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LIVE AND (DON'T) LET DIE: THE IMPACT OF COVID-19 AND PUBLIC SUPPORT ON FRENCH FIRMS

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The views expressed in this working paper are those of the authors and do not necessarily represent positions of the French Treasury. Its publication aims at stimulating debate and generating comments and criticism.

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Abstract

The Covid crisis has had a massive impact on the economy, especially on firms. The French Treasury has developed a microsimulation tool which allows to estimate the impact of the crisis, and of public measures taken in response to it, on financial health at the firm level. This tool is based on an accounting model similar to the one used in several publications, however it also integrates observed data at the firm level on the magnitude of the shock on firms and their use of the public support. In particular, it makes use of observed data on the evolution of the turnover, employment and payroll of firms, as well as their use of the short-time work scheme, the solidarity fund for SMEs and payroll taxes deferrals. Such a tool allows to simulate the evolution of illiquidity, insolvency and indebtedness at the firm level, taking into account the heterogeneity among firms. Results show that the financial health of firms has deteriorated in 2020 compared to a year without crisis, but public support – mostly the short-time work scheme and, for small firms, the solidarity fund – has considerably limited the increase in the number of illiquid or insolvent firms. Moreover, the impact of the crisis varies across industries and insolvency affects productive firms more than it does in normal times. Finally, the increase of firms' debt in 2020 may impair investment during the recovery. Relying on a dynamic model of corporate investment under financial constraint, we estimate that the debt overhang caused by the crisis could reduce corporate investment by almost 2% during the recovery phase. This figure does not take into account the measures of the French recovery plan, such as the production tax cut or the “prêts participatifs” scheme. A similar model shows R&D spending to be more resilient to the deterioration of firms' financial health.

Keyword: Covid-19, insolvency, illiquidity, debt, investment, R&D

JEL: G33, D24, G31, O31, G32, D22

Résumé

La crise liée à la pandémie de Covid-19 a eu un impact majeur sur l'économie, et en particulier sur les entreprises. La DG Trésor a développé un outil de micro-simulation permettant d'estimer l'impact de la crise sur la situation financière des entreprises au niveau individuel, ainsi que l'effet des mesures mises en place. Cet outil repose sur un modèle comptable similaire à celui employé par plusieurs travaux récents, mais il a l'avantage d'intégrer des données individuelles observées sur l'année 2020 concernant le choc subi par les entreprises et les dispositifs de soutien dont elles ont bénéficié. Il repose ainsi sur des données récentes, entreprise par entreprise, sur l'évolution du chiffre d'affaires, de l'emploi, de la masse salariale, ainsi que sur le recours à l'activité partielle, au fonds de solidarité et aux reports de cotisations sociales. Un tel outil permet de simuler l'évolution de la liquidité, de la solvabilité et de l'endettement des entreprises au niveau individuel, en tenant compte de l'hétérogénéité des entreprises. Les résultats montrent que si la situation financière des entreprises s'est dégradée en 2020 par rapport à une année sans crise, les politiques publiques – en premier lieu l'activité partielle et, pour les petites entreprises, le fonds de solidarité - ont fortement limité le nombre d'entreprises illiquides ou insolvables. L'impact de la crise est en outre très différencié selon les secteurs et l'insolvabilité touche des entreprises plus productives qu'habituellement. L'augmentation de l'endettement des entreprises en 2020 risque de peser sur l'investissement en phase de reprise de l'activité : selon notre modélisation dynamique de l'investissement des entreprises sous contraintes financières, le surcroît d'endettement des entreprises pourrait conduire à un moindre investissement d'environ 2 % en phase de reprise. Ce chiffre ne prend pas en compte l'impact des mesures de relance, comme la baisse des impôts de production ou le dispositif de prêts participatifs. Une modélisation similaire sur la R&D suggère que celle-ci est plus résiliente à la dégradation de la situation financière des entreprises.

Mots-clés : Covid-19, entreprises, insolvabilité, illiquidité, endettement, investissement, R&D

JEL: G33, D24, G31, O31, G32, D22

Introduction[1] [2]

In April 2020, the French Treasury started developing a microsimulation tool to model the impact of the Covid-19 crisis on the balance sheet and income statement of French firms.[3] This tool has been improved continuously since then and this paper presents its latest update. Analysis and simulation from the model were presented to the Committee for the Monitoring and Evaluation of Support Measures for Companies Confronted with the Covid-19 Epidemic chaired by Benoit Coeuré at different stages.[4] The microsimulations have been used in order to measure the evolution of firms' financial health across sectors, size and productivity levels, and to evaluate the impact of public support measures ("short-time work" scheme, SMEs "solidarity fund", tax deferral and relief[5]) during the crisis.

During the lockdowns, firms experienced both a supply *and* a demand shock: the production capacity of firms was reduced, due to the disruption of supply chains and mobility restrictions for workers; at the same time, demand addressed to firms took a hit, as households spending was curtailed by the lockdowns and the uncertainty about future income. The shock has weakened firms' balance sheets and significantly increased their debt. This debt overhang can undermine future economic growth, in three ways: 1) it diminishes the firm resilience to subsequent shocks, 2) it increases the risk of business failures and 3) it can curb investment and employment during the recovery, because over-indebted firms will be tempted to deleverage before investing or hiring. Generous public support may alleviate these risks. If not targeted, though, they may also end up helping low-productivity firms to survive at the expense of the extensive margin of productivity growth.

The aggregated impact of the crisis may be followed through indicators such as the evolution of firms' debt or the number of bankruptcies. However, such indicators only provide a partial picture of the situation of French firms. The crisis had a heterogeneous impact on firms, depending on their sector and financial characteristics. The resilience of the firm to a given shock depends to a major extent on its pre-crisis level of cash and equity. But the shock itself was also very different across firms, depending not only on their type of activity, but also their localisation[6] or their degree of digitalisation.[7] A micro-level tool is thus necessary to fully grasp the heterogeneity of the impact of the crisis, and to assess firm liquidity and solvency (which is not yet observed in the data).

Several articles have already used firms' individual data in order to simulate the impact of the crisis.[8] Demmou *et al*. (2020a) from the OECD use Orbis data in order to simulate the impact of the crisis on firms' liquidity in European countries, using an accounting model of the evolution of cash flow under Covid-19. Demmou *et al*. (2020b) extend this analysis to insolvency. Focusing on SMEs, Gourinchas *et al*. (2020) also use Orbis data but rely on a structural modelling of firms' behaviour to gauge the impact of the crisis on firms' liquidity. Guerini *et al*. (2020) focus on French firms, using exhaustive corporate financial statements (Fare), and simulate the impact of the crisis on both liquidity and solvency. Cros *et al*. (2020) use French bankruptcy data at the firm level in order to predict the corporate failures in the trade sector. The literature also provides macro forecasts of bankruptcies: Allianz Research, quoted by

[1] We would like to thank all the data providers, without which these simulations would have been way less developed: Insee, DGFiP, Acoss, Dares (see Appendix for the list of all data used in this study). We thank in particular Rémi Monin (Dares) and Aliette Cheptitski (Insee) for their insight on the data used in this work. Also, we would like to thank Agnès Bénassy-Quéré, Hind Benitto, Isabelle Benoteau, Emmanuel Bétry, Antoine Deruennes, Thibault Guyon, Dorian Roucher and Stéphane Sorbe for their invaluable guidance and continued support on this work.

[2] The access to some confidential data, on which this work is based, has been made possible within a secure environment offered by the CASD – Centre d'accès sécurisé aux données (Ref. 10.34724/CASD).

[3] See A. Bénassy-Quéré, "Equity gaps in the French corporate sector after the great lock-down", *Blog French Treasury,* 25 August 2020, for some elements on the previous version of the microsimulation tool.

[4] The Committee for the Monitoring and Evaluation of Support Measures for Companies Confronted with the Covid-19 Epidemic chaired by Benoit Coeuré has been created by Mandate letter issued by the Prime minister on the 21 April 2020, in accordance with the Amending Finance Law of the 23 March 2020. Our results have been presented to the Committee during the session of July 22th, 2020 and March 15th, 2021. In particular, in early development stages, the model incorporated a simulation of the use of public support schemes instead of observed data.

[5] See Box 1 for more details.

[6] Insee, Economic Outline 7 May 2020.

[7] Faquet and Mallardé (2020), "Digitalisation in France's business sector", *Trésor-Economics* n° 271.

[8] We restrict the literature to papers including data on French firms.

the ECB (2020), forecasts bankruptcies for 19 countries. Banerjee *et al*. (2020) also project business bankruptcies using macro forecasts.

Our model is similar to the accounting model used by Demmou *et al*. (2020a) or Guerini *et al*. (2020). It uses the Fare database produced by Insee,[9] as in Guerini *et al*. (2020). In addition, our model makes use of newly available firm-level 2020 data in order to better simulate corporate balance sheets. In particular, we use observed monthly turnover from VAT declarations, quarterly workforce and payroll from social declarations, monthly benefits from the short-time work scheme, SME solidarity fund and social contribution deferrals. Since this data is available at firm-level, we can take into account the full heterogeneity in the impact of the crisis and the use of support schemes.

In the next section, we outline the structure of our microsimulation tool measuring the impact of Covid-19 on French firms, presenting the underlying accounting model and the data it uses (section 2).

In section 2, we present the main results of the microsimulation tool in terms of illiquidity, insolvency and indebtedness, compare them with those of existing models and describe their dynamics throughout the year. We also evaluate the effect of public support measures in reducing the impact of the crisis and analyse how this impact varies depending on firms' characteristics, such as their sector or their size. We analyse how firms which become insolvent because of the crisis compare in terms of productivity with firms which are vulnerable in normal times.

Finally, in section 3, we use our microsimulation tool to gauge the impact of financial constraints on investment and R&D. Investment is mainly driven by expected demand, but can be hampered by financial constraints. Indeed, the literature finds that access to funding can be restricted for firms with high debt and low profits. We therefore estimate a dynamic model of investment and R&D under financial constraints and apply our microsimulation tool to evaluate the impact of the crisis through the channel of debt overhang.

[9] National Institute of Statistics and Economic Studies.

1. Structure of the microsimulation tool

1.1 The model

The model simulates the income statement of firms over time. In the opening period, firms have a certain amount of cash. Then, at each given period (each month in our model), they incur revenue gains or losses. To reduce the losses, they can adjust their operating expenses: variable expenses, like purchases of intermediate goods and services, can be reduced but fixed expenses, such as rent or wages, have to be paid. At the same time, firms benefit from public support measures: for example, “short-time work” enables firms to shift wages from fixed to variable expenses. Finally, in each period, firms use their cash to cover the losses. When the stock of cash reaches zero (a point at which firms are deemed to be illiquid due to the crisis), it is assumed that firms borrow to cover their expenses. If their debt exceeds their assets, firms are deemed insolvent.

1.1.1 Cash flow modelling

During each period *t*, firm *i* generates a cash flow CF_{it} corresponding to its net operating income, which is the difference between revenue R_{it} and operating expenses (or costs) C_{it}:

$$CF_{it} = R_{it} - C_{it} \quad (1)$$

In the following, the pre-crisis level of each variable is denoted with a 0 subscript. Denoting by $s_{it} \leq 1$ the shock to the revenue compared to pre-crisis level (e.g. $s_{it} = 0.6$ if revenue is down by 60%), we have:

$$R_{it} = (1 - s_{it})R_{i0} \quad (2)$$

There are different kinds of operating expenses, such as costs of intermediate inputs, wages or taxes. We will decompose these costs as:[10]

$$C_{it} = VC_{it} + W_{it} + FC_{it} + T_{it} \quad (3)$$

where VC_{it} denotes variable costs (materials, etc.) of firm *i* at period *t*, W_{it} denotes wages, FC_{it} denotes fixed costs (rents, etc.) and T_{it} are taxes.

Each kind of cost adjusts to the economic shock in a different way. We assume that variable costs closely follow the revenue loss, since they can be reduced quickly. Conversely, fixed costs remain constant. Wages, which are usually considered a fixed cost, may adjust to some extent. Following Guerini *et al*. (2020), all cost variables are defined with the same equation but depend on a different adjustment factor which reflects their reaction to the shock. For any cost variable *c*, its value at time *t* for firm *i* depends on an adjustment factor $0 \leq \gamma_{c,t} \leq 1$ such that:

$$c_{it} = (1 - \gamma_{c,t})c_{i(t-1)} + \gamma_{c,t}(1 - s_{it})c_{i0} \quad (4)$$

Thus, the value of such a cost at time *t* is a weighted average of its value during the previous period and of the value it would have if it were to adjust fully to the shock. When $\gamma_{c,t} = 0$, we have $c_{it} = c_{i0}$ for all *t* and the variable remains constant. Conversely, if $\gamma_{c,t} = 1$, then $c_{it} = (1 - s_{it})c_{i0}$ and the variable adjusts immediately (see Graph 1).

In this setting, the adjustment factor may be time-dependent as firms learn from the crisis. When confronted to a large and unexpected shock, firms may initially be reluctant or unable to adjust, because they are uncertain about the magnitude or the length of the shock and because they were not prepared to react: for some costs, the adjustment factor may be low at the beginning of the crisis, but higher in the next periods because firms are able to anticipate more accurately the magnitude of the shock.

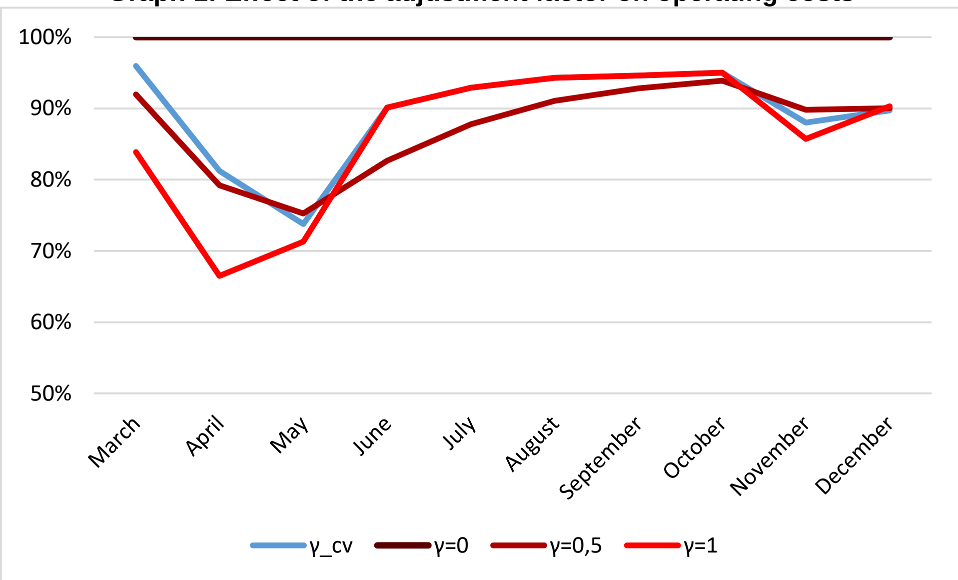
[10] See Appendix for more details on the division between fixed and variable expenses.

In the above setting, the following assumptions are made for each kind of cost:

- Fixed expenses remain constant: $\gamma_{FC,t} = 0$.
- Variable expenses adjust during the crisis: a firm facing a negative revenue shock is able to cut part of its inputs. However, the adjustment of the variable expenses may not be instantaneous. Thus, assumptions are made regarding the value of the adjustment factor at each period (see next paragraph).
- Taxes remain constant:[11] $\gamma_{T,t} = 0$.
- Wages adjust following observed payrolls: $W_{it} = (1 - p_{it})W_{i0}$, where p_{it} is the payroll shock observed in our data.

We assume that the adjustment factor of variable costs $\gamma_{VC,t}$ increases over time, since firms get a better insight on economic perspectives, but that it increases more slowly when the shock is larger, under the hypothesis that larger shocks are more difficult to anticipate. Thus, firms adjust quite slowly in March 2020, since the shock is massive and unexpected. Afterwards, they adjust faster and faster as time passes and as the shock decreases, until the new lockdown of November acts as an exogenous shock not totally expected by firms (but more expected than in March). Our preferred calibration is, for each month from March to December 2020, $\gamma_{VC,t} = \{0.25, 0.5, 0.75, 1, 1, 1, 1, 1, 0.75, 0.75\}$. The choice of the calibration is admittedly arbitrary and results are sensitive to this choice, but our calibration looks realistic and is close to similar works (see Appendix for sensitivity analysis).

Graph 1: Effect of the adjustment factor on operating costs



Note: Theses curves represent the monthly value of variable costs, as a percentage of their pre-crisis level, depending on the adjustment factor. When γ=0, costs are fixed, and when γ=1, costs are variable and adjust proportionally to the activity shock. With the calibration chosen in our microsimulation (blue curve), these costs fall down to 74% of their initial level in May.

[11] Taxes are mostly paid the following year (even if there are advance payments). For the sake of simplicity, they are assumed not to be immediately influenced by the crisis.

1.1.2 Public support

Four public support schemes (Box 1) are incorporated in the model:[12]

- the short-time work scheme is simulated through the payroll shock: since we have actual data on firms' payroll, we can directly track the impact of the scheme on firms' payroll throughout the year;
- the SME solidarity fund is modelled as a cash subsidy FS_{it} for eligible companies which will increase the net cash flow;
- tax and social contributions relief TR_{it} and deferrals TD_{it} are also treated as monthly cash subsidies for eligible firms, but deferrals increase firms' debt, as they are to be paid later.

With public support, the cash flow equation becomes $CF_{it} = R_{it} - C_{it} + FS_{it} + TD_{it} + TR_{it} \quad (5)$.

For the sake of comparison, we alternatively simulate firms' income statement with no public support, in which case the amount received through the solidarity fund, tax deferral and tax relief scheme are nil. For the short-time work scheme, we make use of firm-level observed data on the scheme to impute the corresponding payroll to the firms. Hence, we assume that, had the short-time work not been in place, the furloughed workforce would have been paid by the firms rather than laid-off (yet, our simulation takes into account observed lay-offs during 2020[13]).

Box 1: Public support during the crisis in France

The **short-time work scheme** seeks to prevent lay-offs by compensating firms for the wages of workers who cannot work. The scheme was strongly reinforced at the beginning of the crisis in order to help companies cope with their costs.[14] At the peak of April 2020, over 8 million workers were benefitting from this scheme. While the generosity of this scheme was fully warranted during the lockdown phase (full funding of the worker benefit – 84% of its net wage with a floor at minimum wage), the scheme was recalibrated and tightened for the recovery phase to balance the financial support with the need to provide an incentive to resume activity. According to Ministry of Employment, Labour and Social Cohesion's estimates, almost 2.4 billion hours were financed from March to November 2020, for a public cost of more than €25bn.

The **SME solidarity fund ("*Fonds de solidarité*")** is a direct subsidy scheme for SMEs particularly affected by the crisis.[15] As of spring 2020, the fund was two-pronged:

- The first and most important part of the fund targeted small firms (less than 10 employees) with sales lower than €1M and taxable profits lower than €60k. Additional conditions were: 1) having been subject to a mandatory administrative closure due to sanitary constraints,[16] or 2) having suffered a revenue loss of at least 50%. This first part of the fund compensates for the revenue loss, capped at €1.5k;

- The second part of the fund provided more funding under the following conditions: 1) having at least one employee, 2) having available assets lower than very short-term debt (30 days), and 3) having been denied a loan by a bank. This second part provides subsidies that range from €2k to €5k, depending on the revenue.

[12] Here, guaranteed loans are not distinguished from regular loans. We disregard precautionary borrowings since their counterpart is increased cash.
[13] In this way, with the short-time work scheme, p_{it} measures both the short-time work shock and the lay-off shock. In the counterfactual situation without any short-time work scheme, p_{it} corresponds only to a lay-off shock. Simulating the employment behaviour of the firms in the counterfactual without short-time work is a complicated task that goes beyond the scope of present simulation.
[14] Decree 2020-325 of March the 25th.
[15] Ordinance 2020-317 of March the 25th, 2020-371 of March the 30th and 2020-552 of May the 12th.
[16] The corresponding activities were listed by a decree and available on the internet.

The fund underwent several evolutions during the year with changes to the eligibility criteria, the amount of the subsidy and the computation formula. The main evolution happened during the second lockdown (November-December). As of December 2020, the following changes were introduced:

- The removal of criteria on revenue and taxable profits;
- The removal of the employee threshold for firms highly impacted by the crisis (regarding a list "S1" of activities set by a decree);
- If the firm is subject to a mandatory administrative closure or is highly impacted by the crisis (list "S1") with an at least 50% shock on revenues, the subsidy is equal to its revenue loss, capped at €10k, or is equal to 20% of the 2019 turnover, capped at €200k;
- If the firm performs an activity depending on a sector highly impacted by the crisis (list "S1bis" set by a decree), has less than 50 employees and suffers at least 50% shock on revenues, the subsidy is equal to 80% of its revenue loss (beyond €1.5k) capped at €10k or is equal to 15 to 20% of the 2019 turnover (for a loss respectively greater than 50 and 70%), capped at €200k;
- For the other firms with less than 50 employees and at least a 50% shock on revenues, the subsidy is equal to its revenue loss, capped at €1.5k.

In 2020, about €11.5bn have been granted through the fund.

Tax and social contribution deferrals and reliefs: payroll taxes and more precisely employer's social contributions were the largest part of those deferrals (corporate tax deferrals only represented €3bn). This paper only simulates the impact of payroll tax deferral. At the end of 2020, payroll tax deferrals represented €49bn (however, a significant part of these deferrals was paid by the end of the year). A tax relief for payroll taxes, for SMEs only, has been provided,[17] under conditions of 1) belonging to an industry particularly affected by the crisis (accommodation and food services, tourism, culture) and 2) incurring at least a 50% revenue shock.

1.1.3 Illiquidity, insolvency, and debt

The evolution of firms' cash balance is simulated in the following way. In each period, the (positive or negative) cash flow is added to the cash balance. When the cash balance reaches 0, the firm is said to be illiquid. In general, when a firm becomes illiquid, it has to liquidate some assets, raise equity or borrow to finance its operations. In our simulation, we assume that in each period, illiquid firms borrow to avoid having a negative cash balance. Borrowing deteriorates the balance sheet of the company and can eventually trigger insolvency, when firm's debt becomes larger than its assets.

We denote by CB_{it} firm *i*'s cash balance at the end of period *t*, $\mathbf{1}(.)$ a dummy function, and x^+ (x^-) the positive (resp. negative) part of any integer x (i.e. $x^+ = \max(x, 0)$ and $x^- = \max(-x, 0)$).

In each period, $CB_{it} = \left(CB_{i(t-1)} + CF_{it}\right)^+$, which means that, as long as it stays positive, the cash balance at the end of period *t* is equal to the previous cash balance plus the cash flow of period *t*. When it becomes negative, the cash balance is brought back to zero by borrowing. We define the following variables:

$$Illiquidity_{it} = \mathbf{1}\left(CB_{i(t-1)} + CF_{it} < 0\right) \qquad (6a)$$

$$Debt_{it} = Debt_{i(t-1)} + \left(CB_{i(t-1)} + CF_{it}\right)^- \qquad (6b)$$

$$Assets_{it} = Assets_{i0} + CB_{it} - CB_{i0} \qquad (6c)$$

$$Insolvency_{it} = \mathbf{1}(Assets_{it} < Debt_{it}) \qquad (6d)$$

[17] Article 18 from the Third Supplementary Budget Act of 2020.

Thus, the negative part of the cash balance is added at each period to the debt of the firm, and the variation of its assets is equal to the variation of its cash balance.

One can note that all firms stay in the simulation until its end, even if they get illiquid or insolvent. Illiquidity and insolvency provide information on the financial health of firms but do not necessarily involve business failure. Illiquidity means that the firm does not have enough cash to cover its immediately required payments; in turn, insolvency means that it has more debt than assets. An illiquid firm can survive by liquidating assets, borrowing or raising equity, and an insolvent firm can survive as long as it does not get illiquid.

In theory, the closest proxy to business failure should be insolvent firms becoming illiquid. However, this remains a very imperfect proxy in practice, as business failures (and their timing) depend on qualitative information that stakeholders use to assess a firm's future. In particular, our data is not precise enough to identify those assets that may be liquidated easily, and whether debts are short or long term. Also, for many very small firms, the initial cash balance is very low and thus they might end up illiquid even with very small shocks. Furthermore, the activity of courts were reduced during the first lockdown and regulatory changes were made that temporarily modified the dates for characterising and declaring a "suspension of payments" for firms unable to meet their financial obligations. Indeed, like in other advanced economies, the number of business failures decreased in France during the 2020 crisis, compared to pre-crisis.[18] For all these reasons, we will consider illiquidity and insolvency as indicators of firms' vulnerability rather than as proxies for business failures.

1.1.4 Limitations

There are several limitations to our microsimulation, some related to data limitations and some to the model.

First of all, some expenses not modelled here can impact the cash flows: for instance, our model considers financial expenses and financial income as constant, which is a simplifying assumption, especially in a period of financial instability. Investment is also disregarded since it is difficult to simulate such behaviour in the middle of a crisis. Moreover, we do not model both current assets and liabilities: therefore we make the assumption that assets do not lose value and that debt is rolled over. Also, our data does not allow sufficient granularity, for example on the precise type of expenses, or the duration of liabilities to distinguish short and long term debts. In particular, we do not model the working capital requirement:[19] there is for instance no specific hypothesis concerning accounts receivable or payable.

On the modelling side, this microsimulation tool only provides a partial equilibrium framework in which there is no interaction between firms, while inter-firms credit for instance may have been strongly affected when activity fell. Above all, the results rely on hypotheses about firms' behaviour – notably about the cost adjustment and the cost structure of the firm – and even with the introduction of actual data, results still partly depend on a number of modelling assumptions.

For these reasons, the microsimulation tool presented in this paper is better suited to assessing the short-term impact of large shocks (such as the Covid-19 crisis) rather than the long-term consequences of smaller shocks.

1.2 Data and modelling of shocks

1.2.1 Data sources

Our microsimulations use French firms' financial statements available in the Fare database produced by Insee. Fare 2018 is an exhaustive dataset of French firms' financial statements, built from tax declarations for the year 2018. It comprises both balance sheets and income statements of more than 4 million firms. The dataset gathers both general information (size, industry, etc.) and accounting information (cash, revenues, expenses, assets, liabilities, etc.) about French firms. We use the latest

[18] See Banque de France data.

[19] Difference between operating current assets and operating current liabilities.

available version of Fare to date, and thus we make the underlying assumption that the financial situation of firms in 2020 (in absence of Covid shock) was similar to their situation in 2018.

We exclude from the analysis some sectors with strong specificities: agriculture (AZ), finance and insurance (KZ) and public administrations (OQ). Moreover, we exclude firms for which data may be incomplete, for example small firms whose tax regime is the individual income tax rather than the corporate income tax. At the end of the day, our microsimulation is based on 1 821 189 firms which represent 82% of the value-added and 84% of employees in the French economy.

We assume that firms' financials statements are representative of their financial situation at the beginning of the crisis in March 2020. The simulation starts in March 2020 and ends in December 2020. Each period lasts one month: $t \in \{M_i, i = 3, \ldots, 12\}$.

The simulation also incorporates observed data (see Appendix for more details) on:

- turnover, from the VAT database, from March to June;
- workforce and payroll, from the Epure database, from March to September (this data is quarterly);
- short-time work scheme, from the Sinapse database, from March to September;
- SME solidarity fund, from Chorus, from March to November;
- social contributions deferral, from the Rep-Covid database, from March to October.

We also make use of losses of activity estimated by the Insee in its *Economic Outlooks* (observed for the three first quarters and predicted for the last one), which they provided to us in a monthly-version aggregated at the sectoral level (NACE 17).

All this data is merged at the firm level (based on their Siren identifier). We first describe how we compute shocks from the observed data and then how we deal with missing data, including for the end of 2020.

1.2.2 Computing shocks at firm level

Shocks on revenue and payroll are computed as relative variations to pre-crisis level. These relative deviations are then applied to the end-2018 financial statements. This methodology allows us to control for changes occurred at firm level between 2018 and 2019, for example for fast-growing firms.

We now describe in detail the computation we made for each of our model variables:

- To estimate the revenue loss s_{it}, we divide monthly revenue from March 2020 to June 2020 by the average monthly revenue over the March 2019 to February 2020 period. We only used VAT data for firms declaring their revenue for each month of the period going from March 2019 to June 2020, to restrict this input to firms for which pre-crisis data is robust.
- In order to estimate the payroll shock p_{it}, we divide the total amount of payroll during each of the 2020 quarters by the average payroll over the four quarters of 2019. We again restricted our sample to firms for which we have data for each of the 2019 and 2020 quarters. Since our model is on a monthly basis, we transform our quarterly payroll shocks into monthly payroll shocks. To do so, we rely on sector-level activity trajectories provided by Insee. For each quarter, we compare the payroll shock p_{iq} to the Insee revenue shock i_{iq} of the firm over the quarter, and then we normalise with the monthly Insee shock i_{it}: $p_{it} = (p_{iq}/i_{iq}) \times i_{it}$.[20] Thus, the monthly payroll shock will have the level of the quarterly payroll shock and the trajectory of the monthly revenue shock.
- For payroll tax deferrals, we divide their amount by the total social contributions of the firm, for each month, which then allows us to apply a tax deferral shock to the firm's social contributions that we simulate into our model. One may note that we compute the shock on the remaining tax

[20] We also bound the shock between −1 and 1.

debt in October from the dataset. Therefore, deferrals which were already cleared by October are not taken into account: thus we underestimate the effect of the measure on liquidity. Let ESR_{i0} be the employer's social contribution.[21] During the crisis, this amount is reduced by the payroll shock p_{it} (no social contributions are paid when employees benefit from the short-time work scheme) and by the tax deferral shock td_{it}, with $TD_{it} = (1 - td_{it})(1 - p_{it})ESR_{i0}$.

- We do not have actual data on tax reliefs, hence we simulate them based on eligibility criteria (Box 1), and then reduce to 0 the social contributions of eligible firms. The calculation is similar to payroll tax deferral: part of the social contribution is already reduced by the short-time work scheme. Therefore, $\mathbf{1}_t^e$ being the predicted eligibility for tax relief at period t, $TR_{it} = \mathbf{1}_t^e(1 - p_{it})ESR_{i0}$. If firms benefit from both deferrals and reliefs,[22] we do not add them and set $TD_{it} = \max(TD_{it} - TR_{it}, 0)$. Again, tax relief eligibility has changed over time but one important issue for the first lockdown is that it applied for months from February (without any shock) to May. Thus, we compute the unshocked tax relief for February as a liquidity subsidy occurring in March (firms in March benefit from a "double-hit" relief: the subsidy from both February and March).
- Finally, the monthly amounts granted though the solidarity fund are used directly in our model, as subsidies. For December, we simulate the eligibility at the individual level and then compute a take-up rate so that the aggregated monthly amount corresponds to our last estimation.

1.2.3 Filling for missing data

Two problems remain to be solved concerning the data: how to deal with missing values and how to extend the dataset until the end of the year.

Concerning the first problem, not all firms are present in all databases. We assume that public support databases are exhaustive in the sense that if a firm is not in the database, it did not benefit from public support.[23] For the VAT or Epure databases, the reason why a firm is not in the database might be more difficult to identify. One reason might be that those firms do not exist anymore: since our model is based on 2018 data, some firms might have ceased activity. Alternatively, these datasets are not exhaustive: Epure only contains data about firms which declare wage bills and small firms are not compelled to report their value added on a monthly-basis. For firms for which we do not have data, we use the sector-level shock (at the NACE 17 level) applied to individual data. Out of the 1 821 189 observations in our dataset (which represent 82% of the value-added and 84% of employees in France), 795 701 have an individual revenue shock and 805 242 have an individual payroll shock (which represent respectively 61% and 74% of the total value-added, and 62% and 78% of jobs).

The second problem is that the data is not available up to the end of the year 2020 at the time of writing. Thus, we have to make assumptions in order to extend the analysis to the whole year. For each variable we want to extend (except the solidarity fund), we use the trajectory of the sector-level Insee monthly shocks:

- For the solidarity fund, we compute eligibility criteria at firm level in December and the maximum amount each firm could have obtained: we then assume that all firms get a fixed proportion of this amount and determine this proportion so that the total amount granted by the fund in December corresponds to the latest estimations made.
- For any other shock variable *x* (revenue, payroll, short-time work compensations and tax deferrals) for which we have data from March to month *m*, we need to extend the trajectory to the end of the year. Since the only data we have until the end of the year is the sector-level Insee shock, we use it as baseline. When plugging the Insee trend on the variable *x*, we make

[21] In practice, tax deferral concern both employer and employee social contributions but the Fare dataset only identifies employer contributions.
[22] In practice, reliefs have been announced after that some firms already benefitted from deferrals but we make the assumption that tax relief occurs at the employment period).
[23] For instance, if a firm is not in the SMEs solidarity fund database, we assume it did not get any subsidy from the fund.

use of all data points we have for this variable *x* to make the extension more robust, and we use them to determine a correction factor we apply to the sector-level shock to simulate *x*. More formally, if we have individual data for months $M_3, \dots, M_m$ (m being equal to 6 in the case of revenue, 9 in the case of payroll and 10 in the case of tax deferral) and sector-level Insee shocks i_j for every month from March to December, we compute the correction factor $c = \frac{x_3 + \cdots x_m}{i_3 + \cdots i_m}$ at the firm level, and then compute the extended values $x_j = c \times i_j$, for all $j > m$.

Finally, we bound all our shocks between –100% and +100%, because firm-level data might contain outliers. Since the level of activity of a firm may vary a lot, individual shocks may be very high: for example, a small firm may double its turnover in one year. However, these large variations may not be representative, since they may result from firm restructuring. Also, since our initial data is from 2018, and variations are measured compared to 2019, some inconsistencies can appear. For example, if the firm had a very low 2019 turnover, applying the 2020/2019 variation to the 2018 turnover will overestimate it. Thus, we assume that no firms can increase their revenue, payroll, etc. by more than 100% (see Appendix for a sensibility analysis to this hypothesis).

1.2.4 Descriptive statistics on the main parameters of the model

Table 1 displays the profile of the main shocks introduced in the model.

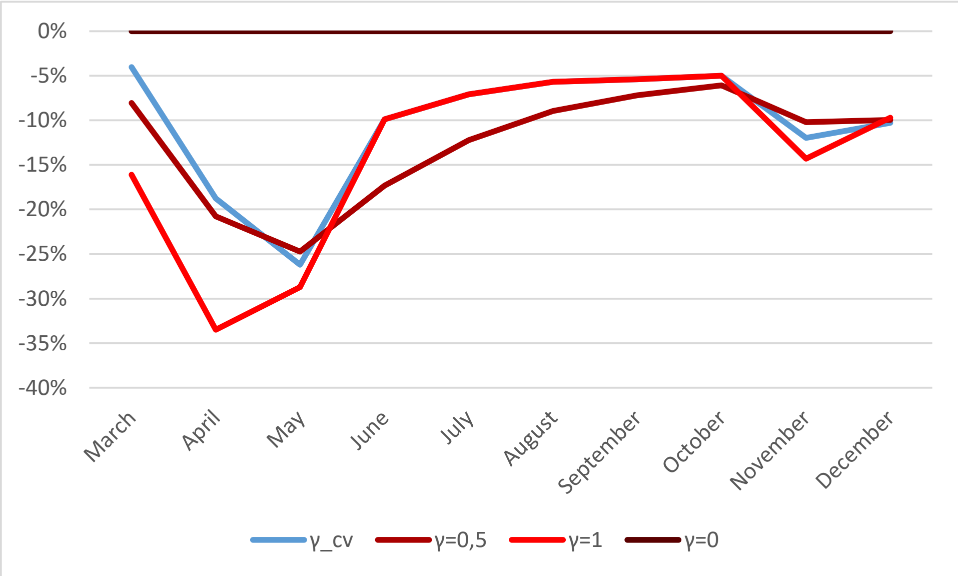
Table 1. Aggregated inputs in the simulation, year 2020
(aggregate shocks in % relative to pre-crisis level, public support in €bn)

	March	April	May	June	July	August	Sep.	Oct.	Nov.	Dec.	Total
Revenue shock	−16.1%	−33.5%	−28.7%	−9.9%	−7.1%	−5.7%	−5.4%	−5.0%	−14.3%	−9.7%	−13.6%
Payroll shock	−12.7%	−26.8%	−17.6%	−8.5%	−10.4%	−6.8%	−5.9%	−4.6%	−13.0%	−8.8%	−11.5%
Solidarity fund (Bn€)	0.8	1.0	0.6	0.2	0.0	0.1	0.1	0.7	2.3	2.2	7.9
Social contribution deferrals (Bn€)	0.8	1.2	1.6	1.3	0.7	0.7	0.7	1.0	0.9	0.6	9.5
Social contribution reliefs (Bn€)	2.1	0.5	0.5	0	0	0	0	0	0.8	0.9	4.8

Note: In our simulation, the weighted average of the revenue shock was −16.1% in March. The total amounts received through the public support schemes do not correspond to the official data on the total amounts disbursed in these schemes, since our model does not include all firms.

Graph 2 compares the shocks on revenue, payroll and variable costs. The shocks differ the most between March and May, the revenue shock being larger and the variable costs adjusting more slowly. From June until the end of the year, the three shocks are broadly similar on aggregate.

Graph 2: Aggregated revenue, payroll and variable costs shocks in the simulation (% of pre-crisis level)



Note: Theses curves represent the monthly trajectory of the revenue shock, the payroll shock and the variable costs shock, compared to a pre-crisis level. According to our simulation, revenue fell down to 67% of its pre-crisis level in April.

2. Simulation results

2.1 Measures of the impact of the crisis

In this section, we present the results of our microsimulation regarding the illiquidity, insolvency, and debt of French companies after the 2020 Covid crisis. Our simulation allows us to identify illiquid or insolvent firms at the end of the year. To assess the effect of the crisis, these numbers are compared to the number of illiquid or insolvent firms predicted by the model in the absence of economic shocks. Some firms were already illiquid or insolvent at the beginning of the simulation (March 2020).[24] Here, we focus on firms which are *newly* illiquid or insolvent, i.e. firms which become illiquid or insolvent during the year.

Table 2. Illiquidity, insolvency, and debt in 2020 for different scenarios

	Number of firms becoming illiquid (% of total)	Number of firms becoming insolvent (% of total)	Number of firms becoming both insolvent and illiquid (% of total)	New debt (in €bn) compared to March 2020
March-December - **no crisis scenario**	283 995 (15.6%)	66 127 (3.6%)	189 367 (10.4%)	71.7
March-December - **crisis without public support**	656 139 (36.0%)	215 849 (11.9%)	372 727 (20.5%)	167.6
March-December - **crisis with public support**	437 006 (24.0%)	119 379 (6.6%)	239 830 (13.2%)	148.3

Note: In our simulation, 283 995 firms (15.6% of the total number of firms in the simulation) which were not illiquid in March 2020 would have become illiquid in 2020 in the counterfactual scenario (no crisis). With crisis, taking into account the public support, 437 006 firms would have become illiquid at some point in 2020. This number would have been 656 139 without public support. The number of firms that are both insolvent and illiquid is higher than the number of insolvent firms because some firms which were initially insolvent may become illiquid. Additional debt incorporates tax liabilities.

[24] The number of illiquid firms at the beginning of the simulation is negligible (6 006), but the number of insolvent firms is high (315 829). This is why we do not count firms which are initially illiquid or insolvent to measure the impact of the crisis.

One can see (Table 2) that public support has been crucial in alleviating the shock on corporate balance sheets. With public support, the number of firms which would have been in liquidity distress at some point during 2020 increases by 8.4 percentage points (pp) compared to the baseline scenario (no crisis),[25] hence much less than without public support (20.4pp). The impact is similar on insolvency which increases by 3.0pp with public support, while it increases by 8.3pp without it.[26] Unsurprisingly, public support also reduces the amount of additional debt taken on by firms to weather the shock, albeit more weakly: an extra €76.6bn with public support, compared to €95.9bn without. The effect on debt is weaker compared to the one on shares of illiquid or insolvent firms because of a composition effect: if public support has successfully mitigated the impact on small firms and avoided a massive increase in the number of affected firms, it has helped larger firms to a lesser extent, but still, some have generated a large debt.

Comparing these figures to the real increase in firms' debt during the crisis (roughly €190bn from March to December[27]) is difficult for several reasons. First, the scope of the simulation is smaller than the whole economy. Second, we assume that firms do not liquidate their assets nor raise equity, while they may do it. Finally, firms may also have borrowed for precautionary reasons during the crisis, which we do not take into account.

2.2 Comparison with other studies

As mentioned in the introduction, several studies have used microsimulations to estimate the impact of the Covid-19 crisis on the financial health of firms. Most of these studies use their results to analyse the efficiency of public policies. We restrict the comparison to studies focusing on French companies (some studies also include companies from other countries). Comparing the results of these studies is not easy because they differ in terms of modelling assumptions, data sources, public support schemes taken into account, and output variables.

Modelling assumptions. While Gourinchas *et al*. (2020) build a structural modelling of firms' behaviour in order to distinguish three kinds of shocks (supply, demand, and productivity), Demmou *et al*. (2020a, 2020b), Guerini *et al*. (2020) and our study are based on similar accounting models. The calibration varies greatly across authors, though. For instance:

- Due to the earlier dates of the other studies, they do not model the second lockdown contrary to our study;
- The adjustment of firms' variable expenses differs between studies: Demmou *et al*. (2020a, 2020b) use a constant coefficient equal to 0.8, Guerini *et al*. (2020) implement a dynamic adjustment but with a constant coefficient equal to 0.25, while we implement a dynamic adjustment factor varying between 0.25 and 1 during the year;
- In the presence of the short-time work scheme, the adjustment of payroll to the shock may depend on a fixed coefficient of 0.8 (Demmou *et al*. (2020a, 2020b)), of 1 (spontaneous adjustment, Guerini *et al*. (2020)), while it is observed in the data in our paper;

[25] One should remember that the no crisis scenario does not correspond to real numbers but is simulated. Results should be only considered relatively to this scenario and not in terms of level. Furthermore, in the no crisis scenario, since the revenue of firms remain either positive or negative for the whole period, we cannot compute a monthly evolution.
[26] As an aside, our model identifies a number of firms which have been better off during the year, either because they got positively affected by the crisis (for example, firms in the tech sector) or because they benefitted from a public support larger than their needs. For example, if the number of new insolvent firms jump from 66 127 to 94 905, the number of insolvent firms because of the crisis (which would not have been insolvent without crisis) is 47 044 and 18 266 escaped insolvency because of the crisis.
[27] See Banque de France data.

- Fixed expenses as well as taxes can adjust very slowly (Demmou *et al*. (2020a, 2020b)) or not adjust at all (Guerini *et al*. (2020) and our paper);

- The simulation is conducted on a weekly basis (Gourinchas *et al.* (2020)), a 15-days basis (Guerini *et al.* (2020)), or a monthly basis (Demmou *et al.* (2020a, 2020b) and our study).

Data sources. Demmou *et al*. (2020a, 2020b) and Gourinchas *et al*. (2020) use the Orbis database and make international comparisons. Guerini *et al*. (2020) and our paper rely on the same exhaustive database on financial statements of French companies (Fare). The contribution of our paper is to include multiple sources of observed data, as explained in section 1. Each study restricts the final sample according to its research question: Gourinchas *et al*. (2020) focus on SMEs (less than 250 employees), while Demmou *et al*. (2020a, 2020b) exclude firms with less than 3 employees. Our cleaning procedure is close to Guerini *et al*. (2020), except that they also exclude the crafts sector from their analysis.

Public support schemes. All studies take into account short-time work, which is modelled as a switch of the wage bill from fixed to variable expenses, except in Gourinchas *et al*. (2020) which simulate an 8-week full labour subsidy. Demmou *et al*. (2020a) also include debt moratoria and tax relief in their evaluation. Our paper includes short-time work, SMEs solidarity fund, and tax deferral and relief.

Output variables. Two studies focus on liquidity alone (Gourinchas *et al*. (2020) and Demmou *et al*. (2020a)), another on solvency alone (Demmou *et al*. (2020b)) and two studies cover both liquidity and solvency (Guerini *et al*. (2020) and our paper). A direct comparison of the results is however difficult, especially because some studies do not provide information about the illiquidity rate (resp. insolvency rate) in the counterfactual situation without any shock (the no-Covid scenario).

Keeping these limitations in mind, Table 3 compares the main results of the studies. For studies covering multiple countries, we use whenever possible results for France. When these specific results are not available, we use cross-country estimations (see the note of the table for more explanation).

Additionally, we compare our results with those of an earlier version of our model, which made no use of observed data at firm level over the Covid crisis (see Appendix for a full description of this version). In this version of the model, the revenue shocks are monthly sectoral shocks (in NACE 17), based on losses of activity estimated by the Insee in its Economic Outlooks (observed for the three first quarters and forecasted for the last quarter). The payroll shocks are estimated using quarterly sectoral data published by Acoss (NACE 38). The solidarity fund is simulated: eligibility criteria are determined at the individual level and then sectoral take-up rates are computed so that the aggregate amount corresponds to the amount reported. Finally, social contribution exonerations are simulated, as it is the case in the latest version of our model, and deferrals are simulated as a percentage of revenue shocks so that the total amount corresponds to the amount reported.

The earlier, fully simulated, version of our model (*full simu*) finds a lower share of insolvent firms than the latest version (*main simu*). This seems logical, as the fully simulated version uses aggregate shocks, and thus captures less heterogeneity than the model based on observed data. Since vulnerable firms are a “tail-end” of some distributions, it is not surprising that better capturing heterogeneity allows us to identify more vulnerable firms. In the fully simulated version, there are fewer illiquid firms or insolvent firms and less debt (€129bn compared to €148bn with observed data).

Table 3. Comparison of different simulations (% of firms)

Illiquidity				
	(1) No crisis	(2) Crisis – No public support	(3) Crisis – Public support	Δ (3) – (1)
French Treasury (main simu)	15.6%	36.0%	24.0%	8.4pp
French Treasury (full simu)	15.6%	34.4%	21.8%	6.2pp
Demmou *et al.* (2020a)	-	30%	10%	-
Guerini *et al.* (2020)	3.8%	13.8%	10.1%	6.3pp
Gourinchas *et al.* (2020)	9.0%	16.9%	11.3%	2.3pp
Insolvency				
	(1) No crisis	(2) Crisis – No public support	(3) Crisis – Public support	Δ (3) – (1)
French Treasury (main simu)	3.6%	11.9%	6.6%	3.0pp
French Treasury (full simu)	3.6%	9.9%	4.9%	1.3pp
Demmou *et al.* (2020b)	-	-	7%	-
Guerini *et al.* (2020)	1.8%	4.4%	3.2%	1.4pp

Note: According to our main simulation, without crisis 15.6% of firms would become illiquid, compared to 24.0% with crisis and public support. For Gourinchas *et al.* (2020), the number with public support is computed by combining the figure without support and the estimated effect of public policies. For Demmou *et al.* (2020a, 2020b), figures are read on graphics, and not specific to France in the case if insolvency.

2.3 Dynamics of the impact

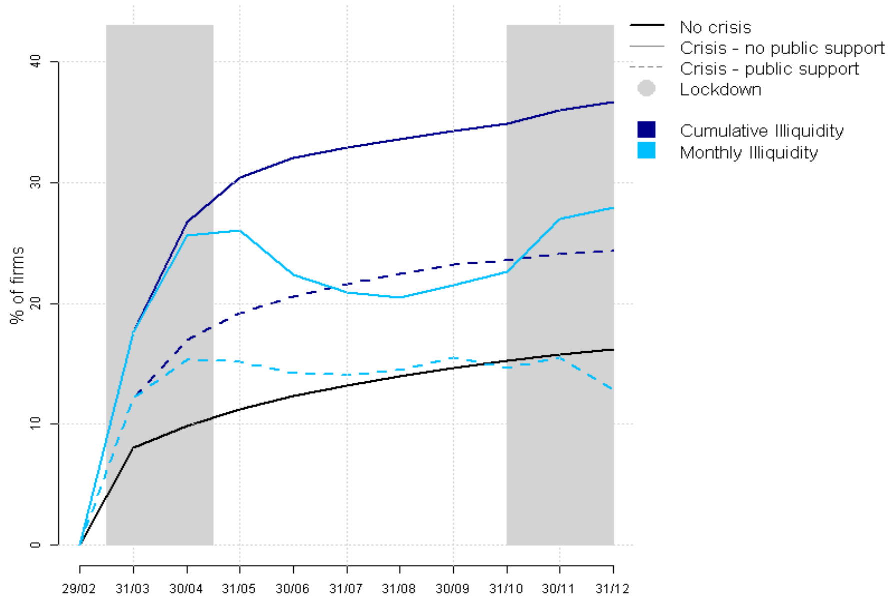
Graphs 3 presents the cumulative share of *newly* illiquid or insolvent firms from March 2020 to December 2020, *ie*. the proportion of firms which have been in liquidity distress (or insolvency) since March, as well as the cumulative extra debt contracted by (newly illiquid) firms over this period. We compare the situations with and without public support. Graphs also show the monthly share of illiquid and insolvent firms in the economy and the debt generated each month.[28]

Graph (3a) shows that most of the increase in the cumulative share of illiquid firms comes from the first lockdown. Public support reduced the increase during the first lockdown, and the increase remains slow afterwards, despite the second lockdown. We can also see that the share of illiquid firms each month decreases in the aftermath of the first lockdown, because firms were able to obtain positive cash flows in order to partially rebuild their cash balance. Without public support, the share of monthly illiquid firms during the second lockdown is as high as during the first lockdown, but the cumulative share does not increase much, showing that it is the same firms that are facing difficulties. With public support, this monthly share becomes even lower than in the no crisis scenario, showing that public measures mitigated the impact on firms' liquidity.

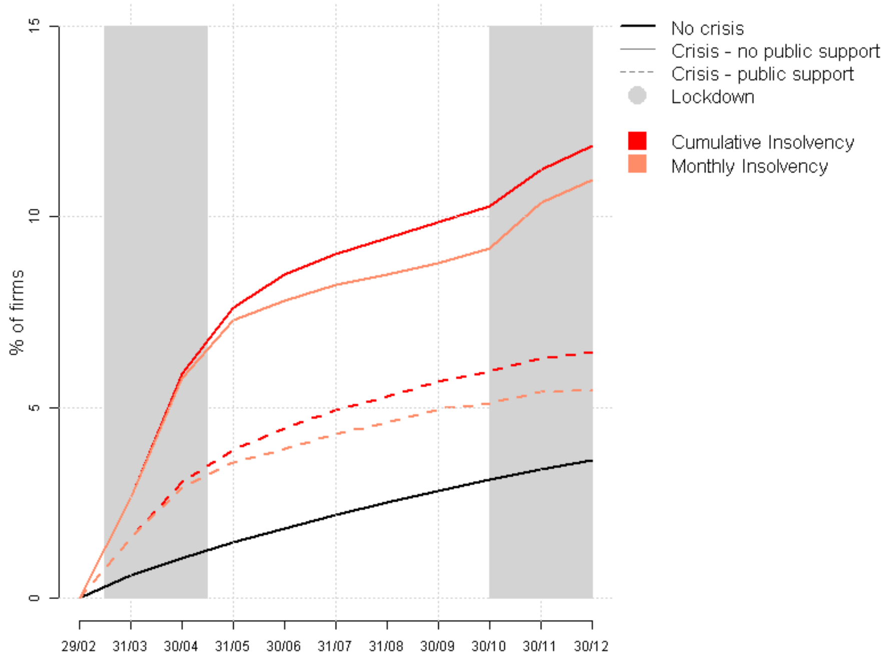
[28] The cumulative debt is equal to the sum of monthly generated debt, but it is not the case for the shares of illiquid or insolvent firms because firms which are illiquid for several months are counted only once.

Graph 3: Evolution of illiquidity, insolvency and debt, year 2020

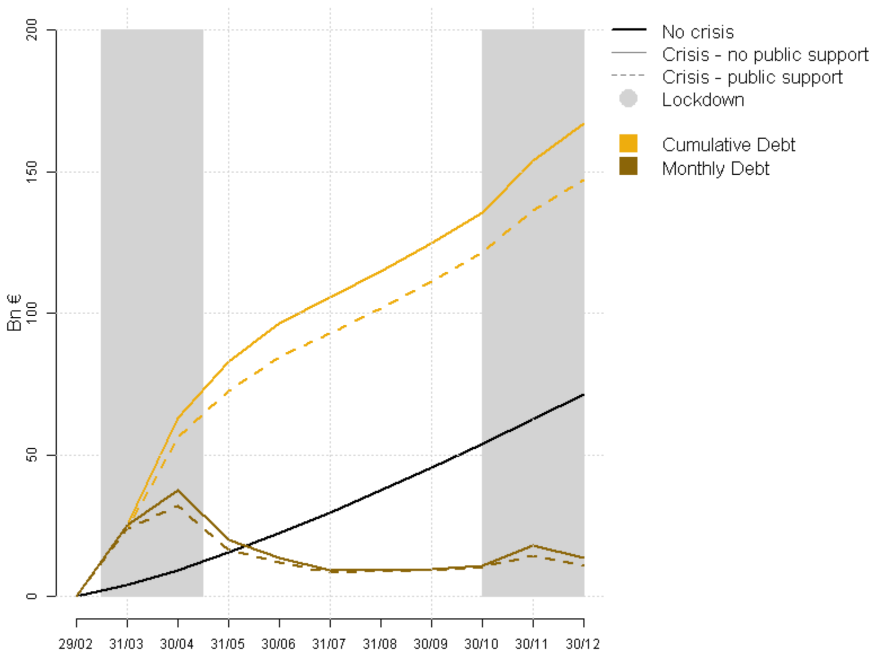
(a) Share of newly illiquid firms (in % of total number of firms)



(b) Share of newly insolvent firms (in % of total number of firms)



(c) Additional debt during the crisis (€bn)



Note: Cumulative and monthly evolution of the share of newly illiquid and newly insolvent firms in the total number of firms, and additional debt generated by the crisis, with (dashed line) or without (full line) public support. "Newly" means that we exclude initially illiquid firms for Graph (a) and (c), and initially insolvent firms for Graph (b). "Cumulative" means that we count all firms that got illiquid or insolvent since March. The simulations stop at the end of the year. Additional debt includes payroll tax deferrals.

Graph (3b) shows the cumulative number of newly insolvent firms over time. An important share of the increase in insolvency occurs during the first lockdown. The number of newly insolvent firms in the scenario with public support reached 2.9% of the total number of firms in May, against 5.8% without public support (and 1.5% without crisis). During the second lockdown, public support further limited the increase of the insolvency rate. Contrary to illiquidity, there is no large difference between the cumulative share and the monthly share of insolvent firms, because firms that get insolvent might stay so even if they get positive cash flow later, while illiquid firms get liquid as soon as they get positive cash flow.

Finally, Graph (3c) shows that the increase of debt is much more pronounced than in a no-crisis scenario, but that the impact of public support is limited. Most of the debt is generated during the first lockdown. One has to note that this additional debt is, by definition, only generated by illiquid firms, and that we do not simulate any reimbursement. Furthermore, it only corresponds to necessary borrowing made because of some liquidity distress after all public support is received, and does not encompass precautionary borrowing. Finally, part of this debt is in fact a debt to the government sector resulting from the payroll tax deferrals.

2.4 The role of public support measures

Government intervention has had a crucial role in mitigating the effect of the crisis. We decompose the effect of public support between (i) short-time work scheme (STW) alone, (ii) STW and SME solidarity fund (SF), and (iii) the combination of STW, SF and social contributions deferral and relief (Graph 4). These results focus on the cumulative share of newly illiquid or insolvent firms from March 2020 to December 2020 (we present similar results on debt and on the number of firms that become both illiquid and insolvent in the Appendix)[29].

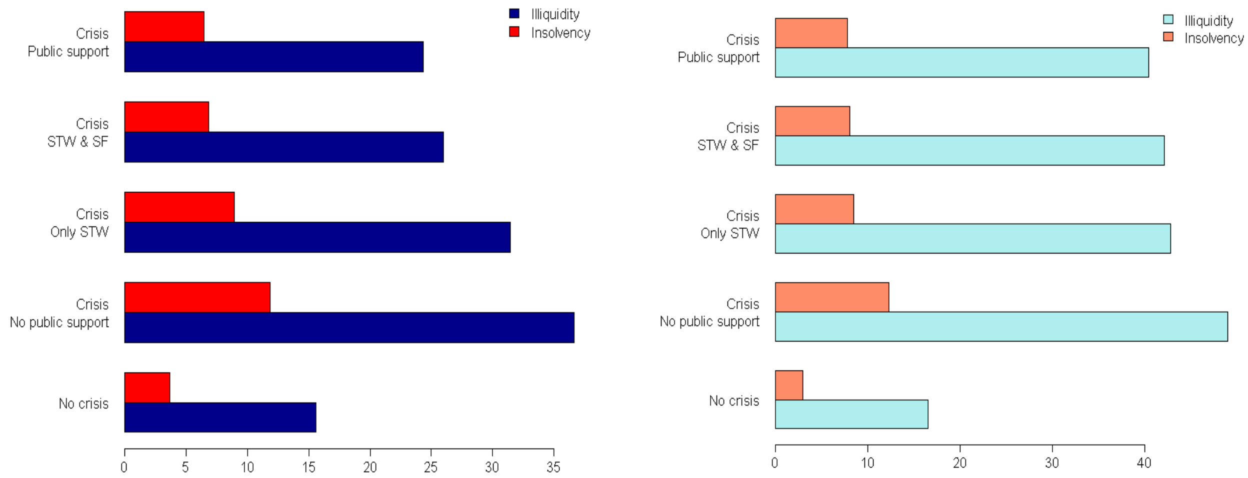
[29] One should note that in this decomposition, public schemes are added in this specific order to estimate their effect: STW, then SF and then social contributions deferrals and reliefs. In particular, another order would provide slightly different estimates. However, we have estimated the impact of these three policies introduced in different orders and got similar results.

Considering results in percentage of the number of firms (Graph 4a), the short-time work scheme alone clearly reduces illiquidity and insolvency in the economy. The insolvency rate (resp. illiquidity rate) is reduced by about 3pp (resp. 5.3pp) after taking into account the short-time work scheme. The SME Solidarity fund has also a marked impact on the financial constraints of firms, with an additional 2.1pp decrease in the incidence of insolvency (resp. 5.5pp for illiquidity). Finally, the combination of social contribution reliefs and deferrals reduces the illiquidity rate by 1.7pp, but has a limited impact on the insolvency rate (0.3pp) since deferrals are neutral for the solvency of firms.

Results are broadly similar when we consider the share of illiquid and insolvent firms in the total number of employees (Graph 4b). However, in this setting the effect of public support is mainly triggered by the short-time work scheme: the effect of support policies such as the Solidarity fund is smaller than in Graph 4a, notably because the Solidarity fund focuses on SMEs. Again, it is worth stressing that neither insolvency nor illiquidity are synonyms of failure. In this way, even if the cumulative share of employees working in insolvent firms is about 7.7% – despite public support – this will not imply that 7.7% of employees will lose their jobs due to firms' financial distress.

Graph 4: Decomposition of the effect of public support measures in 2020

(a) Share of newly insolvent or illiquid firms (% of total number of firms) **(b) Share of newly insolvent or illiquid firms (% of total number of employees)**



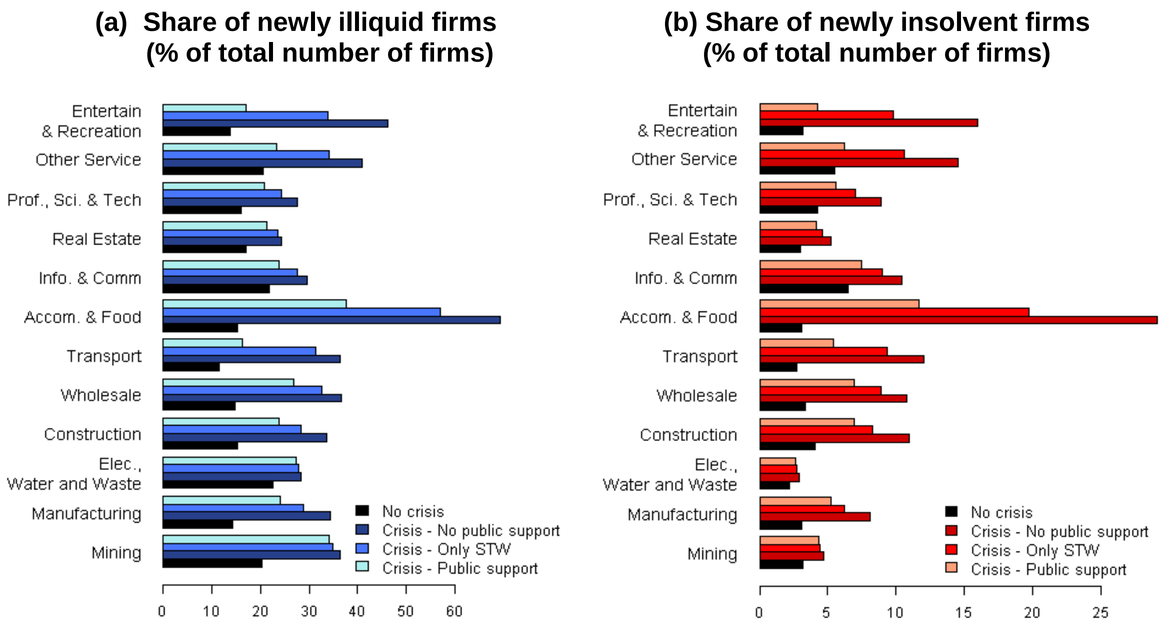
Note: Cumulated number of newly illiquid (resp. insolvent) firms over the total number of firms in graph (a) and the number of employees in newly illiquid (resp. insolvent) firms over the total number of employees in graph (b). Results are computed at the end of the simulation (total over March-December). STW: short-time work scheme, SF: SMEs solidarity fund.

2.5 Heterogeneity of the impact

The aggregate results hide the heterogeneity of the impact of the shock among firms. In this subsection, we explore the impact across industries, firm size and age groups, and depending on firm location.

Graph 5 shows that the cumulated increase in the proportion of newly illiquid firms is very high in the accommodation and food services activities (from 15% without crisis to 38% with crisis and public support) compared to other industries. The share of insolvent firms is multiplied by four in this sector (from 3% to 12%). Again, we see a marked impact of public support: without it, both the illiquidity and the insolvency rate would be way larger for all sectors (for example 29% of insolvency in the accommodation and food services activities without support, compared to 12% with support). The impact of specific public schemes varies across industries, the short-time work scheme accounting for roughly half of the impact in general.

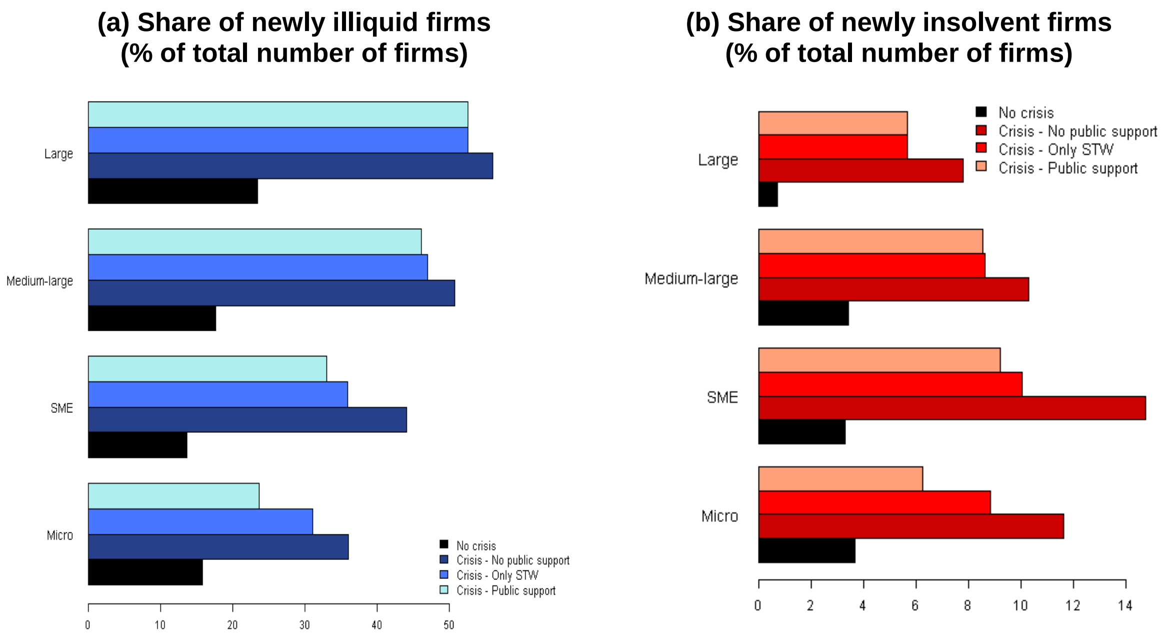
Graph 5: Effect of the crisis by industry, end 2020



Note: Decomposition of the effect of the crisis by industry in terms of newly illiquid (a) and newly insolvent firms (b). "Newly" means that we exclude for the analysis initially illiquid (resp. insolvent) firms. For a given industry, rates are computed as the cumulative number of newly illiquid (resp. insolvent) firms over the total number of firms, during the March-December 2020 period. STW: short-time work scheme.

Graph 6 presents the same results depending on the size of firms. The rise in illiquidity is smaller for microenterprises than for larger firms: while it only increases by 8pp for this category, it increases by at least 19pp in all others. Similarly, while insolvency only increases from 3.7% to 6.2% for microenterprises, it more than doubles for larger firms. Public support is especially effective in reducing insolvency among microenterprises (the increase being limited to 2.5pp instead of 8pp) and this effect comes mainly from the Solidarity fund, while the relief is mainly due to short-time work for larger firms.

Graph 6: Effect of the crisis by size, end 2020

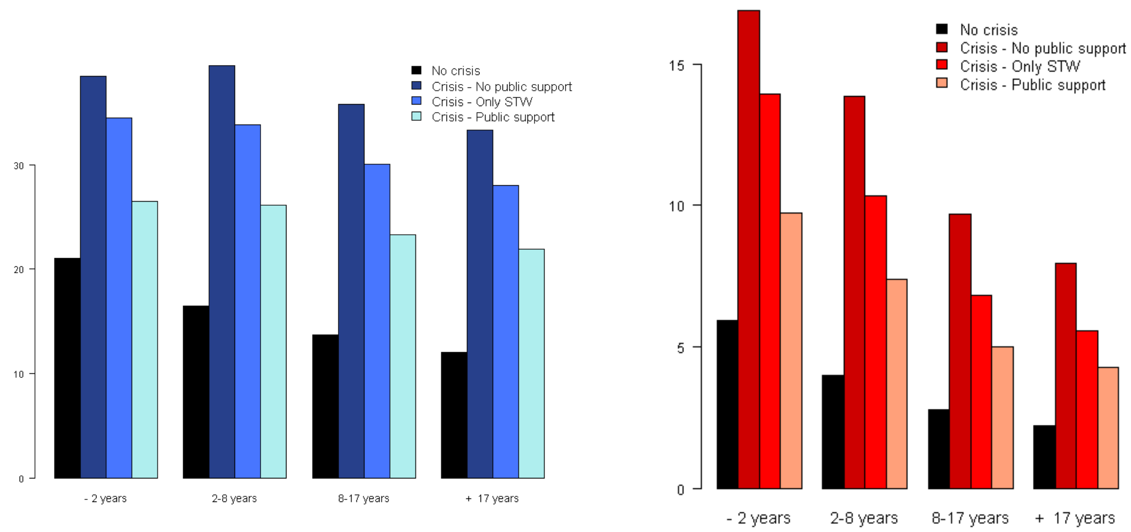


Note: Decomposition of the effect of the crisis by size in terms of newly illiquid (a) and newly insolvent firms (b). "Newly" means that we exclude for the analysis initially illiquid (resp. insolvent) firms. For a given size, rates are computed as the cumulative number of newly illiquid (resp. insolvent) firms over the total number of firms, during the March-December 2020 period. STW: short-time work scheme.

Graph 7 looks at illiquidity and insolvency depending on the age of firms. The literature highlights that crises leave scars on young firms, creating “lost generations”, as explained by Calvino *et al*. (2020). It is therefore important to identify if the crisis has more of an impact on young firms. We find that, although young firms are more likely to be illiquid or insolvent before the crisis than older firms, the increase compared to a “normal” year is relatively larger for older firms.

Graph 7: Effect of the crisis by age, end 2020

(a) Share of newly illiquid firms (% of total number of firms) | **(b) Share of newly insolvent firms (% of total number of firms)**



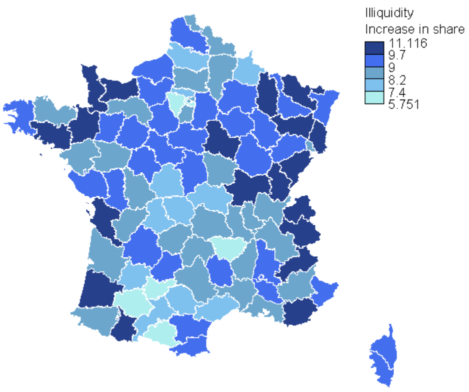
Note: Decomposition of the effect of the crisis by age in terms of newly illiquid (a) and newly insolvent firms (b). “Newly” means that we exclude for the analysis initially illiquid (resp. insolvent) firms. For a given age, rates are computed as the cumulative number of newly illiquid (resp. insolvent) firms over the total number of firms, during the March-December 2020 period. STW: short-time work scheme.

Finally, Graph 8 considers the geographical impact of the crisis. We map the difference between the share of newly illiquid (resp. insolvent) firms with and without the crisis, taking into account public support in the first case. Some departments in North Eastern France, which was particularly hit by the pandemic and where lockdowns and curfews have lasted longer, appear to suffer more from both illiquidity and insolvency. Illiquidity and insolvency are also high in some departments on the western coast of France and in the Alps − possibly due to the effect of the crisis on tourism. Those results remain mainly robust after industry-adjustment,[30] which also shows the especially strong impact of the sanitary crisis in Île-de-France.

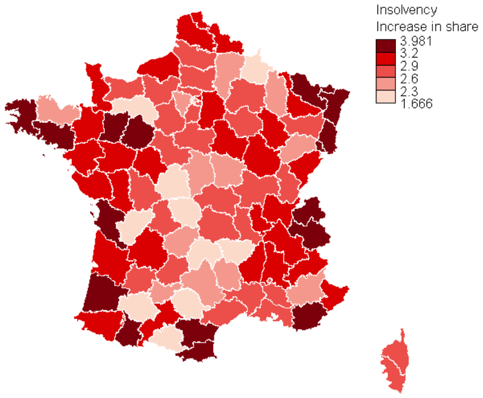
[30] We apply to French *département* the national industry structure in order to correct both insolvency and illiquidity from localized industry specification.

Graph 8: Effect of the crisis by location, end 2020

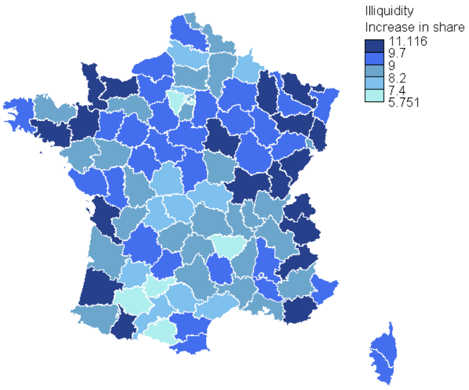
a) Increase in the share of illiquid firms with public support (pp)



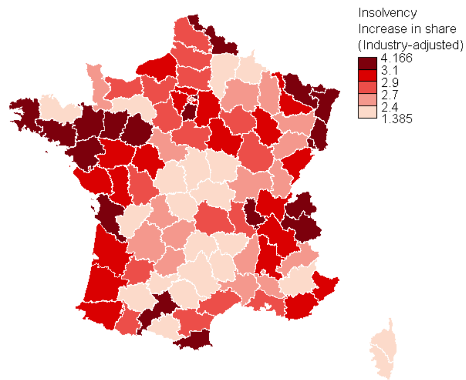
b) Increase in the share of insolvent firms with public support (pp)



c) Increase in the share of illiquid firms with public support (pp, industry-adjusted)



d) Increase in the share of insolvent firms with public support (pp, industry-adjusted)



Note: Decomposition of the effect of the crisis by location in terms of cumulative share of newly illiquid and newly insolvent firms during the March-December 2020 period. "Newly" means that we exclude for the analysis initially illiquid (resp. insolvent) firms. We map the difference (or increase in share) between a no crisis scenario and a scenario with crisis and with public support. Maps (c) and (d) apply the national industry structure to every *département*.

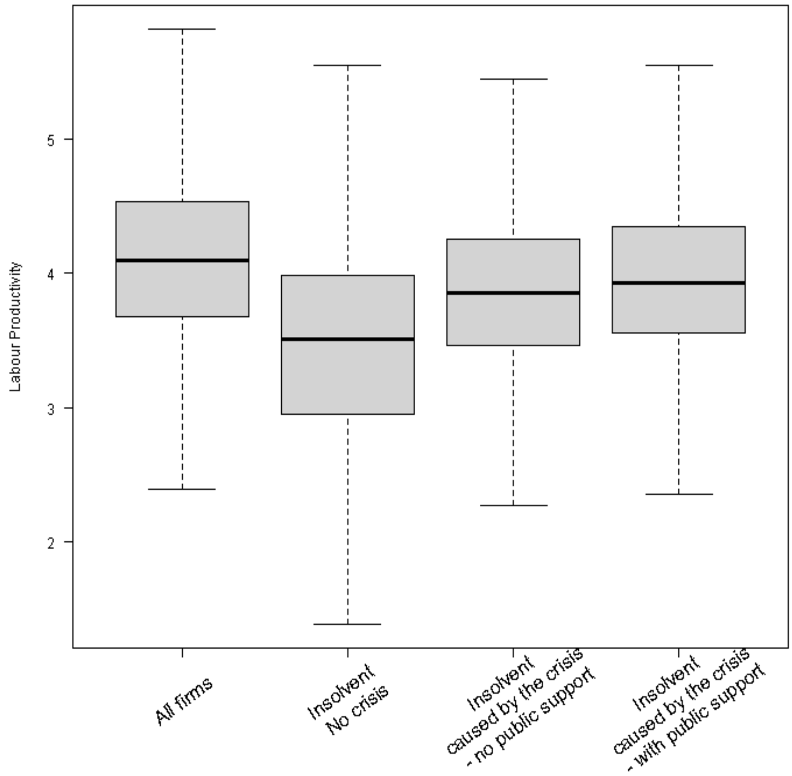
2.6 Productivity of vulnerable firms

An important question is the effect of the crisis on the so-called "creative destruction" in the economy.[31] Our model predicts a significant rise in the number of insolvent firms, with a magnitude depending on the industry and size of companies. If the market selection operated by the crisis only affected the least productive firms in the economy, the crisis would have an efficiency-enhancing cleansing effect, which could ultimately enable production factors (labour and capital) to be reallocated towards the most efficient firms.

[31] See A. Bénassy-Quéré, "2021, zombie year?", *Blog French Treasury* for some explanations on the role of destructive creation during the Covid crisis, or David, Faquet and Rachiq (2020), "The contribution of creative destruction to productivity growth in France", *Trésor-Economics* n° 273.

Our simulation shows that this creative destruction is less efficient during the Covid crisis than in "normal" times. According to our chosen measure of labour productivity (logarithm of the pre-crisis ratio of value-added on number of employees), insolvency caused by the crisis remains concentrated on the least productive firms but it affects firms with a higher average productivity than in a counterfactual scenario without crisis (Graph 9). Moreover, public support measures do not modify the productivity distribution of insolvent firms, which is not surprising since the measures do not discriminate much between firms.

Graph 9: Distribution of labour productivity among groups of firms

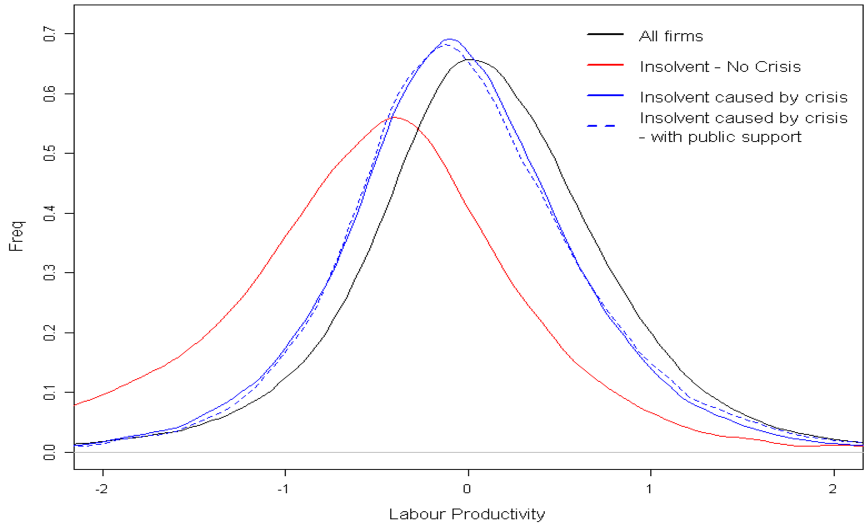


Note: Labour productivity (in log). The microsimulation sample is restricted to firms with at least one employee. Boxplot outlines, for the labour productivity of our different groups of firms, the minimum and maximum (after the removal of outliers), median and quartiles of the distribution.

These results could possibly be explained by composition effects, for instance if firms in more productive sectors are more affected by the Covid shock. In Graph 10, we correct our labour productivity measure by industry and size effects[32] and results remain robust: insolvency affects more efficient firms during the crisis than in "normal" times, with public support having a neutral impact on the distribution of insolvent firms in terms of labour productivity.

[32] We plot the residuals from the following regression: $log\left({}^{VA}/_{\#Employees}\right) = \beta_1 Industry + \beta_2 size + \varepsilon_{it}$.

Graph 10: Distribution of labour productivity among sector-size groups of firms



Note: Labour productivity (in log) is adjusted for both industry and size fixed effects. The sample is restricted to firms with at least one employee. The black curve represents the distribution of labour productivity across firms in the whole economy. The red curve represents the same distribution but for the subsample of firms becoming insolvent in the year in a scenario without crisis. The full blue curve outlines the distribution for the subsample of firms becoming insolvent in the year in a scenario with crisis but without public support. The dashed blue line outlines the same distribution but in a scenario with all the public support measures (short-time work, tax deferral, tax relief, SMEs Solidarity Fund).

2.7 Drivers of illiquidity, insolvency, and debt

One may wonder what the main drivers of vulnerability during the Covid crisis are, compared to its usual drivers. To answer this question, we use a simple regression model of the probability for a firm to be both illiquid and insolvent because of the crisis (*ie*. firm which would not have been both illiquid *and* insolvent without crisis). We restrict our sample to firms which are identified as being illiquid and insolvent at the end of 2020 (in the crisis scenario and with public support) and use the following specification in a probit model:

$$\Pr(nv_i = 1) = F(\alpha_i X_i) \qquad (7)$$

where nv_i is a binary variable equal to 1 if firm *i* becomes illiquid and insolvent during 2020 but would not without crisis, and X_i is a set of characteristics of the firm. F is the Gaussian distribution function. We consider first nonfinancial characteristics such as industry, size, age and location, and then introduce financial characteristics such as assets, debt, cash, productivity and employment. Variables are for the year 2018, as we want to analyse the impact of pre-crisis characteristics. We also add a Covid shock (in this case the April turnover shock) to estimate to what extent these new vulnerabilities are more explained by the shock or by initial vulnerabilities.

Table 4 presents the estimation results. First, we find some expected results: firms in sectors which were more affected by the crisis[33] are more at risk of becoming vulnerable due to the crisis. This result holds when we use specific sectors instead of broadly defined sectors: accommodation and food services, which are the most affected, is the sector the most at risk. Second, we find that medium-size firms are the most affected by the crisis, large and very small firms being less affected. Third, we find that financial characteristics matter less than in normal times: firms with limited assets or cash, or a high level of debt, have a lower probability than usual to face difficulties. We also see that firms with higher productivity are more affected than usual by the crisis. Finally, as expected, firms facing a large economic shock have more chance than usual to become vulnerable.

[33] Sectors labelled S1, S1bis and S2, which were defined by the French government respectively as the sectors most affected by the crisis, sectors depending on S1 sectors and sectors targeted by administrative closures.

Table 4. Determinants of being both illiquid and insolvent during the Covid crisis

Variable	*(1)*	*(2)*	*(3)*	*(4)*
Age	0.011***	0.011***	0.006***	0.006***
Sector "S1"	0.524***		0.361***	0.141***
Sector "S1bis"	0.121***		0.055***	0.135***
Sector "S2"	0.120***		−0.003***	0.031***
Industry		−0.093***		
Wholesale and retail trade		0.318***		
Transporting and storage		0.580***		
Accommodation and food service		0.834***		
Microenterprise	0.175***	0.184***	0.426***	0.397***
SME	0.453***	0.449***	0.414***	0.396***
Medium-large companies	0.254***	0.252***	0.308***	0.313***
Île-de-France region	−0.199***	−0.173***	−0.191***	−0.156***
Total assets (log)			0.732***	0.738***
Debt (log)			−0.794***	−0.802***
Cash (log)			0.120***	0.126***
Productivity			0.002***	0.002***
Employment			−0.000***	−0.000***
April revenue shock				1.131***
Pseudo-R^2	0.04	0.06	0.14	0.15
AIC	291 220	283 510	155 466	153 179
Number of observations	239 830	239 830	130 704	130 704

Note: For these four regressions estimated by a probit model, the dependent variable is the fact of being illiquid and insolvent because of the crisis (i.e. firms which would not have been illiquid and insolvent without crisis). In third and fourth regressions, the sample is restricted so that all financial variables are defined. For sectors, the reference is all sectors which are not displayed and for firms' category, it is large enterprises. Sectors S1, S1bis and S2, correspond respectively to the sectors most affected by the crisis, sectors depending on S1 sectors and sectors targeted by administrative closures.

3. The impact of financial constraints on investment and R&D

3.1 A quick overview of the literature

The financial constraints generated by the Covid crisis, such as low cash flows and debt overhang, could have a long-term impact on corporate investment and R&D. A firm might be unable to fund a profitable investment (i.e. one with a high net present value or high Tobin's *q*) because, when the risk of default is high, the returns will accrue mainly to senior debt holders rather than to new investors (Myers (1977)). The firm will therefore try to deleverage before investing. Several empirical papers show that investment is indeed sensitive to both low cash flows and debt overhang for large panels of countries (Bond and Meghir (1994), Mulier *et al.* (2016), Alanis *et al.* (2018) and Kalemli-Özcan *et al.* (2019) – see Appendix).

The case of R&D is more ambiguous. On the one hand, R&D is structurally risky and cannot be easily collateralised, which would make it even more sensitive to financial constraints. On the other hand, R&D is a long-term investment with high adjustment costs, which makes it more resilient during a crisis. Empirically, the estimations of the sensitivity of R&D to financial constraints are much more ambiguous than for tangible investment (Bond *et al.* (2005), Brown *et al.* (2012) and Cincera *et al.* (2015) for instance). Several papers emphasize the resilience of innovation in time of crisis (Babina *et al.* (2020), Gompers *et al.* (2020)), though the decision to implement a new R&D project (extensive margin) would be far more sensitive to the financial constraints than the amount of financing devoted to an existing R&D plan– the intensive margin (Mancusi and Vezzulli (2010), Savignac (2006), Peters *et al.* (2017), Chen *et al.* (2020) − see Appendix).

3.2 A dynamic model of investment and R&D

The estimation of investment equations is based on the Fare (see section 1) dataset for the years 2009 to 2018. We exclude firms which have less than 10 employees at least one time during this period. We also remove outliers (see Appendix for more details), so that our investment equations are estimated on an unbalanced panel of 90,590 firms for 733,680 observations.

For R&D equations, we merge Fare data with the R&D tax credit dataset,[34] available from 2009 to 2016, which contains almost-exhaustive information on R&D spending of French companies. The sample is restricted to firms having at least one year of R&D activity, *ie.* 13,431 firms for 90,413 observations.

We estimate a dynamic model of investment with error-correction inspired by Mairesse *et al.* (2000) (see Box 2*).* The equation of interest for the investment takes the following form:

$$\frac{I_{it}}{K_{it-1}} = \beta_1 \frac{I_{it-1}}{K_{it-2}} + \beta_2 \Delta\ln(\mathrm{R_{it}}) + \beta_3 \Delta\ln(\mathrm{R_{it-1}}) + \rho(\ln(K_{it-2}) - \ln(R_{it-2})) + f(.)_{it-1} + \alpha_i + \mu_{jt} + \epsilon_{it} \qquad (8)$$

Let I_{it} be the investment of firm *i* at *t* (gross fixed capital formation). K_{it} is the capital computed thanks to a permanent inventory method (see Appendix). $\ln(K_{it})$ is the logarithm of capital and $\ln(R_{it})$ the logarithm of sales; $\Delta\ln(\mathrm{R_{it}})$ is therefore sales growth rate; $f(.)$ is a function of firm's financial constraints measured in our preferred setting as a combination of cash flow rate ($\frac{CF_{it}}{K_{it-1}}$) and leverage ($\frac{D_{it}}{K_{it-1}}$).

The model includes firm fixed effects α_i, industry-time fixed μ_{jt} effects (capturing the business cycle of the industry) and an idiosyncratic error term. In equation (1), β_1 is an autoregressive term, β_2 and β_3 are proxies for the accelerator aspect of the model (we predict a positive value of both coefficients). We add to the accelerator model the error correction term where ρ is expected to be negative, meaning that if capital exceeds its desired long-term level (see Box 2) the firm will cut its gross investment.

This dynamic model of tangible investment can also be applied to R&D (see Box 2). The equation of interest for R&D spending take the following form:

$$\frac{RD_{it}}{G_{it-1}} = \beta_1 \frac{RD_{it-1}}{G_{it-2}} + \beta_2 \Delta\ln(\mathrm{R_{it}}) + \beta_3 \Delta\ln(\mathrm{R_{it-1}}) + \rho(\ln(G_{it-2}) - \ln(R_{it-2})) + f(.)_{it-1} + \alpha_i + \mu_{jt} + \epsilon_{it} \qquad (9)$$

With RD_{it} the R&D spending, G_{it} the stock of knowledge of the firm computed thanks to a permanent inventory method (see Appendix). Other variables as well as interpretations are similar to the investment model except that elements of $f(.)$ are normalised by the stock of knowledge. The knowledge stock is the abstract equivalent of tangible capital K_{it} applied to R&D and innovative investments. Just like tangible capital, the stock of knowledge of a firm increases with R&D investment and is subject to depreciation.

Once coefficients of equations (8) and (9) are estimated, our microsimulation model enables us to compute the increase in debt for firms after the crisis (so-called "additional Debt"), that enters linearly into equations (8) and (9).

[34] The R&D tax credit dataset, constructed by the DGFiP and the Statistical Office of the French Ministry of Higher Education (SIES). Schweitzer (2019) warns about the potential under-estimation of R&D spending in this dataset compared to the R&D survey (not exhaustive) of the SIES.

One must note that these estimations do not take into account the recovery plan measures which aim at supporting investment, such that the lowering of production taxes or the "equity loans" and subordinated bonds scheme (*prêts participatifs et obligations Relance*).

Box 2: A dynamic model of investment and R&D

Let one assume that firms have a Cobb-Douglas production function $f(K_t, L_t) = A_t L_t^{\beta} K_t^{\alpha}$. Then the optimal long-term demand for capital (in logarithm) K_t^* is equal to:

$$\ln(K_t^*) = \ln\big(f(K_t, L_t)\big) + \ln(\alpha) - \ln\left(\frac{\partial f(K_t, L_t)}{\partial K_t}\right) \stackrel{\text{def}}{=} \ln(R_t) + \ln(\alpha) - \ln\left(\frac{\partial f(K_t, L_t)}{\partial K_t}\right) \qquad (A1)$$

With $\ln(R_t)$ the firm sales in logarithm and $\frac{\partial f(K_t,L_t)}{\partial K_t}$ the user cost of capital, unobservable for the econometrician at the micro-level (it depends on the price of investment, depreciation and interest rate). We will suppose that the combination of industry, time and individual fixed effects will enable us to approximate such a cost in order to equate $k_t^* \approx r_t + constant$.

We make the assumption than the path linking the actual level of capital to this optimum follows a deep and autoregressive adjustment:

$$\ln(K_{\mathrm{it}}) = \alpha_0 + \gamma_1 \ln(K_{it-1}) + \gamma_2 \ln(K_{it-2}) + \beta_0 \ln(R_{it}) + \beta_1 \ln(R_{it-1}) + \beta_2 \ln(R_{it-2}) + \epsilon_{it} \qquad \text{(A2)}$$

Which can be written in an error-correction model after a first-difference transformation of the variables.

$$\begin{aligned} \Delta\ln(K_{it}) = {} & \alpha_0 + (\gamma_1 - 1)\Delta\ln(K_{it-1}) + \beta_0 \Delta\ln(R_{it}) + (\beta_0 + \beta_1)\Delta\ln(R_{it-1}) + \\ & (\gamma_1 + \gamma_2 - 1)(\ln(K_{it-2}) - \ln(R_{it-2})) + \qquad \text{(A3)} \\ & (\beta_0 + \beta_1 + \beta_2 + \gamma_1 + \gamma_2 - 1)\ln(R_{it-2}) + \epsilon_{it} \end{aligned}$$

Finally, we assume an equation of capital transition: $K_{it} = (1 - \delta_i)K_{it-1} + I_{it}$. Therefore:

$$\Delta\ln(K_{it}) = \ln\left(\frac{K_{it}}{K_{it-1}}\right) = \ln\left(\frac{(1-\delta_i)K_{it-1} + I_{it}}{K_{it-1}}\right) = \ln\left(1 + \frac{I_{it} - \delta_i K_{it-1}}{K_{it-1}}\right) \approx \frac{I_{it} - \delta_i K_{it-1}}{K_{it-1}} = \frac{I_{it}}{K_{it-1}} - \delta_i \qquad \text{(A4)}$$

If we incorporate (A4) in (A3) we obtain the equation of interest (A5) that is to say an accelerator model of investment with error correction. Financial constraints can enter linearly in such an equation:

$$\begin{aligned} \frac{I_{it}}{K_{it-1}} = {} & \alpha_0 + (\gamma_1 - 1)\frac{I_{it-1}}{K_{it-2}} + \beta_0 \Delta\ln(R_{it}) + (\beta_0 + \beta_1)\Delta\ln(R_{it-1}) + (\gamma_1 + \gamma_2 - 1)(\ln(K_{it-2}) - \ln(R_{it-2})) \\ & + (\beta_0 + \beta_1 + \beta_2 + \gamma_1 + \gamma_2 - 1)\ln(R_{it-2}) + \alpha_i + \epsilon_{it} \qquad \text{(A5)} \end{aligned}$$

R&D spending follow the same reasoning. We make the assumption that the production function of the firm depends on both the tangible capital K_t and the stock of knowledge of the firm G_t. In this way, we can derive an equivalent optimal long term demand for knowledge g_t^* similar to (A1) with a user cost of knowledge depending upon researcher wages, depreciation of knowledge and interest rate. We also assume an equation of knowledge transition: $G_{it} = (1 - \delta_i')G_{it-1} + R_{it}$ with δ_i' the depreciation rate for R&D and R_{it} the R&D spending of the firm. In this way we can derive an equivalent equation of (A5) but for R&D spending:

$$\begin{aligned} \frac{RD_{it}}{G_{it-1}} = {} & \alpha'_0 + (\gamma'_1 - 1)\frac{RD_{it-1}}{G_{it-2}} + \beta'_0 \Delta\ln(R_{it}) + (\beta'_0 + \beta'_1)\Delta\ln(R_{it-1}) + \left(\gamma'_1 + \gamma'_2 - 1\right)(\ln(G_{it-2}) - \ln(R_{it-2})) + \\ & \left(\beta'_0 + \beta'_1 + \beta'_2 + \gamma'_1 + \gamma'_2 - 1\right)\ln(R_{it-2}) + \delta'_i + \epsilon'_{it} \qquad \text{(A6)} \end{aligned}$$

Equations (8) and (9) are estimated with GMM (Generalized Method of Moments) using lags of covariates as instruments following Arellano-Bond (1991). In practice, we try not to add too many instruments in the estimation[35] because their efficiency decreases with their number (Roodman (2009)). In the Appendix, we propose a set of robustness tests for our estimations.

[35] The set of instruments is detailed above regression tables.

3.3 Results

3.3.1 Investment

Estimation of equation (1) can be found in Table 5. Specification (1) estimates a simple accelerator model of investment, (2) and (3) add cash flows and debt leverage to the model. Results are coherent with the literature (see Appendix): accelerator terms play a key role in the determination of investment. As expected, the coefficient on the error correction term is always significant and negative. Both low profits and high debt leverage have a negative impact on investment (significant at the 10% threshold in the case of the debt leverage): a 1 pp increase of the debt ratio is expected to decrease the investment ratio by 0.04pp while a 1 pp decrease of cash flows is expected to decrease the investment ratio by 0.05pp.

Due to the heterogeneous effect of the Covid-19 crisis on firms' financial constraints and industry specificities in the adjustment of capital, we estimate specification (3) of the dynamic model of investment per industry (Table 6).

Our results show a strong heterogeneity between industries: although sales growth, error correction (the gap between actual and desired level of capital) and cash flows coefficients are almost always significant in the expected sign, debt leverage is significant only for a limited number of sectors. For firms in the manufacturing industry (responsible for a large part of tangible investment), we find a strong effect of both current and lagged sales growth (a 1pp increase in current sale growth is associated with an additional 0.22pp in investment ratio) but also a strong effect of cash flows. Finally, leverage has an expected negative impact on investment for the manufacturing industry: a 1pp increase in leverage decreases investment by 0.03pp.

Estimates from Table 6, combined with results about the "additional debt" due to the health crisis, computed from our microsimulation tool (see section 2), can be used to assess the decrease in investment through the channel of debt overhang. Table 7 provides the main results. In this exercise we make the assumption that both demand and cash flows will come back to pre-crisis levels and we focus on the long-term impact of the increase in debt leverage. Even with public support, debt overhang caused by the crisis reduces investment in France by almost 2%, compared to a scenario with no crisis.

Table 5. Investment Equations (GMM)

Dependent Variable: $InvestmentRatio_{i,t}$	(1)	(2)	(3)
$InvestmentRatio_{i,t-1}$	0.160*** (0.0577)	0.052*** (0.0124)	0.097*** (0.0321)
$SalesGrowth_{i,t}$	0.0218*** (0.0803)	0.153 (0.158)	0.186** (0.0730)
$SalesGrowth_{i,t-1}$	−0.028 (0.0428)	0.0611*** (0.0041)	0.0606*** (0.0231)
$ErrorCorrection_{it-2}$	−0.0209* (0.0124)	−0.0573*** (0.0188)	−0.0567*** (0.0246)
$CashFlowRatio_{i,t-1}$		0.0350* (0.0192)	0.0519*** (0.0138)
$DebtRatio_{i,t-1}$			−0.0351* (0.0201)
Fixed industry x time effect	Yes	Yes	Yes
N	537,197	537,197	537,197
AR(1)	−9.78***	−5.89***	−4.05***
AR(2)	0.60	−1.72*	−1.50
MMSC - AIC	7.06	−0.68	−0.61
#Instruments	37	30	33
Sargan Hansen test (p-value)	0,00***	0,25	0,15

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Table presents GMM estimation pooling all observations. Values in parenthesis are robust standard errors. Sargan-Hansen test evaluates the validity of the exogeneity of instruments (H_0: overidentifying restrictions are valid). Arellano-Bond tests (AR(1), AR(2)) for absence of higher-order serial correlation are also provided (H_0: zero autocorrelation in the first-differenciated errors at order k). We report the number of instruments (#Instruments) but also the Andrews and Lu (2001) Akaike model and moment selection criteria (MMSC-AIC). All models are Diff-GMM estimations. Instruments are lagged variables from t-3 to t-5 in (1) and lagged variables from t-2 to t-3 for (2) and (3). All specification includes industry x time fixed effects.

Table 6. Investment Equations by industry (GMM)

Dependent variable: $InvestmentRatio_{i,t}$	(BE) Manuf.	(FZ) Construction	(GZ) Wholesale	(HZ) Transport	(IZ) Accom. & Food	(JZ) Info. & Comm.	(LZ) Real Estate	(MN) Prof., Sci. & Tech.	(RU) Entertain & Recreation
$InvestmentRatio_{i,t-1}$	0.0649* (0.0352)	0.126 (0.169)	0.275 (0.179)	−0.0273 (0.0331)	0.0543* (0.0326)	0.104*** (0.0346)	−0.0173 (0.128)	0.0556 (0.0425)	0.164*** (0.0219)
$ErrorCorrection_{it-2}$	−0.0731*** (0.0199)	−0.0483* (0.0280)	−0.0290 (0.0450)	−0.0620** (0.0262)	−0.0561** (0.0239)	−0.0274 (0.0208)	0.0144 (0.0187)	−0.0500* (0.0282)	−0.00325 (0.0220)
$SalesGrowth_{i,t}$	0.223*** (0.0804)	0.0642* (0.0360)	0.332** (0.148)	−0.0954 (0.104)	0.390** (0.165)	0.274*** (0.0858)	0.0992 (0.0808)	0.286*** (0.0860)	0.180** (0.0900)
$SalesGrowth_{i,t-1}$	0.0736*** (0.0172)	0.0493** (0.0251)	−0.0779 (0.0680)	0.0909*** (0.0243)	0.0387* (0.0226)	0.0246 (0.0201)	0.00303 (0.0189)	0.0112 (0.0272)	0.00876 (0.0246)
$CasfFlowRatio_{i,t-1}$	0.0715*** (0.0161)	0.0491*** (0.0101)	0.221*** (0.0701)	0.0523*** (0.0156)	0.0726*** (0.0217)	0.0475*** (0.0147)	0.00801 (0.0311)	0.0986*** (0.0288)	0.0799** (0.0328)
$DebtRatio_{i,t-1}$	−0.0264* (0.0148)	−0.00432 (0.0109)	−0.0621** (0.0271)	0.0605*** (0.0140)	−0.0145* (0.00744)	−0.0251** (0.0108)	−0.00442 (0.00441)	−0.0189 (0.0184)	−0.0398*** (0.0150)
Fixed time effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	138,230	93,413	135,133	38,680	41,914	12,101	5,060	53,086	14,319
AR(1)	−26.2***	−3.91***	−5.74***	−16.33***	−22.10***	−11.35***	−2.61***	−12.86***	−16.57***
AR(2)	−1.08	0.96	0.14	2.03**	0.88	2.91**	−1.38	3.11**	0.17
MMSC – AIC	−3.06	−0.42	0.44	−5.02	−4.88	−1.73	−6.23	−11.39	−7.16
#Instruments	24	18	16	15	17	22	19	22	20
Sargan hansen test (p-value)	0,22	0,11	0,11	0,55	0,19	0,14	0,31	0,92	0,23

Note: * p < 0.10, ** p < 0.05, *** p < 0.01. Table presents GMM estimation by industry. Values in parenthesis are robust standard errors. Sargan-Hansen test evaluates the validity of the exogeneity of instruments (H_0: overidentifying restrictions are valid). Arellano-Bond tests (AR(1), AR(2)) for absence of higher-order serial correlation are also provided (H_0: zero autocorrelation in the first-differentiated errors at order k). We report the number of instruments (#Instruments) but also the Andrews and Lu (2001) Akaike model and moment selection criteria (MMSC-AIC). Specifications (BE), (FZ), (GZ), (HZ) , (MN) are Diff-GMM using lagged variables from t-2 to t-3 for sales growth, error correction, cash flow ratio, debt leverage and t-3 to t-4 for investment ratio. (IZ), (JZ), (LZ) and (RU) are Sys-GMM adds difference in t-3 for sales growth, investment ratio, cash flow ratio and debt leverage.

Table 7. Investment losses caused by additional debt

	Additional Debt	Investment losses
Crisis - No Public Support	+96 €bn	−2.5%
Crisis - With Public Support	+77 €bn	−2.0%

Note: Fare 2009-2018, French Treasury microsimulations. Additional debt is computed thanks to our microsimulation model. Investment losses correspond to results from equation (1). Additional debt incorporates tax liabilities.

3.3.2 R&D

Estimates of equation (2) are outlined in Table 8. Specification (1) presents the dynamic model of R&D with error correction and financial constraints for all industries. Models (2) to (4) propose estimates per industry.[36] Model (5) estimates investment equation (as in Table 5) in order to assess whether tangible investment in our R&D sample behaves differently from the whole sample of firms. The investment model in (5) appears coherent with the previous estimation in terms of error correction, sales growth and cash flow ratio. However, the impact of leverage is not significant anymore.

While both the accelerator effect and the error correction term (the gap between actual and desired level of R&D) have a substantial effect on R&D spending, financial constraints such as debt overhang and drop in cash flows are not found to have any significant effect on R&D spending. Therefore, according to the model, there may be no drop in R&D caused by profit reduction and debt overhang and Covid-19 will not have long-term impact on R&D spending through the channel of financial constraints. Still, the crisis could affect R&D spending in the short term due to its negative effect on demand.

[36] It is worth-noticing that for firms involved in R&D, there is a significant gap between the industry reported by the firm and the industry which will benefit from the R&D. Information about both “reported industry” and “actual industry” are available in R&D Surveys (French Ministry of Higher Education). For instance, around 60% of R&D invested in (MN) - Prof., Sci. & Tech will actually benefit the French pharmaceutical industry. In order to correct from this discrepancy between “reported industry” and “actual industry”, we use an external source and compile R&D surveys from 2004 to 2017 in order to cover all our sample (making the assumption that industry does not change through time).

Table 8. R&D Equations (GMM)

Dependent variable: $R\&DRatio_{i,t}$ or $InvestmentRatio_{i,t}$ (5)	(1) All	(2) Manufacturing	(3) Info. & Comm.	(4) Service	(5) All
$R\&DRatio_{i,t-1}$ or $InvestmentRatio_{i,t-1}$ (5)	−0.0254 (0.0224)	0.00331 (0.0342)	−0.0185 (0.0224)	0.0573 (0.0682)	0.0273 (0.0744)
$ErrorCorrection_{it-2}$	−0.210*** (0.0682)	−0.128** (0.0525)	−0.244** (0.101)	−0.158** (0.0769)	−0.0622* (0.0355)
$SalesGrowth_{i,t}$	−0.403 (0.308)	−0.175 (0.187)	0.184 (0.128)	−0.0179 (0.156)	0.134** (0.0596)
$SalesGrowth_{i,t-1}$	0.173*** (0.0548)	0.0884* (0.0468)	0.216*** (0.0714)	0.142** (0.0571)	0.0499* (0.0262)
$CasfFlowRatio_{i,t-1}$	−0.0114* (0.00626)	−0.00122 (0.00441)	−0.00327 (0.0119)	−0.0122 (0.00874)	0.0400* (0.0238)
$DebtRatio_{i,t-1}$	0.00292 (0.00205)	0.000953 (0.00187)	0.00177 (0.00176)	0.00103 (0.00105)	0.00688 (0.00565)
Fixed effect	Industry x Time	Time	Time	Time	Industry x Time
N	61,272	38,305	8,934	14,033	61,272
AR(1)	−3.58***	−2.76***	−3.96***	−2.46**	−7.96***
AR(2)	−0.22	0.99	−0.67	1.07	−0.52
MMSC - AIC	−6.99	−1.61	−8.75	−5.66	−2.93
#Instruments	27	18	18	18	34
Sargan Hansen test (p-value)	0,79	0,09	0,41	0,35	0,06

Note: * p < 0.10, ** p < 0.05, *** p < 0.01. Table presents GMM estimation for R&D equations (1), (2), (3) and (4) and for investment equation (5). Values in parenthesis are robust standard errors. Sargan-Hansen test evaluates the validity of the exogeneity of instruments (H_0: overidentifying restrictions are valid). Arellano-Bond tests (AR(1), AR(2)) for absence of higher-order serial correlation are also provided (H_0: zero autocorrelation in the first-differenciated errors at order k). We report the number of instruments (#Instruments) but also the Andrews and Lu (2001) Akaike model and moment selection criteria (MMSC-AIC). Models (1) to (4) are Diff-GMM with the following instruments: industry x time or only time dummies, lag t-2 to t-4 for R&D ratio and sales growth, lag t-2 for the error correction term and lag t-3 to t-5 for cash flow ratio and debt leverage. Model (5) uses industry x time dummies, lag t-3 to t-6 for investment ratio, lag t-2 to t-3 for the error correction term and finally lag t-2 to t-5 for the remaining variables.

Conclusion

This paper assesses the impact of the crisis on the financial situation of French firms in 2020. We implement a microsimulation model using firm-level observed data on the shock (on activity and payroll) and on the use of public support for more than 1.8 million firm. Our baseline estimates show that illiquidity, insolvency and indebtedness increase during the crisis, but the impact is significantly reduced by public support measures. For instance, the cumulative insolvency rate over the March-December period rises from 3.6% to 6.6% because of the crisis, but would have increased to 11.9% without public support.

We report a significant heterogeneity of the impact of the crisis by industry, size, age and localisation. Moreover, we document that creative destruction is impaired during the crisis: insolvency caused by the crisis affects more productive firms on average than it does in normal times.

The increase of firms' financial constraints in the aftermath of the crisis might reduce their investment during the recovery. We quantify the extent of the problem, analysing the impact of debt overhang on both tangible investment and R&D. Our estimates suggest that the debt overhang could decrease corporate investment by about 2% in the medium term. R&D appears more resilient to the increase in debt.

However, these estimates do not take into account the positive impact of public measures aiming at supporting investment. First, the lowering of production taxes by €10bn from 2021 will help enhance French firms' competitiveness and investment. Second, specific actions have been taken in response to the crisis to strengthen corporate balance sheet in order to prevent a potential slowdown of investment. For example, the French recovery plan includes a "prêts participatifs et obligations Relance" scheme targeting companies affected by the crisis but with manageable levels of debt and investment plans to finance. The scheme rests on up to €20bn of "equity loans" (subordinated long term debt) and subordinated bonds, with a public guarantee of up to 30% of losses at the portfolio level.

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APPENDIX

1. Data sources and descriptive statistics

1.1 Data sources

Our microsimulation tool relies on multiple data sources.

1.1.1 Firms' financial statements (Fare – Insee)

The main database is the one providing financial statements for French firms. The Fare database is produced by the Insee from the tax declarations of French firms. For each firm, it provides detailed information about its characteristics (age, sector, location, number of employees) and its financial statements, notably its balance sheet (liabilities and assets) and its income statement (revenues and expenses). Thanks to this data, we calibrate the cost structure of firms and we estimate their operating income under different scenarios. The latest available version of this database corresponds to the 2018 financial statements. The data contains almost all French firms. We exclude some sectors with strong specificities: agriculture (AZ), finance and insurance (KZ) and public administrations (OQ). Moreover, we exclude firms for which data may be incomplete, for example small firms whose tax regime is the personal income tax rather than the corporate income tax. At the end of the day, our microsimulation is based on 1 821 189 firms.

1.1.2 Losses of activity (Insee and DGFiP)

Sector-level activity shocks were calibrated by the Insee in its *Economic Outlooks* at an aggregated level (NACE 17). Insee provided us with monthly estimations, based on the published quarterly national accounts for the three first quarters and on projections for the last one.

Firm-level activity shocks are based on value-added tax (VAT) files provided by the Public Finances Directorate General – DGFiP. The data was available to September, but since tax declarations can be strongly disrupted during the summer, we only made use of them until June. In order to use only robust estimations of revenue losses, we made use of this data only for firms which had declared a revenue each month from March 2019 to June 2020. To compute shocks, we therefore compare their monthly revenue from March 2020 to June 2020 to the average monthly revenue between March 2019 and February 2020. We made use of firms declaring their revenue monthly and quarterly.

1.1.3 Firms' wage bills (Epure – Insee)

In order to calibrate the adjustment of firm-level payrolls, we use quarterly data collected by Insee from firms' social declarations. For each firm, we get the number of employees and the total payroll. Since this data is available two months after the end of the quarter, it provides information on the evolution of the workforce and payroll during the crisis. We used this data for the three first quarters of 2020.

1.1.4 Short-time work (Sinapse – Dares)

The SINAPSE database produced by Statistical Department of the Labour, Employment and Economic Inclusion Ministry (DARES) contains firms' application forms to the short-time work scheme and goes down to the employee-level. It provides, for each month, the amount of subsidy granted by the scheme, the number of employees who benefitted from it, the number of hours they worked and didn't work, and it allows to compute the salary of the corresponding employees. However, this data only relates to employees who actually benefitted from the scheme and does not provide information on the whole payroll of the firm. The data is available from March until September.

1.1.5 SME solidarity fund (DGFiP)

The data on the SME solidarity fund is provided by DGFiP. At firm level, we have, for each month, the amount of subsidy granted by each of its two components. The data is available from March to November 2020.

1.1.6 Tax deferrals (Acoss)

The tax deferral database (REP-COVID) produced by the Central Agency of Social Security Organisms – ACOSS – contains monthly individual information on tax deferrals for the March-October 2020 period. It enables us to compute a tax deferral rate on employers' social contributions.

1.2 Definition of key financial variables

The concept of cash flow we compute is quite close to an EBITDA, but does not correspond to it exactly. Using tax declarations variables, we take net turnover as revenues and all operating expenses as costs, except amortizations, depreciations and provisions. We also consider the financial result (gross financial income – financial expenses) as constant and add it to the operating income.

Among operating expenses, we consider all costs as being variable except taxes, "other operating expenses" and a certain proportion of "other purchases and external expenses", since it contains in particular rental charges. We only have data for two sub-items of these charges: rental charges that we consider fixed, and outsourcing that we consider variable. For each sector, we compute the ratio between these two items and then apply it to total external expenses at the firm level to recover an estimate of fixed costs.

We define cash as the sum of cash and marketable securities. For debt, we add up all kinds of debts declared in liabilities.

1.3 Key firm statistics

In the section, we describe the whole sample of firms (1,821,189 firms), the sample of firms for which we have individual 2020 revenue shocks (795,701 firms) and the one of firms for which we have 2020 individual payroll shocks (805,242 firms). The latter two samples have 551,232 firms in common.

First we see that microenterprises are underrepresented in samples with 2020 data (Table A1.1).

Table A1.1. Firms' distribution by size

(%)	Full sample	Firms with 2020 turnover	Firms with 2020 payroll
Share in the full sample	*(100 %)*	*(44 %)*	*(44 %)*
Large	0.01	0.02	0.02
Medium-Large	0.35	0.75	0.73
SME	7.96	15.33	16.08
Micro	91.68	83.90	83.17
Total (sub-)sample	100	100	100

Note: the table provides the distribution of firms according to their size in three samples: the whole sample, the sample of firms with individual information from their 2020 VAT declarations (sample with individual revenue shock) and the sample of firms with individual information on their 2020 payroll (sample with individual payroll shock). Since the whole simulation is done at the legal entity level, we compute firms' size at this level.

The main sector in the sample is wholesale and retail trade, and this industry is even more represented among firms for which we have 2020 individual data (Table A1.2).

Table A1.2. Firms' distribution by industry

(%)	Full sample	Firms with 2020 turnover	Firms with 2020 payroll
Mining and quarrying	0.08	0.11	0.11
Manufacturing	6.95	8.89	10.10
Electricity, gas, steam and air conditioning supply	1.53	0.37	0.10
Water supply, sewerage, waste management and remediation	0.41	0.41	0.56
Construction	16.11	17.21	17.44
Wholesale and retail trade	21.45	26.39	26.65
Transportation and storage	4.41	3.48	3.78
Accommodation and food services	9.85	9.23	12.75
Information and communication	3.97	3.65	3.34
Real estate	9.18	5.73	2.98
Professional, scientific and technical	11.81	11.89	10.04
Administrative and support service	6.35	5.52	4.22
Education	1.48	1.07	1.31
Arts, entertainment and recreation	1.35	1.14	1.13
Other services	5.08	4.88	5.49
Total	100	100	100

Note: the table computes the distribution of firms according to their industry in three samples: the whole sample, the sample of firms with individual information from their 2020 VAT declarations (sample with individual revenue shock) and the sample of firms with individual information on their 2020 payroll (sample with individual payroll shock).

It is also interesting to look at the initial vulnerability of firms: the share of firms with a negative result, the share of insolvent firms, and the median debt/assets ratio. First, one can notice than small firms are usually way more often insolvent than large firms (Table A1.3). Indeed, share of insolvent firms is larger among young firms, and thus among small ones. However, large firms also often have negative results.

Table A1.3. Initial financial vulnerability by size

(%)	Share of firms with negative net income	Share of insolvent firms (debt/assets>1)	Median debt/asset ratio
Large firms	22.22	2.08	60.12
Medium-large	21.87	3.87	61.24
SMEs	18.65	6.84	59.54
Microenterprises	29.40	18.32	60.05
All firms	28.52	17.35	59.99

Note: shares of firms with negative net income, insolvent (debt > assets) and median solvability ratio by firms' size.

In terms of sectors, one can see that some services, such as accommodation or entertainment, were already quite vulnerable before the crisis, with many firms generating losses and having high debt ratios (Table A1.4).

Table A1.4. Initial financial structure by industry

(%)	Share of firms with negative net income	Share of insolvent firms (debt/assets>1)	Median debt/asset ratio
Mining and quarrying	33.00	14.43	47.16
Manufacturing	24.28	12.69	55.75
Electricity, gas, steam and air conditioning supply	53.21	38.72	90.10
Water supply, sewerage, waste management and remediation	25.59	8.50	42.04
Construction	22.72	15.75	59.72
Wholesale and retail trade	26.66	15.76	62.73
Transportation and storage	19.12	12.19	55.36
Accommodation and food services	29.87	21.00	69.43
Information and communication	35.67	16.46	51.04
Real estate	37.47	24.60	66.59
Professional, scientific and technical	28.77	11.40	47.42
Administrative and support service	35.08	23.56	68.01
Education	37.80	19.31	59.48
Arts, entertainment and recreation	40.96	25.77	71.04
Other services	22.28	18.18	55.65

Note: shares of firms with negative net income, insolvent (debt > assets) and the median solvability ratio by industry.

1.4 Economic shocks

Here we compare the activity shocks used in the simulation to losses of activity estimated by the Insee at sectoral level (A17) in its *Economic Outlooks*. In both cases, we rely on monthly data. We compare these shocks in April 2020, since it is the month with the largest hit.

Activity shocks are calculated at the firm level based on VAT files. This source is relatively noisy, though, and we had to clean it before using. First, this dataset contains a lot of zeroes, especially during the summer as accountants may delay their declarations to the following month during holidays: this is why we only used the data up to June and did not make use of the third quarter of the year. Second, since there are many missing values, we only use firms which made a declaration each month (or each quarter) since the beginning of 2019, in order to be sure to get robust variations. Thus, our use of VAT data is not exhaustive but aims at limiting the biases. We have checked the consistency between this dataset and industry-level shocks from Insee (Table A1.5). There are some gaps in a few sectors, but these are sectors with few firms. However, two sectors showcase large gaps with no apparent reason: construction and real estate activities. These gaps may occur because of invoicing delays.

At the aggregated level, the Insee shock is smaller than our shock, but one can see that if we compute the Insee shock on our perimeter of our firms, it becomes larger.

Table A1.5. Activity shock by industry in April 2020

Revenue loss relative to March 2019-February 2020	Industry-level shock from Insee	Turnover shock based on VAT files
Manufacture of food products, beverage and tobacco products	13.1%	12.1%
Manufacture of coke and refined petroleum products	28.8%	60.5%
Manufacture of machinery, computer, electronic and electrical products	38.5%	39.3%
Manufacture of transport equipment	68.7%	66.8%
Manufacture of other industrial products	38.1%	33.0%
Mining and quarrying, energy, water supply, waste management and remediation	26.9%	13.9%
Construction	65.1%	28.5%
Wholesale and retail trade	44.9%	33.3%
Transportation and storage	39.4%	34.1%
Accommodation and food services	67.6%	80.8%
Information and communication	12.4%	13.1%
Real estate	3.4%	34.6%
Scientific and technical activities; Administrative and support services	23.5%	21.4%
Education	27.0%	28.4%
Other services	46.7%	51.7%
Whole economy (in simulation sample)	29.3% (37.7%)	33.5%

Note: April shocks on activity at the industry level according to the Economic Outloooks (Insee) and individual VAT dataset (Turnover shock) used in our simulation. Number in parenthesis represents the Insee activity shock of April applied to our specific sample (firms in the main version of the microsimulation). When VAT data is missing, we apply the sector-level shock.

We perform a similar comparison with data on payrolls (Table A1.6), comparing the shock we use in the simulation to the industry-level shocks published by Acoss. Here we will compare the payroll shocks during the second quarter of 2020 on our sample using Acoss published data[37] (they are published in NACE 38 but here we use NACE 17 as for turnover) to the payroll shock we computed directly from the Epure database.

Again we see that both shocks look very similar at the industry level. One may notice the very large payroll shock in accommodation and food services: while in most activities, the share of people who have been laid off or who have been put in short-time work is substantially smaller than the fall in revenue, for food and accommodation this is not the case. This can probably be explained by the fact that first, most of these firms simply had to close during lockdowns and second, this type of activities requires less support functions who have to remain functional even in periods of low activity.

[37] "La masse salariale et les effectifs salariés du secteur privé au troisième trimestre 2020", *Acoss Stat* n° 316 – December 2020.

Table A1.6. Payroll shock by industry

Payroll decline in 2020Q2 compared to 2019Q4	Industry-level shock (Acoss)	Firm-level shock (Epure)
Manufacture of food products, beverage and tobacco products	10.6%	10.3%
Manufacture of coke and refined petroleum products	0.1%	−3.5%
Manufacture of machinery, computer, electronic and electrical products	12.5%	10.2%
Manufacture of transport equipment	22.9%	14.8%
Manufacture of other industrial products	15.0%	13.8%
Mining and quarrying, energy, water supply, waste management and remediation	4.5%	−4.5%
Construction	18.9%	16.1%
Wholesale and retail trade	19.4%	16.8%
Transportation and storage	17.0%	20.3%
Accommodation and food services	61.3%	59.9%
Information and communication	9.8%	8.9%
Real estate activities	13.9%	12.0%
Scientific and technical activities; Administrative and support services	21.3%	19.0%
Education	18.0%	26.4%
Other services	36.8%	40.2%
Whole economy (in simulation sample)	17.1% (19.5%)	17.6%

Note: Q2 shocks on payroll at the industry level according to Acoss publications and individual Epure dataset (Payroll shock) used in our simulation. Number in parenthesis represents the Acoss payroll shock of Q2 applied to our specific sample. For the Acoss shock, we reproduce the seasonally-adjusted payroll shock relative to the fourth quarter of 2019.

2. Robustness and additional results

2.1 Robustness of our results

In Table A2.1, we evaluate the robustness of our results to alternative specifications: each column reports one of our four main indicators (share of new illiquid firms, share of new insolvent firms, share of new illiquid and insolvent firms and debt generated between March and December 2020) across different scenarios. For each indicator, we provide its value in the no crisis scenario and in the crisis with public support scenario, values in the no crisis scenario being the same as in the main simulation for most of these variants.

The first scenario (specification (1)) replaces Fare 2018 by Fare 2017. The results are quite similar but the debt is smaller, partly because we have fewer firms in the sample. We then vary the definition of the financial variables. In specification (2), liquidity is limited to cash (thus excluding marketable securities): the results are very similar, except that the amount of generated debt is larger. Then, we restrict debt to loans (specification (3)): liquidity stays unchanged, but solvency results are way more lenient, since the initial level of debt we consider is smaller. In specification (4), we add all debts (and notably tax and social liabilities) except advances from consumers and debts from suppliers: liquidity is still unchanged, but solvency results are closer to the ones of our main simulation. It should be reminded here that we assume no credit constraint: the amount borrowed is the cash shortfall, and the type of debt is irrelevant.

Finally, we look at cash flows rather than financial results (specification (5)). Since for most firms financial result is negative, this leads to slightly less deteriorated figures.

The next robustness exercise is to change the adjustment factors to the shock. In specification (6), we assume that variable costs adjust instantly ($\gamma_{VC,t}$ =1 for all *t*). As one can expect from this "optimal" adjustment, results predict less impact of the crisis on all variables. Then we make different scenarios with a constant adjustment factor: with $\gamma_{VC,t}$ =0.8 for all *t* (specification (7)) as in Demmou et *al*. (2020a, 2020b), the impact of the crisis is smaller than in the main simulation, while it is larger with $\gamma_{VC,t}$ =0.25 for all *t* (specification (11)) as in Guerini et *al*. (2020). Our main simulation is closer to the case $\gamma_{VC,t}$ =0.5 for all *t* (specification (9)). We also look at scenarios with dynamic adjustment, with a time gap of one month, earlier (specification (8)) or later (specification (10)), compared to our main simulation: this variation leads to non-negligible variations in the results, but it does not modify overall message.

Then, we assume that firms do not adapt at all and that all costs are fixed (specification (12), which corresponds to $\gamma_{VC,t}$ =0 for all *t*). This is a kind of worst case scenario, where firms get less revenue but cannot adjust their costs other than labour costs (we still assume that wages adapt according to the payroll shock, since it is the observed behaviour of firms in real data, as in the next scenario). One can see that the results are dramatically deteriorated, with the amount of debt doubling. The other polar case is when there are no fixed costs (specification (13)), assuming that all fixed costs are variable. This is almost a best-case scenario, although we still assume that costs do not adjust perfectly because of the adjustment factor.

We also test the dependence to our assumptions of firm-level shocks to be bounded between −1 and 1. Since the level of activity is positive, there is no surprise in requiring that shocks are less than 1. However, bounding shocks to −1 (*ie*. requiring that variables do not double) is arbitrary. We first compare with a bound of 0 (specification (14)): here, revenue and payroll cannot increase in 2020 compared to 2019. Results are quite close, but a bit less pessimistic: it may seem surprising at first sight, but one has to remember that bounds are applied to both revenue and payroll shocks. While bounding revenue shocks to 0 drastically deteriorates the results, bounding payroll shocks to 0 limits the costs and thus improves firm results. Indeed, our payroll data contains more outliers and this is why the payroll effect dominates. Then, we put some arbitrary larger bound on the shock (specification (15)), with a 10 times increase cap. The impact is limited due to the small number of firms concerned.

Finally, we test the sensibility of our simulations to the observed data, by replacing each data source by a simulated alternative. First, we replace individual revenue shocks by Insee's sectoral shocks (specification (16)): results are more lenient, with less vulnerable firms, as can be expected from data with less heterogeneity. Then, we replace individual payroll shocks by Acoss' sectoral shocks (specification (17)): the results we get are close but slightly milder than in the main version. Next, we replace the amounts of solidarity fund by its simulated version (specification (18)), with essentially unchanged results. Finally, we also replace tax deferrals by their simulated counterpart (specification (19)), which generates only slight differences. All in all, one can see that the main dependence among our observed data is on the revenue shock, which is logic since the trajectory of variable costs depend on it.

All in all, with all these variants of the simulation, one can see that our results seem quite robust. The main differences are obtained when changing the definitions of the financial variables: the definition of cash is important for the absolute amount of debt, the initial definition of debt matters strongly when we identify insolvent firms and the distinction of the fixed and variable costs is critical in how firms are affected by the crisis. The estimations are also quite sensitive to the speed of adjustment of variable costs.

Table A2.1. Robustness tests

(no crisis scenario)	Share of illiquid firms (% of total)	Share of insolvent firms (% of total)	Share of firms that are both insolvent and illiquid (% of total)	New debt (in €bn) in Dec. 2020 compared to March 2020
(0) Main simulation	24.0% *(15.6%)*	6.6% *(3.6%)*	13.2% *(10.4%)*	148.3 *(71.7)*
(1) Fare 2017	23.4% *(14.9%)*	6.4% *(3.4%)*	12.8% *(9.8%)*	133.8 *(63.8)*
(2) Cash only	24.7% *(16.2%)*	6.6% *(3.6%)*	13.3% *(10.4%)*	164.2 *(77.5)*
(3) Debt as loans only	24.0% *(15.6%)*	2.9% *(2.6%)*	4.8% *(4.5%)*	148.3 *(71.7)*
(4) No supply chain debt	24.0% *(15.6%)*	4.3% *(3.1%)*	9.4% *(8.2%)*	148.3 *(71.7)*
(5) Without financial result	23.3% *(15.1%)*	6.4% *(3.5%)*	12.6% *(9.9%)*	135.3 *(57.9)*
(6) Immediate adjustment	19.1% *(15.6%)*	4.8% *(3.6%)*	11.0% *(10.4%)*	101.4 *(71.7)*
(7) 80% adjustment	20.2% *(15.6%)*	5.1% *(3.6%)*	11.3% *(10.4%)*	108.4 *(71.7)*
(8) 1-month earlier adjustment	21.8% *(15.6%)*	5.7% *(3.6%)*	12.1% *(10.4%)*	124.0 *(71.7)*
(9) 50% adjustment	22.7% *(15.6%)*	5.9% *(3.6%)*	12.3% *(10.4%)*	130.9 *(71.7)*
(10) 1-month later adjustment	25.5% *(15.6%)*	7.2% *(3.6%)*	13.9% *(10.4%)*	166.1 *(71.7)*
(11) 25% adjustment	25.9% *(15.6%)*	7.3% *(3.6%)*	14.0% *(10.4%)*	171.9 *(71.7)*
(12) No variable costs	32.2% *(15.6%)*	11.3% *(3.6%)*	18.9% *(10.4%)*	337.3 *(71.7)*
(13) No fixed costs	21.8% *(15.6%)*	5.5% *(3.6%)*	11.6% *(10.4%)*	176.3 *(71.7)*
(14) No positive shocks	23.6% *(15.6%)*	6.2% *(3.6%)*	12.8% *(10.4%)*	146.7 *(71.7)*
(15) Shocks bounded to 10	24.2% *(15.6%)*	6.7% *(3.6%)*	13.4% *(10.4%)*	150.1 *(71.7)*
(16) No individual revenue shock	22.3% *(15.6%)*	5.8% *(3.6%)*	12.2% *(10.4%)*	136.4 *(71.7)*
(17) No individual payroll shock	23.6% *(15.6%)*	6.2% *(3.6%)*	12.9% *(10.4%)*	147.2 *(71.7)*
(18) No individual solidarity fund data	24.0% *(15.6%)*	6.5% *(3.6%)*	13.2% *(10.4%)*	148.3 *(71.7)*
(19) No individual tax deferral data	24.1% *(15.6%)*	6.4% *(3.6%)*	13.2% *(10.4%)*	146.5 *(71.7)*

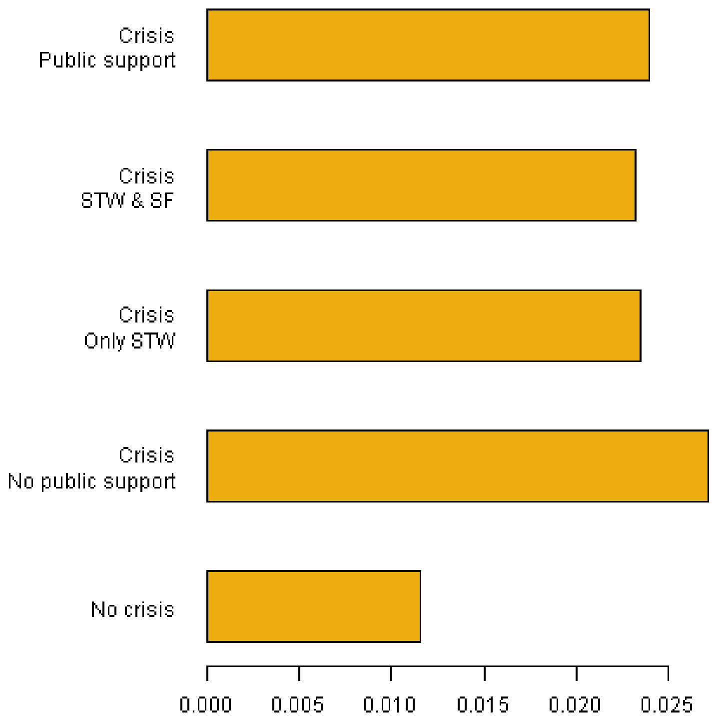
Note: The table presents different robustness tests which definitions are explained above. Definitions are the same as in Table 2. Numbers in parenthesis provide figures for the no crisis scenario.

2.2 Additional results

2.2.1 Additional debt

In this section we provide additional results concerning the impact of the crisis on debt. All results are normalised by the total asset of firms (pre-crisis). In Graph A2.1**,** we decompose the effect of public support between short-time work scheme (STW), STW and SMEs Solidarity Fund (STW & SF) and finally the combination of the different public policies: short-time work, solidarity fund, social contributions deferrals and relief. While the share of illiquid and of insolvent firms is dramatically reduced by public support, this is not the case of additional debt. This result is mainly driven by a relatively small number of large firms which increase their debt dramatically.[38]

Graph A2.1: Decomposition of the effect of public policies on the increase in debt/assets from March to Dec. 2020



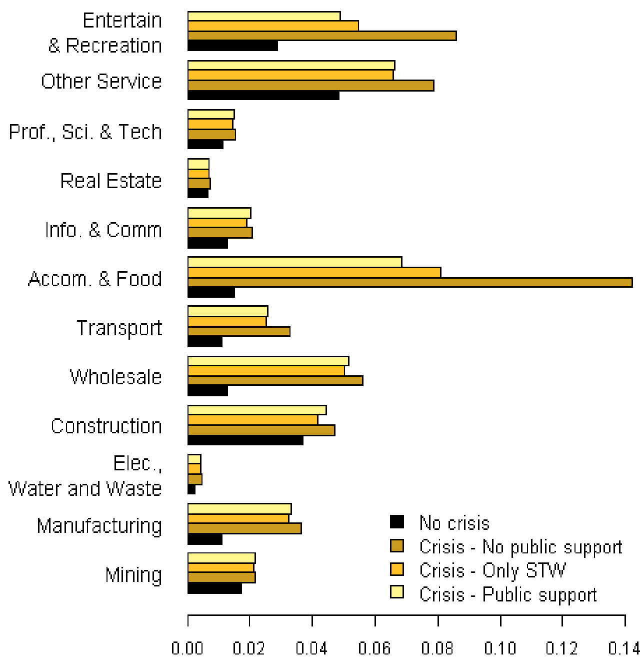
Note: increase in debt/assets in different scenarios, between March and December 2020. STW: Short-time work Scheme, SF: SMEs Solidarity Fund. Additional debt incorporates tax liabilities.

In Graph A2.2 we represent the heterogeneity of the impact according to respectively industry, size and age of firms. The increase in debt/assets concerns especially accommodation and food (+5.4pp) but also trade (+3.9pp) and manufacturing (+2.2pp). The ratio increases more for large and medium-large firms (+0.9pp for medium-large firms) than for microenterprises (+0.7pp).

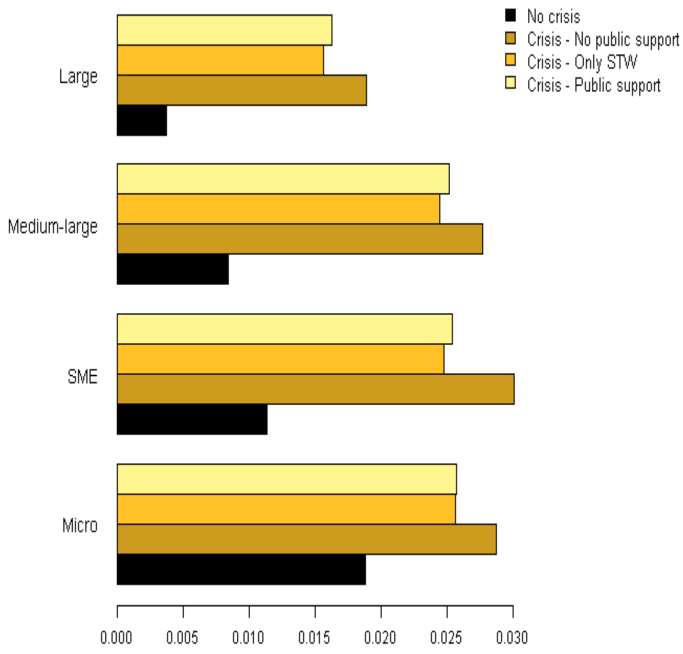
[38] The slight increase in the debt/asset with all the public support compared to the debt/asset with only short-time work scheme and the SMEs Solidarity Fund is due to tax deferrals and especially tax deferrals constituted by liquid firms.

Graph A2.2: Effect of the crisis on additional debt (% of assets)

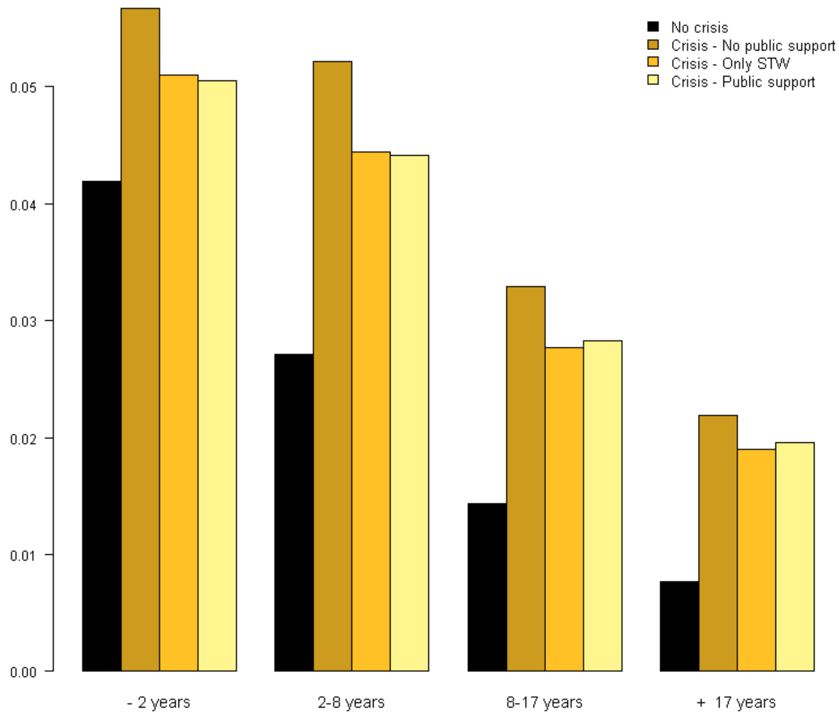
(a) Industry



(b) Size



(c) Age



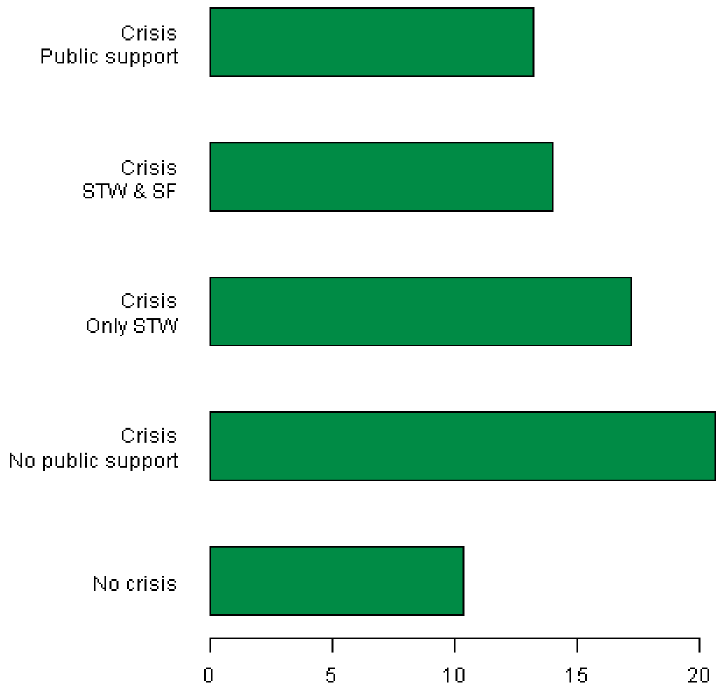
Note: Decomposition of the effect of the crisis by industry (a), size (b) and age (c). Results are computed in terms additional debt, normalised by total assets. STW: short-time work scheme. Additional debt incorporates tax liabilities.

2.2.2 Illiquid and insolvent firms

As explained in the paper, the closest proxy to business failure in theory should be insolvent firms which have a liquidity shortfall, labelled "newly illiquid and insolvent firms". We estimate that the covid crisis increases the level of newly illiquid and insolvent firms by 2.8 percentage points (from 10.4% without crisis to 13.2%).

In Graph A2.3 we decompose the effect of public support between short-time work scheme (STW), STW and SMEs Solidarity Fund (STW & SF) and finally the combination of the different public policies: short-time work, solidarity fund, social contributions deferrals and relief. Both short-time work and SMEs Solidarity Fund reduces the rate of new illiquid and insolvent firms by more than 3 percentage points. Tax deferrals and reliefs have a more limited impact.

Graph A2.3: Decomposition of the effect of public policies on the proportion of simultaneous illiquidity and insolvency, in percentage points



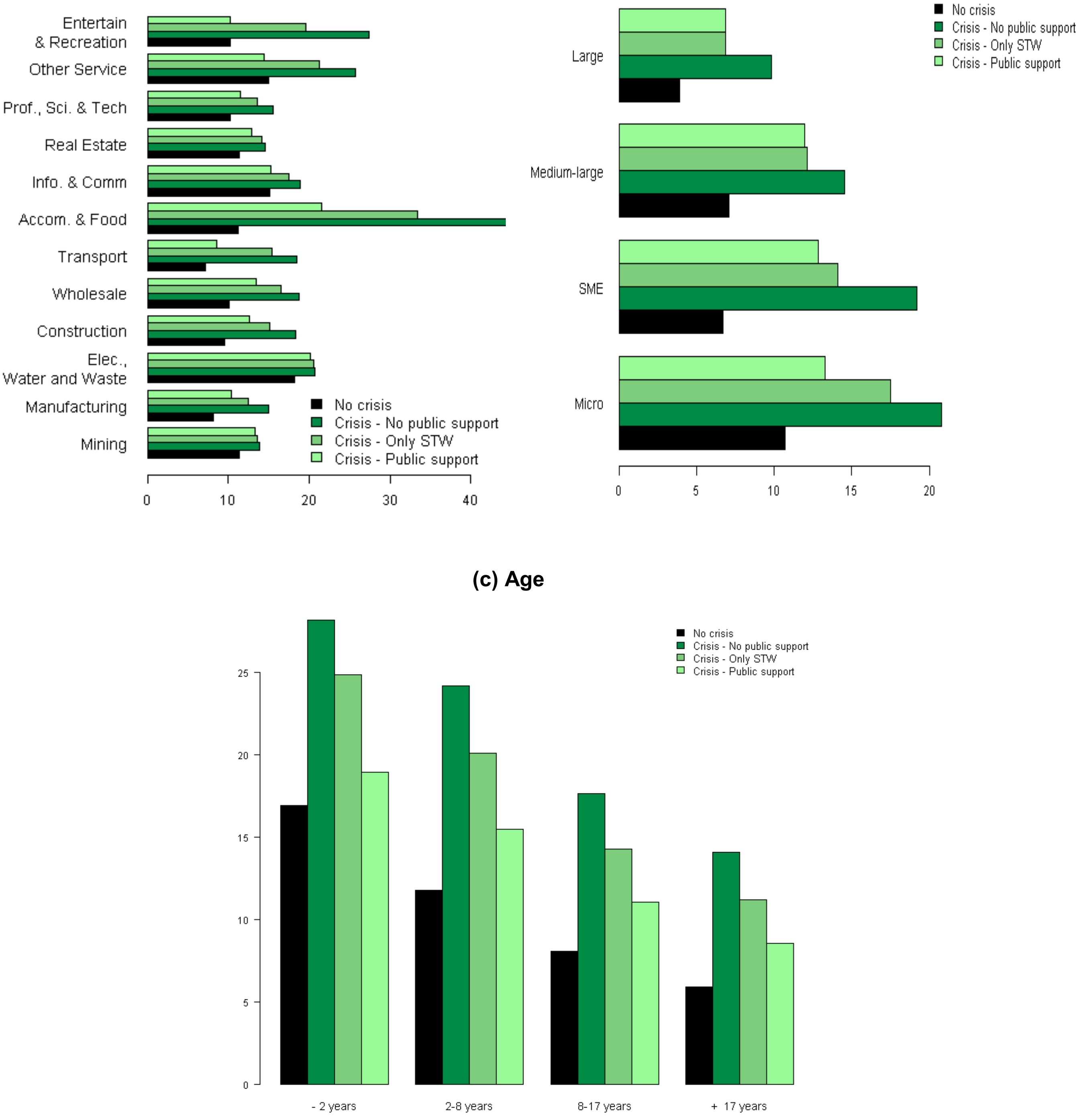
Note: Graphs of the decomposition of the effect of public support for newly illiquid and insolvent firms. Illiquidity is computed as net illiquidity. "Newly" means that we exclude firms are initially both illiquid and insolvent. Results are computed at the end of the simulation (Dec. 2020). Rates are computed as the cumulative number of newly illiquid and insolvent firms over the total number of firms. STW: Short-time work Scheme, SF: SMEs Solidarity Fund.

In Graph A2.4 we represent the heterogeneity of the impact according to respectively industry, size and age of firms. We see that micro firms (+2.5pp) are less impacted than medium-sized firms (+5.1pp) when public support is taken into account. Young firms are also slightly less impacted (+2pp for firms which are 2 years old or younger rather than +2.7pp for firms which are 17 years old are older).

Graph A2.4: Effect of the crisis on simultaneous illiquidity and insolvency

(a) Industry **(b) Size**

(c) Age



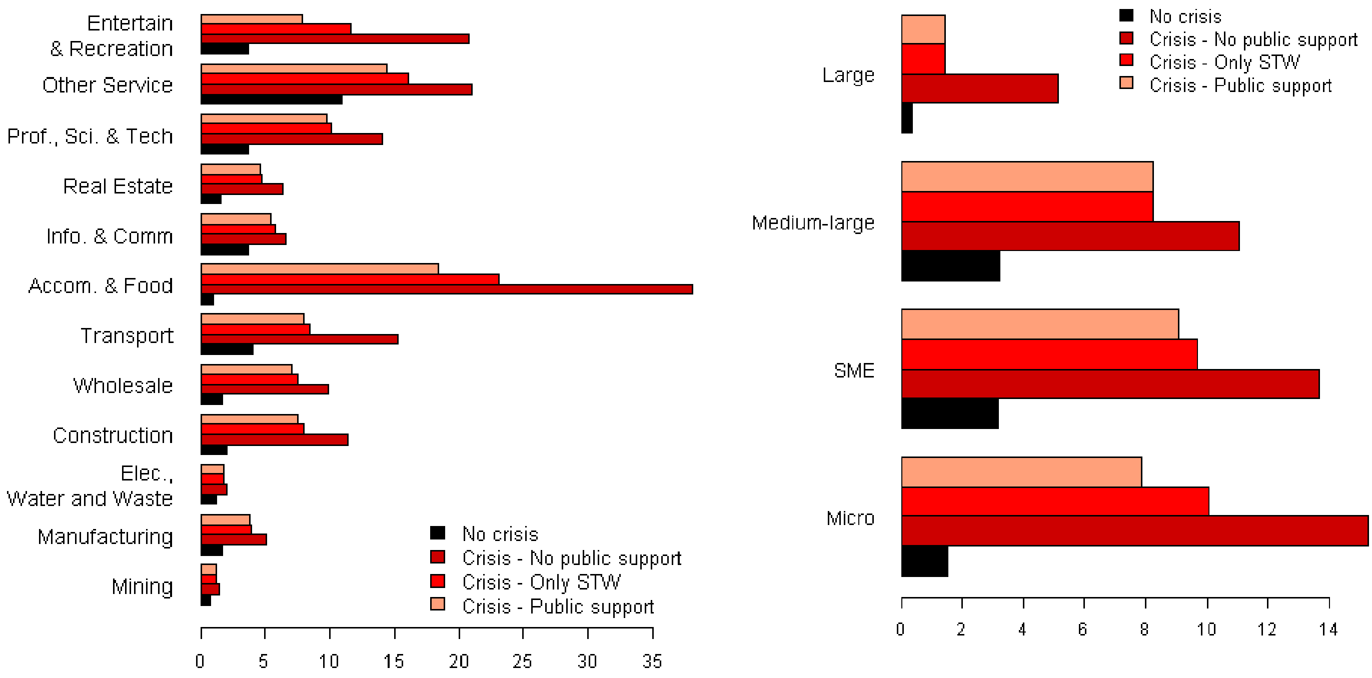
Note: Decomposition of the effect of the crisis by industry (a), size (b) and age (c). Results are computed in terms of newly simultaneous illiquidity and insolvency rate. Illiquidity is computed as net illiquidity. "Newly" means that we exclude firms that are initially both illiquid and insolvent. Rates are computed as the cumulative number of newly illiquid and insolvent firms over the total number of firms. STW: short-time work scheme.

2.2.3 Results in terms of employment

In this section we compute the heterogeneity of the shock based on number of employees concerned by insolvency rather than the number of insolvent firms (Graph A2.5).

Graph A2.5: Effect of the crisis on the share of employees in insolvent firms

(a) Industry **(b) Size**



Note: Decomposition of the effect of the crisis by industry (a) and size (b) for employees concerned about newly insolvency. “Newly” means that we exclude initially insolvent firms. For a given size or industry, rates are computed as the cumulative number of employees in newly insolvent firms over the total number of employees. STW: Short-time work Scheme.

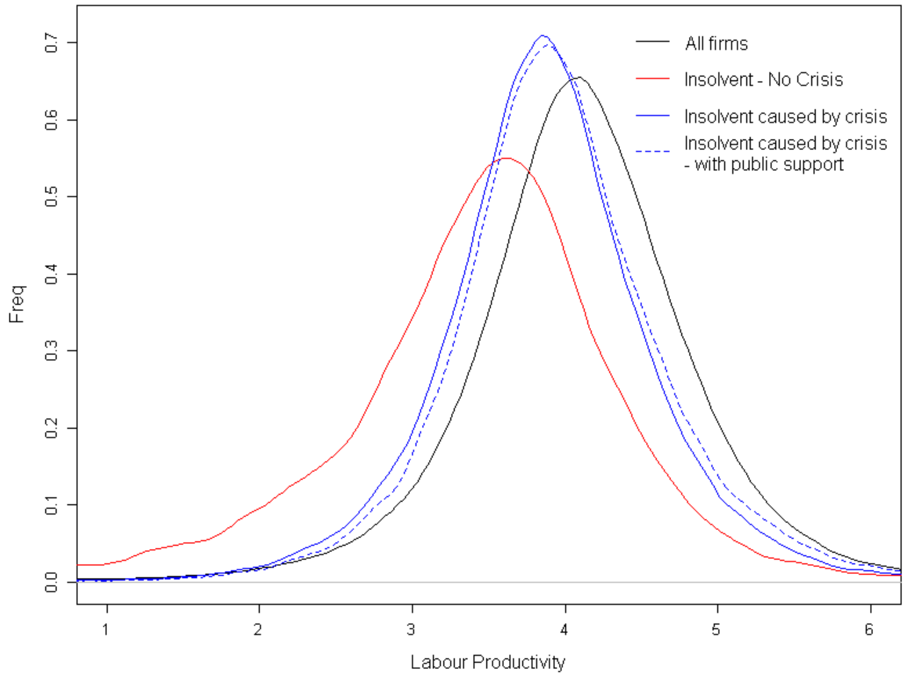
2.2.4 Productivity of vulnerable firms

In the paper, we outline different distributions of labour productivity, controlling for industry and size. Graph A2.6 presents uncorrected distributions of the different populations: all firms, firms becoming insolvent during 2020 without crisis and firms becoming insolvent in the year because of the crisis (with or without public support).

The results do not differ from the distributions presented in the paper:

- insolvent firms without any crisis are, as expected, firms with a low productivity;
- the crisis shifts the distribution of productivity of insolvent firms toward more efficient firms, and therefore insolvent firms due to the crisis have an higher labour productivity than the firms becoming insolvent without a crisis, but the productivity levels remain lower than in the whole economy;
- public support does not modify the shape of the distributions.

Graph A2.6: Distribution of labour productivity (uncorrected for sector size)

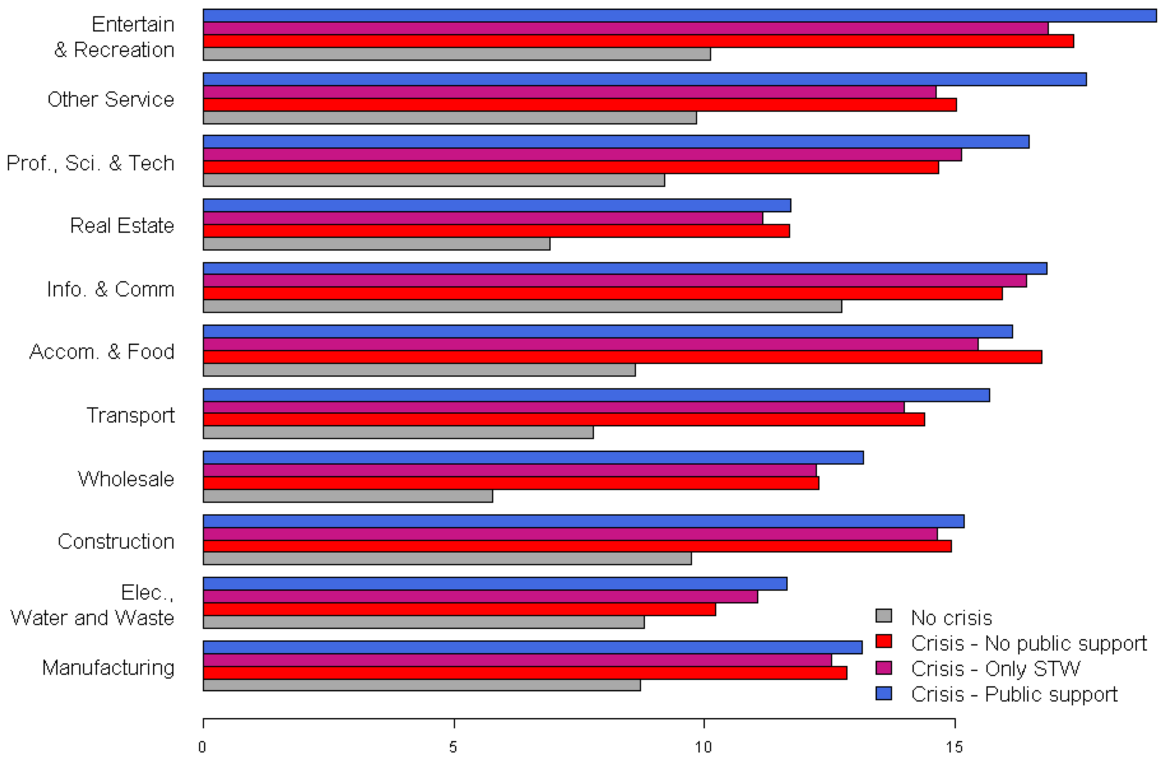


Note: Labour productivity (in log). The sample is restricted to firms with at least one employee. The black curve represents the distribution of labour productivity for the whole economy. The red curve represents the same distribution but for the subsample of firms becoming insolvent in the year without crisis. The full blue curve outlines the distribution for the subsample of firms becoming insolvent in the year without public policies. The dashed blue line outlines the same distribution but with the different public policies (short-time work, payroll tax deferral, tax relief, SMEs Solidarity Fund).

However, productivity varies strongly across industries. Moreover, the shock is also industry-specific (see Table A1.5). In Graph A2.7 we focus on the share of firms which are in top quartile of productivity among insolvent firms. For the vast majority of industries, the share of high productivity firms among newly insolvent firms increases with the crisis but such a rise is quite limited, except for particularly harmed industries such as accommodation and food, or entertainment and recreation where the share of insolvent firms among efficient firms skyrockets (respectively an increase of +76% and +85%).

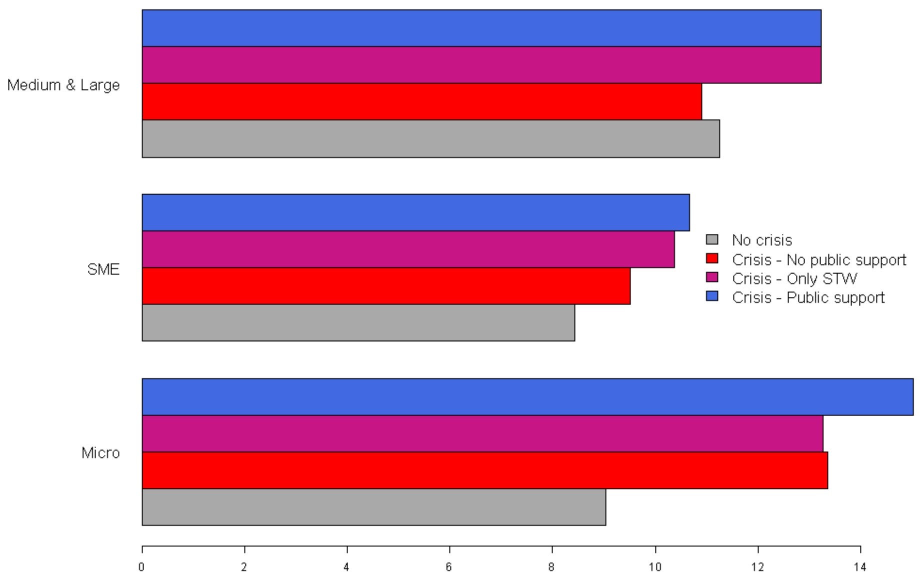
Since larger firms on average display higher labour productivity, it is interesting to focus on the top quartile of productivity depending on firms' size (Graph A2.8). Results remain robust: for a given size category, the share of high productivity firms increases with the crisis but the rise is quite limited.

Graph A2.7: Share firms in the top quartile of productivity among insolvent firms (by industry)



Note: Labour productivity (in log). The top quartile is computed at the industry level. The sample is restricted to firms with at least one employee. STW: Short-time work scheme.

Graph A2.8: Share firms in the top quartile of productivity among insolvent firms (by size)



Note: Labour productivity (in log). The sample is restricted to firms with at least one employee. The top quartile is computed at the size level. We group medium-large and large firms in order to respect the statistical confidentiality. STW: Short-time work scheme.

3. Fully simulated version

3.1 Description of the simulation

Before introducing observed data, the model was already simulated based on Fare 2018, on industry-level shocks and on assumptions concerning cost adjustment and the take-up of public support. The same filters were applied to the data, and thus the perimeter of the sample of firms in the fully simulated version is the same as in our main version.

The fully simulated version is also a monthly-based simulation which starts in March 2020 and ends in December 2020. Each period lasts one month and $t \in \{M_i, i = 3, \dots, 12\}$. The economic shocks s_{it} are revenue losses relative to the pre-crisis level, as measured at the industry level (NACE 17) by the Insee. It is worth noticing that until September (from M_3 to M_9), sector-level shocks are *observed* – from the National Accounts – while the last three months of the year (from M_{10} to M_{12}) are *predicted* shocks. The data used for these shocks dates from December 2020, and thus includes both the impact of the curfew and the second lockdown on the different industries during the three last months of the year.

For the short-time work scheme, we also make use of aggregate data. The one we use is the published estimation of payroll by Acoss (seasonally adjusted) at the sectoral level (NACE 38). There, data was available at the time of writing for the three first quarters and so we extended these estimations using our extension method presented in the article.

The SMEs solidarity fund is also simulated. With Fare, we can simulate the eligibility criteria to the fund at the firm level, except that we do not know the individual monthly revenue losses of firms, so we have to make assumptions on the uptake. Therefore, we proceed as follows: we identify eligible firms and compute the maximal amount they could have obtained based on their size, annual revenue and taxable profits, then we compute the distribution of the solidarity fund by industry, and each eligible firm in a given industry receives the amount of subsidy granted to its industry divided by the number of eligible firms in it. For December, as the observed total amount granted were not available yet, we used projections.

As for the SMEs solidarity fund, tax deferrals and tax reliefs are based on simplified hypotheses.[39] We simulate two waves of potential tax reliefs: the first lockdown concerns 4 months of employer's social contribution (ESR hereafter): 1 month without any shock (February) and 3 months shocked (March to May). Thanks to the short-time work scheme, the employer's social contribution from March to May is significantly shrunk, so is the tax relief (the firm does not have to pay the payroll taxes for employees out of work). The second lockdown concerns 2 months shocked. Finally, we simulate eligibility criteria based on industry and shock intensity. Formally, for eligible firms, $TR_i = ESR_{i0} + \sum_{t \in \{3,4,5,11,12\}} (1 - p_{it}) ESR_{i0}$.

We make simplified assumptions in order to simulate tax deferrals. First, we compute the maximal of tax deferral that firms could obtain. The reasoning is the same as for tax relief: thanks to the short-time work scheme, payroll taxes are reduced proportionally to the payroll shock p_{it}. Finally we make the assumption that the tax deferral are proportional to the activity shock: $TD_{it} = (1 - k \times s_{it})(1 - p_{it}) ESR_{i0}$. The parameter k is chosen for the estimated amount of tax deferral to be close to the observed one.

Table A3.1 provides the aggregate shocks with the fully simulated version, which are very close to the ones of the main version.

[39] It is worth noticing that wages in our model correspond to gross salaries plus employer's social contribution (payroll tax).

Table A3.1. Aggregate shocks used in the fully simulated version, year 2020

	March	April	May	June	July	August	Sept.	Oct.	Nov.	Dec.	Total
Revenue shock	−21.7%	−40.7%	−21.8%	−8.3%	−7.5%	−5.9%	−6.0%	−5.2%	−15.3%	−10.3%	−14.3%
Payroll shock	−9.6%	−30.3%	−19.0%	−9.1%	−4.4%	−3.5%	−2.3%	−3.9%	−11.9%	−7.9%	−10.2%
Solidarity fund (M€)	0.9	1.0	0.7	0.3	0.1	0.1	0.2	0.7	2.3	2.2	8.4
Tax relief and deferrals (Bn€)	3.9	2.6	2.0	0.7	0.6	0.4	0.4	0.4	2.2	2.1	15.4

Note: In the fully simulated version, the aggregate average revenue shock is −21.7% in March 2020 relative to March 2019-February 2020. The amounts of public policies do not correspond to the total amount granted by these policies, since our perimeter of firms is not exhaustive.

3.2 Comparison of the results

The results of the fully simulated version of the tool (Table A3.2) are very close to those obtained in the main simulation with observed data.

Table A3.2. Illiquidity, insolvency and debt in 2020 in the fully simulated version

	Number of firms becoming illiquid (% of total)	Number of firms becoming insolvent (% of total)	Number of firms becoming both insolvent and illiquid (% of total)	New debt (in €bn) compared to March 2020
Without crisis	283 995 (15.6%)	66 127 (3.6%)	189 367 (10.4%)	71.7
With crisis – without public support	27 217 (34.4%)	181 061 (9.9%)	339 965 (18.7%)	149.3
With crisis – with public support	396 992 (21.8%)	88 747 (4.9%)	212 696 (11.7%)	129.1

Note: In our simulation, 283 995 firms (15.6% of the total number of firms in the simulation) which were not illiquid in March 2020 would have been illiquid in 2020 in the counterfactual scenario (no crisis). With crisis, taking into account the public support, 396 992 firms would have been illiquid at some point in 2020. This number would have been 627 217 without public support. The number of firms that are both insolvent and illiquid is higher than the number of insolvent firms because some firms which were initially insolvent may become illiquid. Additional debt incorporates tax liabilities.

The fully simulated version showcases a lower impact of the covid crisis on vulnerable firms. While the main version predicted an increase of 8.4pp of the share of illiquid firms and 3.0pp for insolvent firms during the crisis (with public support) compared to the no crisis scenario, they only increase respectively by 6.2pp and 1.3pp in the fully simulated version. The number of insolvent and illiquid firms even decreases. Amounts of additional debt are also reduced: it increases by €57bn with this version, against €77Bn in the main one.

One can see that the revenue shock is slightly larger in this version and the payroll shock is slightly smaller. Thus, one could expect that the impact of covid would be higher in this version. However, the fully simulated version captures way less heterogeneity than the main one. Since shocks are sectoral, few firms will have very large impacts, as opposed to the main version. Thus, since illiquidity and insolvency are tail-end phenomena, it is not surprising to get less of them.

4. More on the impact of financial constraints on investment and R&D

4.1 Literature

4.1.1 Financial constraints and investment

Even though corporate investment depends strongly on demand factors – and on the anticipation of demand – supply factors also contribute. Here we study the impact of the deterioration of firms' balance sheets due to the crisis.

For a long time, the literature on corporate investment has stressed the role of Tobin's *q* (Tobin (1969), Lucas et Prescott (1971) and Hayashi (1982)) in the determination of investment: a firm invests until the increase in the firm's value following a marginal increase in capital invested is equal to the cost of such a marginal unit. However, even if the investment is profitable, the firm may not be able to fund it due to financial constraints.

For instance, in Myers and Majluf (1984), the bank does not have private information on the quality of the investment and will protect himself from the uncertainty by claiming a premium – such a premium might rise with the debt leverage and the absence of cash flows in the firm. In Myers (1977), when there is a risk of debt overhang, returns from the investment often benefit senior debt-holder rather than new investors or shareholders. In this way, a high Tobin's *q* might not be enough to raise new debt in order to finance the investment.

Empirically, the sensitivity of investment to cash-flows and debt leverage has been demonstrated for a large panel of countries at different periods and with different methodologies. In this way, economists used for instance dynamic models of investment and introduced linearly the cash flow and/or the debt leverage (see for instance Bond and Meghir (1994) on US data or more recently Crespi (2007) on Italian firms or Kalemli-Özcan *et al.* (2019) on a large panel of countries). Mairesse *et al.* (2000), Bond *et al.* (2005) or Mulier (2016) estimate dynamic error-correction models which enable them to take into account imbalances between actual and optimum levels of capital. Finally, following the pioneer work of Whited (1992) and Whited-Wu (2006), some papers present structural estimations of financial constraints based on Euler equations. Teurlai (2003) and more recently Guillou (2019) estimate such structural models on French data.

Table A4.1 synthesizes estimations from investment models available in the literature. For each paper (see Bibliography in the paper), we present the specification which is closest to our own modelling of investment. Column 1 of the table presents the results of our paper (Table 5 – specification (3)).

It is worth noticing that the comparison is difficult due to:

- Modelling of the accelerator. Papers: 1) sometimes add deeper autoregressive terms in the equation, 2) add an error-correction term, 3) model deeper lags of the sales growth and/or use Tobin's Q (considered as sales growth in our stylized table);
- Modelling of financial constraints. Cash flows are usually used in the equation but the choice in the lags (from *t* to *t-2*) differs. Debt is sometimes added but in a square transformation (Bond and Meghir (1994)). Other proxies for financial constraints can be added to the equation (index of financial constraints, interaction effects, etc.);
- Estimation method. Although the vast majority of the papers presented in Table A4.1 implement a GMM approach, using lags of the covariates as instruments, some papers prefer OLS regressions;
- Data. Except Kalemli-Özcan *et al.* (2019) and Nicolas (2019), papers presented in our stylized table are estimated with data before the 2008 crisis with sample of different sizes

on different countries. Moreover, Debt or *cash-flows* are sometimes defined differently. For instance, some papers (Alanis *et al.* (2018) for example) do not estimate directly the impact of leverage on investment but use instead an index of debt overhang (the debt leverage weighted by default risk for example). Finally, normalization can vary: for instance, some papers normalize directly by the asset rather than by a measure of capital computed through a permanent inventory method (PIM).

Those limits being said, we can outline some stylized facts about the expected magnitude of the coefficients in investment models:

- The short-term accelerator effects $(\mathrm{SalesGrowth}_{it}, \mathrm{SalesGrowth}_{it-1})$ have a sizeable, positive impact of the investment;
- Error-correction is significant and oscillates between -0.08 and -0.2. In other words, the gap between actual and targeted capital is reduced by a $8-20\%$ rate per year Our paper outlines a slower rate of adjustment (6%) which can be explained by the composition of the investment variable (for instance we include land investment which cannot be quickly adjusted).

Tableau A4.1. Investment models in the literature

Dependent Variable $InvestmentRatio_{i,t}$	French Treasury (2020)	Mulkay *et al.* (2000)	Mulier *et al.* (2016)	Kalemli-Özcan *et al.* (2019)	Alanis *et al.* (2018)	Bond et Meghir (1994)	Crespi et Scellato (2007)	Bond *et al.* (2005)	Nicolas (2019)
$InvestmentRatio_{i,t-1}$	0.097 (0.0321)	−0.048 (0.101)	−0.182 (0.028)	-	-	0.4857 (0.0406)	0.012 (.)	0.010 (0.060)	0.129 (0.013)
$ErrorCorrection_{i,t-2}$	−0.0567 (0.0246)	−0.109 (0.032)	−0.191 (0.020)	- -	- -	- -	- -	−0.084 (0.053)	-
$SalesGrowth_{i,t}$	0.186 (0.0730)	0.068 (0.108)	−0.075 (0.101)	- -	- -	- -	0.074 (.)	0.149 (0.044)	0.023 (0.003)
$SalesGrowth_{i,t-1}$	0.0606 (0.0231)	0.096 (0.093)	0.153 (0.031)	0.0628 (0.0012)	0,034 (.)	- -	0.084 (.)	0.122 (0.045)	- -
$CashFlowRatio_{i,t-1}$	0.0519 (0.0138)	0.115 (0.059)	0.057 (0.014)	0.1683 (0.0047)	0.079 (.)	0.1201 (0.0172)	0.514 (.)	0.147 (0.100)	0.034 (0.014)
$DebtRatio_{i,t-1}$	−0.0351 (0.0201)	- -	–-	−0.0952 (0.0028)	−0.048 (.)	−0.0416 (0.0200)	−0.258 (.)	- -	-
Fixed effects	Industry x Time	Time	Industry x Time	Industry x Country	Time	Time	Time	Time	Time
Only France	Yes	Yes	Yes	No	No	No	No	No	Yes
Data	Fare (Insee)	Suse (Insee) + R&D survey (MESRI)	Bureau Van Dijk	Bureau Van Dijk	Compustat	Compustat	Capitalia (Investment bank)	Compustat	Fiben (BdF)
N	537,197	5,832	404,366	3,722,889	54,667	5,941	6,210	666	22,608
Period	2009-2018	1982-1993	1996-2008	2000-2012	1979-2010	1974-1986	1998-2003	1985-1994	2012-2016
Article	Table 6	Table 13	Table 5	Table 4	Table 2	Table 2	Table 3	Table 4	Table 14

Source: Cf. Bibliography. This table presents stylized results from the literature concerning investment equations. Methodological limits of the benchmark are presented above. Results in parenthesis are standard errors, some papers only present t-statistics not reported here. Insee if the French National Institute for Statictics and Economic Studies, MESRI is the French Ministry for Higher Education, Research and Innovation, BdF is the Banque de France.

4.1.2 Financial constraints and R&D

Theoretically, the increase of financial constraints has an ambiguous effect on R&D spending. On the one hand, the effect of imperfect information and uncertainty mentioned for the tangible investment should ratchet up in the case of R&D because it is structurally risky and cannot be easily collateralised.[40] In this way, access to the credit market might be more difficult for R&D spending and firms should fund such spending internally. In this way, Brown *et al.* (2009) emphasize the fact that R&D is often funded by cash, especially for SMEs. Bates *et al.* (2009) go as far as saying that the general rise in corporate cash between 1980 and 2006 is – at least partly – driven by the increase of R&D both at the intensive and extensive margin.

However, R&D is an intangible investment based on human capital (for instance 80% of the R&D tax credit in France is devoted to wage expenses) which is quite sticky and therefore resilient to a shock. Moreover, R&D is a long-term investment with high adjustment costs. In this way, only firms with low *ex ante* financial constraints initiate R&D projects. Such a selection effect might explain why R&D spending or, at its intensive margin at least, quite resilient to shocks.

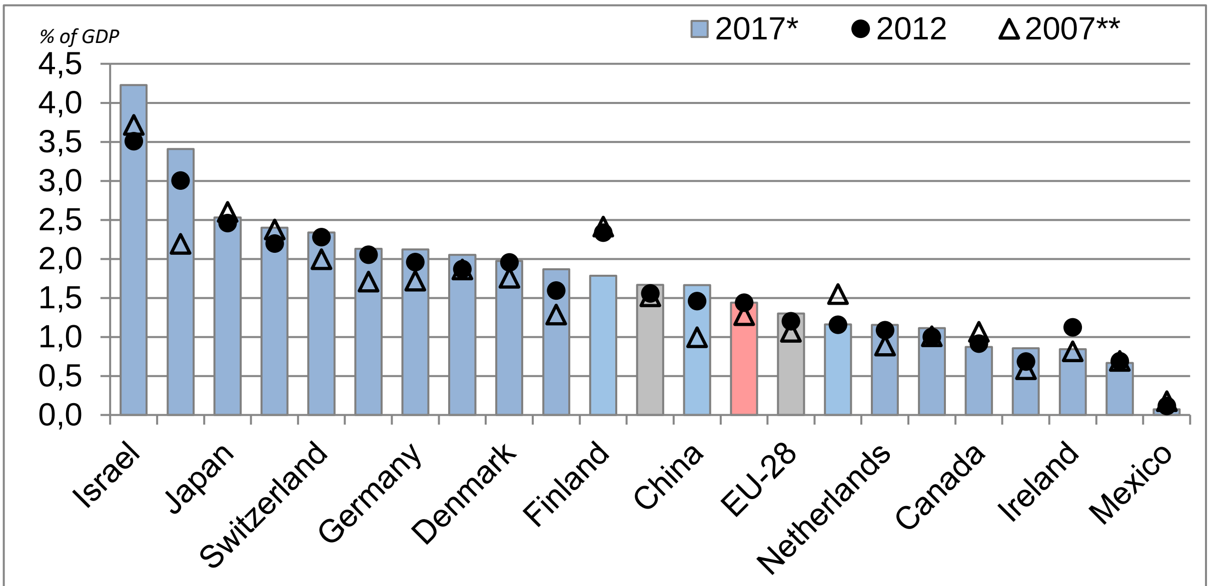
Empirically, the estimation of the sensitivity of R&D to financial constraints are much more ambiguous than for tangible investment. In this way, in their dynamic error-correction model Bond *et al.* (2005) and Mairesse *et al.* (2000) do not find any significant impact of financial constraints on R&D. Brown *et al.* (2012) and Cincera *et al.* (2015) outline the effect of cash flows but only after controlling for R&D smoothing thanks to cash and to the initialisation of new equity. Finally, Aghion *et al.* (2012) estimate a significant but low impact of a financial constraint index on R&D.

The Great Financial Crisis of 2008 exemplifies the resilience of R&D spending. From a macro point of view, GDP fell quicker and more intensively than corporate R&D. R&D tended to continue its growth in many countries between 2007 and 2012 (Graph A4.1). In France such a resilience underpinned particularly on the R&D Tax Credit reform of 2008. From the micro point of view, some studies suggest that innovative firms managed to smooth their R&D investment during the crisis of 2008 thanks to their accumulated cash (Chung (2017) on Korea). Recent literature has emphasized the resilience of innovation activities: Babina *et al.* (2020) outlines the strong resilience of innovation outputs to the Great Depression of 1929 especially thanks to efficient reallocation of inventors across firms. Gompers *et al.* (2020) survey venture capitalists during the Covid-19 crisis and also showcase that innovative firms promoted by VCs seldom report a strong negative shock on their activities and that VCs did not modify the allocation of their time between start-up management and looking for new investment.

However, many studies – as well as our paper – focus on the intensive margin, that is to say the effect of financial constraints for firms which already have a R&D activity. The literature outlines the fact that the extensive margin, that is to say the decision to implement a new R&D project, is far more sensitive to the financial constraints and to the crisis (see reduced-form estimation by Mancusi and Vezzulli (2010) or Savignac (2006) for France but also evidence from dynamic structural model in Peters *et al.* (2017) and Chen *et al.* (2020)). Finally, financial constraints triggered by economic downturns may not have a strong effect on the total stock of R&D in the economy - the intensive margin – but can reallocate R&D between high-impact risky projects towards less ambitious ones: Bernstein *et al.* (2020) for instance stress that since the beginning of the crisis, job seekers on the innovation market turned away from early-stage start-up and shifted their search towards larger firms.

[40] For large firms, patents can play the role of collateral to access the credit market, especially in a period of uncertainty (Hall *et al.* (2015)). The elasticity of R&D to financial constraints is therefore theoretically lower for large firms because: 1) they have solid balance sheet, 2) they can collateralise more easily their R&D.

Graph A4.1: Corporate R&D expenditure (in % of GDP)



* 2016 for Ireland.
** 2008 for Switzerland.
Source : OECD, PIST-2019-2 and MESRI-DGESIP/DGRI-SIES for France (Statistical Office of the French Ministry of Higher Education).

Methodological issues inherent to papers' comparison mentioned above are still relevant for R&D. Moreover, R&D data are scarce, especially for panel datasets, so the samples are relatively limited. Moreover, the estimation of an R&D equation partly underpins on a normalization variable called "knowledge stock", G_{it}, an abstract concept for which depreciation is unknown (and therefore calibrated). Some papers rather consider a log transformation $\ln(RD_{it})$ rather than $\frac{RD_{it}}{G_{it-1}}$.

Due to the large variance between estimations, there is no clear stylized facts from the literature (Table A4.2). Cash flows and debt overhang are not always significant or they become significant after adding covariates such as issuing new equity for listed firms or by estimating models on subsamples according to their age – financial constraints being more important for young small firms than for mature ones.

Table A4.2. R&D models in the literature

Dependent Variable $R\&DRatio_{i,t}$	French Treasury (2020)	Aghion *et al.* (2012)	Bond *et al.* (2005)	Cincera *et al.* (2015)	Mulkay *et al.* (2000)	Brown *et al.* (2012)	Brown *et al.* (2009)	Ogawa (2004)
$R\&DRatio_{i,t-1}$	−0.0254 (0.0224)	- -	−0.132 (0.060)	−0.157 (0.067)	−0.046 (0.126)	1.249 (0.142)	0.403 (0.130)	- -
$ErrorCorrection_{i,t-2}$	−0.210 (0.0682)	- -	−0.064 (0.039)	−0.104 (0.065)	−0,219 (0,062)	- -	- -	- -
$SalesGrowth_{i,t}$	−0.403 (0.308)	−0.018 (0.003)	0.424 (0.186)	−0.124 (0.065)	0.134 (0.075)	- -	- -	
$SalesGrowth_{i,t-1}$	0.173 (0.0548)	−0.014 (0.003)	0.138 (0.069)	0.085 (0.065)	0.079 (0.080)	−0.046 (0.013)	−0.013 (0.017)	- -
$CashFlowRatio_{i,t-1}$	−0.0114 (0.00626)	- -	−0.049 (0.184)	0.028 (0.009)	−0.044 (0.080)	−0.126 (0.117)	−0.004 (0.045)	- -
$DebtRatio_{i,t-1}$	0.00292 (0.00205)	- -	- -	- -	- -	- -	- -	−0.0452 (.)
Fixed effects	Industry x Time	Time	Time	Time	Time	Time	Industry x Time	Time
Only France	Yes	Yes	No	No	Yes	Yes	No	No
Data	Fare (Insee) + GECIR (MESRI)	Fiben (BdF)	Compustat	Compustat	Suse (Insee) + R&D (MESRI)	Compustat	Compustat	Compustat
N	61,272	73,237	666	1,675	2,028	356	12,248	1,641
Period	2009-2016	1993-2004	1985-1994	2004-2008	1982-1993	1995-2007	1990-2004	1991-2001
Article	Table 8	Table 5	Table 5	Table3	Table 15	Table 2	Table 2	Table 4

Source: Cf. Bibliography. This table presents stylized results from the literature concerning investment equations. Methodological limits of the benchmark are presented above. Results in parenthesis are standard errors, some papers only present t-statistics not reported here. Insee if the French National Institute for Statistics and Economic Studies, MESRI is the French Ministry for Higher Education, Research and Innovation, BdF is the Banque de France.

4.2 Descriptive statistics

Our investment sample contains 90,590 firms totalling 733,680 observations from the Fare dataset (2009-2018). We exclude firms which have less than 10 employees at least one year in the period. We also exclude outliers by removing extreme values that is to say observations in top/bottom 1% for the following variables: investment ratio, debt leverage, cash flow ratio, error correction and sales growth. We do not balance our panel in the main results.

The R&D sample contains 13,431 firms totalling 90,413 observations from 2009 to 2016. Because Fare dataset does not contain information about R&D, we use the R&D Tax credit dataset, constructed by the DGFiP and the Statistical Office of the French Ministry of Higher Education (SIES), which contains almost-exhaustive information about R&D spending at the firm level. Even though this dataset is used in the vast majority of panel studies with French data, it is worth noticing that Schweitzer (2019) warns about the potential under-estimation of R&D spending in this dataset compare to the R&D survey (not exhaustive) of the SIES. We also make the simplified hypothesis that a firm not in the R&D Tax Credit dataset has no R&D at all. Unlike for investment, we do not exclude from the analysis small firms but we do remove extreme values (top/bottom 1% for the following variables: investment ratio, R&D ratio, debt leverage, cash flow ratio, error correction and sales growth). Finally, as explained in the paper, the definition of industry for R&D firms is not straightforward: there is a significant gap between “administrative” industry stated in financial statements (Fare) and the “actual” industry of R&D investment. For instance, around 60% of R&D invested in (MN) − Prof., Sci. & Tech − will be in fact devoted to the French pharmaceutical industry. In order to correct this discrepancy between “reported industry” and “actual industry”, we use an external source and compile R&D surveys from 2004 to 2017 in order to cover all our sample (assuming that industry does not change through time).

In both samples, the combination of lags and differences in our estimation method restricts the analysis to firms observed at least 4 years.

We will define the following variables:

- *I*: net tangible investment of the firm (land, technical installation, materials, tools, transport,…);
- *K*: tangible capital of the firm computed by a permanent inventory method and ln(*K)* the logarithm;
- *R*: firm sales (*r* the logarithm);
- *RD:* R&D investment of the firm (both in capital and labour);
- *G*: stock of knowledge of the firm computed by a permanent inventory method and ln(G) the logarithm;
- *CF*: cash flows of the firm proxied by the operating surplus;
- *D*: total debt of the firm;
- δ^I: capital depreciation calibrated by industry capital consumption from National Accounts (Insee);
- δ^R: R&D depreciation calibrated as 15% as in Mairesse *et al.* (2000);
- A: net asset of the firm;
- *K'*: intangible and financial assets.

As explained in Bond *et al.* (2007), econometric models of investment do not directly use gross tangible asset as a measure of firms' capital because such a reported asset is correlated to reported depreciations which obey to tax allowances, creating measurement errors. In this way, a vast majority of papers compute individual series of tangible capital based on permanent inventory method. In our paper, we implement a simple transition capital equation using capital depreciation at the industry-level *j* (NACE 17 level):

$K_{it} = (1 - \delta_{jt}^{I})K_{it-1} + I_{it}$ and initialize tangible capital thanks to the net tangible asset of the firm in the first observation: $K_{i0} = A_{i0} - K'_{i0}$. However the lack of historical records for both A_{i0}, K'_{i0} is obviously a limit in the quality of our capital measurement.

Symmetrically, the stock of knowledge of the firm G_{it} is also unknown to the econometrician. Worst, no aggregated information on knowledge depreciation is available in national statistics. Following Mairesse *et al.* (2000) we calibrated $\delta^{R} = 0.15$ meaning that knowledge is depreciated at a uniform 15% rate per year. We use the same transition capital equation: $G_{it} = (1 - \delta_{jt}^{R})G_{it-1} + RD_{it}$ and initialize the stock of knowledge as in Cincera *et al.* (2015) by weighting the first R&D investment observed by the depreciation rate: $G_{i0} = {}^{R_{i0}}/_{\delta^{R}}$.

Table A4.3 provides descriptive (pooled) statistics for our estimation sample on investment. Because we exclude firms with less than 10 employees, the average number of employees in firms is 77 with a large variance. Each year, firms invest about 7% of their tangible capital. Firms' sales growth in the sample come close to 4% per year with a strong variance because 50% of firms have a growth smaller than 2%. Tangible capital depreciation is about 8% across time which is standard. Finally, our firms are characterized by an important indebtedness: the stock of debt represents on average 96% of the capital of the firm.

Tableau A4.3. Descriptive statistics on the estimation sample (investment)

	Mean	Median	Sd
Number of employees	77	21	1076
$InvestmentRatio_{i,t}$	0.07	0.03	0.08
$SalesGrowth_{i,t}$	0.04	0.02	0.15
$CashFlowRatio_{i,t}$	0.15	0.12	0.20
$DebtRatio_{i,t}$	0.96	0.81	0.63
$ErrorCorrection_{i,t-2}$	−0.96	−0.98	0.60
δ^{I}	0.08	0.08	0.02

Source: Fare 2009-2018 (Insee) and National Account 2009-2018.

Note: statistics are pooled across firms and time periods. *Sd* corresponds to standard deviation.

Table A4.4 provides descriptive (pooled) statistics for our estimation sample on R&D. Firms in the R&D sample are bigger than in the investment sample (171 employees on average) with a higher growth rate which can be expected because such a sample gathers innovative firms. Finally, innovative firms in the sample our more indebted but generate as operating surplus as in the investment sample (the cash flow rate is close to 14%).

Tableau A4.4 Descriptive statistics on the estimation sample (R&D)

	Mean	Median	Sd
Number of employees	171	35	1639
$RDRatio_{i,t}$	0.15	0.12	0.38
$InvestmentRatio_{i,t}$	0.07	0.04	0.11
$SalesGrowth_{i,t}$	0.08	0.04	0.28
$CashFlowRatio_{i,t}\ \frac{CF_{it}}{K_{it-1}}$	0.14	0.12	0.89
$CashFlowRatio_{i,t}\ \frac{CF_{it}}{G_{it-1}}$	2.41	0.50	6.64
$DebtRatio_{i,t}\ \frac{D_{it}}{K_{it-1}}$	1.30	0.84	2.52
$DebtRatio_{i,t}\ \frac{D_{it}}{G_{it-1}}$	15.4	4.27	36.0
$ErrorCorrection_{i,t-2}$ $\ln(K_{it-2}) - \ln(R_{it-2})$	−0.8	−0.8	0.7
$ErrorCorrection_{i,t-2}$ $\ln(G_{it-2}) - \ln(R_{it-2})$	−2.4	−2.4	1.67
δ^I	0.10	0.09	0.02
δ^R	0.15	0.15	0

Source: Fare 2009-2016 (Insee) and National Account 2009-2016 and GECIR 2009-2016 (MESRI-DGFiP).

Note: statistics are pooled across firms and time periods. *Sd* corresponds to standard deviation.

4.3 Robustness

We ran several robustness checks. Table A4.5 and Table A4.6 evaluate the sensitivity of our results to the specification for investment and R&D respectively. More precisely, we propose several specifications of the financial constraints $f(.)_{it-1}$ in both equation (8) and equation (9).

$$\frac{I_{it}}{K_{it-1}} = \beta_1 \frac{I_{it-1}}{K_{it-2}} + \beta_2 \Delta\ln(\mathrm{R_{it}}) + \beta_3 \Delta\ln(\mathrm{R_{it-1}}) + \rho(\ln(K_{it-2}) - \ln(R_{it-2})) + f(.)_{it-1} + \alpha_i + \mu_{jt} + \epsilon_{it} \qquad (8)$$

$$\frac{RD_{it}}{G_{it-1}} = \beta_1 \frac{RD_{it-1}}{G_{it-2}} + \beta_2 \Delta\ln(\mathrm{R_{it}}) + \beta_3 \Delta\ln(\mathrm{R_{it-1}}) + \rho(\ln(G_{it-2}) - \ln(R_{it-2})) + f(.)_{it-1} + \alpha_i + \mu_{jt} + \epsilon_{it} \qquad (9)$$

Column (1) of both tables reports the results of the paper (see Table 6 and Table 8**).** For investment regressions, due to computation time in GMM estimation, we provide robustness checks for the manufacturing industry only. For R&D equations we add industry x time fixed effects.

Column (2) replaces gross debt by net debt (debt less the liquidity). Results remain robust: debt has still no impact on R&D investment but it decreases the tangible investment.

Column (3) adds more lags in cash flows. For investment equations, it is worth noticing that while cash flows remain significant (at least for *t-1* and *t-2*), debt has no impact on investment anymore.

Column (4) combines both the debt ratio and its squared value. Such a specification does not alter our results and the squared debt ratio is non-significant.

Column (5) adds to the equation variation in cash holdings (in *t-1* and *t-2*). Such a specification is especially important for R&D (Brown *et al.* (2012): cash reserves are used by firms to smooth R&D investment and should have a negative correlation with R&D, once controlled by all other variables, because reductions in cash holdings mean releasing cash for R&D smoothing. Introducing variations in cash holdings should improve the quality of the estimation of the impact of financial constraints. Although variations in cash holdings are significant for tangible investment (and do not alter the results), it has no impact for R&D investment.

Tableau A4.5 Robustness checks (GMM specification − Investment)

Dependent Variable: $InvestmentRatio_{i,t}$	(1)	(2)	(3)	(4)	(5)
$InvestmentRatio_{i,t-1}$	0.0649^{*} (0.0352)	0.175^{**} (0.0741)	0.0646^{***} (0.0245)	0.0593^{*} (0.0320)	0.0967^{*} (0.0403)
$SalesGrowth_{i,t}$	0.223^{***} (0.0804)	0.358^{***} (0.104)	0.0528 (0.0567)	0.194^{*} (0.100)	0.113 (0.0915)
$SalesGrowth_{i,t-1}$	0.0736^{***} (0.0172)	0.105^{***} (0.0288)	0.0598^{***} (0.0116)	0.0768^{***} (0.0161)	0.0470^{**} (0.0233)
$ErrorCorrection_{it-2}$	-0.0731^{***} (0.0199)	-0.0846^{***} (0.0305)	-0.0540^{***} (0.0129)	-0.0765^{***} (0.0187)	-0.0486^{*} (0.0253)
$CashFlowRatio_{i,t}$			−0.0511 (0.0929)		
$CashFlowRatio_{i,t-1}$	0.0715^{***} (0.0161)	0.148^{***} (0.0285)	0.0660^{*} (0.0375)	0.0620^{***} (0.0206)	0.119^{***} (0.0258)
$CashFlowRatio_{i,t-2}$			0.0194^{***} (0.00707)		
$DebtRatio_{i,t-1}$	-0.0264^{*} (0.0148)	-0.0851^{***} (0.0173)	0.00665 (0.0131)	-0.0320^{*} (0.0178)	-0.0267^{*} (0.0152)
$(DebtRatio_{i,t-1})^2$				0.00434 (0.00552)	
$\frac{\Delta Cash\ Holding_{it}}{K_{it-1}}$					-0.175^{***} (0.0568)
$\frac{\Delta Cash\ Holding_{it-1}}{K_{it-2}}$					-0.0217^{**} (0.0106)
Fixed effect Time	Yes	Yes	Yes	Yes	Yes
N	138230	123800	117250	138230	138230
AR(1)	-26.28^{***}	-13.86^{***}	-38.09^{***}	-24.66^{***}	-22.39^{***}
AR(2)	−1.07	-1.68^{*}	-1.89^{*}	−1.29	−0.47
MMSC - AIC	−3.06	0.38	−8.39	−4.52	−8.41
#Instruments	18	20	23	20	21
Sargan Hansen test (p-value)	0,22	$0{,}04^{**}$	0,38	0,27	0,73

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Table presents GMM estimation on manufacturing firms. Values in parenthesis are robust standard errors. Sargan-Hansen test evaluates the validity of the exogeneity of instruments (H_0: overidentifying restrictions are valid). Arellano-Bond tests (AR(1), AR(2)) for absence of higher-order serial correlation are also provided (H_0: zero autocorrelation in the first-differenciated errors at order k). We report the number of instruments (#Instruments) but also the Andrews and Lu (2001) Akaike model and moment selection criteria (MMSC-AIC). All models are Diff-GMM estimations. All specification includes time fixed effects. Differences in number of observations *N* are due to outliers (see Appendix 3.2 for explanations) and negative debt values for specification (2) and deeper lags on cash flows for specification (3).

Tableau A4.6 Robustness checks (GMM specification − R&D)

Dependent Variable: $RDRatio_{i,t}$	(1)	(2)	(3)	(4)	(5)
$RDRatio_{i,t-1}$	−0.0254 (0.0224)	−0.0257 (0.0199)	−0.116 (0.181)	−0.0255 (0.0215)	−0.247 (0.513)
$SalesGrowth_{i,t}$	−0.403 (0.308)	−0.528* (0.276)	−0.195 (0.800)	−0.564 (0.381)	−0.339 (0.477)
$SalesGrowth_{i,t-1}$	0.173*** (0.0548)	0.155*** (0.0470)	0.227 (0.166)	0.137** (0.0643)	0.225 (0.172)
$ErrorCorrection_{it-2}$	−0.210*** (0.0682)	−0.191*** (0.0579)	−0.293 (0.240)	−0.167** (0.0783)	−0.288 (0.232)
$CashFlowRatio_{i,t}$			−0.0107 (0.0367)		
$CashFlowRatio_{i,t-1}$	−0.0114* (0.00626)	−0.0120** (0.00599)	−0.00656 (0.0334)	−0.0116* (0.00610)	−0.0103 (0.00675)
$CashFlowRatio_{i,t-2}$			-0.00175 (0.0152)		
$DebtRatio_{i,t-1}$	0.00292 (0.00205)	0.00620 (0.00380)	0.00362 (0.00250)	0.00598 (0.00500)	0.00459 (0.00384)
$(DebtRatio_{i,t-1})^2$				−0.000 (0.000)	
$\frac{\Delta Cash\ Holding_{it}}{G_{it-1}}$					0.0020 (0.014)
$\frac{\Delta Cash\ Holding_{it-1}}{G_{it-2}}$					−0.000 (0.003)
Fixed effect Industry x Time	Yes	Yes	Yes	Yes	Yes
N	61272	61272	47885	61272	61052
AR(1)	−3.58***	−4.49***	−2.27**	−2.17**	−3.14***
AR(2)	−0.22	−0.13	−0.39	−0.89	−0.35
MMSC - AIC	−6.99	−6.47	−5.33	−5.37	−5.54
#Instruments	27	27	29	28	29
Sargan Hansen test (p-value)	0,80	0,83	0,60	0,91	0,78

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Table presents GMM estimation for all firms. Values in parenthesis are robust standard errors. Sargan-Hansen test evaluates the validity of the exogeneity of instruments (H_0: overidentifying restrictions are valid). Arellano-Bond tests (AR(1), AR(2)) for absence of higher-order serial correlation are also provided (H_0: zero autocorrelation in the first-differenciated errors at order k). We report the number of instruments (#Instruments) but also the Andrews and Lu (2001) Akaike model and moment selection criteria (MMSC-AIC). All models are Diff-GMM estimations. All specification includes time and industry fixed effects. Differences in number of observations *N* are due deeper lags on cash flows for specification (3) and missing values on liquidity holding for equation (5).

Finally in Table A4.7 we present robustness tests for investment regressions concerning estimation methods and sample selection. As explained above, due to computation time in GMM estimation, we have performed robustness checks for the manufacturing industry only and Column (1) presents the results of the paper.

Column (2) uses System-GMM rather than Diff-GMM adding as instruments the lagged difference of covariates. Therefore, $\Delta\frac{I_{it-3}}{K_{it-4}}, \Delta\Delta r_{it-3}, \Delta\frac{CF_{it-3}}{K_{it-4}}, \Delta\frac{D_{it-3}}{K_{it-4}}$ are also valid instruments of the equation. Even if Sargan-Hansen test may cast doubt on the validity of our instruments, the coefficients appear robust to the change in the estimation method.

Column (3) computes simple Within estimators of the equation (1) with OLS. Even though both autoregressive and debt leverage coefficients change in magnitude, all coefficients remain significant with the expected sign.

Finally, Columns (4), (5) and (6) replicate the same robustness checks (Diff-GMM, Sys-GMM and OLS regressions) but after balancing our dataset. Again, coefficients appear robust to balancing.

Tableau A4.7 Robustness checks (Econometric methodology Investment)

Dependent Variable: $InvestmentRatio_{i,t}$	Diff-GMM Unbalanced (1)	Sys-GMM Unbalanced (2)	OLS Unbalanced (3)	Diff-GMM Balanced (4)	Sys-GMM Balanced (5)	OLS Balanced (6)
$InvestmentRatio_{i,t-1}$	0.0649* (0.0352)	0.127*** (0.00907)	−0.0943*** (0.0045)	0.0465* (0.0271)	0.137*** (0.0100)	−0.061*** (0.00473)
$SalesGrowth_{i,t}$	0.223*** (0.0804)	0.0702* (0.0422)	0.100*** (0.00193)	0.188*** (0.0690)	0.0777* (0.0464)	0.0996*** 0.00229)
$SalesGrowth_{i,t-1}$	0.0736*** (0.0172)	0.0383*** (0.00744)	0.120*** (0.0025)	0.0852*** (0.0138)	0.0417*** (0.00824)	0.115*** (0.00252)
$ErrorCorrection_{i,t-2}$	−0.0731*** (0.0199)	−0.0322*** (0.00846)	−0.165*** (0. 00268)	−0.0866*** (0.0162)	−0.0355*** (0.00930)	−0.158*** (0.000715)
$CasfFlowRatio_{i,t-1}$	0.0715*** (0.0161)	0.0524*** (0.00716)	0.0240*** (0.0027)	0.0462*** (0.0147)	0.0458*** (0.00829)	0.0240*** (0.0032)
$DebtRatio_{i,t-1}$	−0.0264* (0.0148)	−0.0225*** (0.00409)	−0.0131*** (0.00138)	−0.0114 (0.0141)	−0.0261*** (0.00462)	−0.0127*** (0.00156)
Fixed effect Time	Yes	Yes	Yes	Yes	Yes	Yes
N	138230	138230	138230	104752	104752	104752
R^2	-	-	0.09	-	-	0.10
AR(1)	−28.28**	−47.61***	-	−27.71***	−44.37***	-
AR(2)	−1.07	−0.14	-	−1.53	−0.27	-
MMSC - AIC	−3.05	−2.80	-	−1.14	0.15	-
#Instruments	18	24	-	22	24	-
Sargan Hansen test (p-value)	0,22	0,07*	-	0,05*	0,03**	-

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Table presents GMM estimation for all firms. Values in parenthesis are robust standard errors. Sargan-Hansen test evaluates the validity of the exogeneity of instruments (H_0: overidentifying restrictions are valid). Arellano-Bond tests (AR(1), AR(2)) for absence of higher-order serial correlation are also provided (H_0: zero autocorrelation in the first-differenciated errors at order k). We report the number of instruments (#Instruments) but also the Andrews and Lu (2001) Akaike model and moment selection criteria (MMSC-AIC). Except OLS estimations, all models are Diff-GMM estimations. All specification includes time fixed effects. Differences in number of observations *N* for specifications (4), (5), (6) are caused by the balancing of the panel dataset.