

The Great Lockdown and the Small Business: Impact, Channels and Adaptation to the Covid Pandemic

May 6, 2024

Abstract

In this paper we estimate the effects of the pandemic on Tunisian small and medium-sized enterprises (SMEs) and examine their adaptation processes during the first lockdown. Three simultaneous shocks are examined employing a Difference-in-Differences (DID) framework applied to the national firm census: the labor input shock, the demand shock and the intermediate input shock. We show that SME performance in the first year of the crisis was heavily affected by a combination of labor input, demand and intermediate input shocks, but only the effects of the demand and intermediate input shocks persisted in the following year. Using our own firm survey, we examine three kinds of adaptation strategies: workplace and process adaptation, and trade credit. We find that firms in non-essential sectors were less able to adapt during the first lockdown, suggesting that firm adaptation seems to be more driven by capability than by necessity.

Keywords: Crisis, Covid-19, lockdown, SME, adaptation

JEL classification: D22, L25, O14, O16

1 Introduction

Understanding the nature of an economic shock and how firms adapt to it are key in mitigating its consequences, preparing for recovery and handling future shocks. The de-

mand/supply nature of the Covid-19 crisis and the channels through which it was transmitted to the whole economy entail different policy implications (Baqae and Farhi, 2022). This crisis exposed economists and policy makers to an unprecedented level of complexity in terms of shocks, including various initial and high-order supply and demand shocks. The labor input shock resulted from the mandatory closure of businesses, the implementation of social distancing, the level of coronavirus infections or fear of infection. The shortage of intermediate inputs is the consequence of the reduction in labor witnessed by intermediate-input industries. Meanwhile, the demand shock resulted from the intersectoral and intertemporal shift in the composition of household expenditure. Households' demand for high contact-intensive goods and services such as dining out, entertainment, and travel was reduced, while demand for non-perishable food, sanitary products and healthcare services increased. Furthermore, they opted to postpone consumption in the present, referred to by Baldwin and Tomiura (2020) as the wait-and-see effect, which also occurred as a result of income loss due to the lockdown and other containment measures.

In this paper, our goal is to gather lessons from the pandemic and set up a framework of analysis that could be applied in response to future shocks. Our first aim is to quantify the impact of the crisis on SMEs and disentangle the main channels through which they were affected. Our second objective is to identify which types of SMEs performed better during the crisis and thereafter. Finally, we wish to understand which firms adapted better to the crisis and how. This knowledge can help improve the targeting of financial support to SMEs in developing countries facing shocks other than the Covid-19 crisis but affecting the economy in a similar way. For instance, natural disasters or conflicts disrupt production capabilities and infrastructure, severely hampering supply chains. Concurrently, these events might reduce consumer spending due to displacement, loss of income, uncertainty, as well as the indirect demand for intermediate inputs.

The three channels through which the pandemic affected SMEs are the labor input shock, the demand shock and the intermediate input shock. Our key variables are the variation of these shocks across industries. The labor input shock captures exposure to the risk of closure, using a dummy variable which takes the value 1 if a firm operates in a non-essential

industry. The demand shock captures the decrease in households' purchasing power and is proxied by the industrial mean of changes in US firms' annual earnings forecast before and after the outbreak of Covid-19. Finally, the intermediate input shock captures the potential disruptions in input provision and is measured as the industrial share of firms experiencing intermediate input constraints derived from the World Bank's Enterprise Survey Follow-up on Covid-19. We run a Difference-in-Differences model on the panel data drawn from the Tunisia's national firm census.

While demand and supply shocks are the fundamental hazards, other factors may exert an influence by amplifying or mitigating these hazards. We identify three sources of amplification/mitigation: technological adaptation, credit constraint and firm heterogeneity. We first examine these sources using the national census. More precisely, we add a triple interaction of the shock measures with firm or industry characteristics to the baseline model. Firm characteristics include size, export status and foreign ownership whereas technological adaptation and credit constraint are proxied respectively by the industrial teleworkability and external finance dependence indices. To further investigate SMEs' actual adaptations in terms of technology and finance, we ran a survey of Tunisian SMEs right after the first lockdown. Three prominent kinds of adaptation implemented by firms were examined: workplace adaptation, process adaptation and the use of trade credit.

Overall, we find that SME performance in 2020 was heavily affected by a combination of labor input, demand and intermediate input shocks, but only the effects of the demand and intermediate input shocks persisted in 2021. Additionally, the shocks caused by the pandemic exacerbated the divide between outward-looking and domestic firms as outward-looking firms and those owned by foreign entities demonstrated better adaptability and resilience. Our findings also highlight that firm adaptation seems to be more driven by capability than by necessity. Furthermore, younger and larger firms, along with exporters and foreign-owned businesses, were more inclined to adopt process adaptation. Finally, managers with university degrees exhibited a greater tendency toward teleworking, whereas experienced managers benefited from improved access to trade credit.

Our paper contributes to the literature on the impacts of "negative shocks" on SMEs in

three ways. Firstly, it is among a small number of papers that look at these impacts at the firm level in developing countries. The uniqueness of our data set makes it possible to estimate the effects of the Covid crisis on the entire Tunisian SME population and control for time-invariant unobservable heterogeneity. Moreover, working on two years of observations allows us to study firms' behavior in the midst of crisis and recovery, whereas most papers have solely focused on the first months of the crisis. Furthermore, this paper quantifies the impact of various simultaneous shocks induced by the pandemic. From the technical point of view, we provide a comprehensive set of measures of shocks at the industry level. These measures neither limit themselves to the Tunisian context nor to the Covid context. Other measures of economic shocks can be constructed in the same manner for other countries and crises. From the practical point of view, being informed about which firms are more sensitive to certain shocks than others is important in order to enable better timing and targeting of public support. Finally, with our own survey on SMEs carried out after the first lockdown, we are able to provide evidence on the determinants of firm adaptation.

The rest of the paper is structured as follows. Section 2 reviews the relevant literature. Section 3 provides the context of the first lockdown and the Tunisian economy in 2020. The data and methodology are described in Section 4. Section 5 presents our results. Finally, Section 6 concludes.

2 Literature Review

Our paper relates to several strands of literature. The first one seeks to decompose shocks at the macroeconomic level. Given the vastness and prevalence of this literature, we only cite here the Covid-19 related papers. [del Rio-Chanona et al. \(2020\)](#) were among the first authors who predicted the first-order supply and demand shocks on sectoral output, employment and wages. They estimate that the Covid-19 crisis and containment measures reduced aggregate output by one fifth, total employment by one quarter and total wage income by nearly one fifth. The aggregate effects were dominated by supply shocks. [Brinca et al. \(2021\)](#) measure the shifts in labor supply and demand curves using a structural-vector-autoregression model and monthly sectoral data. They also found that more than two

thirds of the aggregate drop in the growth rate of working hours growth rate during the lockdown could be attributed to the labor input shock. [Baqae and Farhi \(2020\)](#) and [Barrot et al. \(2021\)](#) focus on the first-order and second-order supply effects of social distancing measures and suggested that the nonlinearities of the production network, together with the heterogeneity of the shocks, could make the second-order shock very costly in terms of its effects on output. [Guerrieri et al. \(2022\)](#) examine the demand shock triggered by the negative supply shocks and find that this secondary shock could be larger than the initial shock if the intersectoral elasticity of substitution was less than the intertemporal one. [Baqae and Farhi \(2022\)](#) incorporate nominal frictions into a disaggregated Keynesian model featuring both multiple sectors and multiple factors. In the presence of complementarities, negative supply shocks outweigh negative demand shocks in terms of output loss and generate Keynesian spillovers as well as further output loss. Lastly, [Pichler et al. \(2020\)](#) extend the traditional input-output model to account for simultaneous demand and supply shocks and factored in a degree of firm rationing to obtain the bottom-up impact estimates. They show the important amplification effects of the production network which were even greater in the presence of micro-level coordination failures. The common findings of this literature are that (i) labor supply supply shocks predominated during the lockdown; (ii) demand and supply shocks varied substantially across industries; (iii) the higher-order shocks were much larger than the initial shocks and (iv) nonlinearities, complementarities and market frictions, in most of the cases, amplified the shocks.

The literature studying the impact of Covid-19 more specifically at the firm level shows a heterogeneous impact depending mainly on firm size and the level of development of their country of operation. Based on a US survey of 28,000 firms, [Alekseev et al. \(2022\)](#) find that larger and older firms are more likely to continue operating during the crisis and that they were more concerned about demand shocks as opposed to supply shocks. [Apedo-Amah et al. \(2020\)](#) confirm the disproportionate impact on small firms with a survey of 51 countries and 100,000 businesses. Using a survey covering 35,000 small businesses in Latin America, [Guerrero-Amezaga et al. \(2022\)](#) predict a substantial impact in the medium term on small firms, due to the low levels of public assistance that these firms benefited from. Drawing

on firm surveys in 38 countries, [Aga and Maemir \(2022\)](#) show that Sub-Saharan African firms are disproportionately impacted by the health crisis, due to structural pre-pandemic characteristics. The authors also find a higher propensity to adapt to shocks incurred as result of the Covid-19 pandemic in Sub-Saharan Africa, despite lower financial and technological resources. Using a panel survey of 5,000 UK firms, [Bloom et al. \(2020\)](#) highlight the major contraction of less productive firms in 2020-21, which partly offsets the significant reduction in within-firm productivity on overall total factor productivity. Drawing on firm-level data on 34 countries, [Muzi et al. \(2022\)](#) also find a higher probability of exit of unproductive firms, characterized by low levels of digitalization and innovation. Recent significant contributions to this strand of literature also draw attention to resilience factors. For instance, [Barry et al. \(2022\)](#) study how three forms of corporate flexibility - workplace, investment and finance - affect firms' employment and investment plans. Notably, high workplace flexibility was not only important for planned employment growth, but also boosted planned capital spending when coupled with high investment flexibility. Using the domain/website density and data on small business performance aggregated at the metropolitan level, [Mossberger et al. \(2023\)](#) highlight the role of digital economic activity and its effect on the resilience of small businesses in the US metropolitan regions. Meanwhile, [Aristei and Gallo \(2023\)](#) conclude that sound environmental management practices relieved the impacts of the Covid-19 pandemic, while pre-crisis credit constraints acted as an amplifier of the negative impacts. Finally, [Chen et al. \(2023\)](#) show that exporting firms performed better during the lockdown by means of online operations, trade credit and asset sales.

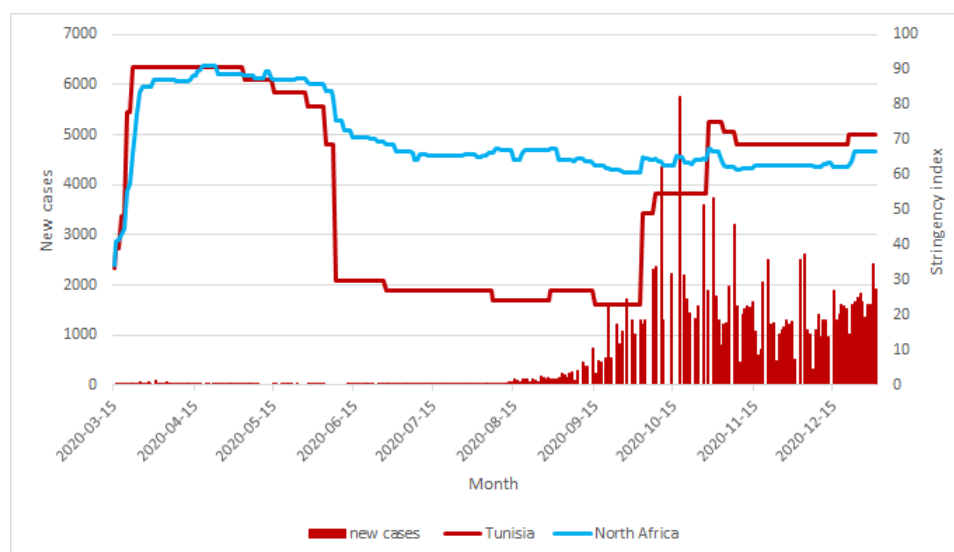
Our paper also draws on a third strand in the literature that looks at the effects of and responses to other shocks (financial crisis, terrorist attacks, etc.) at the firm level. These studies exploit the exogenous variation in the shocks or in the predisposition to shocks across industries or economies. For instance, [Tong and Wei \(2008\)](#) and [Isyuk \(2013\)](#) use the variation in sectoral demand sensitivity and firm financial constraints to isolate the effect of demand shock and credit supply shock on firm stock prices during the 2007-2009 financial crisis. The index of demand sensitivity was constructed by [Tong and Wei \(2008\)](#) based

on the response of consumer confidence, proxied by firm stock prices, to the September 11 attacks. They find that firms were more affected by the contraction of credit than the reduction in consumer confidence. [Calomiris et al. \(2012\)](#) study the change in equity returns of firms around the world during the financial crisis. They find lower equity returns in firms that were sensitive to the global demand shock, the credit crunch and equity sales pressures. [Claessens et al. \(2012\)](#) compile firm-level data from 42 countries to study the three transmission channels of the financial crisis: credit supply, domestic demand and trade. They conclude that firms in higher demand- and trade-sensitive industries experienced more output loss. [Nguyen and Qian \(2014\)](#) use a survey of Eastern European firms and reached the same conclusion, namely that the demand shock was more damaging to firms' sales and employment than the credit shock. In the same spirit, [Coviello et al. \(2022\)](#) examine firm responses to a persistent adverse demand shock using a quasi-experiment: the 2008 law imposing fiscal rules that affected only Italian municipalities with a population greater than 5,000. They show that firms responded to a persistent demand shock by cutting capital rather than labor.

3 First lockdown and Tunisian economy in 2020

In the wake of the trauma caused by the explosion in the number of confirmed cases of Covid-19 infection in Italy and France, Tunisia's main economic partners and preferred destinations of its migrants, the country imposed one of the strictest lockdowns in the world (stringency index of 91) from March 2020 (after the detection of the first infected case) to the beginning of May 2020. Borders and schools were closed, internal movements forbidden and only workplaces pertaining to essential industries (food, public utilities, etc.) were kept open ([Marouani et al., 2022](#)).

Figure 1: Number of daily Covid cases and stringency of restrictions in Tunisia in 2020



Source: Author's creation using data by [Hale et al. \(2021\)](#)

The success in terms of low infections and the high economic cost (GDP decreased by 21% in the second quarter of 2020) led to the government lifting almost all restrictions in the summer of 2020, as shown in Figure 1. However, the resurgence of cases in fall 2020 led the authorities to reimpose high restrictions, particularly harmful for service sector firms which account for a high share of the Tunisian economy, resulting in a total GDP loss of 9% at the end of 2020. The cost was particularly high for SMEs given the limited provision and extension of financial support made available by the government. Only 25% of SMEs applied for or received any form of state assistance to overcome the crisis ([Krafft et al., 2021](#)).

4 Data and Methodology

4.1 Methodology

4.1.1 Shock evaluation

As mentioned above, the supply and demand shocks induced by the lockdown and Covid-19 were aggregate shocks, but their effects were notably heterogeneous across industries. We deploy these sectoral variations of shocks to decompose their effects on Tunisian SMEs.

As the baseline model, we apply the traditional two-way-fixed-effect (TWFE) DID specification. The model is set up as follows:

$$y_{ijrt} = \gamma_1 LS_j \cdot Post + \gamma_2 DS_j \cdot Post + \gamma_3 IS_j \cdot Post + \beta X_{ijr(t-1)} + \alpha_j + \eta_r + \lambda_t + \epsilon_{ijrt} \quad (1)$$

where y_{ijrt} is the annual sales of firm i in industry j and district r .¹ The dummy variable $Post$ takes the value 1 if a firm is observed in 2020 and the value 0 otherwise. α_j and η_r capture time-invariant industry-specific and district-specific effects, while λ_t accounts for the time trend. A set of firm covariates $X_{ijr(t-1)}$ controls for pre-crisis time-varying firm-level characteristics, including firm age (in logarithm), square of age, size, foreign ownership and export status. We adjust the standard errors by clustering them at the 4-digit NAT² industry level. The labor input shock, LS_j , measures exclusively the direct effect of the mandatory lockdown in April and May 2020. The demand shock, DS_j , is a proxy for the demand shifts induced by the Covid-19 pandemic. The intermediate input shock, IS_j , measures sectoral exposure to intermediate input shocks. Details on the identification of these shocks are presented in section 4.2. Except for the labor input shock, which is a dummy, other shocks are standardized. We expect the estimations of γ_1 , γ_2 and γ_3 to be negative, meaning that the shocks have a negative association with firm sales.

One question arising from the initial analysis is whether specific firm characteristics, like size, export orientation, foreign ownership, or financial constraints, etc., drive the impact of shocks. This would imply heterogeneity in the impact of shocks across firms. To explore this heterogeneity, we re-estimate the baseline model and introduce, one at a time, the interactions between shocks and specific firm attributes that might influence the effect of the shocks:

$$y_{ijrt} = \pi_1 Covariate_{ij(t-1)} \cdot Post + \pi_2 Covariate_{ij(t-1)} \cdot Shock_j + \pi_3 Shock_j \cdot Covariate_{ij(t-1)} \cdot Post + \gamma_1 LS_j \cdot Post + \gamma_2 DS_j \cdot Post + \gamma_3 IS_j \cdot Post + \beta X_{ijr(t-1)} + \alpha_j + \eta_r + \lambda_t + \epsilon_{ijrt} \quad (2)$$

¹Alternatively, in Appendix Tables, y_{ijrt} will also capture firm i employment.

²Following the 2009 Tunisian Nomenclature of Activities 2009.

where $Shock_j$ is the labor input, demand, or intermediate input shock and $Covariate_{ijr(t-1)}$ is a set of relevant firm characteristics, which are detailed below.

Firm size is a fundamental characteristic considered in empirical analyses of firm performance during a crisis. Research indicates that smaller firms tend to experience disproportionately larger negative effects, attributed to their limited resources and the quality of their entrepreneurs (Gertler and Gilchrist, 1994; Varum and Rocha, 2013; Cowling et al., 2015; Apedo-Amah et al., 2020; Alejandro Fernández-Cerezo and Moral-Benito, 2023). Moreover, significant variation exists between and within subgroups of small firms, indicating that interventions aimed at all SMEs may not be efficient (Cowling et al., 2015; Brucal and Grover, 2023).

The relationship between firm resilience and export orientation is less straightforward. On the one hand, export-oriented firms have higher productivity, quality and exhibit learning-by-exporting behaviors, hence, they are expected to perform better during recession times (Atkin et al., 2017; Burger et al., 2017; Chen et al., 2023). On the other hand, firms with greater sensitivity to trade might be more vulnerable to global crisis (Claessens et al., 2012). In this paper, we distinguish between partial and total exporters, defined by Articles 10 and 21 of the *Code d'Incitation aux Investissements*. These firms benefit from special tax exemptions, according to Articles 12 and 22 of the same law. Moreover, during the Covid-19 crisis, total exporters were granted the right to sell up to 100% of their output on the domestic market³.

The literature also suggests that firm resilience may vary based on the ownership structure, particularly between foreign-owned and locally-owned firms. Foreign-owned firms are expected to perform better because they are more productive and have access to international credit (Helpman et al., 2004; Burger et al., 2017; Georgopoulos and Glaister, 2018).

We also interact the shocks with two sectoral financial and technological characteristics (in this case $Covariate_{ijr(t-1)}$ is replaced by $Covariate_j$). Dependence on external financing sources has long been recognized as an important variable for predicting firm resistance to

³100% in food health product industries and 50% in other industries

crises. The less firms depend on external financing resources, the fewer financial limitations they face (Braun and Larrain, 2005; Tong and Wei, 2011; Isyuk, 2013). Finally, crucial to firm resilience during the Covid-19 crisis was teleworkability - employees' capability to work from home. Studies on firm responses to Covid-19 suggest that teleworkability is a key factor influencing the resilience of firms. The construction of these two variables is presented below in section 4.2.

4.1.2 Firm adaptation to shocks

Facing strict mandatory closure, a firm in a non-essential industry can adjust its workplace practices by shifting all its activities online to allow its employees to work from home. Meanwhile, a firm in an essential industry, in response to mobility restrictions, can adapt its working processes and products to reduce physical contact among employees and with clients. Both firms, however, experienced a sudden loss in their revenue, requiring an urgent and rapidly implemented financial alternative in order to survive through the extended lockdown. In this paper, we study the mitigation effect of prominent firm adaptations to the labor input shock generated by the lockdown. For this purpose, we run a firm survey conducted after the first lockdown in 2020 and presented in detail in section 4.2.3. Three specific adaptations are examined: workplace adaptation, process adaptation and the use of trade credit. The identification of these three forms of adaptation is also presented in section 4.2.3.

First, we look at the impact of the three shocks on firm sales change in our survey. Given that the survey data is cross-sectional, we adjust Equation 1 as follows:

$$y_{ijg} = \alpha_0 + \gamma_1 LS_j + \gamma_2 DS_j + \gamma_3 IS_j + \beta X_{ijg} + \alpha_j + \eta_g + \epsilon_{ijg} \quad (3)$$

where y_{ijg} is the percentage change in sales of firm i in industry j and region g during the lockdown compared to the same month of the previous year. α_j and η_g capture the unobserved industry- and region-specific effects. We adjust the standard errors by clustering them at the 2-digit NAT industry level. The level of fixed-effect controls and clusters is more aggregate than in Equations 1 and 2 as we have only 829 observations in the firm

survey. In addition to the covariates included in the baseline equation, we incorporate firm import status and two manager characteristics – experience and education level – as control variables.

In order to investigate the determinants of firm adaptation, we replace the sales changes in Equation 3 by firm adaptations. The model below is estimated with linear probability estimator:

$$Adapt_{aijg} = \alpha_0 + \gamma_1 LS_j + \gamma_2 DS_j + \gamma_3 IS_j + \beta X_{ijg} + \alpha_j + \eta_g + \epsilon_{ijg} \quad (4)$$

where $Adapt_{aijg}$ is one of the three adaptation dummies.

In the last step, we introduce all three adaptation variables into Equation 3 to see whether firm adaptation strategies are associated to better performance:

$$y_{ijg} = \alpha_0 + \sum_{a=1}^3 \pi_a Adapt_{aijg} + \gamma_1 LS_j + \gamma_2 DS_j + \gamma_3 IS_j + \beta X_{ijg} + \alpha_j + \eta_g + \epsilon_{ijg} \quad (5)$$

4.2 Data and variable construction

4.2.1 Sectoral variables

Labor input shock: The mandatory closure during the lockdown manifested itself mainly as a labor input shock affecting non-essential industries, with stores and plants suddenly forced to close, and thousands of workers prohibited from leaving their houses in order to go to work as a result of emergency measures imposed by the government. As Tunisia experienced a low infection rate during most of the year 2020, the main source of labor input shock in that year was due to the strict lockdown policy. We constructed our own list of essential (or non-essential) industries for Tunisia by gathering information from announcements by government agencies. We end up with a list of non-essential industries at the 4-digit NAT level. Our measure of the direct shock induced by the lockdown is a dummy which takes on the value 1 if the firm operated in a non-essential 4-digit industry, and 0 otherwise.

Demand shock: Following Barry et al. (2022) and Hong et al. (2020), we calculate the demand shock as the industrial mean of changes in US firms' annual earnings forecast

before and after the outbreak of Covid-19. Given that February 20 is the starting date of the pandemic in the US, we use January 2020 as the most recent non-pandemic forecast period and May 2020 as the revision accounting for the pandemic. The data are provided by the Institutional Brokers' Estimate System (IBES)⁴. We calculate the firm-level change in forecasts made between January and May 2020, then take the average value at the 3-digit-NAICS (North American Industry Classification System) level. Finally the measure is mapped from the 3-digit NAICS to the 3-digit NAT codes. The demand shock is multiplied by -1 before being standardized so that the increase in a negative demand shock is negatively associated with firm performance.

The use of a US proxy of certain industry characteristics has been widely practiced in applied economics (see the survey by [Ciccone and Papaioannou \(2016\)](#)), as the US measure is deemed to have less distortions compared to less developed economies. For instance, demand sensitivity in the US in the wake of the September 11 terrorist attacks ([Tong and Wei, 2008](#)) has been deployed in various papers to estimate the effects of the financial and sovereign debt crises on firms across the world ([Tong and Wei, 2011](#); [Claessens et al., 2012](#); [Nguyen and Qian, 2014](#)).

Despite the extensive literature based on this practice, there remains the need to exercise caution, due to the underlying assumption that the pattern of sectoral demand contraction is analogous across countries. This assumption is particularly problematic, given the differences in technological availability, consumer preferences, and the range of substitute products between the two countries. First of all, to rule out the fact that US firms might adapt better to the Covid shock, we use US firms' annual earnings forecast instead of the real earnings. In addition, we construct an equivalent measure of demand shock using the real change in Tunisian stock prices before and after the lockdown. Tunisia's stock market in 2020 was composed of the 60 largest companies in the country, many of which operate in the financial sector. Thus the demand shock calculated from these data is at best considered as an indicator for a limited part of the economy. We plug the two data sets to the firm data and calculate the correlation coefficient. It varies between 0.29-0.58 depending on the

⁴The earnings forecast are firstly adjusted to account for the fact that a certain fraction of the fiscal year had already been completed before the pandemic.

choice of the time window.

Intermediate input shock: While intermediate supply shortage was an aggregate problem due to the interruption of the global value chain, a large part of it is still industry-specific (Balleer and Noeller, 2023). We calculate a survey-based measure of intermediate input shortage from the World Bank’s Enterprise Survey Follow-up on Covid-19. These cross-section surveys follow the baseline Enterprise Survey and are designed to provide quick information on the impact and adjustments that Covid-19 has brought about in the private sector. The questionnaire contains a question on firms’ production during the last month before the survey. Specifically, firms are asked to compare their supply of inputs, raw materials, or finished goods and materials purchased to resell for the last completed month with the same month in 2019, indicating whether it increased, remained the same, or decreased. If firms answer “decreased”, then it is classified as constrained input. We aggregate the share of firms having a reduced material supply at the 3-digit-*ISIC* industrial level across 33 countries surveyed from 2020 to 2022 around the world. This measure thus captures industry-specific rather than country-specific intermediate constraints. Similar to the demand shock, the intermediate supply shock is also mapped to the 3-digit-*NAT* codes and standardized.

Teleworkability (Telework): To quantify this feature, we use the classification of teleworkable jobs developed by Dingel and Neiman (2020). Their classification covers the questions on work context and generalized work activity in O*NET⁵, a US survey database on the nature of occupations and their task composition. The authors define a list of statements that excludes the possibility of telework. If none of these statements are true, the occupation can be performed from home and takes the value 1, otherwise it takes the value 0. The index is available at the 5-digit *SOC*⁶ level. We map it to the *NNP-14*⁷ codes then aggregate it at the 3-digit *NAT* level.

External finance dependence (EFD): We proxy firm sensitivity to financial shocks by the external finance dependence (Rajan and Zingales, 1998) of US firms over the period 2010-2019 in the Compustat data base. To smooth temporal fluctuations and reduce the effects

⁵US’s Occupational Information Network

⁶US’s Standard Occupational Classification

⁷Tunisia’s 2014 National Occupational Classification

Table 1: Summary statistics of RNE firms (2016-2020)

	N	Mean	SD	Min	Max
<i>Panel A: Firm outcomes</i>					
Log of sales	45087	14.065	1.494	-7.212	18.080
Log of employment	45087	2.841	0.858	-1.386	5.234
<i>Panel B: Industrial shocks</i>					
Labor input shock	45087	0.735	0.441	0.000	1.000
Demand shock	45087	0.006	0.874	-1.374	3.754
Intermediate input shock	45087	-0.002	0.985	-4.068	3.813
<i>Panel C: Firm characteristics</i>					
Log of age	45087	2.604	0.761	0.000	4.787
Sq. Log of age	45087	7.358	3.777	0.000	22.920
Medium	45087	0.143	0.350	0.000	1.000
Partial exporter	45087	0.145	0.352	0.000	1.000
Total exporter	45087	0.186	0.389	0.000	1.000
Foreign	45087	0.093	0.291	0.000	1.000
<i>Panel D: Industrial characteristics</i>					
Telework	44401	-0.239	0.832	-0.997	2.522
EFD	44401	0.101	0.964	-8.991	6.223

of outliers, we sum firm use of external finance and investment over 2010–2019 and then take the ratio of these sums. We then take the industry median at the 3-digit SIC code level and map it to the 3-digit NAT level.

4.2.2 RNE panel data

Our main data set comes from the national firm census (RNE) of the Tunisian National Institute of statistics (INS). It covers exhaustively data on all firms registered with the tax authorities. This is an exceptional feature of the RNE, as highlighted by [Rijkers et al. \(2014\)](#). Alongside the ability to track firm entry and exit, these key features enable the tracking of firms over time while controlling for attrition bias.

The RNE provides information on formal firm activity code, characteristics (age, size, ownership and export status) and performance (sales and employment). For this study, we mostly restrict the data set to SMEs in the period 2016-2020, with an extension to 2021 for a part of the analysis . SMEs are defined as firms that have 5 to 200 employees. Table 1 describes the descriptive statistics of firm outcomes, shocks and the firm/industrial characteristics of our data set.

4.2.3 COVID-19 survey data and SME adaptation

To investigate SME adaptation, we run a firm survey conducted after the first lockdown in 2020. The survey provides us with firms' and managers' characteristics, including firm age, size, import status, export status (non, partial, total exporter) as well as ownership (local or foreign); manager's experience and education. It also covers strategic management questions containing details about firm performance as well as the strategies adopted for coping with the pandemic. Firm performance during the lockdown is proxied by changes in sales in May 2020 with respect to sales in May 2019.

Table 2 describes the data derived from this firm survey and the sectoral variables used in this study. Figure 2 and Figure 3 compare firm distribution and average sales growth in the RNE panel data set and the survey data set. Manufacturing firms and hotel/restaurants are overrepresented in the survey data set. Furthermore, the average variation in sales in May 2020 (in comparison to May 2019) is much larger than that of the entire year 2020 (with reference to the entire year 2019) due to the fact that most firms were completely shut down during April and the first half of May 2020.

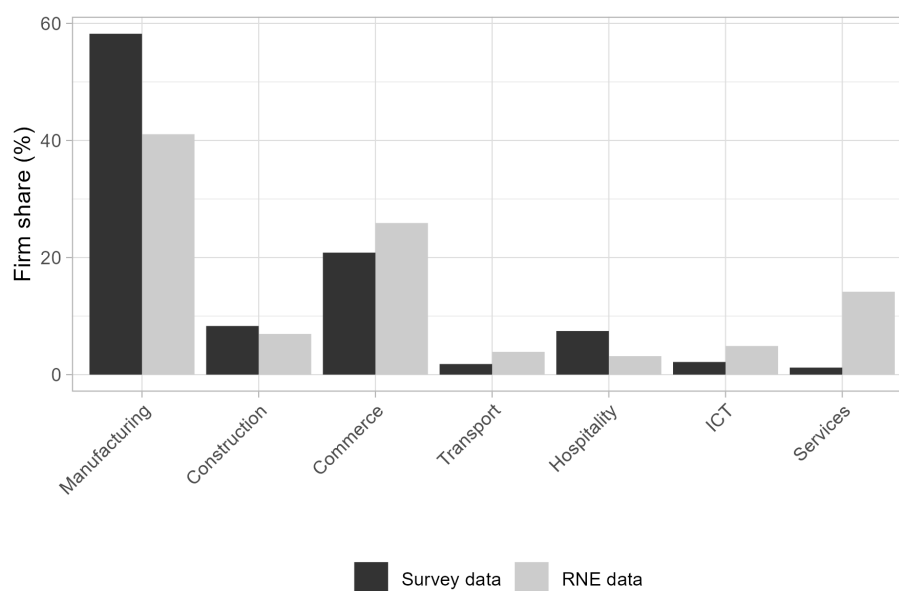


Figure 2: Firm distribution across sectors (%)

Firm adaptations are constructed as follows. Firms are identified as having implemented a process adaptation if they responded yes to any of the following questions:

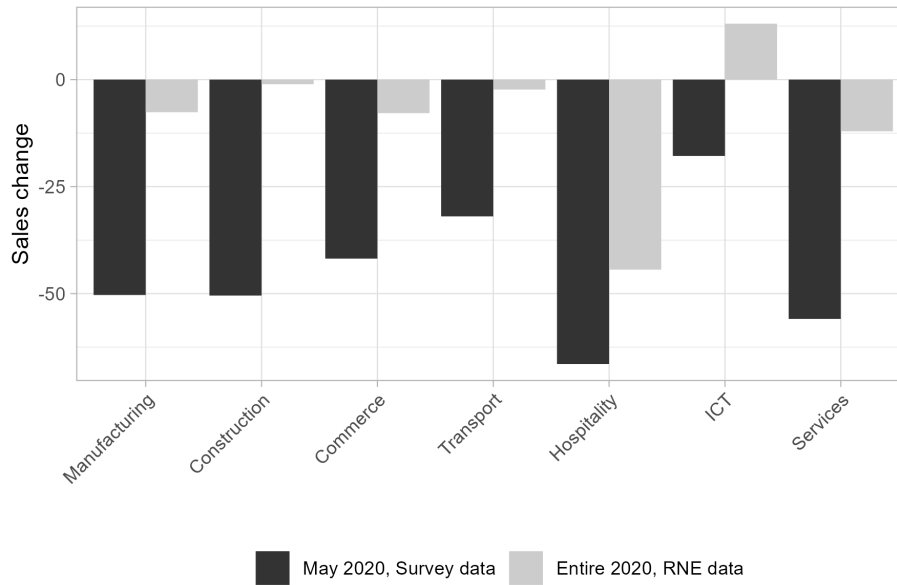


Figure 3: Sales change across sectors (%)

Table 2: Average outcomes and characteristics of firms in control and treatment groups - Survey data

	N	Mean	SD	Min	Max
Panel A: Firm outcomes					
Sales change (%), 05/2019-05/2020	829	-49.397	44.406	-100.000	100.000
Panel B: Firm adaptations					
Use of trade credit	829	0.176	0.381	0.000	1.000
Process adapt.	829	0.188	0.391	0.000	1.000
Workplace adapt.	829	0.227	0.419	0.000	1.000
Panel C: Industrial shocks					
Labor input shock	829	0.768	0.422	0.000	1.000
Demand shock	829	0.044	0.979	-1.603	4.317
Intermediate input shock	829	0.031	0.994	-3.514	3.480
Panel D: Firm characteristics					
Log of age	829	2.409	0.835	0.000	4.477
Sq. Log of age	829	6.499	3.823	0.000	20.047
Medium	829	0.244	0.430	0.000	1.000
Importer	829	0.522	0.500	0.000	1.000
Partial exporter	829	0.112	0.316	0.000	1.000
Total exporter	829	0.186	0.389	0.000	1.000
Foreign	829	0.127	0.333	0.000	1.000
Experience	829	12.241	8.006	1.000	42.000
bachelor's degree	829	0.657	0.475	0.000	1.000
Panel E: Industrial characteristics					
EFD	817	0.030	1.008	-1.428	6.549
Telework	817	-0.182	0.829	-0.853	3.190

1. Did your company start selling online to reduce proximity to clients?
2. Did your company start selling over the phone to reduce proximity to clients?
3. Did your company change your product to reduce proximity to clients?
4. Did your company change its mode of transportation due to mobility restrictions?
5. Did your company change its imported/exported products to cope with the pandemic?

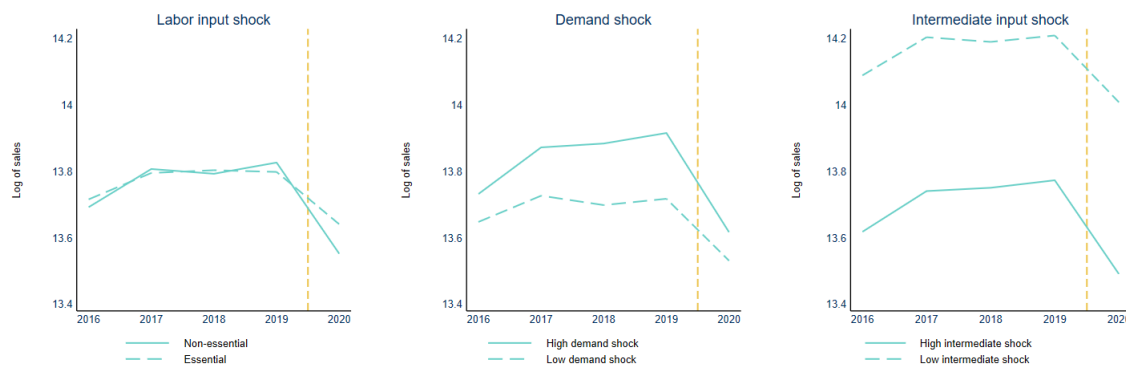
Firms are identified as having implemented a workplace adaptation if all or some of their employees were able to work from home. Firms that could sell online or over phone did not necessarily have their employees to work from home. Indeed, among 12% firms that were able to turn their storefront into an online business, only 65% of these firms had their employees work from home.

5 Results

5.1 Baseline results

Figure 4 plots the mean of the log of sales over time for our control and treatment groups. The treated firms include firms in non-essential industries, industries with demand shocks above the 2020 sample median (high demand shock) and industries with intermediate input shocks above the 2020 sample median (high intermediate input shock). Conversely, the control group include firms in essential industries, industries with demand below the median (low demand shock) and industries with intermediate input shocks below the median (low intermediate input shock). Despite the different levels, the two groups have roughly similar trends in all shocks. Furthermore, there is a clear divergence in firm performance when the Covid-19 pandemic broke out in 2020, due to the labor input and demand shocks.

Table 3 displays the results of the baseline Equation 1 for SME sales. Columns (1)-(3) include one shock at a time. Column (4) includes the three shocks altogether. The effect of the labor input shock on SME sales is significant and negative. Firms in non-essential activities experienced a level of sales 15.6 percent lower than those in essential activities. Column (2) exposes a negative association between the demand shock and SME sales: one



Notes: This graph plots the mean of the log of sales over time for our control and treatment groups. The treated firms include firms in non-essential industries, industries with demand shocks above the 2020 sample median (high demand shock) and industries with intermediate input shocks above the 2020 sample median (high intermediate input shock).

Figure 4: Sales trends (2016-2020)

standard deviation increase in demand shock is associated with an 11 percent loss in sales. Finally, Column (3) shows that Tunisian SMEs also suffered a negative influence resulting from the intermediate input shock, although the magnitude is lower than that of the demand shock: one additional standard deviation in intermediate input shock is associated with a 7.3 percent loss in firm sales. When we introduce the three shocks at the same time in Column (4), the coefficients associated to the three shocks are lower, but still negative and significant.

Figures 5 and 6 plot the average changes in the log of sales conditional on the demand and intermediate input shocks. The difference between the average annual sales change of firms whose demand shock is in the 75th percentile and firms whose demand shock is in the 25th percentile is -0.07 log points ($-0.12 - (-0.05)$). For the intermediate input shock, the difference between average annual sales change of firms whose shock is in the 75th percentile and firms whose shock is in the 25th percentile is -0.04 log points ($-0.104 - (-0.06)$).

5.2 Robustness check

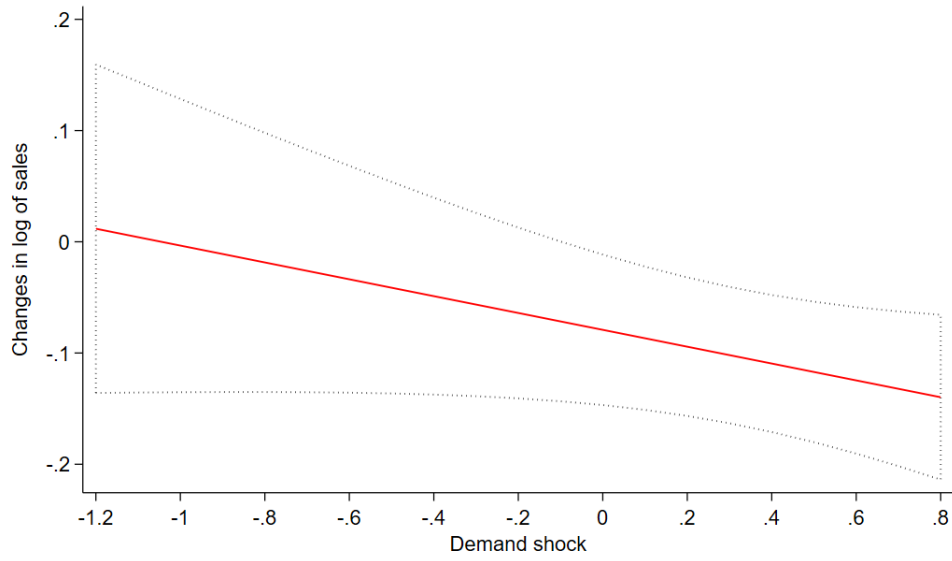
According to [D'Haultfœuille et al. \(2023\)](#) and [Callaway et al. \(2024\)](#), using two way fixed effects (TWFE) for continuous treatment can lead to biased estimates in the presence of heterogeneous treatment effects. Units actually receiving a higher dose of treatment might react differently had they received a lower dose of treatment. Given this potential bias of

Table 3: Effects of the shocks on SME's sales

	(1)	(2)	(3)	(4)
Labor input shock x Post	-0.156*** (0.038)			-0.108** (0.047)
Demand shock x Post		-0.110** (0.044)		-0.076* (0.045)
Intermediate input shock x Post			-0.073** (0.033)	-0.037* (0.019)
Log of age	0.164** (0.070)	0.162** (0.070)	0.162** (0.070)	0.163** (0.070)
Sq. Log of age	-0.027* (0.015)	-0.026* (0.015)	-0.026* (0.015)	-0.026* (0.015)
Medium	1.353*** (0.050)	1.354*** (0.050)	1.353*** (0.050)	1.354*** (0.050)
Partial exporter	0.380*** (0.039)	0.381*** (0.039)	0.382*** (0.039)	0.380*** (0.039)
Total exporter	0.137** (0.060)	0.137** (0.060)	0.137** (0.060)	0.137** (0.060)
Foreign	0.319*** (0.061)	0.320*** (0.061)	0.320*** (0.061)	0.320*** (0.061)
Year FE	Yes	Yes	Yes	Yes
4-digit Industry FE	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes
N	45,076	45,076	45,076	45,076
R-sq	0.521	0.521	0.521	0.521

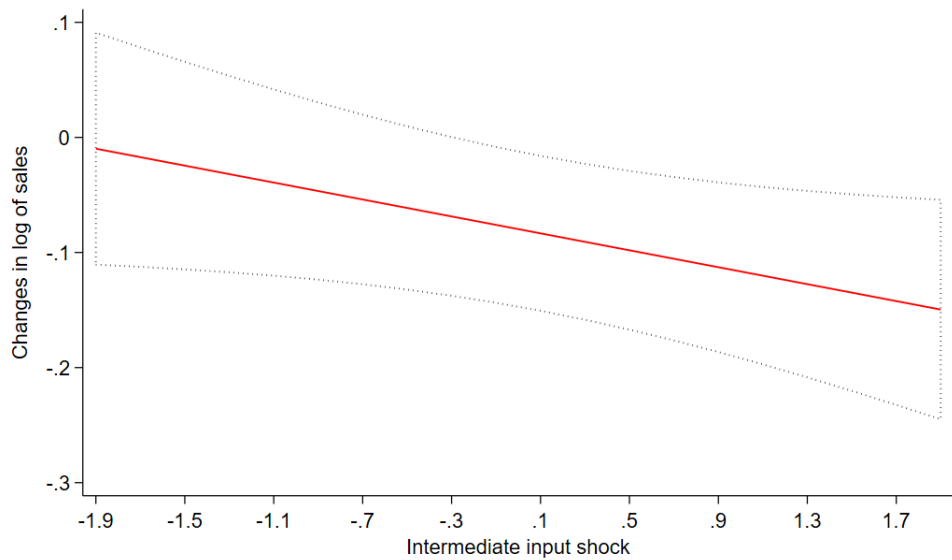
Notes: All models apply the two-way fixed-effect estimator. Standard errors are clustered at the 4-digit industry level.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$



Notes: This graph plots the treatment effects across varying levels of demand shock, based on estimates derived from Equation 1. Equation 1 estimates the effect of the three shocks on firm sales, while controlling for industry-specific and district-specific effects, the time trend, and time-varying firm characteristics.

Figure 5: Treatment effects of demand shock



Notes: This graph plots the treatment effects across varying levels of intermediate input shock, based on estimates derived from Equation 1. Equation 1 estimates the effect of the three shocks on firm sales, while controlling for industry-specific and district-specific effects, the time trend, and time-varying firm characteristics.

Figure 6: Treatment effects of intermediate input shock

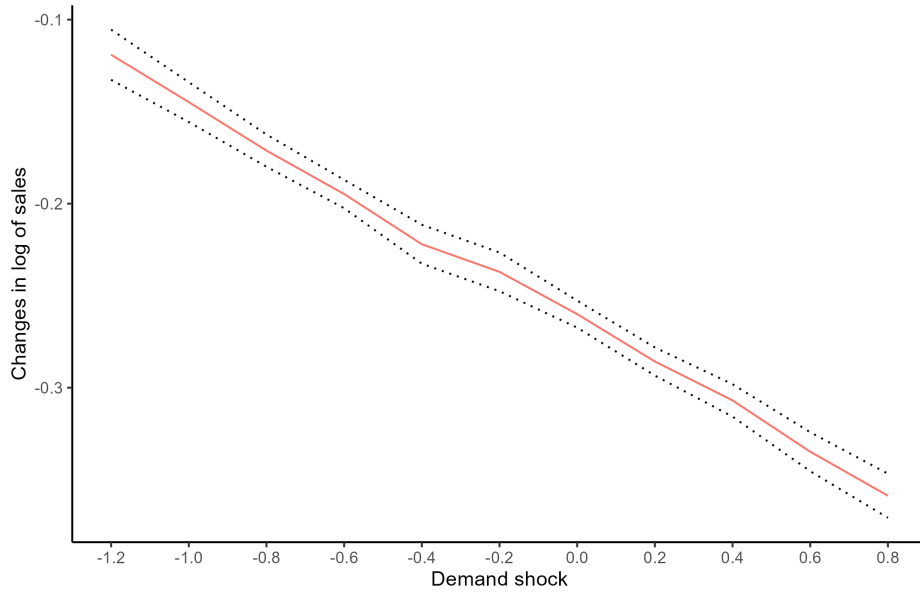
the TWFE, we employ the method proposed by [Callaway and Huang \(2020\)](#) as a robustness check. The main idea is to construct a counterfactual distribution of the potential outcome Y for each value of treatment T by integrating the predicted conditional distribution over the observed covariate X .

For this analysis we use the annual change in log of sales between 2019 and 2020 as the dependent variable. This leaves 10,755 observations. Firm covariates are the same as those used in Equation 1. The 3-step procedure estimation of [Callaway and Huang \(2020\)](#) is as follows. First, we estimate the conditional quantiles $\hat{Q}_{Y|T,X}(\tau|t, x)$, then invert them to obtain the conditional distributions $\hat{F}_{Y|T,X}(y|t, x)$. Second, we average \hat{F} over X while fixing $T = t$ to obtain the counterfactual distribution $\hat{F}_{YT}^C(y|t)$. Finally, we estimate the average treatment effects using the counterfactual distribution \hat{F}^C .

Figures 7 and 8 plot the expected changes in log of sales conditional on the demand and intermediate input shock with adjustment for differences in the covariates, respectively. The graphs show that annual sales loss is increasing in level of shocks. To make it comparable to our baseline estimates, we also calculate the p25/p75 gap. The difference between the average annual sales change of firms whose demand shock is in the 75th percentile and firms whose demand shock is in the 25th percentile is -0.11 log points ($-0.32 - (-0.21)$). Similarly, for the intermediate input shock, the corresponding gap between annual sales changes is -0.09 log points ($-0.304 - (-0.215)$). These figures are -0.07 log point and -0.04 log point respectively in our baseline. The inflation of the estimates using this method might be attributed to the lack of pre-trend control, as we use only 2019 in the pre-treatment period.

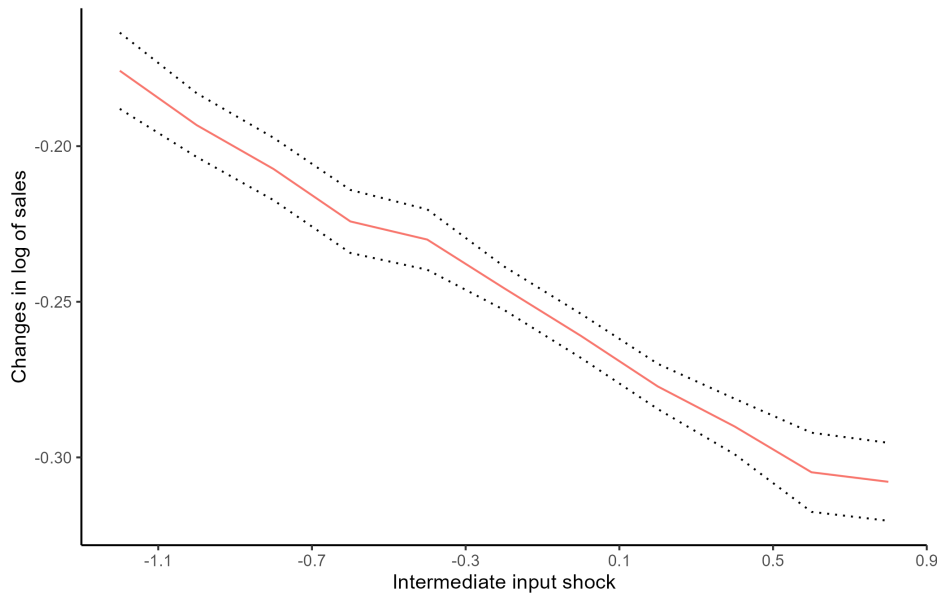
5.3 Survival bias

Another issue that might affect our baseline estimate is survival bias. Indeed, if the attrition rate varies across sectors because of the pandemic, this may bias the estimates based solely on the performance of incumbents. The RNE database has a variable that identifies firm exit. Using this variable gives a small attrition rate of 0.4 percent in 2020 among the examined industries. However, firms that had newly exited might fail to report their operational status. Therefore, we reclassify observations with missing or zero sales record as exits.



Notes: This graph plots the treatment effects across varying levels of demand shock using the counterfactual distribution of change in log of sales from 2019 to 2020. The counterfactual distribution adjusts for differences in observed firm characteristics.

Figure 7: Expected changes in log of sales conditional on demand shock



Notes: This graph plots the treatment effects across varying levels of intermediate input shock using the counterfactual distribution of change in log of sales from 2019 to 2020. The counterfactual distribution adjusts for differences in observed firm characteristics.

Figure 8: Expected changes in log of sales conditional on intermediate input shock

Table 4 reports the attrition rate overtime according to this definition. The attrition rate jumps to 11.3 percent in 2020, which necessitates further examination of the correlation between attrition and shocks. In Column (1) of Table 5, we estimate the linear probability of non-missing on firm characteristics and the interactions of shocks with the post-treatment dummy. The Table shows that firms with a non-missing sales record experienced a smaller impact of the labor input shock. Furthermore, a positive correlation is observed between the probability of reporting non-missing data and the firm’s age, size, and export status. Column (1) suggests that attrition may indeed induce a bias which we investigate further in columns (2) to (4).

We conduct two different strategies to check the sensitivity of our estimates. First we run a two-step Heckman procedure to account for the survival bias. Column (2) presents the second step of the Heckman model, which includes the Inverse Mills Ratio estimated from the first step, and which is significant.⁸ The results displayed in Column (2) remain consistent with our baseline estimation. However, the effect of the demand shock is not significant anymore but the estimated standard error is close to the baseline estimate ($t_{stat} = -1.62$; $p\text{-value} = 0.106$). Second, we address missing values in firm sales through two alternative imputation methods: (1) employing the year-industry average (Column (3)); (2) predicting log of sales via a regression on firm characteristics, industry, district, and year dummies (Column (4)). The estimations of Equation 1 using these two imputed variables yield results closely aligned with those of the baseline model.

Table 4: Attrition rate over time

	N	Attrition rate
2016	9076	0.139
2017	9791	0.238
2018	10088	0.092
2019	10799	0.09
2020	12182	0.113

⁸We follow Fleck and Kilby (2010) and assume that “identification relies on the selection equation normality assumption as we have no a priori theoretical basis for exclusion restrictions”, p. 189 footnote 18.

Table 5: Robustness check: Attrition

	(1) Probability of non-missing	(2) 2nd step Heckman	(3) Imputed log of sales Average	(4) Imputed log of sales Regression
Labor input shock x Post	-0.022*** (0.006)	-0.109** (0.046)	-0.099** (0.047)	-0.098** (0.042)
Demand shock x Post	-0.000 (0.003)	-0.072 (0.044)	-0.075* (0.043)	-0.063* (0.037)
Intermediate input shock x Post	0.000 (0.004)	-0.034* (0.019)	-0.037* (0.019)	-0.033* (0.017)
Log of age	0.028** (0.013)	0.116* (0.070)	0.145** (0.064)	0.171*** (0.063)
Sq. Log of age	-0.005* (0.003)	-0.019 (0.015)	-0.023 (0.014)	-0.028** (0.014)
Medium	0.039*** (0.006)	1.303*** (0.057)	1.249*** (0.054)	1.351*** (0.046)
Partial exporter	0.067*** (0.006)	0.283*** (0.051)	0.367*** (0.038)	0.380*** (0.037)
Total exporter	0.032*** (0.008)	0.094 (0.063)	0.132** (0.054)	0.139*** (0.053)
Foreign	0.013 (0.011)	0.301*** (0.061)	0.294*** (0.056)	0.316*** (0.055)
Inv_Mills		-0.813*** (0.213)		
Year FE	Yes	Yes	Yes	Yes
4-digit Industry FE	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes
N	49,755	45,076	49,755	49,755
R-sq	0.081	0.522	0.531	0.546

Notes: In column (1), we estimate the probability of non-missing sales, as defined in Section 5.3, using the linear probability model. In Column (2), (3) and (4), we estimate the effect of the shocks on firm sales. Column (2) presents the second step of the Heckman model, which includes the Inverse Mills Ratio estimated from the first step to compensate for the selective attrition. Column (3) and (4) report the estimates of equation (1) using the imputed log of sales. Column (3) imputes log of sales from the year-industry average. Column (4) imputes log of sales from a regression of log of sales on firm characteristics, industry-, district- and year-dummies. Standard errors are clustered at the 4-digit industry level.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

5.4 Event study and effects of the shocks in 2021

One pertinent question to ask is whether these effects endure over time. To explore this, we incorporate the recently released 2021 firm census into our analysis. In Table 6, we introduce interactions between the shocks and dummy variables for 2020 and 2021 to investigate how their effects evolved. Notably, results in Column (4) suggest that the influence of the labor input and demand shocks dissipated by 2021. However, the influence of the intermediate input shocks endured, possibly attributable to the shutdown of intermediate input suppliers in 2020.

Table 6: Effects of the shocks on SME's sales (2016-2021)

	(1)	(2)	(3)	(4)
Labor input shock x 2020	-0.159*** (0.038)			-0.109** (0.048)
Labor input shock x 2021	-0.035 (0.034)			0.000 (0.042)
Demand shock x 2020		-0.113** (0.045)		-0.079* (0.047)
Demand shock x 2021		-0.072** (0.035)		-0.055 (0.037)
Intermediate input shock x 2020			-0.074** (0.034)	-0.036* (0.019)
Intermediate input shock x 2021			-0.055** (0.023)	-0.033** (0.016)
Year FE	Yes	Yes	Yes	Yes
4-digit Industry FE	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes
Firm control	Yes	Yes	Yes	Yes
N	55,197	55,197	55,197	55,197
R-sq	0.510	0.511	0.510	0.511

Notes: All models apply the two-way fixed-effect estimator and control for firm covariates. Standard errors are clustered at the 4-digit industry level.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

We then conduct an event study by interacting each shock with year dummies, incorporating all three shocks into the specification. 2019 serves as the base year. The estimates are illustrated in Figure 9. The demand and labor input shocks exhibited a pronounced negative effect on firm sales in 2020, while the effect of the intermediate input shock was comparatively weaker. Firms that suffered from the labor input shock in 2020 rebounded quickly in the following year whereas those impacted by higher demand and intermediate input shocks had not recovered yet at the end of 2021. It is worth noting that, given the

positive pre-trend of sales of firms exposed to higher demand shock, it is likely that our estimates of the demand shock effect in Tables 3 and 6 are underestimated. This positive trend prior to 2020 may stem from the fact that the sectors most exposed to the demand shock were those involved in leisure and tourism activities, which happened to have a strong dynamism during the 2016-2019 period. These sectors experienced a sharp drop in 2015 following terrorist attacks, and then bounced back rapidly until the Covid-19 crisis.



Notes: The graphs display the coefficient estimates for the three shocks over time. In this model, we regress firm sales on the interactions of the shocks with year dummies, while controlling for firm covariates, as well as year-, industry-, and regional-specific effects. The regression uses the 2016-2021 data set and takes 2019 as the reference year.

Figure 9: Event study: Differences in log of sales (2016-2021)

5.5 Heterogeneous effects of the shocks

The impact of the COVID-19 crisis on SMEs may have varied depending on firm characteristics and activity. To examine this question, we estimate Equation 2 on the 2016-2020 SME sample. In this model, we interact each of the three shocks with certain firm/industry-level characteristics. The results are displayed in Table 7. If a characteristic (covariate) mitigates the impact of a shock, the coefficient of the triple interaction should have a positive sign. We initially differentiate medium firms from small ones (Column 1). Furthermore, we investigate the impact on outward-looking firms compared to others (Columns 2 and 3). In Column 4, we explore whether foreign firms were more resilient. In Columns 5 and 6, we analyze firms belonging to industries that structurally require more external financing (EFD), making them potentially more vulnerable to shocks, and those in which implementing work-from-home practices is more feasible, hence rendering them less vulnerable to

Table 7: Heterogenous effects of the shocks on firm sales (2016-2020)

	(1)	(2)	(3)	(4)	(5)	(6)
	Medium	Partial exporter	Total exporter	Foreign	EFD	Telework
Panel A: Labor input shock						
Shock*Post	-0.133*** (0.049)	-0.131** (0.051)	-0.150*** (0.047)	-0.128*** (0.047)	-0.110*** (0.034)	-0.114** (0.045)
Shock*Covariate*Post	0.164 (0.104)	0.175** (0.079)	0.406** (0.198)	0.440** (0.221)	-0.062* (0.034)	-0.052 (0.058)
Observations	45076	45076	45076	45076	44391	45076
R ²	0.522	0.522	0.522	0.522	0.523	0.521
Panel B: Demand shock						
Shock*Post	-0.078** (0.039)	-0.078* (0.046)	-0.085** (0.039)	-0.080* (0.043)	-0.035 (0.036)	-0.083** (0.040)
Shock*Covariate*Post	-0.033 (0.111)	0.074 (0.076)	0.184*** (0.068)	0.196* (0.107)	-0.133* (0.077)	-0.061 (0.053)
Observations	45076	45076	45076	45076	44391	45076
R ²	0.522	0.522	0.522	0.522	0.523	0.522
Panel C: Intermediate input shock						
Shock*Post	-0.042** (0.019)	-0.042* (0.022)	-0.061** (0.024)	-0.043* (0.022)	-0.047*** (0.016)	-0.042** (0.020)
Shock*Covariate*Post	0.024 (0.046)	0.072* (0.041)	0.063** (0.031)	0.049 (0.035)	-0.025* (0.014)	-0.010 (0.023)
Observations	45076	45076	45076	45076	44391	45076
R ²	0.522	0.522	0.522	0.522	0.523	0.521

Notes: All models apply the two-way fixed-effect estimator and control for year fixed-effects, 4-digit industry fixed-effects, district fixed-effects and firm covariates. Standard errors are clustered at the 4-digit industry level.

shocks.

Table 7 shows that in most of the specifications, all the shocks remain significantly negative and quite similar in terms of magnitude to those displayed in Table 3. One common feature is that exporters⁹ were more resilient to all three shocks. Meanwhile foreign firms performed better in response to the labor input and demand shocks only. A potential explanation might be the higher financial and technological capabilities of these firms. Furthermore, during the pandemic, totally exporting firms were granted the right to sell up to 100% of their output on the domestic market for health and food products and up to 50% for the remaining products. This policy helped them compensate their loss of sales due to the contraction of international demand. [Chen et al. \(2023\)](#) find a similar result for the impact of the pandemic on exporting vs non-exporting firms in India. Their explanation is based on a better adaptation of exporting firms through the use of ICT, trade credit and asset selling. The next section dealing with firms' adaptation will enable us to dig deeper with regard to these aspects. Finally, it comes as no surprise that firms in higher EFD sectors, *i.e. sectors that depend more on external financing*, were more affected by the demand shock.

5.6 Adaptations and firm resilience

In this section, we use the firm survey conducted after the lockdown to examine firms' coping strategies and the determinants of firm adaptations. Before looking into firm adaptations, we run a regression of firm sales change in May 2020 with respect to May 2019 on firms' characteristics, managers' characteristics and the three shocks, as exposed in Equation 3. The model controls for region fixed effects and 2-digit-NAT industry fixed effects. Standard errors are clustered at the 2-digit-NAT industry level. The results of this specification is reported in Table 8. Only the coefficient on the labor input shock is significant: firms in non-essential industries experienced approximately 33 percentage points fall in sales in comparison to firms in essential industries during the lockdown.

We employ a linear probability model to evaluate the likelihood of firm adaptation to

⁹This category of firms benefits from a range of tax and administrative incentives in Tunisia.

the three shocks conditionally on their characteristics, as presented in Equation 4. Table 9 reports the estimates for firms' workplace adaptation, process adaptation and trade credit in Columns (1), (2) and (3) respectively. It turns out that firms in non-essential industries were less able to adapt than firms in essential industries during the first lockdown. The stringent and abrupt nature of the lockdown may have limited the ability of firms to respond effectively. Another hypothesis is that closed firms may have encountered liquidity constraints, hindering their capacity to invest in adaptation strategies. Simultaneously, firms in essential industries, despite being allowed to operate, also faced difficulties that required them to adjust their activities.

Table 8: Effects of the shocks on SME's sales change 5/2019-5/2020

	(1)	(2)	(3)	(4)
Labor input shock	-33.632*** (4.377)			-32.713*** (4.539)
Demand shock		-10.750* (5.873)		-7.680 (5.012)
Intermediate input shock			-1.477 (4.220)	-0.279 (2.680)
Log of age	-3.881 (7.077)	-5.492 (7.474)	-5.375 (7.239)	-4.018 (7.171)
Sq. Log of age	2.281** (1.104)	2.634** (1.228)	2.582** (1.178)	2.335** (1.128)
Medium	4.038 (3.693)	3.243 (3.727)	2.982 (3.715)	4.095 (3.693)
Importer	10.987*** (3.281)	10.323*** (3.563)	10.209*** (3.575)	11.086*** (3.345)
Partial exporter	11.658 (7.778)	13.198* (7.548)	12.574 (7.738)	11.978 (7.764)
Total exporter	8.059 (4.810)	9.603** (4.483)	9.320** (4.349)	8.266* (4.850)
Foreign	-2.273 (4.045)	-1.522 (4.261)	-0.637 (4.626)	-2.942 (4.007)
Experience	-0.575** (0.229)	-0.601** (0.225)	-0.592** (0.233)	-0.582** (0.224)
College degree	2.741 (3.772)	3.185 (3.554)	3.127 (3.548)	2.722 (3.767)
2-digit Industry FE	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes
N	830	830	830	830
R-sq	0.209	0.183	0.180	0.211

Notes: All models apply the OLS model. Standard errors are clustered at the 2-digit industry level.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Larger (medium) and younger firms were more likely to adopt process adaptation. We also find that exporters were more likely to adopt either workplace or process adaptations and benefited from better access to trade credit. Similarly, foreign firms were more capable of adjusting their sales/production process and obtaining trade credit. This is in line with our findings in Section 5.5 that foreign and outward-looking firms were more resilient thanks to their financial and technological capabilities. Interestingly, firm managers who held a university degree were more inclined to engage in teleworking while experienced managers benefited from better access to trade credit.

Table 9: Determinants of firm adaptations

	(1) Workplace	(2) Process	(3) Trade credit
Labor input shock	-0.062* (0.034)	0.018 (0.027)	-0.177** (0.066)
Demand shock	-0.061 (0.052)	-0.073 (0.055)	-0.066* (0.038)
Intermediate input shock	-0.009 (0.030)	0.015 (0.026)	-0.024 (0.023)
Log of age	0.072 (0.053)	-0.107* (0.063)	0.078 (0.058)
Sq. Log of age	-0.006 (0.011)	0.027 (0.016)	-0.005 (0.013)
Medium	0.012 (0.027)	0.075** (0.030)	0.011 (0.045)
Importer	0.074** (0.034)	0.031 (0.026)	0.038 (0.041)
Partial exporter	0.115 (0.071)	0.201*** (0.066)	0.116** (0.051)
Total exporter	0.111** (0.046)	0.001 (0.046)	0.001 (0.027)
Foreign	0.014 (0.049)	0.260*** (0.073)	0.095* (0.056)
Experience	-0.002 (0.003)	-0.003 (0.003)	-0.006** (0.002)
College degree	0.066** (0.029)	0.027 (0.029)	0.034 (0.027)
2-digit Industry FE	Yes	Yes	Yes
Region FE	Yes	Yes	Yes
N	829	829	829
R-sq	0.232	0.201	0.158

Notes: All models apply the linear probability model. Standard errors are clustered at the 2-digit industry level.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 10 reports the findings from Equation 5, which examines the effectiveness of

firm adaptation strategies in mitigating the impacts of Covid-19. Initially, the equation is estimated using the entire sample (Column 1). The results indicate that firm adaptations, particularly process adaptation and trade credit, were generally associated with better performance during the lockdown.

Subsequently, we investigate whether the influence of firm adaptation differs across industries with varying levels of teleworkability (Columns 2 and 3). High (or low) teleworkability industries are defined as those with a teleworkability index above (or below) the median. It is anticipated that workplace adaptation would have a more pronounced effect on firms in industries with high teleworkability prior to the lockdown. Indeed, our analysis suggests that only firms operating in high-teleworkability industries experienced benefits from workplace adaptation. Conversely, firms in industries with low teleworkability (Column 3) were more likely to benefit from process adaptation and trade credit.

Furthermore, we replicate the same regression analysis for high- and low-external-financial-dependence (EFD) sub-samples (Columns 4 and 5) to explore whether the effect of trade credit is more evident in firms with higher dependence on external financing. Our findings indicate that trade credit is significantly positive only for firms in high-EFD industries (Column 4), namely those belonging to industries with greater reliance on external financing. Interestingly, workplace adaptation also emerged as a mitigating factor for firms in high-EFD industries, suggesting that the adoption of remote work was specific to certain industries and not necessarily a costly adaptation.

Table 10: Mitigation effect of adaptations on SME's sales change 5/2019-5/2020

	All	High telework	Low telework	High EFD	Low EFD
Workplace adapt.	6.369* (3.215)	11.553* (6.012)	3.113 (3.881)	12.651*** (4.139)	1.218 (4.275)
Process adapt.	11.913** (4.761)	9.283 (7.870)	12.803* (7.264)	9.684 (7.060)	14.456* (7.978)
Trade credit	9.320** (4.457)	9.221 (9.362)	10.805* (5.320)	13.791* (7.524)	4.093 (5.101)
2-digit Industry FE	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes
N	829	350	479	379	438
R-sq	0.235	0.260	0.212	0.317	0.189

Notes: All models apply OLS estimator and include the three shocks and firm covariates. Standard errors are clustered at the 2-digit industry level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

6 Conclusion

In this paper, we assess the impacts of economic shocks as a result of the Covid-19 pandemic on SMEs in Tunisia by employing a Difference-in-Differences framework applied to the national firm census. Furthermore, we analyze the heterogeneous effects of the pandemic on firms based on relevant firm and industry characteristics. Finally, we explore the factors influencing firms' adaptations, *i.e.*, workplace practices, process adjustments, and utilization of trade credit, using our own firm survey.

We find that SME performance in 2020 was heavily affected by a combination of labor input, demand and intermediate input shocks. Our estimates are robust to the heterogeneous treatment effect and attrition. We also find that exporting firms performed better in facing the three types of shocks, while foreign firms performed better in response to the labor input and demand shocks only. Not surprisingly, firms in higher external financial dependence (EFD) sectors were more affected by the demand shock. In 2021, the effect of the demand and intermediate input shocks persisted at a relatively similar negative level, while the impact of the labor input and demand shocks were no longer significant. This is in line with the prediction of the macroeconomic literature. Our results suggest that in the context of a short and strict lockdown, once it is brought to an end, the government should redirect its financial support measures away from firms exposed to the labor input shock and toward firms exposed to the demand and intermediate input shock.

Using our firm survey conducted right after the end of the first lockdown, we find that the impact of the labor input shock was predominant during the lockdown period. It is shown that firms in non-essential industries were less able to adapt than firms in essential industries during the first lockdown. In other words, firm adaptation seems to be driven more by capability than by necessity.

Furthermore, younger and larger firms were more likely to adopt process adaptation, while exporters and foreign-owned firms benefited from better access to trade credit and were more capable of adjusting their sales/production process.

We acknowledge that this work, in spite of our efforts, has certain limitations. Firstly, we do not account for evolution of the mobility restrictions when they were applied more

locally and the enforcement became less strict in the following years. Secondly, a key aspect that is conspicuous by its absence is an analysis of Covid-19's impact on the informal sector. This sector does not only account for a significant part of the private sector¹⁰ but is also its most vulnerable component. Further research is thus needed to provide more evidence on this sector, depending on data availability.

References

- Aga, Gemechu and Hibret Maemir**, "COVID-19 and Sub-Saharan Africa Firms: Impact and Coping Strategies," *The Journal of Development Studies*, 2022, pp. 1–29.
- Alekseev, Georgij, Safaa Amer, Manasa Gopal, Theresa Kuchler, John W Schneider, Johannes Stroebel, and Nils Wernerfelt**, "The Effects of COVID-19 on US small businesses: Evidence from owners, managers, and employees," *Management Science*, 2022.
- Apedo-Amah, Marie Christine, Besart Avdiu, Xavier Cirera, Marcio Cruz, Elwyn Davies, Arti Grover, Leonardo Iacovone, Umut Kilinc, Denis Medvedev, Franklin Okechukwu Maduko et al.**, "Unmasking the Impact of COVID-19 on Businesses," 2020.
- Aristei, David and Manuela Gallo**, "Green management, access to credit, and firms' vulnerability to the COVID-19 crisis," *Small Business Economics*, April 2023.
- Atkin, David, Amit K Khandelwal, and Adam Osman**, "Exporting and firm performance: Evidence from a randomized experiment," *The Quarterly Journal of Economics*, 2017, 132 (2), 551–615.
- Baldwin, Richard and Eiichi Tomiura**, "Thinking ahead about the trade impact of COVID-19," *Economics in the Time of COVID-19*, 2020, 59, 59–71.
- Balleer, Almut and Marvin Noeller**, "Monetary Policy in the Presence of Supply Constraints: Evidence from German Firm-Level Data," Technical Report, CESifo Working Paper 2023.

¹⁰Informal employment accounted for 26.8 percent of Tunisia's employment in 2020 according to a report by the ILO and UNDP (2022).

- Baqae, David and Emmanuel Farhi**, “Nonlinear production networks with an application to the covid-19 crisis,” Technical Report, National Bureau of Economic Research 2020.
- and —, “Supply and Demand in Disaggregated Keynesian Economies with an Application to the COVID-19 Crisis,” *American Economic Review*, May 2022, 112 (5), 1397–1436.
- Barrot, Jean-Noël, Basile Grassi, and Julien Sauvagnat**, “Sectoral Effects of Social Distancing,” *AEA Papers and Proceedings*, May 2021, 111, 277–281.
- Barry, John W, Murillo Campello, John R Graham, and Yueran Ma**, “Corporate flexibility in a time of crisis,” *Journal of Financial Economics*, 2022, 144 (3), 780–806.
- Bloom, Nicholas, Philip Bunn, Paul Mizen, Pawel Smietanka, and Gregory Thwaites**, “The impact of COVID-19 on productivity,” Technical Report, National Bureau of Economic Research 2020.
- Braun, Matias and Borja Larrain**, “Finance and the business cycle: international, inter-industry evidence,” *The journal of finance*, 2005, 60 (3), 1097–1128.
- Brinca, Pedro, Joao B. Duarte, and Miguel Faria e Castro**, “Measuring labor supply and demand shocks during COVID-19,” *European Economic Review*, October 2021, 139, 103901.
- Brucal, Arlan and Arti Grover**, “Masters of Disasters: The Heterogeneous Effects of a Crisis on Micro-Sized Firms,” 2023.
- Burger, Anže, Jože P Damijan, Črt Kostevc, and Matija Rojec**, “Determinants of firm performance and growth during economic recession: The case of Central and Eastern European countries,” *Economic Systems*, 2017, 41 (4), 569–590.
- Callaway, Brantly and Weige Huang**, “Distributional effects of a continuous treatment with an application on intergenerational mobility,” *Oxford Bulletin of Economics and Statistics*, 2020, 82 (4), 808–842.
- , **Andrew Goodman-Bacon, and Pedro H. C. Sant’Anna**, “Difference-in-Differences with a Continuous Treatment,” 2024.

- Calomiris, Charles W, Inessa Love, and María Soledad Martínez Pería**, “Stock returns’ sensitivities to crisis shocks: Evidence from developed and emerging markets,” *Journal of International Money and Finance*, 2012, 31 (4), 743–765.
- Chen, Yutong, Sisir Debnath, Sheetal Sekhri, and Vishal Sekhri**, “The impact of Covid-19 containment lockdowns on MSMEs in India and resilience of exporting firms,” *Journal of Economic Behavior & Organization*, 2023, 210, 320–341.
- Cicccone, Antonio and Elias Papaioannou**, “Estimating cross-industry cross-country interaction models using benchmark industry characteristics,” Technical Report, National Bureau of Economic Research 2016.
- Claessens, Stijn, Hui Tong, and Shang-Jin Wei**, “From the financial crisis to the real economy: Using firm-level data to identify transmission channels,” *Journal of International Economics*, November 2012, 88 (2), 375–387.
- Coviello, Decio, Immacolata Marino, Tommaso Nannicini, and Nicola Persico**, “Demand Shocks and Firm Investment: Micro-evidence from fiscal retrenchment in Italy,” *The Economic Journal*, 2022, 132 (642), 582–617.
- Cowling, Marc, Weixi Liu, Andrew Ledger, and Ning Zhang**, “What really happens to small and medium-sized enterprises in a global economic recession? UK evidence on sales and job dynamics,” *International Small Business Journal*, 2015, 33 (5), 488–513.
- del Rio-Chanona, R Maria, Penny Mealy, Anton Pichler, François Lafond, and J Doyne Farmer**, “Supply and demand shocks in the COVID-19 pandemic: an industry and occupation perspective,” *Oxford Review of Economic Policy*, September 2020, 36 (Supplement.1), S94–S137.
- Dingel, Jonathan I and Brent Neiman**, “How many jobs can be done at home?,” Technical Report, National Bureau of Economic Research 2020.
- D’Haultfœuille, Xavier, Stefan Hoderlein, and Yuya Sasaki**, “Nonparametric difference-in-differences in repeated cross-sections with continuous treatments,” *Journal of Econometrics*, 2023, 234 (2), 664–690.

- Fleck, Robert K and Christopher Kilby**, “Changing aid regimes? US foreign aid from the Cold War to the War on Terror,” *Journal of Development Economics*, 2010, 91 (2), 185–197.
- Georgopoulos, Antonios and Keith W Glaister**, “Firm heterogeneity and performance in a turbulent economic environment: evidence from Greece,” *European Management Review*, 2018, 15 (2), 237–254.
- Gertler, Mark and Simon Gilchrist**, “Monetary policy, business cycles, and the behavior of small manufacturing firms,” *The Quarterly Journal of Economics*, 1994, 109 (2), 309–340.
- Gonzalez, Mario Izquierdo Peinado Alejandro Fernández-Cerezo Beatriz and Enrique Moral-Benito**, “Firm-level heterogeneity in the impact of the COVID-19 pandemic,” *Applied Economics*, 2023, 55 (42), 4946–4974.
- Guerrero-Amezaga, Maria Elena, John Eric Humphries, Christopher A Neilson, Naomi Shimberg, and Gabriel Ulysea**, “Small firms and the pandemic: Evidence from Latin America,” *Journal of Development Economics*, 2022, 155, 102775.
- Guerrieri, Veronica, Guido Lorenzoni, Ludwig Straub, and Iván Werning**, “Macroeconomic Implications of COVID-19: Can Negative Supply Shocks Cause Demand Shortages?,” *American Economic Review*, May 2022, 112 (5), 1437–1474.
- Hale, Thomas, Noam Angrist, Rafael Goldszmidt, Beatriz Kira, Anna Petherick, Toby Phillips, Samuel Webster, Emily Cameron-Blake, Laura Hallas, Saptarshi Majumdar et al.**, “A global panel database of pandemic policies (Oxford COVID-19 Government Response Tracker),” *Nature human behaviour*, 2021, 5 (4), 529–538.
- Helpman, Elhanan, Marc J Melitz, and Stephen R Yeaple**, “Export versus FDI with heterogeneous firms,” *American economic review*, 2004, 94 (1), 300–316.
- Hong, Harrison, Jeffrey D Kubik, Neng Wang, Xiao Xu, and Jinqiang Yang**, “Pandemics, vaccines and an earnings damage function,” Technical Report, National Bureau of Economic Research 2020.
- ILO and UNDP**, “L’économie informelle en Tunisie,” Technical Report, ILO and UNDP 2022.

- Isyuk, Varvara**, “Financial versus demand shocks in stock price returns of U.S. non-financial firms in the crisis of 2007,” *International Economics*, May 2013, 133, 29–49.
- Krafft, Caroline, Ragui Assaad, and Mohamed Ali Marouani**, “The Impact of COVID-19 on Middle Eastern and North African Labor Markets: A Focus on Micro, Small, and Medium Enterprises,” in “Economic Research Forum Policy Brief No.,” Vol. 60 2021.
- Marouani, Mohamed Ali, Caroline Krafft, and Ragui Assaad**, “Tunisia COVID-19 Country Case Study,” Technical Report, ERF and ILO Report 2022.
- Mossberger, Karen, Nicholas F. Martini, Meredith McCullough, and Caroline J. Tolbert**, “Digital economic activity and resilience for metros and small businesses during Covid-19,” *Small Business Economics*, April 2023, 60 (4), 1699–1717.
- Muzi, Silvia, Filip Jolevski, Kohei Ueda, and Domenico Viganola**, “Productivity and firm Exit during the COVID-19 Crisis: Cross-country evidence,” *Small Business Economics*, 2022, pp. 1–42.
- Nguyen, Ha and Rong Qian**, “Demand collapse or credit crunch to firms? Evidence from the World Bank’s financial crisis survey in Eastern Europe,” *Journal of International Money and Finance*, 2014, 47, 125–144.
- Pichler, Anton, Marco Pangallo, R Maria del Rio-Chanona, François Lafond, and J Doyne Farmer**, “Production networks and epidemic spreading: How to restart the UK economy?,” *arXiv preprint arXiv:2005.10585*, 2020.
- Rajan, Raghuram G. and Luigi Zingales**, “Financial Dependence and Growth,” *The American Economic Review*, 1998, 88 (3), 559–586.
- Rijkers, Bob, Hassen Aroui, Caroline Freund, and Antonio Nucifora**, “Which firms create the most jobs in developing countries? Evidence from Tunisia,” *Labour Economics*, 2014, 31, 84–102.
- Tong, Hui and Shang-Jin Wei**, “Real Effects of the Subprime Mortgage Crisis: Is it a Demand or a Finance Shock?,” July 2008.

— **and** —, “The Composition Matters: Capital Inflows and Liquidity Crunch During a Global Economic Crisis,” *The Review of Financial Studies*, June 2011, 24 (6), 2023–2052.

Varum, Celeste Amorim and Vera Catarina Rocha, “Employment and SMEs during crises,” *Small Business Economics*, 2013, 40, 9–25.

A Appendix

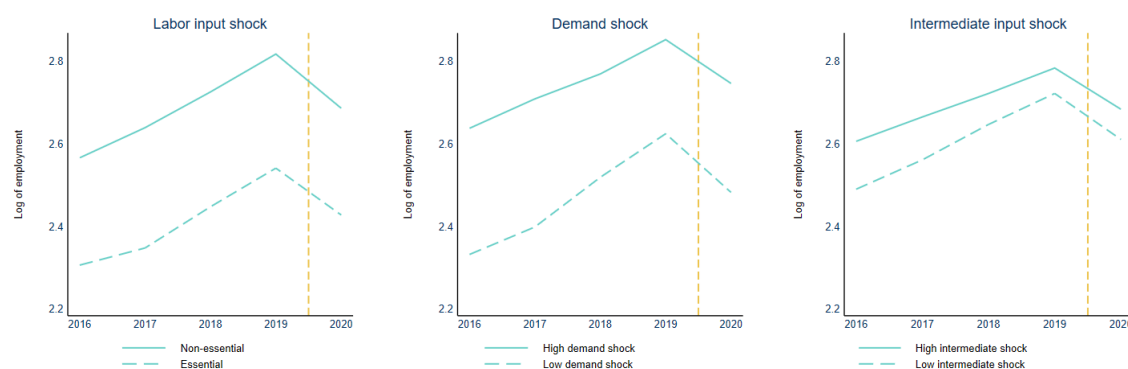
A.4 Descriptive statistics

Table A1: Definition and measurement of variables

Firm-level variable	Definition and measure
<i>National firm census (RNE)</i>	
Log of sales	Unit: Thousands of Tunisian Dinar
Medium	Dummy, capturing whether a firm has a medium size (50-200 employees)
Partial exporter	Dummy, capturing whether a firm exports a part of its output, as defined by Article 21, Code d’Incitation aux Investissements.
Total exporter	Dummy, capturing whether a firm exports all its output, as defined by Article 10 and 11, Code d’Incitation aux Investissements.
Foreign	Dummy which is equal to 1 if a firm is owned by foreigner.
<i>Firm survey</i>	
Change in sales	Change in firm sales in May 2020 compared to firm sales in May 2019, measured in percent.
Medium	idem.
Partial exporter	idem.
Total exporter	idem.
Foreign	idem.
Import	Dummy, capturing whether a firm imports its input.
Experience	Continuous variable proxied by the age of the owner/manager, measured in years
Bachelor’s degree	Dummy, capturing whether the owner/manager has a bachelor’s degree

A.5 Results

A.5.1 Baseline results



Notes: This graph plots the mean of the log of employment over time for our control and treatment groups. The treated firms include firms in non-essential industries, industries with demand shocks above the 2020 sample median (high demand shock) and industries with intermediate input shocks above the 2020 sample median (high intermediate input shock).

Figure A1: Employment trends (2016-2020)

Table A2: Effects of the shocks on SME's employment

	(1)	(2)	(3)	(4)
Labor input shock x Post	-0.034 (0.024)			-0.037 (0.026)
Demand shock x Post		0.002 (0.017)		0.002 (0.016)
Intermediate input shock x Post			0.009 (0.014)	0.009 (0.011)
Log of age	-0.110*** (0.027)	-0.111*** (0.027)	-0.111*** (0.027)	-0.110*** (0.027)
Sq. Log of age	0.035*** (0.006)	0.035*** (0.006)	0.035*** (0.006)	0.035*** (0.006)
Medium	1.475*** (0.025)	1.475*** (0.025)	1.475*** (0.025)	1.475*** (0.025)
Partial exporter	0.142*** (0.015)	0.142*** (0.015)	0.142*** (0.015)	0.142*** (0.016)
Total exporter	0.247*** (0.041)	0.247*** (0.041)	0.247*** (0.041)	0.247*** (0.041)
Foreign	0.081*** (0.019)	0.081*** (0.019)	0.081*** (0.019)	0.081*** (0.019)
Year FE	Yes	Yes	Yes	Yes
4-digit Industry FE	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes
N	45,076	45,076	45,076	45,076
R-sq	0.614	0.614	0.614	0.614

Notes: All models apply the two-way fixed-effect estimator. Standard errors are clustered at the 4-digit industry level.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

A.5.2 Event study



Notes: The graphs display the coefficient estimates for the three shocks over time. In this model, we regress firm employment on the interactions of the shocks with year dummies, while controlling for firm covariates, as well as year-, industry-, and regional-specific effects. The regression uses the 2016-2021 data set and takes 2019 as the reference year.

Figure A2: Event study: Differences in log of employment (2016-2021)

A.5.3 Heterogeneous effects

Table A3: Heterogenous effects of the shocks on firm sales (2016-2021)

	(1)	(2)	(3)	(4)	(5)	(6)
	Medium	Partial exporter	Total exporter	Foreign	EFD	Telework
Panel A: Labor input shock						
Shock*2021	0.005 (0.041)	-0.013 (0.043)	0.005 (0.041)	0.004 (0.041)	0.000 (0.035)	-0.004 (0.040)
Shock*Covariate*2021	-0.039 (0.080)	0.100 (0.078)	0.340 (0.314)	0.070 (0.180)	-0.007 (0.019)	-0.068 (0.043)
Observations	53472	53472	53472	53472	52660	53472
R ²	0.514	0.514	0.514	0.514	0.516	0.514
Panel B: Demand shock						
Shock*2021	-0.051 (0.035)	-0.052 (0.036)	-0.059* (0.035)	-0.053 (0.035)	-0.021 (0.034)	-0.055 (0.035)
Shock*Covariate*2021	-0.031 (0.049)	0.059 (0.043)	0.139** (0.063)	0.034 (0.050)	-0.017 (0.036)	-0.012 (0.034)
Observations	53472	53472	53472	53472	52660	53472
R ²	0.514	0.515	0.514	0.515	0.516	0.514
Panel C: Intermediate input shock						
Shock*2021	-0.032* (0.017)	-0.025 (0.018)	-0.046** (0.021)	-0.038** (0.018)	-0.038** (0.016)	-0.035** (0.017)
Shock*Covariate*2021	-0.011 (0.027)	-0.020 (0.028)	0.035 (0.025)	0.023 (0.030)	0.002 (0.007)	0.002 (0.014)
Observations	53472	53472	53472	53472	52660	53472
R ²	0.514	0.514	0.514	0.515	0.516	0.514

Notes: All models apply the two-way fixed-effect estimator and control for year fixed-effects, 4-digit industry fixed-effects, district fixed-effects and firm covariates. Standard errors are clustered at the 4-digit industry level.

Table A4: Heterogenous effects of the shocks on firm employment (2016-2020)

	(1)	(2)	(3)	(4)	(5)	(6)
	Medium	Partial exporter	Total exporter	Foreign	EFD	Telework
Panel A: Labor input shock						
Shock*Post	-0.046* (0.027)	-0.052* (0.028)	-0.051* (0.029)	-0.045 (0.028)	-0.027* (0.015)	-0.033 (0.023)
Shock*Covariate*Post	0.027 (0.031)	0.112** (0.049)	0.150*** (0.054)	0.268*** (0.095)	-0.063*** (0.022)	0.028 (0.031)
Observations	45076	45076	45076	45076	44391	45076
R ²	0.615	0.614	0.614	0.614	0.615	0.614
Panel B: Demand shock						
Shock*Post	0.006 (0.013)	-0.003 (0.016)	-0.005 (0.014)	0.000 (0.015)	0.006 (0.018)	0.002 (0.014)
Shock*Covariate*Post	-0.067** (0.026)	0.055* (0.033)	0.141*** (0.033)	0.086 (0.053)	-0.004 (0.037)	-0.004 (0.021)
Observations	45076	45076	45076	45076	44391	45076
R ²	0.614	0.614	0.614	0.614	0.615	0.614
Panel C: Intermediate input shock						
Shock*Post	0.012 (0.012)	0.007 (0.013)	0.008 (0.015)	0.012 (0.014)	0.003 (0.008)	0.013 (0.013)
Shock*Covariate*Post	-0.016 (0.023)	0.035* (0.019)	0.002 (0.019)	-0.008 (0.019)	0.005 (0.007)	0.009 (0.010)
Observations	45076	45076	45076	45076	44391	45076
R ²	0.614	0.614	0.615	0.614	0.615	0.614

Notes: All models apply the two-way fixed-effect estimator and control for year fixed-effects, 4-digit industry fixed-effects, district fixed-effects and firm covariates. Standard errors are clustered at the 4-digit industry level.

Table A5: Heterogenous effects of the shocks on firm employment (2016-2021)

	(1)	(2)	(3)	(4)	(5)	(6)
	Medium	Partial exporter	Total exporter	Foreign	EFD	Telework
Panel A: Labor input shock						
Shock*2021	-0.003 (0.019)	-0.005 (0.019)	-0.008 (0.018)	-0.005 (0.018)	0.000 (0.016)	-0.003 (0.018)
Shock*Covariate*2021	-0.010 (0.025)	0.007 (0.044)	0.197** (0.091)	0.111 (0.117)	-0.013 (0.012)	-0.000 (0.019)
Observations	53472	53472	53472	53472	52660	53472
R ²	0.611	0.611	0.611	0.611	0.612	0.611
Panel B: Demand shock						
Shock*2021	-0.013 (0.009)	-0.014 (0.011)	-0.014 (0.010)	-0.012 (0.011)	-0.009 (0.012)	-0.011 (0.011)
Shock*Covariate*2021	-0.010 (0.029)	0.036 (0.024)	0.036 (0.032)	-0.008 (0.041)	-0.012 (0.016)	-0.011 (0.010)
Observations	53472	53472	53472	53472	52660	53472
R ²	0.611	0.611	0.612	0.611	0.612	0.611
Panel C: Intermediate input shock						
Shock*2021	0.008 (0.009)	0.012 (0.009)	0.009 (0.009)	0.009 (0.008)	0.006 (0.008)	0.011 (0.008)
Shock*Covariate*2021	0.001 (0.012)	-0.008 (0.019)	-0.000 (0.014)	-0.001 (0.020)	-0.002 (0.003)	-0.008 (0.007)
Observations	53472	53472	53472	53472	52660	53472
R ²	0.611	0.611	0.612	0.611	0.612	0.611

Notes: All models apply the two-way fixed-effect estimator and control for year fixed-effects, 4-digit industry fixed-effects, district fixed-effects and firm covariates. Standard errors are clustered at the 4-digit industry level.