# One Year of COVID: What Impact did the Pandemic have on the Economic Activity of French Companies? Construction of Individual Counterfactuals and Diagnoses for 2020

**Benjamin Bureau*, Anne Duquerroy*, Julien Giorgi**, Mathias Lé*, Suzanne Scott** and Frédéric Vinas***

**Abstract** – We study the impact of the health crisis on the activity of more than 645,000 French companies using individual data to estimate their monthly turnover. Our microsimulation model is innovative in three ways. First, we quantify the loss of activity with respect to a non-crisis counterfactual situation to take into into account companies' growth trajectories before the pandemic when discussing the consequences of the crisis. Second, we estimate this shock at the individual level to study the heterogeneity of loss of business. We highlight the disparities of the shock both between and within sectors. The sector explains up to 48% of the variance of the monthly activity shocks observed in 2020, a much larger proportion than in a normal year. Finally, we identify four profiles of activity trajectories in 2020. The industry is the primary determinant of belonging to these profiles. Conditionally to the sector, these profiles are also correlated with the organisational adaptation of companies.

JEL Classification: D22, G38, H32
Keywords: COVID-19, economic activity, non-financial corporations, microsimulation

**Banque de France ; **INSEE.* Correspondence: *julien.giorgi@insee.fr*

*The authors would like to thank Jean Boissinot, Nicolas Carnot, Gilbert Cette, Olivier Garnier, Alain Gerbier, Dominique Goux, Loriane Py, Sébastien Roux et Jean-Pierre Villetelle for the many exchanges and advice that enriched this analysis, as well as the participants of the technical meetings of the* Comité de suivi et d'évaluation des mesures de soutien financier aux entreprises confrontées à l'épidémie de Covid-19*, presided by Benoît Cœuré, whose feedback and presentations allowed us to significantly improve our analysis. We also thank Tanguy Aubert, Julien Demuynck, Olivier Hubert et Martial Ranvier for their help.*

Received in October 2021, accepted in April 2022. Translated from "Un an de crise Covid : comment évaluer l'impact de la pandémie sur l'activité économique des entreprises françaises ? Construction de contrefactuels individuels et diagnostics de l'année 2020".
The opinions and analyses presented in this article are those of the author(s) and do not necessarily reflect their institutions' or Insee's views.

Citation: Bureau, B., Duquerroy, A., Giorgi, J., Lé, M., Scott, S. & Vinas, F. (2022). One Year of COVID: What Impact did the Pandemic have on the Economic Activity of French Companies? Construction of Individual Counterfactuals and Diagnoses for 2020. *Economie et Statistique / Economics and Statistics*, 532-33, 3–23. doi: 10.24187/ecostat.2022.532.2069

In early 2020, the COVID-19 pandemic and the restrictive health measures caused an economic shock of a magnitude not seen since the Great Recession (Bartik *et al.*, 2020; Forsythe *et al*., 2020), affecting the supply and demand of goods and services (Baldwin & Di Mauro, 2020). In France, these measures, consisting of several periods of lockdowns and reopening and of a range of evolving measures such as curfews and travel restrictions, caused a sharp downturn in economic activity. Between 2019 and 2020, French gross domestic product (GDP) fell by 7.9% and national income by 6.3% (Amoureux *et al.*, 2021). In April 2020, the decline in added value exceeded 30%, placing France among the worst affected countries in the eurozone (Heyer & Timbeau, 2020). For all of 2020, the added value of French companies decreased by 8.1% and by 8.3% for non-financial corporations (NFCs).

Beyond these trends at the macroeconomic level, our aim in this paper is to evaluate the impact of the health crises on companies' activity more precisely. This means estimating the difference between the levels of activity observed during the crisis and the levels that would have been observed had the crisis not occurred. This "counterfactual" approach is the basis of traditional microeconometrics for assessing public policy.[1] With the COVID-19 pandemic, estimating these counterfactual levels raises new methodological problems. The pandemic affected all companies, making estimations based on the use of control groups obsolete. Moreover, even if the pandemic affected all French companies, its consequences may have been extremely uneven and depended on a multitude of complex factors, which may have different effects or be unobservable. As a result, modelling the companies' activity during this period proved to be either challenging or overly simplistic. Many studies therefore estimated the impact of the crisis by using the observed rates of change in their activity between 2019 and 2020 (Hadjibeyli *et al.*, 2021; Bourlès & Nicolas, 2021), skewing the estimation of the magnitude of the activity shocks. Other more structural approaches forecast different scenarios of the evolution of the pandemic and the health restrictions to estimate the magnitude of the economic shock (Schivardi & Guido, 2020; Gourinchas *et al.*, 2021; OECD, 2020).[2] These studies rely on significant theoretical assumptions whose relevance suffer from a lack of *ex post* verification, in an unprecedented context where such assumptions may not apply. In addition, studies using U.S. data show that self-isolation behaviour did not always follow the same schedule as health restrictions (Glaeser *et al.*, 2021; Gupta *et al.*, 2021; Sears *et al.*, 2020) and that the decisions to reopen businesses did not always coincide with the lifting of restrictions (Balla-Elliott *et al.*, 2020), limiting the relevance of using the restriction timetable when modelling activity. Another avenue explored was the use of survey data (Bloom *et al.*, 2021; Bignon & Garnier, 2020), which may however, be subject to low coverage rates or risks of reporting bias.

This paper aims to overcome these limitations by proposing an innovative method for assessing the impact of the COVID-19 pandemic based on a limited set of assumptions. This analysis relies on an a-theoretical positioning in order to model the activity of all French companies if their activity dynamics had not been altered by the onset of the crisis. Individual monthly activity dynamics after February 2020 is predicted using autoregressive mechanisms before being compared to the observed *ex post* amounts, their difference providing an individual estimation of the impact of the pandemic on activity. The predictions are performed at the company level and are not based on a uniform application of sectoral impacts. In this respect, this work differs from those applying shocks estimated entirely or partially at the sectoral level to individual data, artificially limiting their heterogeneity (Anayi *et al.*, 2020; Blanco *et al.*, 2020; Hadjibeyli *et al.*, 2021).

The sectoral dimension was indeed important in the crisis, as not all sectors were affected at the same intensity (Danieli & Olmstead-Rumsey, 2020; Brinca *et al.*, 2020). In France, differences were observed according to the sectoral intensity of restriction measures (Baleyte *et al.*, 2021; Dauvin & Sampognaro, 2021),[3 4] the dependence of certain sectors on tourism (Škare *et al.*, 2021) and on international value chains (Gerschel *et al.*, 2020; Baldwin & Tomiura, 2020). Similarly, the unprecedented deterioration in expectations as a result of the crisis (INSEE, 2020) may have contributed to an increase in households' precautionary savings and a refocusing of their consumption on basic necessities

1. See, for example, Angrist & Pischke (2008).
2. Most of these studies used their activity loss estimations in financial models to assess companies' liquidity or default risk.
3. At the international level, the direct impact of restriction intensity on activity is illustrated by the strong correlation between the Oxford University restriction index, synthesising the real time degree of restriction associated with national health measures (Hale et al. 2020), and the rate of growth or decline in GDP in the first quarter of 2020.
4. Industrial sectors, construction, transportation, accommodation and "other services" – primarily arts, entertainment and recreational activities, hair and body care services, computer repair, and other personal goods – were particularly affected by these measures.

(Bonnet *et al.,* 2021). However, the sector does not seem to fully explain the diversity of situations experienced by companies, since even within a given sector, the degree of dependence on foreign markets (Brancati & Brancati*,* 2020) and the effects of social distancing measures (Blanchard *et al.*, 2020) had differentiated effects, sometimes leading to a reallocation of activity and employment between "winning" and "losing" companies (Barrero *et al.*, 2020; 2021). The method developed here therefore aims to measure the heterogeneity of individual activity shocks, possibly within the same sector, and consequently to propose a quantification of the sector's contribution to the variability of individual situations observed in 2020.

The use of sub-annual data makes it possible to assess the impact of the crisis both annually and monthly. The use of monthly series of activity shocks allows the cross-sectional analysis of heterogeneity to be supplemented by a dynamic analysis of the diversity of activity trajectories over the course of the pandemic. The short term effect of the pandemic on employment (Barrero *et al.*, 2020), company closures (Gourinchas *et al.*, 2020) and activity (Fairlie, 2020; Bloom *et al.*, 2021) has been regularly highlighted, but some works also underscore the uneven persistence of initial shocks on both activity (Bloom *et al.*, 2021) and employment (Chetty *et al.*, 2020; Cajner *et al.*, 2020). The final objective of this paper is therefore to characterise the diversity of the activity trajectories of French companies in 2020 and provide a typology. The understanding of this typology and of the role played by the sector or companies' other demographic or organisational characteristics allows for a better the understanding of the heterogeneous impact of the health crisis on the activity of French companies.

The remainder of the paper presents the data used (section 1), the methods used to assess the impact (section 2) and the main results (section 3). These results are then discussed in the conclusion.

## 1. Data and Sample Construction

### 1.1. Database Construction

The activity is measured by companies' turnover, which provides a gross measure of economic activity whose estimation is relatively unaffected by reconstruction assumptions. It makes it possible to approach the impact of the crisis on activity independently of the subsequent adjustments in the financial and operational management of companies and of public support measures. The data used are derived from companies monthly value added tax (VAT) declarations to the French tax administration (DGFiP). The turnover of each company can be reconstituted from these declarations by summing up all its operations, whether or not taxable, on the French territory or abroad (Appendix A1). The financial sector, public administrations, as well as the self-employed and sole proprietorships are excluded from the sample.

The series of turnover built from the tax returns require some corrections.[5] Deferred returns, resulting in a null return in one month followed by a return to two months' activity in the next month, were corrected by splitting the activity of the second month between the null month and the catch-up month. Outliers, in terms of level or growth rate, were corrected by returning them to the trend of the series. Finally, companies reporting their turnover too irregularly, for which robust simulations could not be performed, were excluded from the sample. This restriction mainly concerns micro-enterprises with low annual turnover and therefore only marginally affects the coverage rate of the study in terms of turnover (0.2 percentage points).

The VAT returns are enriched with information on the characteristics of companies from FARE 2018-ÉSANE (compilation of companies' annual statistics) aggregate results file – the latest year available. The sample is therefore restricted to companies present in FARE 2018 and reporting their VAT monthly since January 2018. This matching makes it possible to check the consistency of the turnover figures reconstructed from the VAT data. To ensure this consistency, companies whose turnover from FARE differs by more than 35% from the annual turnover reconstructed from VAT returns in 2018 are excluded from the data. Consistency was checked for both the legal units and the profiled groups. Where it was not verified for the legal unit but was for the profiled group, the latter was used in the sample by aggregating the turnover of the legal units comprising it.[6] This condition excludes from the sample some large French companies for which the gaps between balance sheet data and the VAT returns are large.

*5. They are detailed in Bureau* et al. *(2021a, Appendix B, p. 40).*

*6. In business accounting, the turnover of a company's legal units do not exactly sum up. Comparing the turnover from the FARE profiled accounts with the proxy obtained by summing up the turnover from the VAT data makes it possible to keep legal units whose turnover are not consistent but whose approximation at the profiled level is consistent with the balance sheet data. This increases the sample size and coverage rate.*

### 1.2. Sample Description

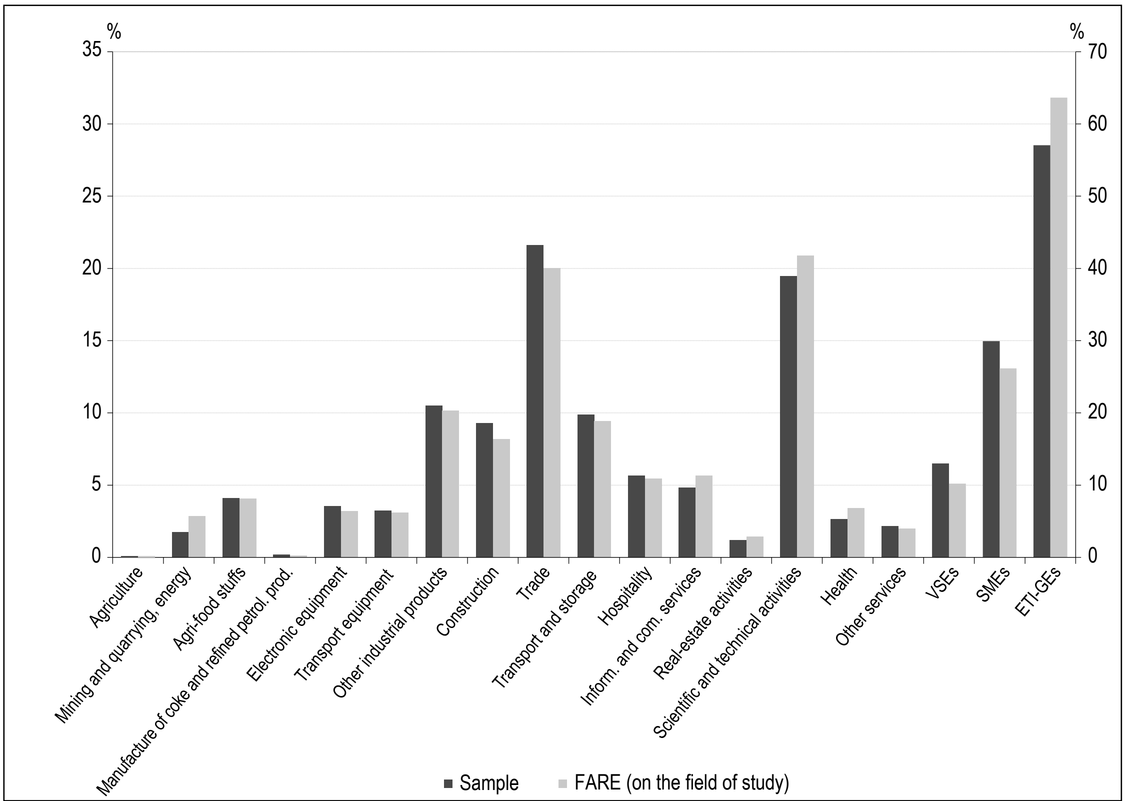
The final sample consists of more than 740,000 legal units, grouped into 645,000 observation units: 578,000 legal units analysed as such and 68,000 profiled groups. It represents 85% of the value added of non-financial corporations (NFCs) in the sectors used in the study, excluding self-employed workers. Out of all NFCs, the sample covers 71% of the value added, including 81% of the value added of intermediate-size and large enterprises (ETI-GEs), 72% of the value added of small and medium-sized enterprises (SMEs) and 38% of the value added of very small enterprises (VSEs), the majority of which are declare their VAT quarterly and annually.

The distribution of employees by sector in this sample is similar to that of all companies in the field of study. Compared with FARE data restricted to the scope of the study, the trade sector is slightly over-represented, and the energy and scientific and technical sectors under-represented. By company size, the workforce structure is comparable with the overall structure, but ETI-GEs are under-represented in the sample to the benefit of SMEs and VSEs (Figure I; for the figures, see Bureau *et al.*, 2021a, Appendix C, p. 41). The adjustments made to the returns thus only marginally distort the picture of the French NFCs population and of their activity.

### 1.3. Use of Survey Data

The study of the factors influencing the situation of companies during the crisis is enriched by the INSEE survey *Impact de la crise sanitaire sur l'organisation de l'activité des entreprises* (Duc & Souquet, 2020). This survey documents the behaviour of companies during the crisis, particularly their strategy for adapting their activity: proportion of employees working remotely, reorganisation of commercial logistics during the lockdowns (development of online sales systems, direct sales or new delivery systems), adaptation of the supply through the development of new products, activities or services, specific investments, especially in new technologies, and the reorganisation of activity via a change in suppliers and commercial partners or the pooling of resources with other companies. The matching with these data restricts the sample to 13,500 companies. To maintain the same representativeness of the sample, the observations are weighted by margin calibration. This matching is

Figure I – **Breakdown of employed staff by sector and company size**




Note: The data from FARE includes all French companies in the field of study. % sector on left axis, % size on right axis.
Sources: DGFiP, VAT returns; INSEE, FARE 2018. Calculations by the authors.

only used in the last stage of the analysis, within the parametric model.

## 2. Methodology

### 2.1. Estimation of the Activity Shocks Attributable to the Crisis

The method consists in estimating activity shocks attributable to the health crisis for each of company in the sample, while ensuring that the aggregation of these individual forecasts is consistent with robust sectoral forecasts.

#### *2.1.1. Estimation of the Non-Crisis Dynamics at the Meso-Economic Level*

A total counterfactual turnover is first estimated at the *size × sector* level. For this, 16 sectors of the A17 aggregate nomenclature[7] and three company sizes (VSE, SME and ETI-GE) are used, for a total of 44 series.[8] The combination of sector and size makes it possible to maintain a fine level of analysis, even at the most aggregated level of the simulations, to take into account the particular seasonality of VSEs in some sectors and to obtain more robust predictions of the amounts of activity generated by VSEs within each sector.

The total turnover of the *size × sector* groups is first reconstructed monthly between January 2015 and January 2020. This period is used to model the non-crisis dynamics of the 44 *size × sector* series *s*. Each series is stationarised[9] then modelled using a SARIMA model by selecting the pair $\left(p_s, q_s\right)$ of autoregressive and moving average parameters wich minimises the Akaike information criterion (AIC) criterion[10] among 64 possible parameter combinations ranging from $\left(p_s = 1, q_s = 1\right)$ to $\left(p_s = 8, q_s = 8\right)$.[11] This procedure provides a robust model of the transformed *size × sector* and stationary series corresponding to equation (1). By noting $Y_{t,s}$ the turnover of the *size × sector* group *s* at date *t*, *B* the delay operator and $X_{t,s} = \left(1 - B^{12}\right) log\left(Y_{t,s}\right)$,[12] each series can be written as:

$$X_{t,s} = \left(\varphi_{1,s} X_{t-1,s} + ... + \varphi_{p_s,s} X_{t-p_s,s}\right) + \varepsilon_{t,s} - \left(\psi_{1,s}\varepsilon_{t-1,s} + ... + \psi_{q_s,s}\varepsilon_{t-q_s,s}\right), \forall s \quad (1)$$

where $\left(\varepsilon_{t,s}\right)_{t=1,...,T}$ designates a gaussian white noise of variance $\sigma^2$. These equations are then used to calculate the monthly optimal linear forecast of horizon *h* for each *size × sector* series. As part of the study, $h \in \left[1,11\right]$, the forecast being made between February and December 2020:

$$X_{T\hat{+}h,s} = EL\left[X_{T+h,s} \mid X_{1,s},...,X_{T,s}\right], \forall h \in \left[1,11\right] \quad (2)$$

The forecasting model is trained over the January 2015-January 2020 period. The transformation of the series of forecasts obtained with equation (2) results in the series $\left(Y_{T\hat{+}h,s}\right)_{h\in[1,11]}$, corresponding to the estimate of counterfactual turnover during each month of 2020 for each *size × sector* group[13][14].

#### *2.1.2. Calculation of the Counterfactual Activity Figures and Individual Shocks*

The second step is to allocate the estimated counterfactual turnover to all companies in each *size × sector* group. This breakdown is done iteratively, starting with February 2020 and ending with December 2020. The monthly market share of each company in its group incorporates its own seasonality and recent development dynamics. Formally, the individual share attributed to each company *i* in the group *size × sector* s in the first month *t* (here, February 2020) is:

$$S_{i,\hat{s},t} = \frac{1}{2}\left(S_{i,s,t-12} + \frac{1}{3}\sum_{j=1}^{3} S_{i,s,t-j}\right) * \left(1 + \frac{1}{2}\frac{\left(\sum_{j=1}^{3} Y_{i,t-j} - \sum_{j=1}^{3} Y_{i,t-12-j}\right)}{\frac{1}{2}\left(\sum_{j=1}^{3} Y_{i,t-j} + \sum_{j=1}^{3} Y_{i,t-12-j}\right)}\right) \quad (3)$$

7. The 17-sector split was preferred because it allowed for better quality forecasts than those obtained with a finer division.

8. Of the 48 groups resulting from cross-referencing the sizes and sectors, those with few companies are merged by sector. In the agriculture and health sectors, companies with more than 10 employees are grouped together. The coke and refined petroleum product sector is a single group.

9. The stationarity of the transformed series is verified by Dickey-Fuller and augmented Dickey-Fuller tests (Dickey & Fuller, 1979).

10. The AIC criterion is $2k - 2\log\left(L\right)$ where L is the likelihood of the estimated model and k the number of free parameters of the model. It is based on a compromise between the quality of the adjustment and the complexity of the model, penalizing models with a large number of parameters to limit the over-adjustment (Akaike, 1998).

11. Once this pair of parameters has been selected, the residuals are tested for the absence of serial autocorrelation, their normality and their whiteness (Box & Pierce, 1970; Ljung & Box, 1978). The significativity of the coefficients associated with the pair of parameters is tested by a z-test. When more than one of these criteria is not verified, the pair of parameters giving the second lowest value for the AIC is selected and the procedure is repeated.

12. The difference to the same month of the previous year is a classic approach to the stationarity of time series. A monthly breakdown of the 44 size × sector series also identified a seasonal trend, justifying the use of 12 months delays.

13. The quality of these size × sector forecasts is tested on 2019. In a crisis-free year, the counterfactual forecasts are expected to match the observed turnover amounts. Over the entire period, the absolute value of the difference between the observed amount and the simulated amount for all series is 2% on average, and the observed amount is within the 95% confidence interval for the predicted amount (details in Bureau et al. 2021a, Appendix F, Figure F.1). For 2019, the model developed allows for better results than naive modeling, attributing as monthly turnover the turnover of the same month of the previous year, for 85% of the months of all 44 size × sector series.

14. These forecasts also coincide with the Banque de France's monthly economic survey (details in Bureau et al., 2021a, Appendix F, Figure F.4). The correlation coefficient between the monthly shocks estimated in the study and by the survey is around 0.8.

with $S_{i,s,t}$ the market share of company *i* within the group *size* × *sector s* at date *t*. The market share attributed to each company in February corresponds to the average of its market share in the previous three months[15] and its market share in February 2019,[16] to which is added an individual weight to incorporate the companies' growth or decline trend over the past year. This coefficient is based on the structure of the Haltiwanger and Davis indicators and is bounded by construction between 0 and 2 and centred around 1 (Davis & Haltiwanger, 1992). Above 1, it allows for the incorporation of a growth trend, and below it, of a decline.

The counterfactual market shares for the months of March ($t$+1) to December 2020 ($t$+10) are calculated in the same way but by replacing the market shares for the months after February 2020 with those estimated in the previous iterations:

$$\begin{cases} S_{i,\hat{s},(t+1)} = \dfrac{1}{2}\left(S_{i,s,(t+1)-12} + \dfrac{1}{3}\left(S_{i,\hat{s},t} + \sum_{j=2}^{3} S_{i,s,(t+1)-j}\right)\right) * \\ \left(1 + \dfrac{1}{2}\dfrac{\left(\left(Y_{i,(\hat{t+1})-1} + \sum_{j=2}^{3} Y_{i,(t+1)-j}\right) - \sum_{j=1}^{3} Y_{i,(t+1)-12-j}\right)}{\dfrac{1}{2}\left(\left(Y_{i,(\hat{t+1})-1} + \sum_{j=2}^{3} Y_{i,(t+1)-j}\right) + \sum_{j=1}^{3} Y_{i,(t+1)-12-j}\right)}\right) \\ S_{i,\hat{s},(t+10)} = \dfrac{1}{2}\left(S_{i,s,(t+10)-12} + \dfrac{1}{3}\sum_{j=2}^{3} S_{i,s,(\hat{t+10})-j}\right) * \\ \left(1 + \dfrac{1}{2}\dfrac{\left(\sum_{j=1}^{3} Y_{i,(\hat{t+10})-j} - \sum_{j=1}^{3} Y_{i,(t+10)-12-j}\right)}{\dfrac{1}{2}\left(\sum_{j=1}^{3} Y_{i,(\hat{t+10})-j} + \sum_{j=1}^{3} Y_{i,(t+10)-12-j}\right)}\right) \end{cases} \quad (4)$$

The monthly market shares are then adjusted so that they sum up to 1 within each group:

$$S_{\widetilde{i,s,t}} = \frac{S_{i,\hat{s},t}}{\sum_{i=1}^{n} S_{i,s,t}} \quad (5)$$

The individual counterfactual turnover is the product of the estimated individual market share and the total counterfactual activity of the group to which the company belongs in month *t*:

$$CA_{\hat{i,s,t}} = S_{\widetilde{i,s,t}} Y_{\hat{t,s}} \quad (6)$$

The estimated monthly activity shock is the difference, in percentage, between the observed turnover and this counterfactual turnover.

$$Choc_{i,s,t} = \left(\frac{CA_{\hat{i,s,t}} - CA_{i,s,t}}{CA_{i,s,t}}\right) * 100 \quad (7)$$

By summing up – month by month or over the year – the counterfactual turnover of the entire sample or of a given sector and comparing it with the aggregate turnover observed in the same area, it is possible to construct aggregate activity shocks. Analyses of the distribution of individual activity shocks as calculated in (7) make it possible to refine these results by identifying winning and losing companies, even within the same sector.

### *2.1.3. Measurement of the Impact of the Crisis by Distributional Indicators of Activity Shocks*

The estimated individual counterfactual turnover figures constitute robust scenarios of what could have been observed for each of the companies based on all the information available at the start of the crisis. However, despite the methodological precautions taken, it is possible that the forecasts at the company level differ from the figures that would have been observed. On the one hand, this is because the individual amounts of turnover declared by the companies are much more volatile than the aggregated amounts, and do not necessarily show the same seasonality. On the other hand, the attribution of the counterfactual market shares is based on the dynamics observed in the year preceding the forecasting exercise, which makes the exercise problematic for companies with a nonlinear growth trajectory. Therefore, even in the absence of a crisis, modelling individual shocks leads to the estimation of shocks that are not necessarily zero and may fluctuate around 0. In this sense, the analysis of the prevalence of winning or losing companies in 2020 and the magnitude of these gains or losses must focus on their distribution and its exceptional nature during the crisis.

The comparison of the distribution of activity shocks in 2020 with the one obtained by replicating the simulation over 2019 makes it possible to compare the deviations of the expected trajectories simulated by the model in the year of the crisis with those of a year without a crisis. The intensity of the distortion of this distribution in relation to 2019, when deviations close to zero are expected, illustrates the intensity of the impact of the health crisis. This distortion is measured with the Hellinger distance, which lies between 0 and 1 and measures the similarity between two statistical distributions. Noting $f$ and $g$, the density functions of the compared distributions, the Hellinger distance is the square root of the following formula[17]:

$$H^2(f,g) = \frac{1}{2}\int\left(\sqrt{f(x)} - \sqrt{g(x)}\right)^2$$
$$= 1 - \int\sqrt{f(x)g(x)}dx$$

15. This moving average smooths out potential one-off results and gives a more robust picture of the company's weight within the group.
16. The market share of the same month of the previous year allows to incorporation of the monthly seasonality of companies, an important element if it differs from the seasonality of the group.
17. The analysis was reproduced with other statistical distances (Kullback-Leibler, Bhattacharyya) for identical conclusions.

The comparison of the distributions of activity shocks is made on annual and monthly shocks. The densities of individual shock distributions are estimated using kernel densities.

The use of individual data highlights the dispersion of the shocks. The contribution of the sector to this heterogeneity must be assessed and to do this, the monthly variance of the individual activity shocks is broken down into a part attributable to the activity sector and a residual part attributable to other factors. The sectoral breakdown used is the finest level of the French classification of activities, with 732 categories. The breakdown method used is standard (Gibbons *et al.*, 2014; Helpman, 2017) and follows the equation:

$$V = Var\left(Choc_{i,s}\right) = \underbrace{\sum_{s} \frac{n_s}{n} \cdot Var_s\left(Choc_{i,s}\right)}_{\text{Within class variance}} + \underbrace{\sum_{s} \frac{n_s}{n} \cdot \left(\overline{Choc_s} - \overline{Choc}\right)^2}_{\text{Between class variance}}$$

with $\overline{Choc} = \frac{1}{n}\sum_{i} Choc_{i,s}$ and $\overline{Choc_s} = \frac{1}{n_s}\sum_{i \in s} Choc_{i,s}$, $Choc_{i,s}$ the shock suffered by the firm $i$ of sector $s$ and $n$ the number of companies in the sample.

## 2.2. Partition of Companies According to Their Shock Trajectory

The constitution of a series of monthly activity shocks for each company in the sample renders the trajectories of all the companies comparable, independently of their expected and observed figures, thus making it possible to identify homogeneous groups among the series of monthly shocks.

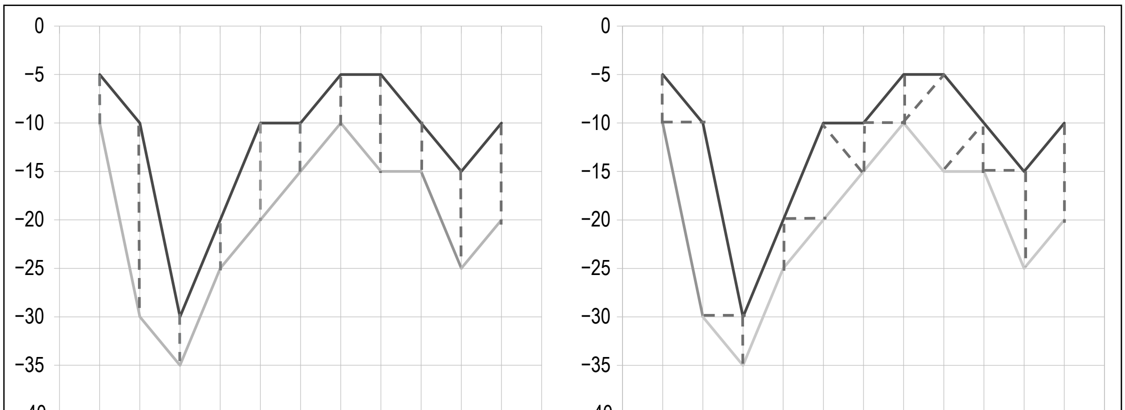
### *2.2.1. Construction of a Typology using Time Series Clustering*

Business shock profiles for 2020 are identified using time series clustering. This method consists in partitioning a population of series into a given number of homogeneous classes according to the dynamic time warping[18] (DTW) distance (Berndt & Clifford, 1994; Ratanamahatana & Keogh, 2004). Figure II illustrates the difference between this distance and a Euclidean distance: the Euclidean approach simply compares the series point by point, whereas the DTW approach compares the series two by two and distorts the order of the points to align them as much as possible. This distortion only occurs within a window of width equal to 10% of the size of the series, i.e. one month (Aghabozorgi *et al.*, 2015).

The monthly shock trajectories are divided into $k$ classes to minimise the DTW distance between elements of the same class (Sardá-Espinosa, 2019). To do this, $k$ trajectories are drawn randomly in the sample to form the centre of each class. The other trajectories are then compared with the different centres and assigned to the class whose centre is closest. When all the series have been classified, the median series of each classe becomes the new centre and the process is repeated until the partition converges or until the maximum number of iterations is reached. The final partition depends on both the number of classes chosen and the initial centres. A 4 class partition was chosen here to optimise the quality of the partition while maintaining a large number of classes.[19] The clustering was

18. Details in Bureau et al. *(2021a, p. 15).*
19. Details in Bureau et al. *(2021a, Appendix H, p. 86).*

Figure II – **Comparison of Euclidean (left) and DTW (right) distances**




Reading Note: The Euclidean distance in March 2020 is the difference between the two series in that month. The DTW distance instead compares the March value of the black series with the February value of the grey series, which it is closer to, and conversely the March value of the grey series is compared with the April value.

repeated ten times to ensure the stability of the final partition. Confusion, i.e. the proportion of companies changing classes between these repetitions, remains close to zero in all these repetitions.

*2.2.2. Explaining the Breakdown of Companies between Profiles: Implementation of a Classification Model*

The identification of the trajectory profiles and the distribution of companies is based exclusively on the estimated monthly activity shocks, but the latter may be correlated with companies' characteristics. To explain retroactively the allocation of companies between these trajectories, we study the correlations between the profile assigned to companies and their characteristics.

The explanatory variables used in the model are the activity sector, the companies' size, their dates of creation and the existence of an export activity, as well as variables relating to the development of online sales, delivery systems, new products or services, reorganisation of the activity, pooling of resources with other companies and the investment in new technologies during the crisis. These variables are taken from FARE and survey data. Matching with survey data restricts the sample to 13,500 companies. To maintain a sample in which the proportion of companies assigned to each trajectory profile is similar to that of the sample and to have an identical distribution in terms of size, activity sector, date of creation and existence of export activity, weights are assigned to companies using a margin calibration method (Deville & Särndal, 1992; Rebecq, 2016). The classification model is an unordered multinomial logit model estimated by neural network with the Broyden-Fletcher-Goldfarb-Shanno[20] method.

## 3. Results

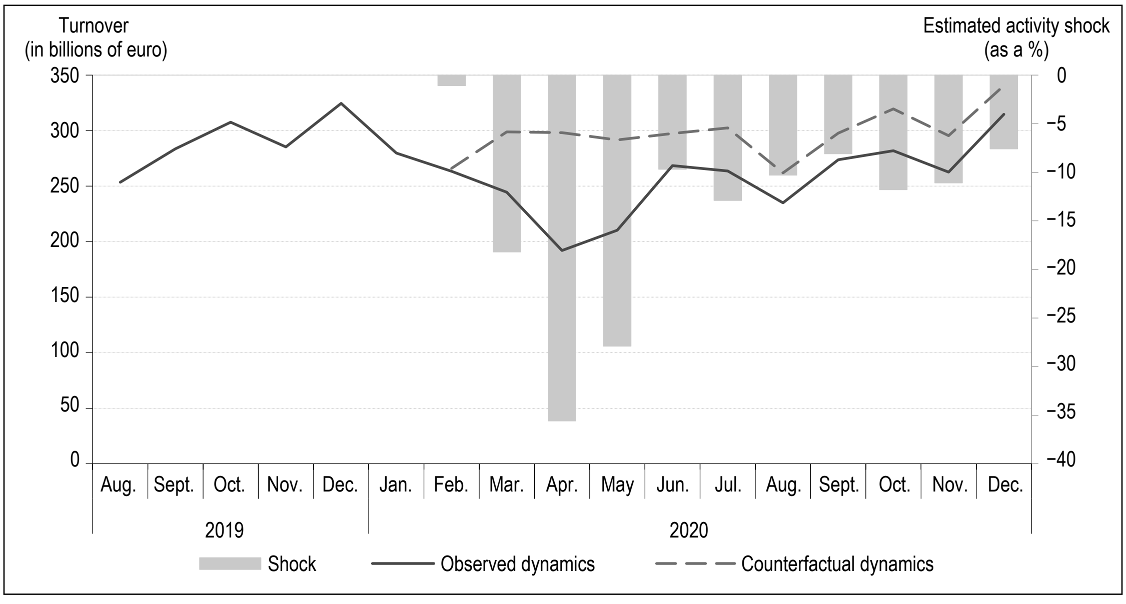
### 3.1. A Very Significant Impact on Business Activity with Varying Magnitude Over the Year

Total economic activity was very slow during the first lockdown of 2020. Between March and May, its level is 27% below its estimated level in the absence of a pandemic (Figure III). In April alone, this difference reaches −35%. Economic activity then rebounded between June and October, while remaining 10% below its expected level. The loss of activity in spring was therefore not offset by higher activity in the summer or early autumn. In the fourth quarter, which includes the second lockdown, the loss of activity is estimated at about 10%. On the one hand, the second lockdown was shorter and less restrictive than the first. On the other hand, companies were more able to adapt their strategies and organisation than at the beginning of the pandemic.

Over 2020, the total amounts of turnover in the French economy deviated from their expected trajectory, with varying degrees of intensity depending on the month studied. These consistently negative deviations at the macroeconomic level are the result of both positive

20. Details in Bureau et al. (2021a, Appendix K, p. 91).

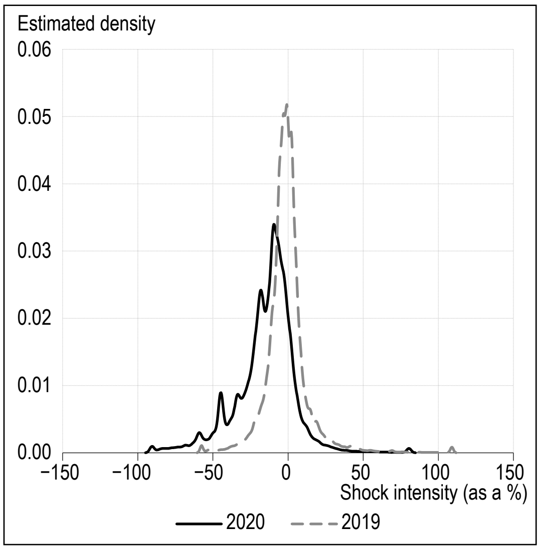
Figure III – **Change in the aggregate activity shock in 2020**




Sources: DGFiP, VAT returns. Calculations by the authors.

and negative activity shocks at the individual level. In the absence of a crisis (2019), the distribution of the modelled individual activity shocks is symmetrical, centred around zero and of low variance. On the contrary, in 2020, the distribution of annual shocks is no longer symmetrical: it has shifted sharply to the left, reflecting a higher proportion of negative shocks (Figure IV). The aggregate activity losses therefore reflect the greater prevalence, in 2020, of negative individual activity shocks, sometimes of great intensity.

Figure IV – **Distributions of individual activity shocks in 2019 and 2020**



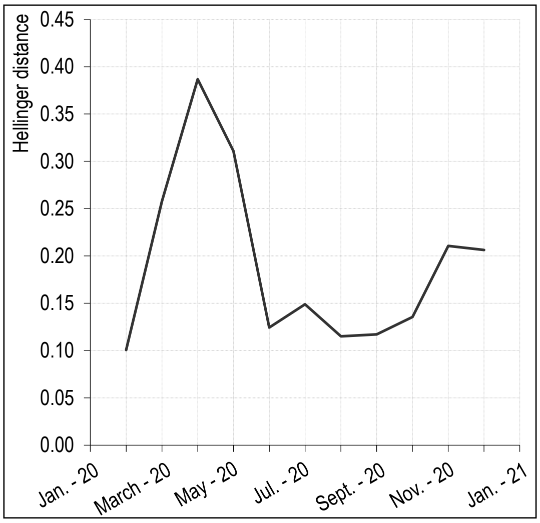

Notes: Density is estimated by kernel.
Sources: DGFiP, VAT returns. Calculations by the authors.

The distortion of the individual activity shock distributions changes monthly based on the intensity of the economic shock. The Hellinger distance, which compares the distributions of the activity shocks for the same month of 2019 and 2020, illustrates this change (Figure V).[21] The measured dissimilarity is very low for the month of February, the first month modelled during the early days of the crisis. Thereafter, the distortion of individual shocks seems to intensify depending on the timing of the restrictive measures: strongest in April before progressively reducing until October, when the curfew and then the second lockdown were introduced.

### 3.2. Heterogeneity of Individual Situations Exceeds Sectoral Affiliation

Even when the impact of the crisis is most severe, the distributions of individual activity shocks reveal that a number of companies experience positive deviations from their expected trajectories. In the midst of the first lockdown,

Figure V – **Hellinger distance between the monthly distributions of individual shocks in 2019 and 2020**




Source: DGFiP, VAT returns. Calculations by the authors.

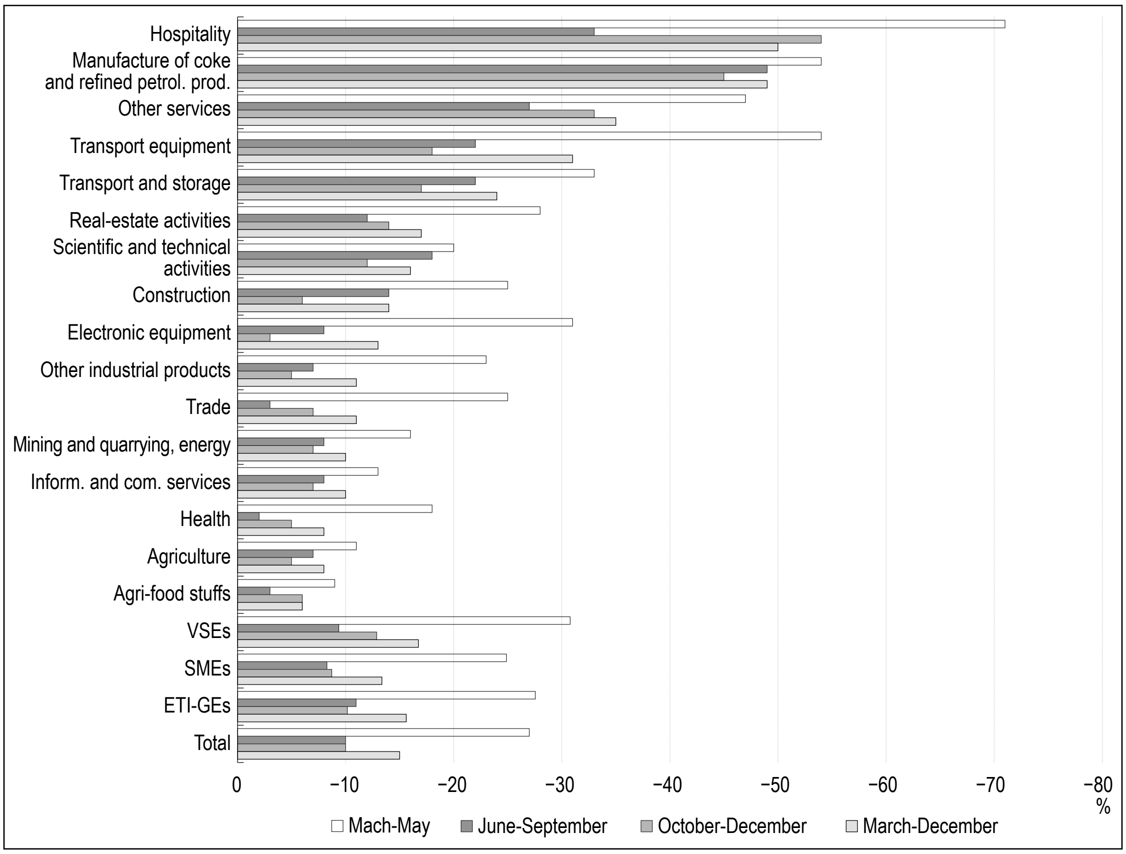
some companies are doing at least as well as they could have in the absence of a crisis. This heterogeneity raises questions, particularly with regard to the role of the activity sector in the observed differences, especially as the dissimilarities between the distributions of activity shocks in 2019 and 2020 are more pronounced during the lockdowns.

Indeed, the first lockdown constituted a shock for all sectors, but of varying magnitude. Hospitality and transportation equipment manufacturing were the two sectors who suffered the biggest losses in economic activity, with estimated activity losses of −71% and −54%, respectively, between March and May (Figure VI). The information and communication, agriculture and agri-food sectors were more resilient (respectively −13%, −11% and −9%). On the contrary, during the second lockdown, only some sectors saw their activity deteriorate significantly after the general moderate recovery in the summer: hospitality (−54%) and "other services" (−33%). For the bulk of the other sectors, the decline in activity was more limited.[22] In several industrial sectors, such as electronics and other industrial products, economic activity rebounded between the two lockdowns and almost recovered to the expected level for the latter (−3% and −5%, respectively).

While cross-sectoral differences are pronounced at this level of division, it is likely that they do not entirely explain the diversity of individual situations experienced by French companies. For each sector, Figure VII presents the main quantiles,

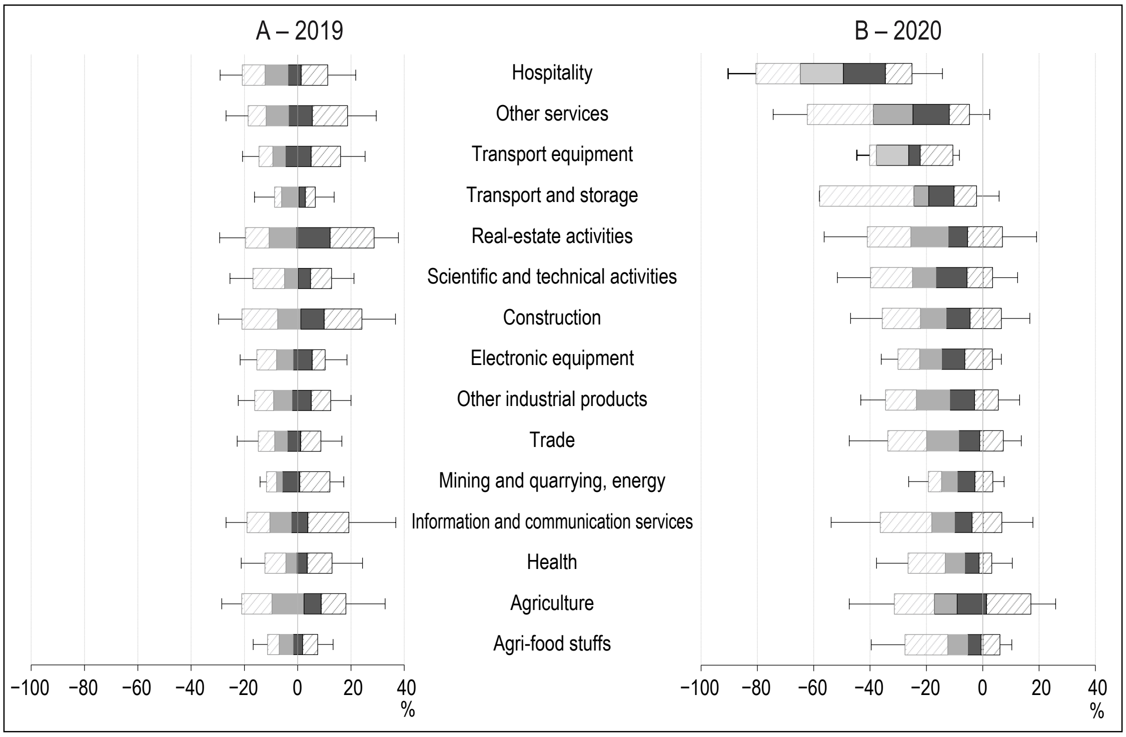
21. *Details in Bureau* et al. *(2021a, Appendix F.1.b, Figures F.2 and F.3).*
22. *Details in Bureau* et al.*, 2021a, Appendix E, p. 62*

Figure VI – **Combined economic activity shock from March to December 2020: sectoral breakdown**




Source: DGFiP, VAT returns. Calculations by the authors.

Figure VII – **Dispersion of the activity shocks by sector in 2019 and 2020**



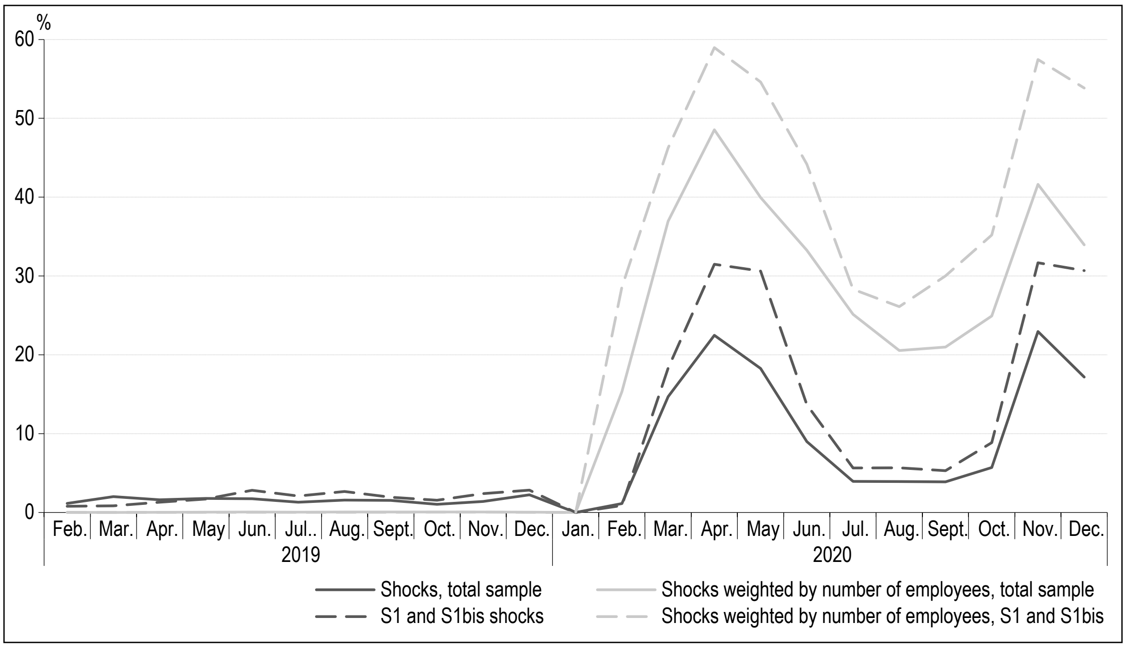

Notes: Each row represents the breakdown of individual activity shocks within a sector via a boxplot. The different segments of the boxes distinguish the quantiles at 10%, 25%, 50% (median), 75% and 90%. The whiskers represent the value of the 5% and 95% quantiles. Due to its low numbers, the coke and refined petroleum product sector is not represented.
Reading Note: In 2020, in the “Hospitality” sector, 5% of employees worked in companies that experienced an activity shock of at least −90.4% or less, and 50% with a shock of −50% or less.
Sources: DGFiP, VAT returns. Calculations by the authors.

weighted by the number of employees,[23] of the distribution of estimated activity shocks for the companies in each sector in 2020 and 2019. In 2020, the majority of companies in each sector experience loss of business, and the situation of the sectors are heterogeneous with very different median shocks. Therefore, each sector displays a substantial dispersion with some highly affected companies, sometimes ceasing all activity, and others that achieve their expected level of activity despite the crisis. These differences observed within a 17-sector breakdown can be explained by the fact that the health restriction measures, particularly the temporary closures, affected more finely defined sectors. At the finest level of the French classification of activities (732 categories or "sub-sectors"), the median annual shocks vary greatly between the sub-sectors of the same aggregate sector, even among those most affected sectors. For example, in hospitality, fast food establishments were more resilient (−34%) than beverage serving (−55%) or catering (−70%) activites, all forced to close in March.[24] For "other services", the largest loss relates to the operation of arts facilities (–80%), while funeral services continued (−4%). Similarly, the least affected sectors, such as trade and food manufacturing, also include heavily affected sub-sectors (department stores −52%, bakeries −23%) and others with moderate gains in activity (retail sale of household appliance +8%, pasta manufacturing +8%).

However, can the diversity of the situations of French companies during the COVID-19 pandemic be solely attributed to the activity sector, even when considered at its finest division? The breakdown of the monthly variance of individual activity shocks between a proportion attributable to the activity sector (732 categories) and a residual proportion allows an assessment of the contribution of the sector to the diversity of business situations. In 2020, the activity sector contributes 43%[25] to the variance of individual activity shocks, much more than in 2019 (Figure VIII). The contribution of the sector to the heterogeneity of shocks is also higher during the months of lockdown, which unevenly affected the various sectors. In April 2020, the sector contributed 48% to the variance of the workforce-weighted shocks. The role of the sector in the dispersion of shocks is also consistently greater in the S1 and S1bis sectors,[26] which were more affected by health restrictions and administrative closures.

*23. The dispersion of individual workforce-weighted activity shocks reflects the dispersion of shocks for employees belonging to these companies. The unweighted dispersion reflects the dispersion of shocks for companies, i.e. for VSEs as they are predominant in both the economy and the sample.*
*24. See Bureau* et al. *(2021b).*
*25. Breakdown with weighting by number of employees.*
*26. The lists of sectors S1 and S1bis are defined by successive amendments to the Decree of 30 March 2020 concerning the solidarity fund. The development of these lists has been reconstructed, month by month, over 2020. The S1 list covers sectors particularly affected by the crisis and administrative closures, particularly in the areas of food service, tourism, event management, culture and sport. The S1bis list covers sectors related to, for example, film distribution and book publishing.*

Figure VIII – **Contribution of the intersectoral variance to the variance of the activity shocks**




Notes: Each curve corresponds to the proportion of cross-sectoral variance in the total variance of shocks, each month.
Reading Note: In April 2020, the cross-sectoral variance represents 23% of the total variance of the sample shocks, 48% when weighted by number of employees.
Sources: DGFiP, VAT returns. Calculations by the authors.

The role played by the activity sector in individual deviations from the modelled activity trajectory is significantly greater in 2020 than in 2019. In 2020, th sector's contribution to the heterogeneity of situations is greater during the months with marked health measures. However, even at its peak, this contribution only represents half of the total heterogeneity, so other factors necessarily influence the observed activity shocks. To jointly address the heterogeneity of individual situations, month by month, and the various factors that can explain these differences between companies and their change over time, the analysis is extended in two stages: first by identifying a relevant typology of the different business trajectories during 2020 to group together companies whose changes in business gains or losses was comparable over the year. Then by studying the determinants of belonging to each trajectory profile using a multinomial classification model.

### 3.3. Four Profiles of Shock Trajectories During the Crisis

Establishing a typology of the individual trajectories of companies in 2020 allows us to identify four standard trajectories of monthly activity shocks in 2020 (Figure IX). Each of these profiles distinguishes itself from the others both by the magnitude of the shock experienced at the beginning of the pandemic and by the resilience displayed, i.e. the capacity to return to its expected non-crisis trajectory. Specifically, the following groups are identified:

- 'Unaffected' companies (36% of companies and 42% of employees):

The first lockdown had a limited impact on these companies, with an mean shock[27] of −14% in April, followed by a recovery towards the expected activity level from June on. With the exception of first lockdown, the distribution of shocks within this group is comparable with that of a "normal" year.

- 'Resilient' companies (38% of companies and 44% of employees):

Their initial loss of activity was more substantial, with a mean impact of −51% in April. From June onwards, losses are lower and the mean impact remains stable at around −20% until the end of the year.

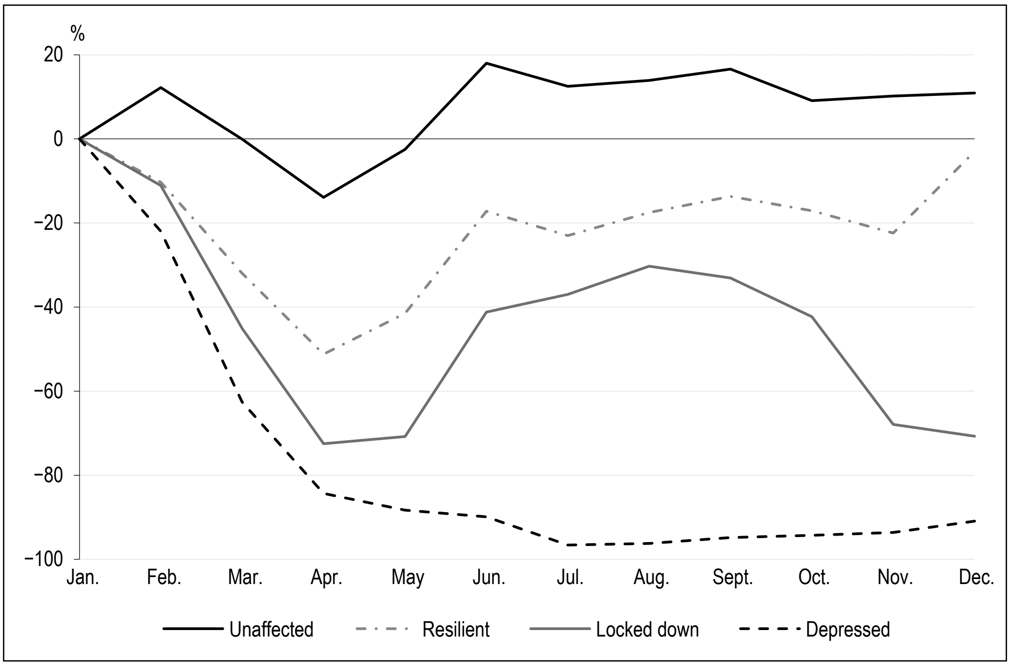
- 'Locked down' companies (20% of companies and 12% of employees):

Their average trajectory is characterised by major lockdown shocks (–72% in April, −70% in November and December) and limited recovery of activity during the summer.

- 'Depressed' companies (6% of companies and 2% of employees):

27. All means are calculated on right-hand winsorized series: shocks higher that the 95th percentile are reduced to the value of this quantile.

Figure IX – **Average shock for each trajectory profile**




Reading Note: Companies in the "Unaffected" profile experienced a mean shock of −14% in April 2020.
Sources: DGFiP, VAT returns. Calculations by the authors.

Their activity collapsed during the first lockdown (−84% on average in April), with no recovery in the summer. The median shocks among these companies are close to −100% from April to December 2020, and a third of them report zero turnover over this entire period.

### 3.4. Characterising the Activity Trajectory of Companies: Beyond the Activity Sector, Organisational Adaptation

The distribution of companies between the trajectory profiles is “unsupervised” and therefore depends only on each company’s estimated activity shocks. The exploration of the correlations between the characteristics of companies and their trajectory profile makes it possible to clarify *ex post* the underlying logic behind the difficulties they may have encountered.

The coefficients resulting from the classification model studying these correlations are statistically significant[28] (Appendix A2). The activity sector is the dominant factor in the distribution of companies between these trajectories. It accounts for almost 85% of the allocation of the companies explained by the model.[29] This proportion is attributable to the very high sectoral dependence of the most affected profiles, which are almost entirely made up of companies from sectors administratively closed during the lockdowns. Conditionally to other variables, the sectors with the highest probability of belonging to the ‘Unaffected’ profile are those of consumer electronics manufacturing, food industry sub-sectors, veterinary activities and the medical sector. In the ‘Resilient’ profile, the majority are manufacturers of jewellery, computers, peripheral equipment and automotive equipment. The sectors with the highest probability of belonging to the ‘Locked down’ profile are those of rail transport, libraries and museums. Finally, in the ‘Depressed’ profile, the sub-sectors of culture, hospitality and tourism, and passenger transport are the most over-represented.

Conditionally to the sector, the effect of other variables on the probability of being in the different classes is significant, but smaller in scale. In other words, the absolute difference in the probability of belonging to a profile is much greater between two different sectors than between two modalities of another variable in the model. However, by expressing the effects of each of these variables as a percentage of change in the probability of being assigned to each profile,[30] several elements emerge (Figure X).

SMEs, particularly VSEs, which were more affected on average during lockdown, have, all things being equal, more chance of belonging to the ‘Locked down’ profile, illustrating the specific difficulties faced by VSEs in a number of sectors.

Exporting companies, in turn, have a higher likelihood of belonging to the ‘Depressed’ profile, probably owing to their dependence on foreign markets and falling external demand. The development of new products and retail systems following the crisis is associated with a higher probability of belonging to the ‘Unaffected’ profile and a lower probability of belonging to the most affected profiles. The same is true for specific investments in new technologies, particularly digital technology. The ability to adapt to health restrictions, particularly those affecting the way in which the supply and distribution of products are organised, was therefore important.

The reorganisation of activity and the pooling of resources with other companies are linked to a higher probability of belonging to both the ‘Unaffected’ and the ‘Depressed’ profiles. Companies that rapidly adapted their businesses were able to maintain their levels of turnover. On the other hand, pooling of resources may have been retrospectively necessary for the most affected companies, explaining a positive marginal effect in the ‘Depressed’ profile by a reverse causality mechanism.

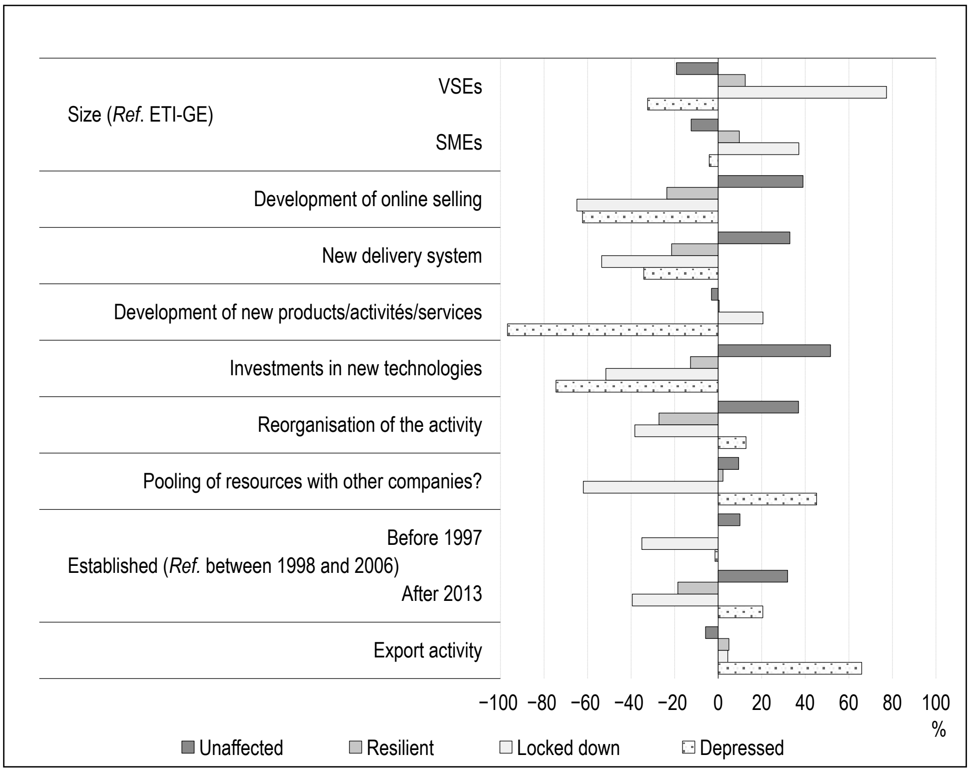
These results allow for a more detailed exploration of the variables correlated with the heterogeneity of the observed situations. In particular, while the sector is indeed the main factor explaining companies’ shock trajectories, the correlations observed with some of their other characteristics, including their adaptation strategy during the crisis, provide a better understanding of the observed dispersion.

28. *The observations are weighted by the coefficients from margin calibration during regression. This weighting can have a positive impact on the significance of the effects displayed.*
29. *Estimate by use of the Cox-Snell (Cox & Snell, 1989) adjusted.*
30. *These effects are based on the calculation of the predicted probabilities at the mean of belonging to each profile for all the modalities of the categorical explanatory variables. Comparing these probabilities by varying only the modality of the same categorical variable, allows us to calculate the relative effect of switching from one modality to another based on the probability of belonging to each profile. Formally, the effect of a binary variable* j *on the probability of belonging to profile* c *is:*

$$Effect_{j,c} = \frac{\mathbb{P}\left(Profile_c \mid X_j = 1, X_{-j}\right) - \mathbb{P}\left(Profile_c \mid X_j = 0, X_{-j}\right)}{\mathbb{P}\left(Profile_c \mid X_j = 0, X_{-j}\right)}, \forall c \in [1,4]$$

*These effects were also calculated by taking the mean of the variations in the predicted individual probabilities, with no impact on the trends in the results. This measure makes the predicted probability changes attributable to each explanatory variable commensurable for each activity trajectory, regardless of the size of these groups. For the use of predicted probabilities for logit models, see Long, 1997; Pryanishnikov & Zigova, 2003; Stratton* et al.*, 2008; Peng & Nichols, 2003; Wulff, 2015.*

Figure X – **Marginal effects of the classification model variables**




Reading Note: Companies that have developed online sales since the start of the crisis are 1.38 times more likely to belong to the 'Unaffected' profile than other companies. In other words, the marginal effect of online sales development on belonging to the 'Unaffected' profile is +38%. Formally:

$$Effect_{Online\,Sales,Profile_1} = \frac{\mathbb{P}\left(Profile_1 \mid X_{Online\,Sales} = 1, X_{-Online\,Sales}\right) - \mathbb{P}\left(Profile_1 \mid X_{Online\,Sales} = 0, X_{-Online\,Sales}\right)}{\mathbb{P}\left(Profile_1 \mid X_{Online\,Sales} = 0, X_{-Online\,Sales}\right)} = 0.38$$

Sources: DGFIP, VAT returns; INSEE, Impact of the health crisis on business organisation and activity survey. Calculations by the authors.

* *
*

A striking result of this analysis is the high prevalence of companies that went through the crisis without deviating from the level of growth they would have experienced without the crisis. The aggregate loss of business is large but hides two dimensions of the crisis. On the one hand, not all companies experienced loss of business, and on the other hand, even if most companies were unable to compensate for the initial shock, a substantial proportion of them were able to recover their business trajectory to approach or even exceed the counterfactual scenario. It is particularly notable, for example, that the 'Unaffected' profile comprises more than a third of companies and employees, more than 'Locked down' and 'Depressed' companies put together. To better understand the consequences of the crisis, it is necessary to identify the companies that fared better at the other end of the spectrum, which includes companies that practically ceased their activity from March onwards. In this respect, organisational adaptations, particularly investments in new technologies, are important as they are correlate to the least affected activity trajectories and seem to have partially mitigated the difficulties associated with some health restrictions defined at the sectoral level. The fact that the ability to implement organisational adaptation strategies after the onset of the crisis may have been uneven among companies raises the question of its role in exacerbating or mitigating situations predating the crisis. In other words, were the activity losses more pronounced for companies that were already in trouble when the crisis began?

The Banque de France rating assesses the risks associated with loans granted to companies by estimating the companies' ability to meet their financial commitments within a three-year horizon[31] and thus offers an indicator of the financial health of companies

31. *The rating is that of December 31st 2019. For profiled groups, the rating for the head of group, as documented in FARE, is used. If the SIREN number of the head of group is not known, the legal unit with the highest highest value-added within the profiled company is used.*

before the crisis.[32] Combining this indicator with the activity trajectory category followed by companies in 2020 shows that the highest rated companies are more often found among the preserved ('Unaffected' and 'Resilient') profiles, while companies considered fragile before the crisis have more often experienced highly affected trajectories ('Locked down' and 'Depressed'). The ratings range from 3++, for companies whose ability to meet their commitments is considered excellent, to P, for companies in insolvency proceedings (i.e. compulsory receivership or liquidation).[33] Among the highest-rated companies (3++) at the end of 2019, 45% were 'Unaffected' (Figure XI). This proportion decreases as the listing levels fall to 30% for companies rated 5 and 12.5% for companies rated P. This gradient reverses for 'Depressed' companies, accounting for 1.5% of companies rated 3++, the lowest share among all rates. This proportion increases as ratings decrease, reaching 7% for companies rated 5, 16% for companies rated 9 and 45% for companies rated P.

These ratings may be correlated with the activity sector or other characteristics of the companies, such as their size or age and even their ability to adapt their behaviour and organisation during the crisis (Bureau *et al.*, 2021a). The statistics presented here are descriptive and should not be analysed independently of the results of the classification model presented,[34] but they do provide an additional lesson: the companies whose trajectory has moved the furthest away from the level of growth that would have been expected in 2020 are those that were already vulnerable before the start of the pandemic. In other words, the impact strictly attributable to the crisis was greater for companies that were vulnerable from the outset. So the crisis may have exacerbated pre-existing differences by weighing more heavily on companies that are already facing difficulties.[35]

The approach developed in this article aims to go beyond the theoretical debates on the crisis

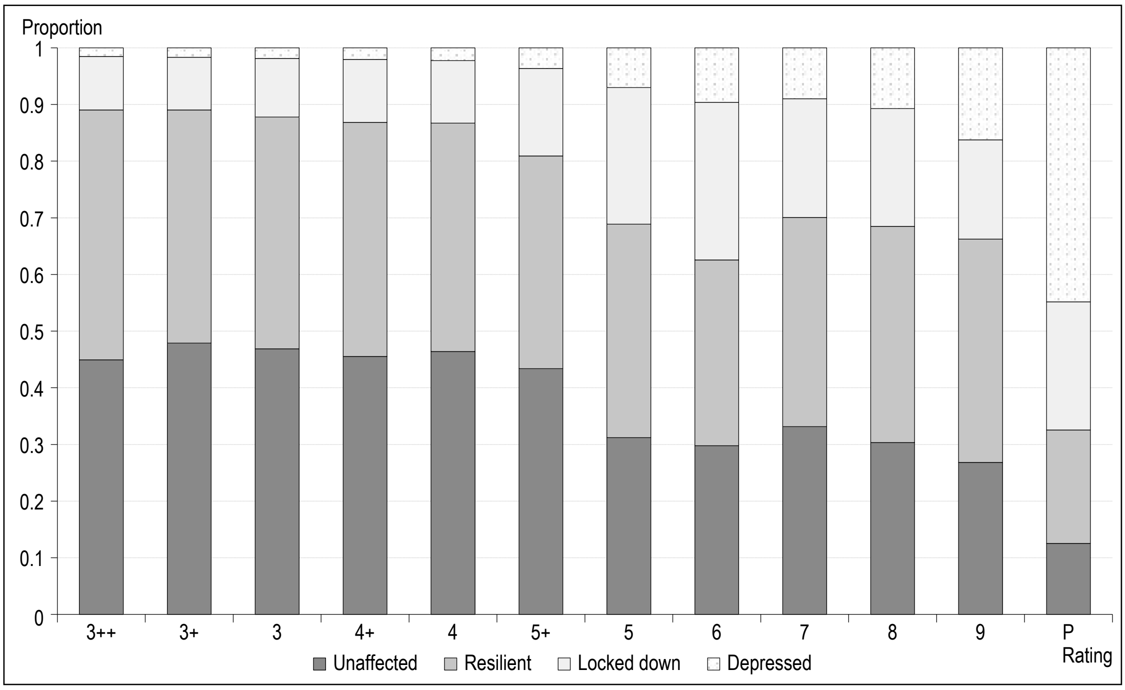
*32. The rating is carried out by the Banque de France on the basis of an analysis of the accounting, financial and judicial information on the companies, their potential payment incidents affecting trade and qualitative information reported by company heads.*

*33. A number of companies are not listed and are given a 0 rating. These are the companies for which Banque de France does not have recent accounting documentation or has not gathered unfavourable information on trade bill payments or judicial information or decisions. These ratings are excluded from the breakdowns presented but account for fairly stable proportion between the different trajectory categories.*

*34. The limited access to these data allowed us to work only on the aggregate breakdown of companies by rating and trajectory profile established by our study. Inclusion in the multinomial model could have provided additional elements.*

*35. These findings echo the Institut des Politiques Publiques (IPP)' assessments that the crisis hit low-productivity companies harder, with a marked sectoral effect (Bach* et al.*, 2020). Here, we show that this impact is more pronounced, even in relation to the trajectory that companies would have experienced without a crisis. Bureau* et al. *(2022) also show that public support measures have not benefited the most fragile companies* ex ante *any more.*

Figure XI – **Breakdown of companies by Banque de France rating as of December 31st 2019 and trajectory of activity in 2020**




Reading Note: Among the companies rated 3++ in 31 December 2019, 45% belong to the "Unaffected" profile.
Sources: DGFIP, VAT returns; Banque de France ratings. Calculations by the authors.

to study the impact that is actually attributable to it. By establishing individual reference scenarios, this work enables us to rethink the consequences of the crisis by taking into account the growth trajectories that companies followed before the pandemic, but also calls for an extension of the analysis to model the financial situations of companies during the crisis, by incorporating both public aid and adaptations of company behaviour (payment of dividends, intermediate consumption, investments). This financial model would enable an assessment of the financial needs of companies by incorporating the amounts of activity achieved (or lost) in 2020 and to quantify the amounts of cash flow required to resume a level of activity consistent with the dynamics experienced before the crisis, which could be estimated thanks to the counterfactuals in this study. These developments are the subject of further work. ☐

## BIBLIOGRAPHY


**Aghabozorgi, S., Shirkhorshidi, A. S. & Wah, T. Y. (2015).** Time-series clustering – A decade review. *Information Systems*, 53, 16–38. http://dx.doi.org/10.1016/j.is.2015.04.007

**Akaike, H. (1998).** Information theory and an extension of the maximum likelihood principle. In: Parzen, E., Tanabe, K., Kitagawa, G. (eds), *Selected Papers of Hirotugu Akaike.* Springer Series in Statistics. New York, NY: Springer. https://doi.org/10.1007/978-1-4612-1694-0_15

**Amoureux, V., Héam, J.-C. & Laurent, T. (2021).** Les comptes de la Nation en 2020. *Insee Première* N° 1860, mai 2020. https://www.insee.fr/fr/statistiques/5387891

**Anayi, L., Button, R., Walker, D., …, & Wise, T. (2020).** Financial Stability Report – Technical annex: updated estimates of the cash-flow deficit of UK companies in a COVID-19 scenario. *Bank of England*, August.
https://www.bankofengland.co.uk/financial-stability-report/2020/updated-estimates-of-the-cash-flow-deficit-of-uk-companies-in-a-COVID-19-scenario-technical-annex

**Angrist, J. D. & Pischke, J. S. (2008)**. *Mostly Harmless Econometrics*. Princeton: Princeton University Press. https://doi.org/10.1515/9781400829828

**Bach, L., Ghio, N., Guillouzouic, A. & Malgouyres, C. (2020).** Impact de la crise et des mesures budgétaires 2020-2021 sur les entreprises. *Conférence sur l'impact de la crise et des mesures budgétaires 2020-2021*. Institut des Politiques Publiques, 16 novembre 2020.
https://www.ipp.eu/wp-content/uploads/2020/11/slides-ENTREPRISES-cepremap-ipp-16nov2020.pdf

**Baldwin, R. & Di Mauro, B. W. (2020).** Economics in the time of COVID-19: A new eBook. *VOX CEPR Policy Portal*. https://cepr.org/sites/default/files/news/COVID-19.pdf

**Baldwin, R. & Tomiura, E. (2020).** Thinking ahead about the trade impact of COVID-19. *Economics in the Time of COVID-19*, 59. https://cepr.org/sites/default/files/news/COVID-19.pdf

**Balla-Elliott, D., Cullen, Z. B., Glaeser, E. L., Luca, M. & Stanton, C. T. (2020).** Business Re-Opening During the COVID-19 Pandemic. NBER *Working Paper* N° 27362. https://www.nber.org/papers/w27362

**Baleyte, J., Bourgeois, A., Favetto, B., Heam, J.-C., Lequien, M. & Ralle, P. (2021).** L'économie française en 2020 : une année de bouleversements. *Insee Analyses* N° 64, mai 2021.
https://www.insee.fr/fr/statistiques/5389038

**Barrero, J. M., Bloom, N. & Davis, S. J. (2020).** COVID-19 is also a reallocation shock. NBER *Working Paper* N° 27137. https://www.nber.org/papers/w27137

**Barrero, J. M., Bloom, N., Davis, S. J. & Meyer, B. H. (2021).** COVID-19 Is a Persistent Reallocation Shock. *AEA Papers and Proceedings*, Vol. 111, 287–291. http://dx.doi.org/10.29338/wp2021-03

**Bartik, A. W., Bertrand, M., …, Luca, M. & Stanton, C. (2020).** The impact of COVID-19 on small business outcomes and expectations. *Proceedings of the National Academy of Sciences*, 117(30), 17656–17666.
https://doi.org/10.1073/pnas.2006991117

**Berndt, D. J. & Clifford, J. (1994).** Using Dynamic Time Warping to Find Patterns in Time Series. *KDD Workshop*, Vol. 10, 359–370. https://www.aaai.org/Library/Workshops/1994/ws94-03-031.php

**Bignon, V. & Garnier, O. (2020).** Mesurer l'impact de la crise COVID-19. *Revue de l'OFCE*, 166(2), 45–57. https://doi.org/10.3917/reof.166.0045

**Blanchard, O., Philippon, T. & Pisani-Ferry, J. (2020).** *A new policy toolkit is needed as countries exit COVID-19 lockdowns*. Bruegel *Policy Contribution* 12.
https://www.econstor.eu/bitstream/10419/237647/1/1726773043.pdf

**Blanco, R., Mayordomo, S., Menéndez, Á. & Mulino, M. (2020).** *Spanish Non-financial Corporations' Liquidity Needs and Solvency After the COVID-19 Shock*. Banco de España.
https://www.bde.es/f/webbde/SES/Secciones/Publicaciones/PublicacionesSeriadas/DocumentosOcasionales/20/Files/do2020e.pdf

**Bloom, N., Fletcher, R. S. & Yeh, E. (2021).** The impact of COVID-19 on US firms. NBER *Working Paper* N° 28314. http://www.nber.org/papers/w28314

**Bonnet, O., Olivia, T. & Roudil-Valentin, T. (2021).** En 2020, la chute de la consommation a alimenté l'épargne, faisant progresser notamment les hauts patrimoines financiers : quelques résultats de l'exploitation de données bancaires. INSEE, *Note de conjoncture*, mars 2021.
https://www.insee.fr/fr/statistiques/5232043?sommaire=5232077

**Bourlès, L. & Nicolas, Y. (2021).** Quel est l'impact de la crise sanitaire sur les secteurs culturels au cours du premier trimestre 2021 ? Ministère de la Culture, DEPS, *Note de conjoncture* N° 2021-3, juillet 2021.
https://www.culture.gouv.fr/content/download/292629/3354238?version=10

**Box, G. E. & Pierce, D. A. (1970).** Distribution of residual autocorrelations in autoregressive-integrated moving average time series models. *Journal of the American Statistical Association*, 65(332), 1509–1526.
https://www.jstor.org/stable/2284333

**Brancati, E. & Brancati, R. (2020).** Heterogeneous Shocks in the COVID-19 Pandemic: Panel Evidence from Italian Firms. *SSRN Electronic Journal*. http://dx.doi.org/10.2139/ssrn.3597650

**Brinca, P., Duarte, J. B. & Faria-e-Castro, M. (2020).** Measuring sectoral supply and demand shocks during COVID-19. *European Economic Review*, 139. https://doi.org/10.1016/j.euroecorev.2021.103901

**Bureau, B., Duquerroy, A., Giorgi, J., Lé, M., Scott, S. & Vinas, F. (2022).** An In-Depth Examination of the Impact of the Health Crisis and the Public Support Measures Implemented on Companies' Financial Situations. *Economie et Statistique / Economics and Statistics*, 532-33, 25–45 (this issue).

**Bureau, B., Duquerroy, A., Giorgi, J., Lé, M., Scott, S. & Vinas, F. (2021a).** Une année de crise Covid : impact sur la dynamique de l'activité des entreprises en France. Une évaluation sur données individuelles. INSEE, *Document de travail N°2021-002*. https://www.insee.fr/fr/statistiques/5411702

**Bureau, B., Duquerroy, A., Giorgi, J., Lé, M., Scott, S. & Vinas, F. (2021b).** Le secteur de l'hébergement-restauration à travers la crise sanitaire de 2020. INSEE, Coll. Insee Références, *Les entreprises en France*, 47–53.
https://www.insee.fr/fr/statistiques/5758810?sommaire=5759063

**Cajner, T., Crane, L. D., Decker, R. A., Grigsby, J., …, & Yildirmaz, A. (2020).** The US labor market during the beginning of the pandemic recession. NBER *Working Paper* N° 27159. https://doi.org/10.3386/w27159

**Chetty, R., Friedman, J. N., Hendren, N., Stepner, M. & The Opportunity Insights Team. (2020).** *How did COVID-19 and stabilization policies affect spending and employment? A new real-time economic tracker based on private sector data.* NBER Vol. 27431. Cambridge, MA: National Bureau of Economic Research.
http://www.nber.org/papers/w27431

**Cox, D. R. & Snell, E. J. (1989).** *The Analysis of Binary Data*, 2$^{nd}$ ed. London: Chapman and Hall.
https://doi.org/10.1201/9781315137391

**Danieli, A. & Olmstead-Rumsey, J. (2020).** Sector-specific shocks and the expenditure elasticity channel during the COVID-19 crisis. *SSRN Electronic Journal*. http://dx.doi.org/10.2139/ssrn.3593514

**Dauvin, M. & Sampognaro, R. (2021).** Dans les coulisses du confinement : modélisation de chocs simultanés d'offre et de demande. OFCE *Working Paper* N° 05/2021.
https://hal-sciencespo.archives-ouvertes.fr/hal-03374280/document

**Davis, S. J. & Haltiwanger, J. (1992).** Gross job creation, gross job destruction, and employment reallocation. *The Quarterly Journal of Economics*, 107(3), 819–863. https://doi.org/10.2307/2118365

**Deville, J. C. & Särndal, C. E. (1992).** Calibration estimators in survey sampling. *Journal of the American Statistical Association*, 87(418), 376–382. https://doi.org//10.1080/01621459.1992.10475217

**Dickey, D. A. & Fuller, W. A. (1979).** Distribution of the estimators for autoregressive time series with a unit root. *Journal of the American Statistical Association,* 74(366a), 427–431. https://doi.org/10.2307/2286348

**Duc, C. & Souquet, C. (2020).** L'impact de la crise sanitaire sur l'organisation et l'activité des sociétés. *Insee Première* N° 1830. https://www.insee.fr/fr/statistiques/4994488

**Fairlie, R. (2020).** The impact of COVID-19 on small business owners: Evidence from the first three months after widespread social-distancing restrictions. *Journal of Economics & Management Strategy*, 29(4), 727–740.
https://dx.doi.org/10.1111%2Fjems.12400

**Forsythe, E., Kahn, L. B., Lange, F. & Wiczer, D. (2020).** Labor demand in the time of COVID-19: Evidence from vacancy postings and UI claims. *Journal of Public Economics*, 189, 104238. https://doi.org/10.1016/j.jpubeco.2020.104238

**INSEE (2020)**. En avril 2020, chute inédite de la confiance des ménages. INSEE, *Informations Rapides* N° 2020-106, 28 avril 2020. https://www.insee.fr/fr/statistiques/4483357

**Gerschel, E., Martinez, A. & Mejean, I. (2020).** Propagation of shocks in global value chains: the coronavirus case. IPP *Note* N°53. https://www.ipp.eu/wp-content/uploads/2020/03/n53-notesIPP-march2020.pdf

**Gibbons, S., Overman, H. G. & Pelkonen, P. (2014).** Area disparities in Britain: Understanding the contribution of people *vs.* place through variance decompositions. *Oxford Bulletin of Economics and Statistics*, 76(5), 745–763. https://doi.org/10.1111/obes.12043

**Glaeser, E. L., Jin, G. Z., Leyden, B. T. & Luca, M. (2021).** Learning from deregulation: The asymmetric impact of lockdown and reopening on risky behavior during COVID-19. *Journal of Regional Science*, 61(4), 696–709. https://doi.org//10.1111/jors.12539

**Gourinchas, P. O., Kalemli-Özcan, Ş., Penciakova, V. & Sander, N. (2020).** *Estimating SME failures in real time: an application to the COVID-19 crisis*. NBER *Working Paper* N° 27877. https://doi.org//10.3386/w27877

**Gourinchas, P. O., Kalemli-Özcan, Ş., Penciakova, V. & Sander, N. (2021).** COVID-19 and SMEs: A 2021 "time bomb"? NBER *Working paper* N° 28418. https://doi.org/10.3386/w28418

**Gupta, S., Nguyen, T., Raman, S., ... & Wing, C. (2021).** Tracking public and private responses to the COVID-19 epidemic: evidence from state and local government actions. *American Journal of Health Economics*, 7(4), 361–404. https://doi.org/10.1086/716197

**Hadjibeyli, B., Roulleau, G. & Bauer, A. (2021).** Live and (don't) let die: the impact of COVID-19 and public support on french firms. Direction générale du Trésor, *Document de travail* N° 2021-2. https://www.tresor.economie.gouv.fr/Articles/2021/04/20/live-and-don-t-let-die-the-impact-of-COVID-19-and-public-support-on-french-firms-1

**Hale, T., Angrist, N., Goldszmidt, R., ... & Tatlow, H. (2021).** A global panel database of pandemic policies (Oxford COVID-19 Government Response Tracker). *Nature Human Behaviour*, 5(4), 529–538. https://doi.org/10.1038/s41562-021-01079-8

**Helpman, E., Itskhoki, O., Muendler, M. A. & Redding, S. J. (2017).** Trade and inequality: From theory to estimation. *The Review of Economic Studies*, 84(1), 357–405. https://doi.org/10.1093/restud/rdw025

**Heyer, É. & Timbeau, X. (2020).** Évaluation de la pandémie de COVID-19 sur l'économie mondiale. *Revue de l'OFCE*, 166(2), 59–110. https://doi.org/10.3917/reof.166.0059

**Ljung, G. M. & Box, G. E. (1978).** On a measure of lack of fit in time series models. *Biometrika*, 65(2), 297–303 https://doi.org/10.2307/2335207

**Long, J. S. (1997).** Regression models for categorical and limited dependent variables. *Advanced Quantitative Techniques in the Social Sciences*, 7.

**OECD (2020).** *Corporate Sector Vulnerabilities during the COVID-19 Outbreak: Assessment and Policy Responses*. OECD Publishing.
https://www.oecd.org/coronavirus/policy-responses/corporate-sector-vulnerabilities-during-the-COVID-19-outbreak-assessment-and-policy-responses-a6e670ea/

**Peng, C. Y. J. & Nichols, R. N. (2003).** Using multinomial logistic models to predict adolescent behavioral risk. *Journal of Modern Applied Statistical Methods*, 2(1), 16. https://doi.org//10.22237/jmasm/1051748160

**Pryanishnikov, I. & Zigova, K. (2003).** Multinomial logit models for the Austrian labor market. *Austrian Journal of Statistics*, 32(4), 267–282. https://doi.org/10.17713/ajs.v32i4.461

**Ratanamahatana, C. A. & Keogh, E. (2004).** Everything you know about dynamic time warping is wrong. *Third workshop on mining temporal and sequential data*.
http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.432.4253&rep=rep1&type=pdf#page=53

**Rebecq, A. (2016)**. Icarus: un package R pour le calage sur marges et ses variantes. *9e colloque francophone sur les sondages*, Gatineau (Canada). http://paperssondages16.sfds.asso.fr/submission_54.pdf

**Sardá-Espinosa, A. (2019).** Time-series clustering in r using the dtwclust package. *The R Journal,* RJ-2019-023. https://doi.org/10.32614/RJ-2019-023

**Schivardi, F. & Guido, R. (2020).** A simple method to estimate firms' liquidity needs during the COVID-19 crisis with an application to Italy. *Covid Economics, Vetted and Real-Time Papers, 35, 51-69.* https://iris.luiss.it/retrieve/handle/11385/198776/104683/SchivardiRomano.pdf

**Sears, J., Villas-Boas, J. M., Villas-Boas, V. & Villas-Boas, S. B. (2020).** Are We #StayingHome to Flatten the Curve? *Department of Agricultural and Resource Economics University of California, Berkeley,* first version April, 5. http://dx.doi.org/10.2139/ssrn.3569791

**Škare, M., Soriano, D. R. & Porada-Rochoń, M. (2021).** Impact of COVID-19 on the travel and tourism industry. *Technological Forecasting and Social Change*, 163, 120469. https://doi.org/10.1016/j.techfore.2020.120469

**Stratton, L. S., O'Toole, D. M. & Wetzel, J. N. (2008).** A multinomial logit model of college stopout and dropout behavior. *Economics of Education Review*, 27(3), 319–331. http://dx.doi.org/10.1016/j.econedurev.2007.04.003

**Wulff, J. N. (2015).** Interpreting results from the multinomial logit model: Demonstrated by foreign market entry. *Organizational Research Methods*, 18(2), 300–325. https://doi.org/10.1177/1094428114560024

**APPENDIX 1**

## CONSTRUCTION OF SERIES OF TURNOVER

The formula for estimating turnover from VAT return data is as follows:

$$CA_{i,t} = CAF_{i,t} + CAE_{i,t}$$
$$\Leftrightarrow CA_{i,t} = \left(BI_{i,t} - AA_{i,t} - AOI_{i,t} + a.b.AONI_{i,t}\right) + \left(UE_{i,t} + HUE_{i,t} + a.\left(1-b\right).AONI_{i,t}\right)$$

with *a* and *b* set by default at 1.

Table A1 – **Dictionary of the variables derived from the VAT returns**

| | |
|---|---|
| Taxable base excluding tax, in France(TB) | Transactions performed in France at a normal rate of 20%<br>+ in metropolitan France at reduced 5.5% rate<br>+ in metropolitan France at reduced 10% rate<br>+ in overseas departments at normal 8.5% rate<br>+ in overseas departments at 2.1% reduced rate<br>+ old rates<br>+ taxable transactions at a particular rate |
| Self-liquidated purchases (SLPs) | Purchase of intra-community services<br>+ Imports<br>+ Intra-community acquisitions<br>+ Delivery of electricity, natural gas, heat or cold taxable in France<br>+ Purchases of goods or services made from a taxable person not established in France |
| Other taxable transactions (OTTs) | Other taxable transactions |
| Other non-taxable transactions (ONTTs) | Other non-taxable transactions |
| Exports to the European Union (EU) | Intra-community deliveries to a taxable person<br>− B2B sales<br>+ Delivey of electricity, natural gas, heat or cold deliveries non-taxable in France |
| Exports outside the European Union (OEU) | Exports outside EU |

**APPENDIX 2**

## RESULTS OF THE CLASSIFICATION MODEL

Table A2 – **Regression results of the mlogit model**

| | *Dependent variable* | | | | | |
|---|---|---|---|---|---|---|
| *Independent variables* | Locked down profile | | Resilient profile | | Unaffected profile | |
| Size: VSEs | 0.330*** | (0.027) | 0.786*** | (0.044) | −0.178*** | (0.054) |
| Size: SMEs | 0.224*** | (0.027) | 0.447*** | (0.044) | 0.090* | (0.054) |
| Date of creation: Before 1997 | 0.385*** | (0.009) | 0.251*** | (0.013) | −0.020 | (0.022) |
| Date of creation: Between 1998 and 2006 | 0.481*** | (0.009) | 0.780*** | (0.012) | 0.091*** | (0.020) |
| Date of creation: Between 2007 and 2012 | 0.343*** | (0.009) | −0.098*** | (0.012) | 0.229*** | (0.019) |
| Export activity | 0.108*** | (0.010) | 0.103*** | (0.014) | 0.566*** | (0.027) |
| Development of online selling | −0.598*** | (0.013) | −1.375*** | (0.022) | −1.304*** | (0.037) |
| Development of new delivery systems | −0.525*** | (0.013) | −1.049*** | (0.022) | −0.703*** | (0.036) |
| Development of new products/services | 0.035*** | (0.011) | 0.219*** | (0.016) | −3.410*** | (0.063) |
| Investment in new technologies | −0.553*** | (0.020) | −1.141*** | (0.029) | −1.784*** | (0.042) |
| Reorganisation of the activity | −0.632*** | (0.013) | −0.797*** | (0.021) | −0.194*** | (0.035) |
| Pooling of resources | −0.068*** | (0.013) | −1.057*** | (0.022) | 0.283*** | (0.026) |
| Remote workforce | −0.004*** | (0.0002) | −0.008*** | (0.0002) | −0.009*** | (0.0004) |
| Constant | −7.878*** | (0.038) | −7.120*** | (0.057) | −7.748*** | (0.072) |
| AIC | 1,199,764.000 | | 1,199,764.000 | | 1,199,764.000 | |
| *N* | | | 13,426 | | | |

*$p$<0.1 ; **$p$<0.05 ; ***$p$<0.01.
Sources: DGFIP, VAT returns; INSEE, Impact of the health crisis on business organisation and activity survey. Calculations by the authors.