger for product innovation. Startups and firms less than five years in business are at least 10 percentage points more likely to innovate products than firms in business over 16 years during the pandemic. By contrast, firms with less than 10 years in business are only about 4 percentage points more likely to engage in process innovations than firms over 16 years of age.

The most significant product innovations for the younger firms involve “New Product to Business” and adding “New Feature to Products” but compared to the oldest firms, they still introduced more “New Products to Market” as well as pivoted to, or engaged “New Customers.” In terms of process innovations, the youngest firms were more innovative at “Changing Delivery”, “Improving Processes”, and “Retraining Workers”; however, the adoption of “Social Distancing” seems not to be impacted by firm age. Also, it is notable that startups and firms under 10 years are not statistically distinguishable in their process innovations.

Overall, these results provide strong support for the Schumpeterian Mark I hypothesis. Innovation rates are much higher among younger than older firms, and their biggest advantages are in new products and other types of product innovation.

4.3 Firm size

Next, we examine the relationship between innovation and firm size in Fig. 2, using employment of one as the reference group. Controlling for all other variables in equation (1), firms are more likely to have any innovation during the pandemic as firm size increases. The increasing propensity is apparent up to firm size of 10-19 employees. The propensity slightly decreases for firms with 50 to 99 employees, and then it increases again in firms with 100 or more employees. Because of the relatively small number of firms in large size categories, standard errors are large.

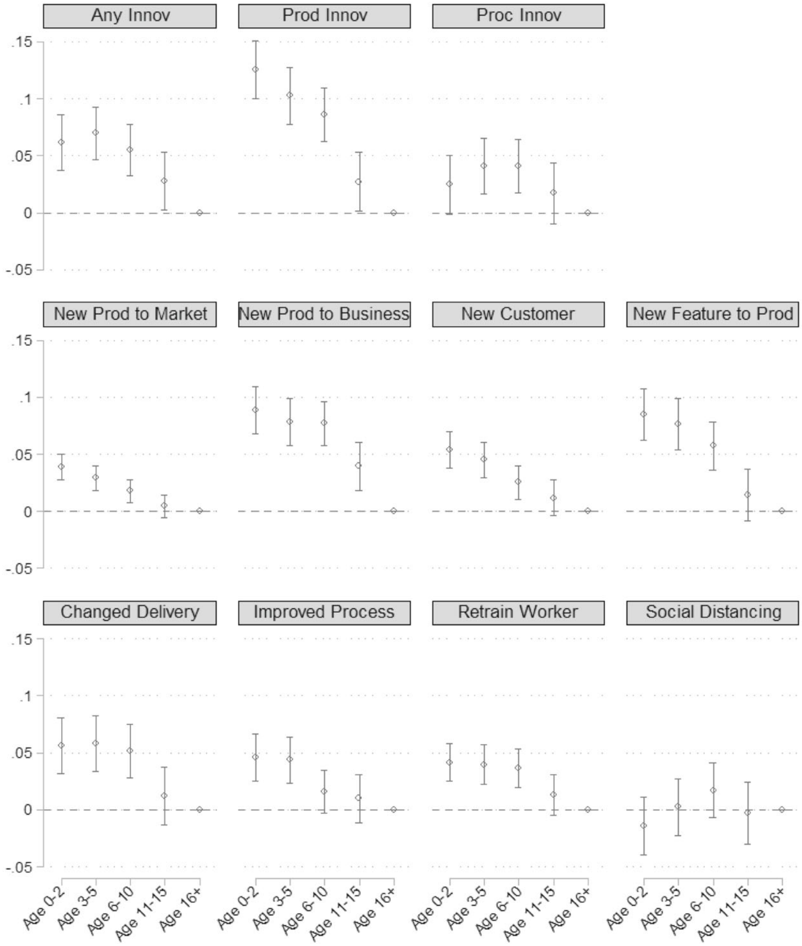

Fig. 1 Innovation Regression Results: Coefficients on Firm Age (Note: Regression coefficients and 95% confidence intervals from estimating equation (1) in the text. Each innovation measure was regressed on firm age, size, and demand met, while controlling for sales changes, factors affecting business operation status, different sources of finance, and 3-digit NAICS industries. This figure shows the results for firm ages in 2020. Results for other variables are shown in other figures. The regression results are in Appendix Tables 15, 16, and 17. N = 12,724)

Product and process innovations follow somewhat similar patterns, but the coefficients for process innovation are much larger and statistically significant for all size groups. Product innovations are statistically significant only for firms having in categories 5-9 and 10-19 employees, relative to single worker establishments.

The coefficient plots for the different types of product innovation show lower magnitudes in the coefficients of firm sizes. The relationships with firm size are close to

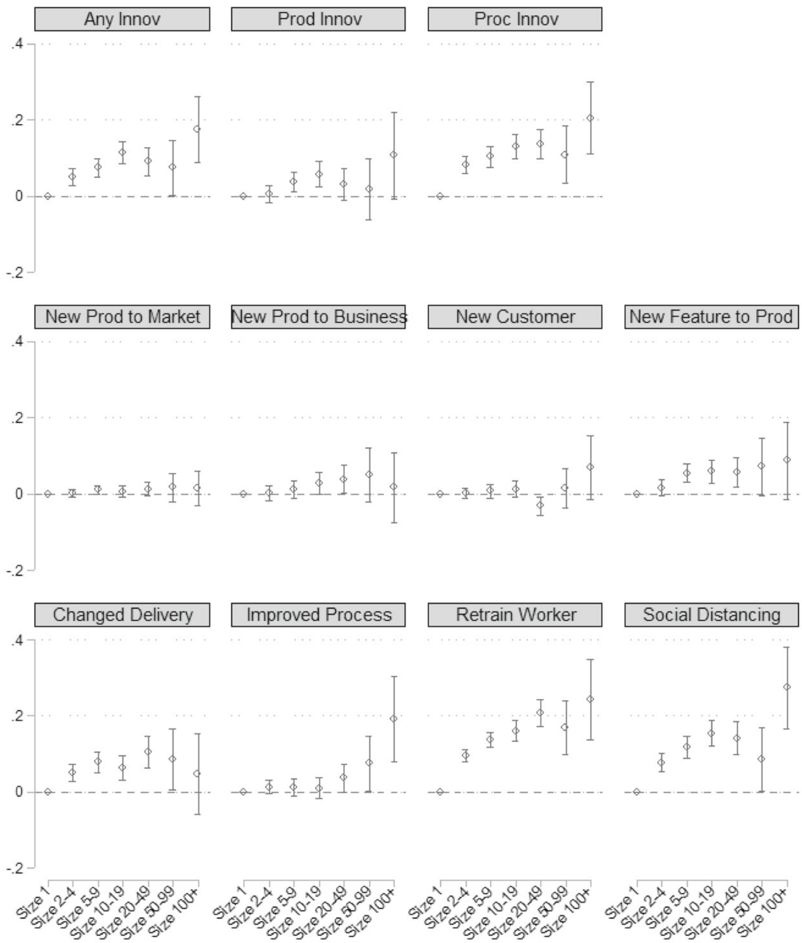

Fig. 2 Innovation Regression Results: Coefficients on Firm Size (Note: Regression coefficients and 95% confidence intervals from estimating equation (1) in the text. Each innovation measure was regressed on firm age, size, and demand met, while controlling for sales changes, factors affecting business operation status, different sources of finance, and 3-digit NAICS industries. This figure shows the results for firm size in January 2020. Results for other variables are shown in other figures. The regression results are in Appendix Tables 15, 16, and 17. N = 12,724)

zero for "New Prod to Market" and "New Customer". "New Feature to Product" does show a clearer association with size, as firms with between 5 and 50 employees are more likely to innovate on their products than firms with fewer than 5 employees, and firms with between 10 and 50 employees who are more likely to innovate a "New Product to their Business".

For the different types of process innovations, the increasing relationship with firm size is largely statistically significant; however, the relationship is much clearer for "Improved Processes", "Retrained Workers" and adopted "Social Distancing". The patterns are less clear with "Changed Delivery" for firms with more than 50 employees decreasing in their relative propensity to innovate in this direction than their smaller firm counterparts.

Overall, the size relationships imply greater process innovation among large firms, but less clearly so for product innovations. The advantage of size in process innovation seems consistent with Schumpeter Mark II, but the finding that innovation in general is rising during the crisis, and that it rises more in large firms, controlling for all other variables, is inconsistent with the Mark II hypothesis. Instead, our findings regarding the size relationship to innovation are more consistent with the trapped factors model of innovation (Bloom et al., 2013), discussed in more detail below.

4.4 Capability: Demand met under social distancing

Next we examine the relationship between innovation and prior organizational capability to meet demand under social distancing.

Figure 3 shows the regression results for the categorical variable representing the amount of demand that could be met under social distancing. The coefficient plots show the propensity of firms to innovate as a function of how much of their pre-COVID demand could be met by adopting social distancing practices, while controlling for other factors. Firms reporting 0 percent of their demand could be met represent firms where person-to-person interactions are likely essential for business operations, while firms reporting 100 percent of their demand can be met would require the least adjustments to accommodate social distancing practices.

The top row of graphs in 3 shows an inverted "U" shape for this relationship, driven largely by process innovations. Firms reporting that between half to three-quarters of their pre-COVID demand could be met were the most likely to have any innovation, most likely a process innovation. On the other hand, firms at the ends of the distribution reporting that either between 1 to 25 percent, or nearly all, of their pre-COVID demand could be met, were the least likely to adopt social distancing, albeit they are both at least 10 percentage points more likely to engage in any innovation than the firms reporting they could not recapture any demand with social distancing.

In the second row of graphs where we disaggregate the different types of product innovations, we see that prior capability to meet demand through social distancing is most associated with adding a "New Feature to Product" or a "New Product to Business" with coefficients that are statistically significantly different from the firms that reported they could not accommodate any social distancing. In the third row of graphs we disaggregate the different types of process innovations and here the relationships are more pronounced. The inverted "U" shape is most evident for the adopted "Social Distancing" and adopted "Changed Delivery" process innovations. Firms that could capture less than 25 percent or more than 75 percent of their pre-COVID demand through social distancing were about 12 and 13 percentage points more likely to take additional measures to implement social distancing, respectively.

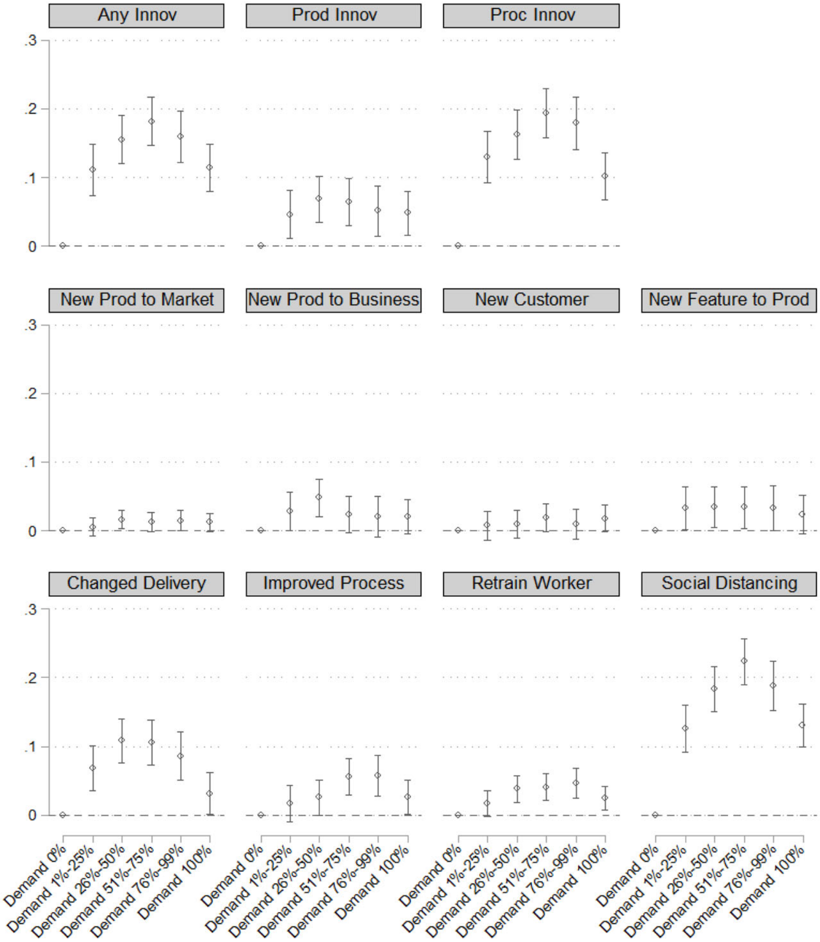

Fig. 3 Innovation Regression Results: Coefficients on Demand Met with Social Distancing (Note: Regression coefficients and 95% confidence intervals from estimating equation (1) in the text. Each innovation measure was regressed on firm age, size, and demand met, while controlling for sales changes, factors affecting business operation status, different sources of finance, and 3-digit NAICS industries. This figure shows the results for the demand met with social distancing. Results for other variables are shown in other figures. The regression results are in the Appendix Tables 15, 16, and 17. N = 12,724)

In relation, firms reporting between 50 to 75 of their demand could be met were 22 percentage points more likely to engage in social distancing relative to firms where social distancing would have no effect. This pattern is mirrored for the "Changed Delivery" innovation; however, the effect size is about 10 percentage points lower. We similarly see that having a pandemic specific advantage such as the ability to accommodate social distancing is also associated with "Improved Processes" and "Retrained Workers".

Overall, these results support an important role for prior capabilities and indicate that the relationship is non-monotonic. Innovation is stimulated the most when a firm needs to develop capabilities to respond to a new situation and when it has an intermediate level of prior experience that aligns with current market opportunities.

4.5 Employment adjustment and trapped factors

Figure 4 presents the coefficients and 95% confidence intervals associated with the variable $|\frac{(E^{Jul}-E^{Jan})}{E^{Jan}}|$ from equation (2). In regards to aggregate innovation measures (any, product, and process innovations), all the coefficients of percent changes in employment are negative and statistically significant, supporting the trapped factor model. The magnitude of the coefficient is larger for process than product innovation. Among the individual types of innovation activities, only "New Feature" is statistically significant among product innovations, whereas the relationship is significant for all types of process innovations. These results suggest that retained employees are redirected to tasks related to changing the existing products or processes rather than creating completely new products during the pandemic.

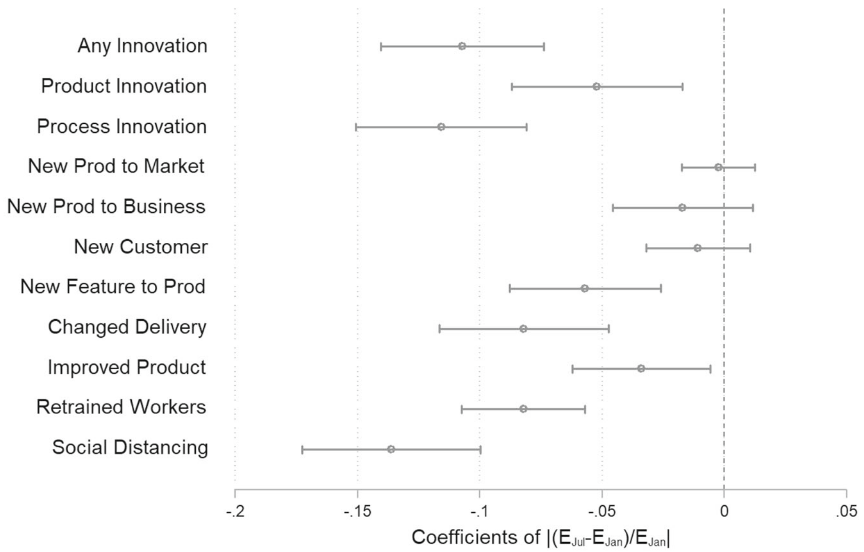

Fig. 4 Innovation Regression Results: Coefficients on Employment Change, Jan-Jul 2020 (Note: Regression coefficients and 95% confidence intervals of $|\frac{(E_{Jul}-E_{Jan})}{E_{Jan}}|$ from estimating equation (2) in the text. Each innovation measure is regressed on firm age, size, and demand met, while controlling for sales changes, factors affecting business operation status, different sources of finance, and 3-digit NAICS industries. The regression results are in the Appendix Tables 24, 25, and 26. N = 6,600)

Together with the result that firm size is positively associated with innovation, the finding that innovation is higher among firms that adjust employment less provides further support for a significant role for trapped factors during a crisis.

4.6 E-sales and teleworking outcomes

Compared with other crises, an unusual aspect of the pandemic is to reduce social interactions and to increase digital transactions and remote work. These could be especially important dimensions for innovation, and to better understand such phenomena, we examine how firm characteristics are associated with both changes in the share of e-sales and teleworkers in the first months of the pandemic.

In Fig. 5, we show the relationship between firm age, firm size, and the share of pre-pandemic e-sales, on the firm's propensity to innovate through increasing e-sales activities during the pandemic. Here we see that startups, firms under 2 years of age, were 6 percentage points more likely to engage in new e-sales activities during the pandemic, and this pattern decreases with firm age such that firms over 16 years in business were the least likely to adopt new e-sales practices. The effect with firm size is not statistically significant across any of the categories, leading us to conclude that

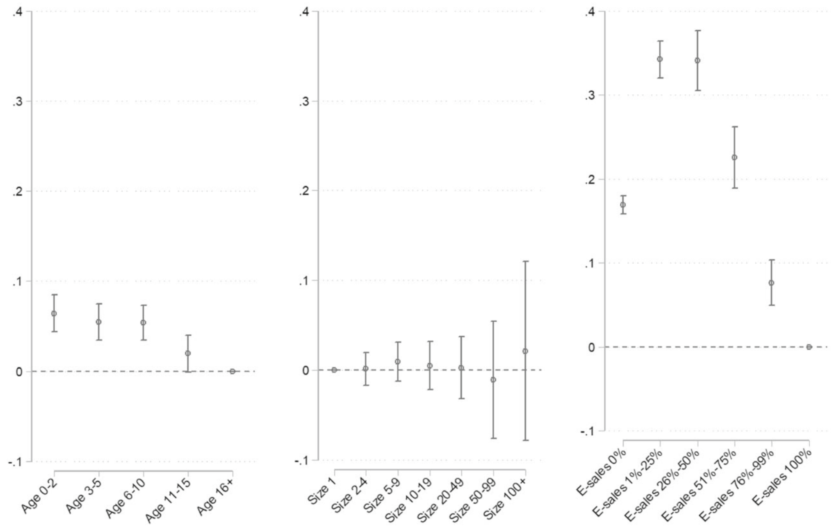

Fig. 5 Regression Results: Change in E-Sales on Age, Size, and the Share of E-Sales in January (Note: An indicator for the change in the share of E-sales from January to July is regressed on firm age, size, and the share of E-sales in January, controlling for sales changes, factors affecting business operation status, different sources of finance, and 3-digit NAICS industries. The figures show the coefficients and 95% confidence intervals for firm age, size, and the share of E-sales in January. The regression results are provided in Appendix Table 23. N = 14,985)

firm size did not impact the decision to expand on e-sales capabilities. This pattern is consistent with the previous findings that product innovation is strongly associated with firm age, while it is weakly related to firm size.

Moreover, we see large coefficients with statistically significant differences from the base category for firms with pre-pandemic capabilities in e-sales. Importantly, here we see the inverted "U" shape again. The base category is firms that had 100 percent of their pre-pandemic sales as e-sales and thus could not increase their share of e-sales any more during the crisis. In reference to this group, firms with 0 pre-pandemic e-sales were 17 percentage points more likely to enter into e-sales, firms with between 1 - 50 percent of the pre-pandemic share of sales online were about 35 percentage points more likely to expand on these capabilities, while firms with between 75 and 99 percent share of sales online were only about 8 percentage points more likely to expand on their e-sales.

Figure 6 provides the results on pre-pandemic teleworking capabilities and their relationship to firm age, firm size, and the propensity to increase teleworking capabilities during the pandemic. The patterns for firm age and firm size as compared to those with e-sales are reversed. The coefficients on firm age are all statistically insignificant, and estimates indicate firm age did not impact the decision to expand on teleworking capabilities. However, the relationship with firm size is clear and increasing with the number of employees. Even firms with just 2 to 4 employees are 8 percentage

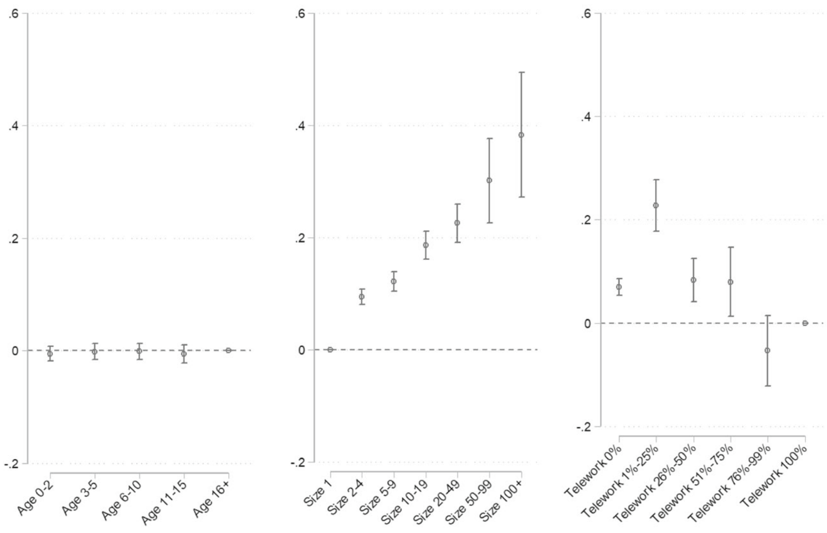

Fig. 6 Regression Results: Propensity to Increase Teleworker Share on Age, Size, and the Share of Teleworkers in January (Note: An indicator for an increase in the share of teleworkers between January and July was regressed on firm age, size, and the share of teleworkers in January, while controlling for sales changes, factors affecting business operation status, different sources of finance, and 3-digit NAICS industries. This figure shows the coefficients and 95% confidence intervals for firm age, size, and the share of teleworkers in January, 2020. The regression results are provided in Appendix Table 23. N = 15,342)

points more likely than single-employee firms to adopt teleworking. This propensity to innovate increases monotonically with size such that firms with over 100 employees were 32 percentage points more likely than single-employee firms to increase their teleworking activities. This pattern is consistent with the previous finding on a strong relationship between process innovation and firm size.

The relationship between the pre-pandemic share of the workforce that was teleworking and an increase in pandemic teleworking is not as clear, because of a relatively small number of observations for the firms with higher share of teleworkers before the pandemic. But it suggests a potential inverted "U" shape with a long right tail. Firms with less than 75 percent of their workforce teleworking pre-pandemic were all more likely to increase their teleworking activities during the pandemic. The highest propensities, about 24 percentage points higher than for firms already at 100 percent teleworking pre-pandemic, are reported for firms that had between 1 to 25 percent of their workforce working remotely before the pandemic. Firms with 76 to 99 percent of pre-pandemic workforce teleworking seem to have decreased their share of remote workforce during the pandemic, but this coefficient is not statistically significant from zero change and may be affected by the small number of firms in our sample for this category.

4.7 Robustness checks

We conducted two robustness checks for the main results. First, we estimate the same specifications with the Probit regressions to check the findings are robust in the nonlinear models. The results are provided in the Appendix Tables 18, 19, and 20. To compare these results with the LPM estimates, we compute the average marginal effects. The overall patterns and magnitudes of the coefficients of firm age, size, and capability from the probit models are qualitatively similar to those from the LPM. These results show that my estimates are robust to different linear and nonlinear models.

Second, we estimate the Seemingly Unrelated Regressions (SUR) to examine if the correlations among innovation measures affect the relationship between innovation measures and firm characteristics. These results are presented in the Appendix Tables 21 and 22. The estimates from the SUR are the same as in the LPM, and the significance of these estimates did not change although the standard errors slightly increased. These findings suggest that each innovation measure in our baseline models provides additional and different information.

5 Discussion

The findings of our empirical investigations are relevant to the theories of innovation we described earlier. A first important result is that both product and process innovation appear to be much higher during the pandemic than during a non-crisis period. Of course, we cannot easily extrapolate to other types of crises, such as wars, natural disasters, and financial meltdowns. But our results provide evidence that a crisis can produce opportunity as well as adversity. Firms respond in creative ways to changes in conditions, even if many of those changes - such as the large revenue shocks - are negative.

A second major finding concerns the Schumpeteraian hypothesis that younger firms are more innovative. We find strong support for this hypothesis across nearly all measures and types of innovation in our data. This result holds even when controlling for the size of the revenue shock, size, detailed industry, and other relevant characteristics. The youthfulness of a firm, therefore, seems to reflect greater agility leading to greater responsiveness to changed conditions. The one exception to this otherwise strong relationship concerns innovation to achieve social distancing, which seems relevant to all firms regardless of age.

Our results concerning the impact of firm size on the extent of innovation generally suggest a positive relationship, although the estimated coefficients are frequently statistically insignificant. The clearest patterns emerge for process innovations. Of course, a major caveat in interpreting our estimates of the firm size relationship is that our data are for small businesses, with only one percent of the sample having 100 or more employees. Nevertheless, the findings seem to be largely inconsistent with the Schumpeter Mark II hypothesis, which would predict that a decrease in rents should lower innovation. The size result is consistent with trapped factors, however, if we recognize that adjustment costs are likely to increase with firm size. Further evidence supporting an important role for trapped factors comes from the relationship of innovation with the extent of employment adjustment, a direct proxy for trapped factors. Firms with less employment adjustment, controlling for the change in revenue, are more likely to have idle inputs that can be used for innovation. The finding that innovation is negatively related with the extent of employment adjustment, all else equal, provides support for the trapped factor hypothesis.

A final hypothesis concerns the extent to which prior capabilities, based on business organization or experience, influence the extent to which firms innovate in response to the pandemic crisis. Controlling for other relevant factors, including firm age, size, industry, and other characteristics, we find that firms organized in such a way that social distancing can be easily adopted are more likely to innovate in a variety of ways. The results are particularly strong for pandemic-related innovations such as changed delivery, improved process, retrained workers, and innovations for social distancing.

Two other pandemic-related types of innovation and prior capabilities that we measure concern e-sales and teleworking. Estimating the propensity to increase each of these, we find a clear negative age relationship for e-sales and a clear positive size relationship for teleworking. Most interesting is the hump (inverse-U) shaped relationship between the propensities to increase each practice with the extent to which the practice had been used by the firm in January 2020. Firms at the extremes of prior experience with the practice - those with no experience and those already using it extensively - tend to increase the practice relatively little, while those with moderate prior experience tend to increase it substantially. Again, these results control for many other factors, including industry, age, size, and the magnitude of the firm-specific COVID shock, among other variables. The findings provide evidence that prior capabilities matter for innovation in the pandemic.

Our findings of higher rates of innovation during the pandemic crisis and systematic patterns with respect to firm age, size, and capabilities suggest the fruitfulness of additional research on related topics. For example, our focus in this paper has not included the impact of government programs, such as the Paycheck Protection Program and Economic Injury Disaster Loans, which may have played important roles in keeping firms operating and could have influenced the extent and types of innovation. Another example is the heterogeneity in the size of the shock may have implications for the patterns of innovation. In this paper, we have used such variables as controls when examining our variables of interest, but they are worthy of investigation in their own right.

6 Conclusion

What factors drive firm-level innovation? Does adversity spur firms to change products and processes and to find new ways of operating in order to adapt to new conditions? Is necessity the "mother of invention"?

Research on these questions has been hampered by the difficulty of observing, measuring, and distinguishing adverse shocks and firm responses. Observed firm behavior generally represents both the shocks and the responses. Business cycle research tends to assume that all firms face the same shock, or that heterogeneity cannot be measured. Existing data is typically annual, which is too low a frequency to capture shocks and responses.

In this paper, we exploit the suddenness and unexpectedness of the pandemic to study firm-level innovation and adaptation responses. We designed and carried out a survey of some 22,000 firms to provide the necessary data for the analysis. Measuring innovation in the early pandemic with a battery of questions partly based on previous innovation surveys, we find a large increase in both product and process innovation activities during the pandemic, but with interesting variation across firms.

The dimensions of variation on which we focus are motivated by theories of innovation for which proxy variables can be measured in our data. Overall, the results provide clear evidence in favor of the Schumpeterian Mark I, trapped factors, and prior capability hypotheses, while they do not support Mark II. During the pandemic, innovation rates are higher for younger firms, larger firms, and those adjusting employment less. Rates exhibit an inverse U-shaped profile with respect to pre-existing capabilities, such as e-commerce and teleworking, such that less innovation occurs for firms already with capabilities they needed and those with essentially no such capabilities, while innovation is highest with moderate amounts. These results hold in regressions including extensive controls, such as industry, age, size, and the magnitude of the shock. We conclude that firms adapt to large, unexpected shocks in creative ways and that the empirical patterns we have uncovered provide a fruitful counterpoint to studies by other scholars of non-crisis contexts. Our research shows that innovation is not confined to large, high-growth, high-tech firms during prosperous times, but also that it is stimulated more widely, including among smaller and non-high-tech firms, during a crisis.

Appendix A

This appendix provides the definitions of variables, descriptive statistics, and robustness checks for the main results.

Table 5 Definitions of Variables

Variable	Definition
Firm Age	
Firm Age 0 to 2	Firm age is between 0 and 2 in January, 2020
Firm Age 3 to 5	Firm age is between 3 and 5 in January, 2020
Firm Age 6 to 10	Firm age is between 6 and 10 in January, 2020
Firm Age 11 to 15	Firm age is between 11 and 15 in January, 2020
Firm Age 16 or more	Firm age is between 16 or more in January, 2020
Firm Size	
Firm Size in Jan 1	Number of workers is 1 in January, 2020
Firm Size in Jan 2 to 4	Number of workers is 2 to 4 in January, 2020
Firm Size in Jan 5 to 9	Number of workers is 5 to 9 in January, 2020
Firm Size in Jan 10 to 19	Number of workers is 10 to 19 in January, 2020
Firm Size in Jan 20 to 49	Number of workers is 20 to 49 in January, 2020
Firm Size in Jan 50 to 99	Number of workers is 50 to 99 in January, 2020
Firm Size in Jan 100 or more	Number of workers is 100 or more in January, 2020
Employment Change	Proportionate changes in the number of workers from January to July, 2020
Demand Met	
Demand Met 0%	0% demand met under social distancing
Demand Met 1% to 25%	1% to 25% demand met under social distancing
Demand Met 26% to 50%	26% to 50% demand met under social distancing
Demand Met 51% to 75%	51% to 75% demand met under social distancing
Demand Met 76% to 99%	76% to 99% demand met under social distancing
Demand Met 100%	100% demand met under social distancing
Sales Change	
Sales Change 100% decline	100% decline in total sales between January and April, 2020
Sales Change 76%-99% decline	76%-99% decline in total sales between January and April, 2020
Sales Change 51%-75% decline	51%-75% decline in total sales between January and April, 2020
Sales Change 26%-50% decline	26%-50% decline in total sales between January and April, 2020

Table 5 continued

Variable	Definition
Sales Change 1%-25% decline	1%-25% decline in total sales between January and April, 2020
Sales Change 0% (No Change)	0% change in total sales between January and April, 2020
Sales Change 1%-50% increase	1%-50% increase in total sales between January and April, 2020
Sales Change 51% or more	51% or more in total sales between January and April, 2020
Factors	
Worker safety	Business operations are affected by worker safety issues
Customer Safety	Business operations are affected by customer safety issues
Reduced demand or cash flow	Business operations are affected by reduced demand or cash flow unrelated to safety concerns affected
Problems accessing private bank credit	Business operations are affected by problems accessing private bank credit
Problems getting credit from suppliers	Business operations are affected by problems getting credit from suppliers
Difficulties getting supplies or inputs	Business operations are affected by difficulties getting supplies or inputs
Difficulties with transportation	Business operations were affected by difficulties with transportation, storage, or warehousing
Government ordered lockdown	Business operations were affected by government ordered lockdown
Finance	
PPP	Firm has received Paycheck Protection Program (PPP)
EIDL	Firm has received Economic Injury Disaster Loan (EIDL)
Other federal support	Firm has received other federal support
Other local support	Firm has received other local support
Bank	Firm has received finance from Bank
Owner	Firm has used finance from own bank account
Family	Firm has received loans from family or friends
Venture Capital (VC)	Firm has received finance from VC
Industry	
Industry	3-digit NAICS industries

Note: The table provides the definitions of innovation measures used in the analysis. All variables are dummies equal to 1 if a firm is relevant to that variable and 0 otherwise

Table 6 Firm Age, SBTC vs. BDS

Firm Age	SBTC All	SBTC Employer	BDS 2018
0 to 2 years	0.195	0.136	0.223
3 to 5 years	0.179	0.165	0.142
6 to 10 years	0.196	0.203	0.160
11 to 15 years	0.133	0.143	0.137
16+ years	0.297	0.351	0.337
Total Number of Firms	21,701	10,915	664,454

Note: The table shows the share of firms in each age category for SBTC All, SBTC Employer, and BDS 2018. SBTC = Survey of Businesses in the Time of COVID; BDS = Business Dynamics Statistics

Table 7 Firm Size, SBTC vs. BDS

Firm Size	SBTC All	SBTC Employer	BDS 2018
1 Emp	0.467	0.143	0.583
2 to 4	0.216	0.347	
5 to 9	0.153	0.246	0.179
10 to 19	0.093	0.150	0.112
20 to 49	0.053	0.085	0.097
50 to 99	0.012	0.019	
100+	0.006	0.010	0.031
Total Number of Firms	16,149	10,053	664,454

Note: The table shows the share of firms in each age category for SBTC All, SBTC Employer, and BDS 2018. SBTC = Survey of Businesses in the Time of COVID; BDS = Business Dynamics Statistics

Table 8 Industry Share, SBTC vs. BDS

Industry	SBTC All	SBTC Employer	BDS 2018
Agriculture, Forestry, Fishing and Hunting	0.009	0.009	
Mining, quarrying, and oil and gas extraction	0.001	0.001	0.001
Utilities	0.001	0.001	0.001
Construction	0.058	0.062	0.098
Manufacturing	0.054	0.058	0.049
Wholesale trade	0.044	0.043	0.068
Retail trade	0.149	0.145	0.094
Transportation and warehousing	0.021	0.021	0.027
Information	0.021	0.019	0.020
Finance and insurance	0.022	0.023	0.039
Real estate and rental and leasing	0.028	0.026	0.055
Professional, scientific, and technical services	0.136	0.125	0.147

Table 8 continued

Industry	SBTC All	SBTC Employer	BDS 2018
Management of companies and enterprises	0.003	0.002	0.005
Administrative and support and waste management	0.037	0.032	0.051
Educational services	0.037	0.039	0.018
Health care and social assistance	0.084	0.092	0.126
Arts, entertainment, and recreation	0.046	0.047	0.025
Accommodation and food services	0.085	0.107	0.092
Other services (except public administration)	0.163	0.146	0.095
Public Administration	0.002	0.001	
Total Number of Firms	20,589	10,475	664,454

Note: The table shows the share of firms in each age category for SBTC All, SBTC Employer, and BDS 2018. SBTC = Survey of Businesses in the Time of COVID; BDS = Business Dynamics Statistics

Table 9 Sales Change, January to April 2020

	Share
100% decline	0.202
76%-99% decline	0.178
51%-75% decline	0.201
26%-50% decline	0.172
1%-25% decline	0.081
0% (No Change)	0.130
1%-50% increase	0.025
51% or more increase	0.010

Note: The table shows the share of firms reporting each category of the amount of the sales change from January to April, 2020. The average sales change percentage from January to April, 2020 is -54.56%. N = 17,826

Table 10 Factors affecting business operations during the COVID-19

	Share
Worker safety	0.508
Customer Safety	0.527
Reduced demand or cash flow unrelated to safety concerns	0.622
Problems accessing private bank credit	0.313
Problems getting credit from suppliers	0.260
Difficulties getting supplies or inputs	0.354
Difficulties with transportation, storage, or warehousing	0.198

Table 10 continued

	Share
Government ordered lockdown	0.679
Direct factors	0.600
Indirect factors	0.861

Note: The table shows the share of firms reporting "very important" for each factor. Variables are defined as dummies equal to 1 if the response is very important for a relevant factor and 0 otherwise. N = 18,406

Table 11 Source of Financial Support

Variables	Mean
PPP	0.349
EIDL	0.306
Other Federal Support	0.034
Other Local Support	0.066
Bank	0.007
Owner	0.016
Family	0.035
VC	0.002

Note: The table shows the share of firms reporting sources of financial support. Variables are defined as dummies equal to 1 if a firm received a relevant financial support and 0 otherwise. N = 22,101

Table 12 Demand Met Under Social Distancing

	Share
Demand Met 0%	0.087
Demand Met 1% to 25%	0.125
Demand Met 26% to 50%	0.189
Demand Met 51% to 75%	0.174
Demand Met 76% to 99%	0.115
Demand Met 100%	0.310

Note: The table shows the share of firms reporting each category of demand met under social distancing. N = 18,740

Table 13 E-commerce Sales in January

Variables	Share
Share of E-sales in January 0%	0.604
Share of E-sales in January 1% to 25%	0.161
Share of E-sales in January 26% to 50%	0.058
Share of E-sales in January 51% to 75%	0.044
Share of E-sales in January 76% to 99%	0.045
Share of E-sales in January 100%	0.089

Note: The table shows the share of firms reporting share of E-sales in total sales in January 2020. N = 17,116

Table 14 Share of Teleworkers in January

	Share
Share of Teleworkers in January 0%	0.878
Share of Teleworkers in January 1% to 25%	0.025
Share of Teleworkers in January 26% to 50%	0.022
Share of Teleworkers in January 51% to 75%	0.009
Share of Teleworkers in January 76% to 99%	0.005
Share of Teleworkers in January 100%	0.062

Note: The table shows the share of firms reporting share of teleworkers in total labor in January 2020. N = 16,531

Table 15 Regressions: Innovation on Size, Age, and Capabilities

	(1) Any Innov	(2) Prod Innov	(3) Proc Innov
Firm Age 0 to 2	0.062***	0.126***	0.025*
	(0.012)	(0.013)	(0.013)
Firm Age 3 to 5	0.070***	0.103***	0.041***
	(0.012)	(0.013)	(0.013)
Firm Age 6 to 10	0.055***	0.086***	0.041***
	(0.011)	(0.012)	(0.012)
Firm Age 11 to 15	0.028**	0.027**	0.017
	(0.013)	(0.013)	(0.014)
Firm Size in Jan 2 to 4	0.051***	0.005	0.083***
	(0.011)	(0.011)	(0.012)
Firm Size in Jan 5 to 9	0.075***	0.037***	0.103***
	(0.013)	(0.014)	(0.014)
Firm Size in Jan 10 to 19	0.114***	0.058***	0.131***
	(0.014)	(0.017)	(0.016)

Table 15 continued

	(1) Any Innov	(2) Prod Innov	(3) Proc Innov
Firm Size in Jan 20 to 49	0.092***	0.031	0.137***
	(0.019)	(0.021)	(0.020)
Firm Size in Jan 50 to 99	0.075**	0.018	0.109***
	(0.036)	(0.041)	(0.038)
Firm Size in Jan 100+	0.176***	0.107*	0.205***
	(0.044)	(0.058)	(0.048)
Demand Met 1% to 25%	0.111***	0.046***	0.130***
	(0.019)	(0.018)	(0.019)
Demand Met 26% to 50%	0.155***	0.068***	0.163***
	(0.018)	(0.017)	(0.018)
Demand Met 51% to 75%	0.182***	0.064***	0.193***
	(0.018)	(0.017)	(0.018)
Demand Met 76% to 99%	0.159***	0.052***	0.179***
	(0.019)	(0.019)	(0.020)
Demand Met 100%	0.114***	0.048***	0.102***
	(0.017)	(0.017)	(0.018)
Observations	12,724	12,724	12,724
R-squared	0.093	0.066	0.101
Sales Shock	YES	YES	YES
Factor	YES	YES	YES
Finance	YES	YES	YES
NAICS 3-digit FE	YES	YES	YES

Note: The table presents estimates from linear probability models. The aggregate innovation measures were regressed on firm age, size, and demand met, while controlling for sales changes, factors affecting business operation status, different sources of finance, and 3-digit NAICS industries. The omitted categories include firm size 0 to 1, firm age 16+, and demand met 0%. Robust standard errors are provided in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 16 Regressions: Product Innovation on Size, Age, and Capabilities

	(1) New Prod to Market	(2) New Prod to This Bus	(3) Diff Custom	(4) New Feature to Prod
Firm Age 0 to 2	0.039***	0.089***	0.054***	0.085***
	(0.006)	(0.011)	(0.008)	(0.012)
Firm Age 3 to 5	0.029***	0.078***	0.045***	0.076***
	(0.006)	(0.010)	(0.008)	(0.011)
Firm Age 6 to 10	0.018***	0.077***	0.025***	0.057***
	(0.005)	(0.010)	(0.007)	(0.011)
Firm Age 11 to 15	0.005	0.039***	0.012	0.014
	(0.005)	(0.011)	(0.008)	(0.012)
Firm Size in Jan 2 to 4	0.004	0.002	0.003	0.017*
	(0.005)	(0.009)	(0.007)	(0.010)
Firm Size in Jan 5 to 9	0.011*	0.011	0.008	0.055***
	(0.006)	(0.011)	(0.009)	(0.012)
Firm Size in Jan 10 to 19	0.007	0.028**	0.013	0.059***
	(0.007)	(0.014)	(0.011)	(0.015)
Firm Size in Jan 20 to 49	0.013	0.039**	-0.031***	0.058***
	(0.009)	(0.018)	(0.012)	(0.020)
Firm Size in Jan 50 to 99	0.018	0.052	0.015	0.073*
	(0.019)	(0.036)	(0.026)	(0.038)
Firm Size in Jan 100+	0.015	0.018	0.071*	0.088*
	(0.024)	(0.047)	(0.043)	(0.052)
Demand Met 1% to 25%	0.005	0.028*	0.007	0.033**
	(0.007)	(0.014)	(0.011)	(0.016)
Demand Met 26% to 50%	0.016**	0.048***	0.010	0.034**
	(0.007)	(0.014)	(0.010)	(0.015)
Demand Met 51% to 75%	0.013*	0.024*	0.019*	0.034**
	(0.007)	(0.014)	(0.010)	(0.015)
Demand Met 76% to 99%	0.015*	0.021	0.010	0.033**
	(0.008)	(0.015)	(0.011)	(0.017)
Demand Met 100%	0.012*	0.021	0.018*	0.024
	(0.007)	(0.013)	(0.010)	(0.015)

Table 16 continued

	(1) New Prod to Market	(2) New Prod to This Bus	(3) Diff Custom	(4) New Feature to Prod
Observations	12,724	12,724	12,724	12,724
R-squared	0.022	0.060	0.049	0.049
Sales Shock	YES	YES	YES	YES
Factor	YES	YES	YES	YES
Finance	YES	YES	YES	YES
NAICS 3-digit FE	YES	YES	YES	YES

Note: The table presents estimates from linear probability models. The product innovation measures were regressed on firm age, size, and demand met, while controlling for sales changes, factors affecting business operation status, different sources of finance, and 3-digit NAICS industries. The omitted categories include firm size 0 to 1, firm age 16+, and demand met 0%. Robust standard errors are provided in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 17 Regressions: Process Innovation on Size, Age, and Capabilities

	(1) Changed Delivery	(2) Improved Prod	(3) Retrained Workers	(4) Changed Proc for Soc Dist
Firm Age 0 to 2	0.057***	0.046***	0.042***	-0.014
	(0.013)	(0.010)	(0.008)	(0.013)
Firm Age 3 to 5	0.058***	0.044***	0.040***	0.002
	(0.012)	(0.010)	(0.009)	(0.013)
Firm Age 6 to 10	0.052***	0.016	0.036***	0.017
	(0.012)	(0.010)	(0.009)	(0.012)
Firm Age 11 to 15	0.012	0.010	0.013	-0.003
	(0.013)	(0.011)	(0.009)	(0.014)
Firm Size in Jan 2 to 4	0.051***	0.013	0.096***	0.078***
	(0.011)	(0.009)	(0.008)	(0.012)
Firm Size in Jan 5 to 9	0.079***	0.013	0.138***	0.118***
	(0.014)	(0.011)	(0.010)	(0.014)
Firm Size in Jan 10 to 19	0.065***	0.011	0.161***	0.155***
	(0.017)	(0.014)	(0.013)	(0.017)
Firm Size in Jan 20 to 49	0.106***	0.036**	0.208***	0.142***
	(0.021)	(0.018)	(0.019)	(0.022)
Firm Size in Jan 50 to 99	0.088**	0.076**	0.170***	0.086**
	(0.041)	(0.037)	(0.036)	(0.042)
Firm Size in Jan 100+	0.048	0.193***	0.243***	0.275***
	(0.054)	(0.057)	(0.054)	(0.055)

Table 17 continued

	(1) Changed Delivery	(2) Improved Prod	(3) Retrained Workers	(4) Changed Proc for Soc Dist
Demand Met 1% to 25%	0.069***	0.017	0.017*	0.126***
	(0.017)	(0.014)	(0.010)	(0.017)
Demand Met 26% to 50%	0.109***	0.026**	0.038***	0.184***
	(0.016)	(0.013)	(0.010)	(0.017)
Demand Met 51% to 75%	0.105***	0.056***	0.041***	0.224***
	(0.017)	(0.014)	(0.010)	(0.017)
Demand Met 76% to 99%	0.086***	0.057***	0.047***	0.188***
	(0.018)	(0.015)	(0.011)	(0.018)
Demand Met 100%	0.031**	0.027**	0.025***	0.131***
	(0.015)	(0.013)	(0.009)	(0.016)
Observations	12,724	12,724	12,724	12,724
R-squared	0.083	0.039	0.091	0.102
Sales Shock	YES	YES	YES	YES
Factor	YES	YES	YES	YES
Finance	YES	YES	YES	YES
NAICS 3-digit FE	YES	YES	YES	YES

Note: The table presents estimates from linear probability models. The process innovation measures were regressed on firm age, size, and demand met, while controlling for sales changes, factors affecting business operation status, different sources of finance, and 3-digit NAICS industries. The omitted categories include firm size 0 to 1, firm age 16+, and demand met 0%. Robust standard errors are provided in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 18 Probit: Innovation on Size, Age, and Capabilities

	(1) Any Innov	(2) Prod Innov	(3) Proc Innov
Firm Age 0 to 2	0.060***	0.127***	0.025*
	(0.012)	(0.013)	(0.013)
Firm Age 3 to 5	0.070***	0.104***	0.041***
	(0.012)	(0.012)	(0.013)
Firm Age 6 to 10	0.055***	0.087***	0.041***
	(0.011)	(0.012)	(0.012)
Firm Age 11 to 15	0.027**	0.029**	0.016
	(0.013)	(0.014)	(0.014)
Firm Size in Jan 2 to 4	0.047***	0.005	0.078***
	(0.011)	(0.012)	(0.011)
Firm Size in Jan 5 to 9	0.074***	0.037***	0.101***
	(0.013)	(0.013)	(0.014)
Firm Size in Jan 10 to 19	0.123***	0.056***	0.132***
	(0.016)	(0.016)	(0.017)
Firm Size in Jan 20 to 49	0.095***	0.030	0.141***
	(0.021)	(0.021)	(0.022)
Firm Size in Jan 50 to 99	0.073*	0.019	0.107***
	(0.038)	(0.040)	(0.040)
Firm Size in Jan 100+	0.196***	0.106*	0.220***
	(0.060)	(0.055)	(0.061)
Demand Met 1% to 25%	0.095***	0.048**	0.121***
	(0.017)	(0.019)	(0.018)
Demand Met 26% to 50%	0.138***	0.070***	0.154***
	(0.016)	(0.018)	(0.017)
Demand Met 51% to 75%	0.168***	0.065***	0.186***
	(0.016)	(0.018)	(0.017)
Demand Met 76% to 99%	0.141***	0.054***	0.169***
	(0.017)	(0.020)	(0.019)
Demand Met 100%	0.098***	0.050***	0.095***
	(0.015)	(0.017)	(0.017)
Observations	12,694	12,692	12,707
Sales Shock	YES	YES	YES
Factor	YES	YES	YES
Finance	YES	YES	YES
NAICS 3-digit FE	YES	YES	YES

Note: The table reports the average marginal effects from Probit regressions. The aggregate innovation measures were regressed on firm age, size, and demand met, while controlling for sales changes, factors affecting business operation status, different sources of finance, and 3-digit NAICS industries. The omitted categories include firm size 0 to 1, firm age 16+, and demand met 0%. Robust standard errors are provided in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 19 Probit: Product Innovation on Size, Age, and Capabilities

	(1) New Prod to Market	(2) New Prod to This Bus	(3) Diff Custom	(4) New Feature to Prod
Firm Age 0 to 2	0.040***	0.094***	0.055***	0.086***
	(0.006)	(0.011)	(0.008)	(0.011)
Firm Age 3 to 5	0.032***	0.082***	0.047***	0.077***
	(0.006)	(0.010)	(0.008)	(0.011)
Firm Age 6 to 10	0.022***	0.079***	0.028***	0.058***
	(0.006)	(0.010)	(0.008)	(0.011)
Firm Age 11 to 15	0.007	0.045***	0.014	0.016
	(0.007)	(0.011)	(0.009)	(0.012)
Firm Size in Jan 2 to 4	0.005	0.002	0.004	0.016
	(0.005)	(0.009)	(0.007)	(0.010)
Firm Size in Jan 5 to 9	0.012**	0.009	0.009	0.053***
	(0.006)	(0.011)	(0.008)	(0.012)
Firm Size in Jan 10 to 19	0.009	0.023*	0.014	0.056***
	(0.007)	(0.013)	(0.010)	(0.014)
Firm Size in Jan 20 to 49	0.015*	0.034**	-0.031**	0.056***
	(0.009)	(0.016)	(0.014)	(0.018)
Firm Size in Jan 50 to 99	0.021	0.047	0.017	0.072**
	(0.017)	(0.031)	(0.024)	(0.035)
Firm Size in Jan 100+	0.015	0.015	0.064**	0.081*
	(0.024)	(0.046)	(0.031)	(0.047)
Demand Met 1% to 25%	0.008	0.030*	0.010	0.034**
	(0.009)	(0.016)	(0.012)	(0.017)
Demand Met 26% to 50%	0.020**	0.049***	0.011	0.036**
	(0.008)	(0.015)	(0.012)	(0.016)
Demand Met 51% to 75%	0.016*	0.026*	0.021*	0.036**
	(0.009)	(0.015)	(0.012)	(0.016)
Demand Met 76% to 99%	0.018*	0.025	0.013	0.036**
	(0.009)	(0.016)	(0.012)	(0.018)
Demand Met 100%	0.016*	0.024	0.019*	0.025
	(0.008)	(0.015)	(0.011)	(0.016)
Observations	12,293	12,673	12,613	12,679
Sales Shock	YES	YES	YES	YES
Factor	YES	YES	YES	YES
Finance	YES	YES	YES	YES
NAICS 3-digit FE	YES	YES	YES	YES

Note: The table reports the average marginal effects from Probit regressions. The product innovation measures were regressed on firm age, size, and demand met, while controlling for sales changes, factors affecting business operation status, different sources of finance, and 3-digit NAICS industries. The omitted categories include firm size 0 to 1, firm age 16+, and demand met 0%. Robust standard errors are provided in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 20 Probit: Process Innovation on Size, Age, and Capabilities

	(1) Changed Delivery	(2) Improved Prod	(3) Retrained Workers	(4) Changed Proc for Soc Dist
Firm Age 0 to 2	0.059***	0.046***	0.043***	-0.015
	(0.013)	(0.010)	(0.009)	(0.013)
Firm Age 3 to 5	0.059***	0.044***	0.039***	0.002
	(0.012)	(0.010)	(0.008)	(0.013)
Firm Age 6 to 10	0.053***	0.016	0.033***	0.016
	(0.012)	(0.010)	(0.008)	(0.012)
Firm Age 11 to 15	0.014	0.010	0.010	-0.003
	(0.013)	(0.011)	(0.009)	(0.014)
Firm Size in Jan 2 to 4	0.052***	0.013	0.116***	0.077***
	(0.011)	(0.009)	(0.008)	(0.011)
Firm Size in Jan 5 to 9	0.076***	0.013	0.143***	0.114***
	(0.013)	(0.011)	(0.009)	(0.013)
Firm Size in Jan 10 to 19	0.063***	0.011	0.155***	0.148***
	(0.016)	(0.013)	(0.010)	(0.016)
Firm Size in Jan 20 to 49	0.101***	0.035**	0.182***	0.135***
	(0.020)	(0.016)	(0.012)	(0.021)
Firm Size in Jan 50 to 99	0.086**	0.071**	0.165***	0.083**
	(0.038)	(0.030)	(0.023)	(0.040)
Firm Size in Jan 100+	0.047	0.156***	0.205***	0.272***
	(0.052)	(0.039)	(0.029)	(0.058)
Demand Met 1% to 25%	0.077***	0.021	0.033**	0.142***
	(0.018)	(0.016)	(0.015)	(0.019)
Demand Met 26% to 50%	0.115***	0.031**	0.053***	0.197***
	(0.018)	(0.015)	(0.014)	(0.018)
Demand Met 51% to 75%	0.113***	0.058***	0.057***	0.235***
	(0.018)	(0.015)	(0.014)	(0.019)
Demand Met 76% to 99%	0.095***	0.060***	0.062***	0.201***
	(0.019)	(0.016)	(0.015)	(0.020)
Demand Met 100%	0.040**	0.029**	0.041***	0.146***
	(0.017)	(0.014)	(0.014)	(0.018)
Observations	12,704	12,670	12,606	12,696
Sales Shock	YES	YES	YES	YES
Factor	YES	YES	YES	YES
Finance	YES	YES	YES	YES
NAICS 3-digit FE	YES	YES	YES	YES

Note: The table reports the average marginal effects from Probit regressions. The process innovation measures were regressed on firm age, size, and demand met, while controlling for sales changes, factors affecting business operation status, different sources of finance, and 3-digit NAICS industries. The omitted categories include firm size 0 to 1, firm age 16+, and demand met 0%. Robust standard errors are provided in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 21 Seemingly Unrelated Regressions: Product Innovation on Size, Age, and Capabilities

	(1) New Prod to Market	(2) New Prod to This Bus	(3) Diff Custom	(4) New Feature to Prod
Firm Age 0 to 2	0.037***	0.090***	0.051***	0.081***
	(0.006)	(0.011)	(0.008)	(0.012)
Firm Age 3 to 5	0.028***	0.078***	0.043***	0.074***
	(0.006)	(0.010)	(0.008)	(0.011)
Firm Age 6 to 10	0.017***	0.077***	0.023***	0.054***
	(0.005)	(0.010)	(0.007)	(0.011)
Firm Age 11 to 15	0.004	0.038***	0.010	0.012
	(0.005)	(0.011)	(0.008)	(0.012)
Firm Size in Jan 2 to 4	-0.001	0.002	-0.005	0.007
	(0.005)	(0.010)	(0.007)	(0.010)
Firm Size in Jan 5 to 9	0.007	0.011	0.001	0.046***
	(0.006)	(0.012)	(0.009)	(0.013)
Firm Size in Jan 10 to 19	0.002	0.027*	0.004	0.050***
	(0.007)	(0.014)	(0.011)	(0.016)
Firm Size in Jan 20 to 49	0.008	0.039**	-0.039***	0.049**
	(0.009)	(0.018)	(0.012)	(0.020)
Firm Size in Jan 50 to 99	0.013	0.049	0.007	0.062
	(0.019)	(0.036)	(0.026)	(0.038)
Firm Size in Jan 100+	0.006	0.008	0.055	0.065
	(0.024)	(0.047)	(0.043)	(0.052)

Table 21 continued

	(1) New Prod to Market	(2) New Prod to This Bus	(3) Diff Custom	(4) New Feature to Prod
Demand Met 1% to 25%	0.005	0.029**	0.009	0.031*
	(0.007)	(0.014)	(0.011)	(0.016)
Demand Met 26% to 50%	0.014**	0.046***	0.010	0.033**
	(0.007)	(0.014)	(0.010)	(0.015)
Demand Met 51% to 75%	0.013*	0.022	0.020*	0.030*
	(0.007)	(0.014)	(0.010)	(0.016)
Demand Met 76% to 99%	0.015*	0.018	0.010	0.031*
	(0.008)	(0.015)	(0.011)	(0.017)
Demand Met 100%	0.010	0.020	0.018*	0.022
	(0.007)	(0.013)	(0.010)	(0.015)
Observations	12,486	12,486	12,486	12,486
R-squared	0.026	0.062	0.056	0.053
Sales Shock	YES	YES	YES	YES
Factor	YES	YES	YES	YES
Finance	YES	YES	YES	YES
NAICS 3-digit FE	YES	YES	YES	YES

Note: The table reports the estimates from seemingly unrelated regressions of product innovation measures on firm age, size, and demand met, while controlling for sales changes, factors affecting business operation status, different sources of finance, and 3-digit NAICS industries. The omitted categories include firm size 0 to 1, firm age 16+, and demand met 0%. Robust standard errors are provided in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 22 Seemingly Unrelated Regressions: Process Innovation on Size, Age, and Capabilities

	(1) Changed Delivery	(2) Improved Prod	(3) Retrain Workers	(4) Changed Proc for Soc Dist
Firm Age 0 to 2	0.058***	0.043***	0.043***	-0.011
	(0.013)	(0.011)	(0.008)	(0.013)
Firm Age 3 to 5	0.058***	0.041***	0.039***	0.003
	(0.012)	(0.010)	(0.009)	(0.013)
Firm Age 6 to 10	0.051***	0.013	0.036***	0.016
	(0.012)	(0.010)	(0.009)	(0.012)
Firm Age 11 to 15	0.010	0.006	0.012	-0.004
	(0.013)	(0.011)	(0.009)	(0.014)
Firm Size in Jan 2 to 4	0.044***	0.001	0.092***	0.078***
	(0.012)	(0.010)	(0.008)	(0.012)
Firm Size in Jan 5 to 9	0.072***	0.004	0.138***	0.117***
	(0.014)	(0.011)	(0.010)	(0.014)
Firm Size in Jan 10 to 19	0.058***	0.000	0.159***	0.151***
	(0.017)	(0.014)	(0.014)	(0.017)
Firm Size in Jan 20 to 49	0.105***	0.031*	0.209***	0.142***
	(0.021)	(0.018)	(0.019)	(0.022)
Firm Size in Jan 50 to 99	0.079*	0.066*	0.169***	0.084**
	(0.041)	(0.037)	(0.036)	(0.042)
Firm Size in Jan 100+	0.024	0.173***	0.239***	0.263***
	(0.055)	(0.056)	(0.054)	(0.055)

Table 22 continued

	(1) Changed Delivery	(2) Improved Prod	(3) Retrain Workers	(4) Changed Proc for Soc Dist
Demand Met 1% to 25%	0.069***	0.017	0.018*	0.125***
	(0.017)	(0.014)	(0.010)	(0.018)
Demand Met 26% to 50%	0.104***	0.026*	0.038***	0.184***
	(0.016)	(0.013)	(0.010)	(0.017)
Demand Met 51% to 75%	0.101***	0.054***	0.041***	0.225***
	(0.017)	(0.014)	(0.010)	(0.017)
Demand Met 76% to 99%	0.085***	0.058***	0.046***	0.190***
	(0.018)	(0.015)	(0.011)	(0.019)
Demand Met 100%	0.033**	0.026**	0.026***	0.133***
	(0.015)	(0.013)	(0.009)	(0.016)
Observations	12,486	12,486	12,486	12,486
R-squared	0.090	0.044	0.092	0.104
Sales Shock	YES	YES	YES	YES
Factor	YES	YES	YES	YES
Finance	YES	YES	YES	YES
NAICS 3-digit FE	YES	YES	YES	YES

Note: The table reports the estimates from seemingly unrelated regressions of process innovation measures on firm age, size, and demand met, while controlling for sales changes, factors affecting business operation status, different sources of finance, and 3-digit NAICS industries. The omitted categories include firm size 0 to 1, firm age 16+, and demand met 0%. Robust standard errors are provided in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 23 Regressions: E-Sales and Teleworkers

	(1) Increased in Sh of E-Sales	(2) Increased in Sh of Telework
Firm Age 0 to 2	0.062***	-0.000
	(0.010)	(0.006)
Firm Age 3 to 5	0.055***	0.001
	(0.010)	(0.006)
Firm Age 6 to 10	0.047***	-0.003
	(0.009)	(0.006)
Firm Age 11 to 15	0.017*	-0.003
	(0.010)	(0.007)
Firm Size in Jan 2 to 4	-0.005	0.075***
	(0.008)	(0.006)
Firm Size in Jan 5 to 9	0.012	0.092***
	(0.010)	(0.007)
Firm Size in Jan 10 to 19	-0.001	0.146***
	(0.012)	(0.010)
Firm Size in Jan 20 to 49	0.000	0.173***
	(0.016)	(0.015)
Firm Size in Jan 50 to 99	-0.004	0.243***
	(0.031)	(0.034)
Firm Size in Jan 100+	0.038	0.319***
	(0.044)	(0.047)
Share of Esales0%	0.171***	
	(0.005)	
Share of Esales 1% to 25%	0.350***	
	(0.010)	
Share of Esales 26% to 50%	0.340***	
	(0.017)	
Share of Esales 51% to 75%	0.218***	
	(0.017)	
Share of Esales 76% to 99%	0.082***	
	(0.013)	

Table 23 continued

	(1) Increased in Sh of E-Sales	(2) Increased in Sh of Telework
Share of Teleworkerst 0%		0.056***
		(0.008)
Share of Teleworkerst 1% to 25%		0.239***
		(0.025)
Share of Teleworkers 26% to 50%		0.096***
		(0.021)
Share of Teleworkers 51% to 75%		0.088***
		(0.033)
Share of Teleworkers 76% to 99%		-0.050
		(0.033)
Observations	14,985	15,342
R-squared	0.121	0.153
Sales Shock	YES	YES
Factor	YES	YES
Finance	YES	YES
NAICS 3-digit FE	YES	YES

Note: The innovation measure was regressed on firm age, size, and demand met, while controlling for sales changes, factors affecting business operation status, different sources of finance, and 3-digit NAICS industries. The omitted categories include firm size 0 to 1, firm age 16+, the share of E-sales 100%, and the share of teleworkers 100%. Robust standard errors are provided in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 24 Regressions: Innovation on Size, Age, and Capabilities

	(1) Any Innov	(2) Prod Innov	(3) Proc Innov
$\lvert (E_{Jul} - E_{Jan})/E_{Jan} \rvert$	-0.107***	-0.052***	-0.116***
	(0.017)	(0.018)	(0.018)
Firm Age 0 to 5	0.061***	0.124***	0.031
	(0.018)	(0.020)	(0.019)
Firm Age 3 to 5	0.082***	0.102***	0.059***
	(0.015)	(0.018)	(0.017)
Firm Age 6 to 10	0.064***	0.083***	0.056***
	(0.014)	(0.017)	(0.016)
Firm Age 11 to 15	0.034**	0.021	0.021
	(0.016)	(0.018)	(0.018)
Firm Size in Jan 2 to 4	0.047***	0.031*	0.059***
	(0.018)	(0.019)	(0.019)
Firm Size in Jan 5 to 9	0.089***	0.072***	0.092***
	(0.019)	(0.020)	(0.020)
Firm Size in Jan 10 to 19	0.126***	0.088***	0.122***
	(0.021)	(0.023)	(0.022)
Firm Size in Jan 20 to 49	0.106***	0.053**	0.128***
	(0.025)	(0.027)	(0.026)
Firm Size in Jan 50 to 99	0.113***	0.083*	0.120***
	(0.041)	(0.049)	(0.043)
Firm Size in Jan 100+	0.179***	0.138**	0.226***
	(0.051)	(0.066)	(0.054)

Table 24 continued

	(1) Any Innov	(2) Prod Innov	(3) Proc Innov
Demand Met 1% to 25%	0.096***	0.057*	0.120***
	(0.030)	(0.030)	(0.031)
Demand Met 26% to 50%	0.129***	0.061**	0.145***
	(0.028)	(0.028)	(0.029)
Demand Met 51% to 75%	0.158***	0.063**	0.170***
	(0.029)	(0.028)	(0.029)
Demand Met 76% to 99%	0.144***	0.053*	0.165***
	(0.030)	(0.030)	(0.031)
Demand Met 100%	0.082***	0.028	0.072**
	(0.029)	(0.028)	(0.029)
Observations	6,600	6,600	6,600
R-squared	0.097	0.078	0.102
Sales Shock	YES	YES	YES
Factor	YES	YES	YES
Finance	YES	YES	YES
NAICS 3-digit FE	YES	YES	YES

Note: The table presents estimates from linear probability models. The aggregate innovation measures were regressed on firm age, size, and demand met, while controlling for sales changes, factors affecting business operation status, different sources of finance, and 3-digit NAICS industries. The omitted categories include firm size 0 to 1, firm age 16+, and demand met 0%. Robust standard errors are provided in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 25 Regressions: Product Innovation on Size, Age, and Capabilities

	(1) New Prod to Market	(2) New Prod to This Bus	(3) Diff Custom	(4) New Feature to Prod
$\lvert(E_{Jul} - E_{Jan})/E_{Jan}\rvert$	-0.003	-0.017	-0.011	-0.057***
	(0.008)	(0.015)	(0.011)	(0.016)
Firm Age 0 to 5	0.051***	0.100***	0.057***	0.094***
	(0.010)	(0.017)	(0.013)	(0.018)
Firm Age 3 to 5	0.030***	0.085***	0.045***	0.085***
	(0.008)	(0.015)	(0.011)	(0.016)
Firm Age 6 to 10	0.022***	0.081***	0.030***	0.056***
	(0.007)	(0.014)	(0.010)	(0.015)
Firm Age 11 to 15	0.011	0.048***	0.012	0.007
	(0.007)	(0.015)	(0.011)	(0.016)
Firm Size in Jan 2 to 4	0.016**	0.015	0.015	0.030*
	(0.007)	(0.015)	(0.011)	(0.016)
Firm Size in Jan 5 to 9	0.025***	0.027	0.023*	0.075***
	(0.008)	(0.017)	(0.013)	(0.018)
Firm Size in Jan 10 to 19	0.016*	0.030	0.025*	0.077***
	(0.010)	(0.019)	(0.015)	(0.021)
Firm Size in Jan 20 to 49	0.016	0.046**	-0.018	0.066***
	(0.011)	(0.023)	(0.015)	(0.025)
Firm Size in Jan 50 to 99	0.037	0.081*	0.039	0.128***
	(0.023)	(0.043)	(0.031)	(0.045)
Firm Size in Jan 100+	0.034	0.029	0.072	0.111*
	(0.029)	(0.053)	(0.047)	(0.059)

Table 25 continued

	(1) New Prod to Market	(2) New Prod to This Bus	(3) Diff Custom	(4) New Feature to Prod
Demand Met 1% to 25%	-0.000	0.058**	0.018	0.040
	(0.013)	(0.024)	(0.018)	(0.027)
Demand Met 26% to 50%	0.006	0.065***	0.010	0.023
	(0.012)	(0.022)	(0.016)	(0.025)
Demand Met 51% to 75%	-0.001	0.056**	0.030*	0.020
	(0.013)	(0.023)	(0.017)	(0.026)
Demand Met 76% to 99%	0.003	0.042*	0.002	0.036
	(0.013)	(0.024)	(0.018)	(0.027)
Demand Met 100%	0.004	0.019	0.017	-0.007
	(0.013)	(0.022)	(0.016)	(0.025)
Observations	6,600	6,600	6,600	6,600
R-squared	0.028	0.079	0.060	0.062
Sales Shock	YES	YES	YES	YES
Factor	YES	YES	YES	YES
Finance	YES	YES	YES	YES
NAICS 3-digit FE	YES	YES	YES	YES

Note: The table presents estimates from linear probability models. The product innovation measures were regressed on firm age, size, and demand met, while controlling for sales changes, factors affecting business operation status, different sources of finance, and 3-digit NAICS industries. The omitted categories include firm size 0 to 1, firm age 16+, and demand met 0%. Robust standard errors are provided in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 26 Regressions: Process Innovation on Size, Age, and Capabilities

	(1) Changed Delivery	(2) Improved Prod	(3) Retrain Workers	(4) Changed Proc for Soc Dist
$\lvert(E_{Jul} - E_{Jan})/E_{Jan}\rvert$	-0.082***	-0.034**	-0.082***	-0.136***
	(0.018)	(0.014)	(0.013)	(0.019)
Firm Age 0 to 5	0.069***	0.053***	0.064***	-0.008
	(0.020)	(0.016)	(0.016)	(0.020)
Firm Age 3 to 5	0.069***	0.054***	0.060***	0.030*
	(0.018)	(0.015)	(0.014)	(0.018)
Firm Age 6 to 10	0.058***	0.027**	0.053***	0.042**
	(0.017)	(0.014)	(0.013)	(0.017)
Firm Age 11 to 15	0.012	0.012	0.010	0.009
	(0.018)	(0.015)	(0.014)	(0.019)
Firm Size in Jan 2 to 4	0.039**	0.004	0.083***	0.069***
	(0.018)	(0.016)	(0.012)	(0.019)
Firm Size in Jan 5 to 9	0.085***	0.010	0.133***	0.109***
	(0.020)	(0.017)	(0.014)	(0.021)
Firm Size in Jan 10 to 19	0.060***	0.002	0.153***	0.167***
	(0.023)	(0.019)	(0.017)	(0.024)
Firm Size in Jan 20 to 49	0.113***	0.027	0.190***	0.131***
	(0.027)	(0.023)	(0.022)	(0.028)
Firm Size in Jan 50 to 99	0.102**	0.075*	0.196***	0.108**
	(0.047)	(0.042)	(0.041)	(0.048)
Firm Size in Jan 100+	0.061	0.210***	0.305***	0.288***
	(0.062)	(0.066)	(0.064)	(0.062)

Table 26 continued

	(1) Changed Delivery	(2) Improved Prod	(3) Retrain Workers	(4) Changed Proc for Soc Dist
Demand Met 1% to 25%	0.056*	0.037	0.049**	0.133***
	(0.029)	(0.023)	(0.020)	(0.030)
Demand Met 26% to 50%	0.083***	0.033	0.065***	0.172***
	(0.027)	(0.021)	(0.019)	(0.028)
Demand Met 51% to 75%	0.073***	0.059***	0.073***	0.218***
	(0.027)	(0.022)	(0.020)	(0.029)
Demand Met 76% to 99%	0.080***	0.069***	0.079***	0.187***
	(0.029)	(0.024)	(0.021)	(0.031)
Demand Met 100%	-0.006	0.014	0.027	0.107***
	(0.027)	(0.021)	(0.018)	(0.028)
Observations	6,600	6,600	6,600	6,600
R-squared	0.098	0.045	0.069	0.097
Sales Shock	YES	YES	YES	YES
Factor	YES	YES	YES	YES
Finance	YES	YES	YES	YES
NAICS 3-digit FE	YES	YES	YES	YES

Note: The table presents estimates from linear probability models. The process innovation measures were regressed on firm age, size, and demand met, while controlling for sales changes, factors affecting business operation status, different sources of finance, and 3-digit NAICS industries. The omitted categories include firm size 0 to 1, firm age 16+, and demand met 0%. Robust standard errors are provided in parentheses. *** p<0.01, ** p<0.05, * p<0.1

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