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The Sectoral Nature of the COVID-19 Shock: A Novel Approach to Quantifying its Economic Impact

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Abstract

This paper assesses corporate financial distress in terms of liquidity and risk of insolvency due to the COVID-19 pandemic. We develop a novel multivariate approach to obtain monthly data on sectoral turnover, exploiting real time data to capture the atypical character of industry-specific disturbances. By combining these data with corporate financial statements, we evaluate the financial impact of the pandemic on the corporate sector in the EU. Our definition of risk of insolvency takes into account not only the equity position of firms, but also risks relating to overindebtedness. The analysis attempts to control for firms that were financially vulnerable already before the pandemic, thus being prone to become at risk of insolvency also in absence of the COVID-19 turmoil. For the EU as a whole, 25% of firms exhausted their liquidity buffers by the end of 2021 (a practical cut-off date of the analysis, not an assumed end of the pandemic). Therefore, such firms faced higher liquidity needs by the end of 2021, some of which were likely met with external support, but in any case were a challenge for sound firm performance. Further, 10% of pre-shock viable firms appear to have shifted into insolvency status as a result of the COVID-19 crisis. These results appear more prominent in sectors that were affected more by the pandemic and the associated containment measures.

JEL Classification: D40, E31, L51.

Keywords: COVID-19, pandemics, nowcasting, output shocks, sectoral impact, NFC, losses, distress.

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1. INTRODUCTION

Global economic activity has been disrupted by successive waves of the COVID-19 pandemic and the associated containment measures, even though emergency support rolled out by numerous governments contributed to dampen their adverse effects. This paper aims at assessing corporate financial distress in terms of liquidity and risk of insolvency due to the pandemic. Compared to the existing literature, this paper enhances the understanding of the pandemic's impact on the non-financial corporate sector in two ways. First, the assessment of the impact of COVID-19 on firms' revenues is based on the results of a multivariate nowcasting model, which uses high-frequency data to quantify monthly shocks to turnover at the country-industry level. Second, the notion of the risk of insolvency adopted in this paper takes into account not only the equity position of firms but also the risks related to high leverage. Further, an effort is made to control for firms that were financially vulnerable already before the pandemic and could have been at risk of insolvency even in the absence of COVID-19.

The pandemic is an exogenous shock with distinctive features, which makes it difficult to explain and forecast economic developments based on previously documented patterns, for example those observed during financial crises.[1] *First*, as argued in Gourinchas et al. (2020) and Guerrieri et al. (2020), supply and demand features of the shock are intertwined and co-determined by a mixture of centrally enforced constraints and voluntary behavioural changes.[2] To identify whether such constraints and behavioural changes are transitory requires novel data with variation in policy regimes, across countries or over time. *Second*, the protracted nature of the pandemic has deepened the heterogeneity of its impact among industries. Already in April 2020, Dingel and Neiman (2020) put forward the link between physical proximity at the work floor and the expected severity of disruption in industrial production and employment. As the COVID-19 shock became more protracted, industries diverged in their sensitivity to the shock. *Third*, the dynamics of the pandemic itself have a very different timeline in various countries. *Finally*, the reaction of governments, firms, and consumers to the pandemic has been evolving, so the adjustment capacity of the economy depends on the country in question and the stage of the pandemic.

The above-mentioned features of the COVID-19 shock make the case for an approach grounded in real time data to model the impact of the pandemic on industrial activity. As such granular and high-frequency data on sectoral activity are not available in a timely manner, we propose an empirical model to fill the gaps in the data. To the best of our knowledge, this paper is the first to explain monthly shocks to industrial turnover in the EU Member States by leveraging the various data sources that track the diffusion of the pandemic, the government response to it, the resulting mobility patterns, as well as the impact of the pandemic on business and consumer confidence.[3,4] This is done empirically by modelling industrial turnover during 2020 and early 2021 as a function of macroeconomic variables, supply and demand linkages, a broad range of pandemic-specific factors, as well as survey data on business and consumer sentiment. We illustrate the strong predictive power of the empirical model for the majority of industries, not only over the initial wave of the pandemic and the subsequent rebound, but also its ability to capture the dampened impact of subsequent surges in

[1] The intrinsic surprise elements in the unfolding of the pandemic, combined with the imperfectly anticipated behavioural response to the easing and reinstatement of restrictions, led to an increase in the variance of forecast errors: e.g. the reduction in EU GDP was 6.2% in 2020, while forecasts anticipated a reduction of 7.4% (EC Spring Forecast 2020). Similarly, initial forecasts on the speed of recovery in 2021 turned out to be too optimistic. See Foroni et al. (2020) for a more formal discussion.

[2] Durante et al. (2021) document significant effects of civic norms on the speed of diffusion of COVID-19.

[3] For an overview of recent developments in the use of real time data in macro forecasting, see Giannone et al. (2017, 2013).

[4] Members of the European Union are likely to experience strong spillover effects from the COVID-19 shock, and to coordinate on the implementation of containment measures and support policies, motivating the focus of this paper. The availability of harmonised monthly data series on industrial turnover for most of these countries facilitates the task.

infection rates on economic activity, underpinning the adjustment capacity of the economy. The good fit of the model gives us confidence that the estimated coefficients can be used to fill data gaps and to predict the path of monthly industrial turnover until the end of 2021 at the NACE 2-digit level in manufacturing and at the NACE 1-digit level in services. The choice of end-2021 is motivated by the need of a practical cut-off date rather than an assumption or assertion of a definitive date of the pandemic

We illustrate the relevance of adopting an industry-specific approach in modelling the impact of the pandemic on economic activity with help of an application that has become widespread in the literature. Specifically, we feed the obtained pattern of monthly industrial turnover into the profit-generating process derived from financial statements at the firm level to obtain the distribution of profitability shocks in each country and industry over 2020-2021. Consequently, we assess the depth and persistence of liquidity distress in the European non-financial corporate sector and quantify the cumulative liquidity needs. Further, we assess the extent to which the sequence of adverse profitability shocks at the industry-country level translated into magnified financial vulnerability, while broadening the notion of financial vulnerability to encompass the risk of zombification.

The main results of this paper are threefold. As regards the impact of the pandemic on industrial activity, we document significant heterogeneity in the industry-specific sensitivity to the initial shock, within manufacturing as well as within services. While this finding is in line with previous studies, our contribution consists in documenting these patterns at a more disaggregated and high-frequency level, while covering a longer time horizon. Specifically, we find that the cumulative shock to turnover over 2020-2021 varies between -34% in the accommodation and food services sector to +3% in the manufacturing of computers and electronics sector.

Additionally, we document that industries differ in their ability to adjust to subsequent surges in infection rates, leading to increasing divergence in the industry-specific trajectories over the second half of 2020 and 2021. A salient example of this divergence is provided by the accommodation and food services industry in comparison to the industry that manufactures transport equipment. Both industries suffered a substantial adverse impact on turnover of the initial outbreak of COVID-19. Yet, while the accommodation and food services industry rebounded less and remained highly sensitive to new waves of the pandemic, the transport equipment industry rebounded strongly without subsequent downturns, resulting in a cumulative shock to output of -5% over 2020-2021. Our empirical model also enables us to evaluate the potential for rebound in the recovery phase, e.g. relatively weak in the wholesale and retail industry as well as in the manufacturing of food production, but relatively strong in several other manufacturing industries.

As regards the impact of the pandemic on liquidity and solvency of the corporate sector, we find that between 25 and 30% of European firms fully exhaust their liquidity buffers and therefore develop higher liquidity needs due to the pandemic. Further, we pick up a 10-percentage point increase in the fraction of European firms that appear at risk of insolvency by the end of 2021, and we document that this magnification in financial vulnerability is linked to the cumulative adverse revenue shock experienced over 2020-2021. We document strong heterogeneity in the extent of liquidity distress and of the increase in the risk of insolvency among countries and industries. The bulk of these differences is attributable to the magnitude and persistence of the shock on turnover. We conclude that reliance on real time data in the modelling of shocks on industrial activity is critical for providing detailed evidence on the impact of the pandemic on financial vulnerability of the corporate sector, as well as for the design and adjustment of policy support in the recovery phase.

This paper feeds into the rapidly expanding literature that evaluates the impact of the pandemic on the liquidity and solvency of the non-financial corporate sector, underpins the dampening effect of support policies, and quantifies the risk of default attributable to the pandemic, together with employment at risk. This line of research uses a historical snapshot of corporate financial statements – most frequently those from 2018 – to estimate the effect of a particular sequence of adverse shocks to turnover on corporate profitability, equity, and liquidity. In terms of the methodology, most studies – including this paper – follow Schivardi and Romano (2020) in adopting a simple accounting approach whereby

adverse shocks on revenue, common to all firms in a sector, are combined with the cost structure specific to the firm to deliver a distribution of profitability shocks in a given country and industry.[5] Studies that adopt this accounting approach use historical estimates of cost elasticities to fluctuations in revenues, scaled down by *ad hoc* short-term adjustment factors, to calibrate imperfect short-term operational flexibility. Gourinchas et al. (2020) clothe this approach in theory by explicitly modelling the cost minimising response of firms to the COVID-19 shock, parameterised as a combination of sector-specific and time-varying supply and demand shocks. In contrast to the accounting approach in the other studies, the modelling approach in Gourinchas et al. (2020) *de facto* assumes relatively high substitutability of labour and material inputs and allows firms to operate immediately under nearly full operational flexibility.

The specific contribution of this paper consists in striking a better balance between the need to carry out a multi-country evaluation of the pandemic's effects on industrial activity in a strongly integrated region and the difficulty of capturing time, industry, and country variation in turnover with sufficient granularity.[6] First, the explicit modelling of industry-specific shocks allows extending the horizon to the end of 2021 while most studies focus on 2020. In addition, significant effort is dedicated to improving firm population coverage, by leveraging the full set of information in financial statements to fill in data gaps, thereby increasing to 23 the number of EU countries included in the analysis.[7] Last, but not least, our paper also connects firm characteristics, such as ex-ante financial vulnerability, to the predictions on the magnitude and duration of liquidity distress. Unlike similar recent studies, our notion of financial vulnerability is not limited to negative equity but takes into account financial leverage and the ability of firms to service their debt obligations. This characterisation can be useful for identifying intrinsically viable firms and for formulating support policies that aim to preserve businesses, which have the potential to contribute to future growth and welfare.

Below is a more detailed outline of our empirical strategy, which consists of three different steps. In the *first step*, we develop an empirical model to explain the observed monthly variation in industrial turnover in 23 countries of the European Union.[8] At the time of writing, Eurostat Short-term Business Statistics (STS) series provided information on observed changes in turnover at the country-industry level for each month between January 2020 and April 2021. The explanatory variables include a rich set of country and/or industry-specific variables – some available at daily and some at monthly frequency – that jointly capture supply and demand determinants of the shock. These explanatory variables include macroeconomic variables such as quarterly GDP, information on the evolution of the pandemic in the country (e.g. basic reproduction number, R-naught), government containment measures, public support measures, proxies of behavioural change (e.g. mobility), industry-specific sentiment indicators (e.g. business confidence), and indicators of exposure to foreign developments through backward and forward supply chain linkages. The estimated coefficients on the variables of interest are used to impute missing data points in 2020 and in the first months of 2021.

[5] This paper updates and refines the preliminary results published in European Commission (2020). A selection of other papers that use the Schivardi and Romano (2020) accounting approach includes: Banerjee et al. (2020), Bodnár et al. (2020), Carletti et al. (2020), Connell Garcia and Ho (2020), Demmou et al. (2021), De Vito and Gomez (2020), Ebeke et al. (2021).

[6] Country-specific studies such as Schivardi and Romano (2020) or Connell Garcia and Ho (2020) rely on granular quantifications of industry-specific shocks while multi-country studies such as Bodnár et al. (2020) or Demmou et al. (2021) tend to combine macro forecasts with information on industry characteristics to deduce industry-specific shocks.

[7] In the raw data, about 50% of observations lack information on some component of costs. Extensive data preparation is required to include more than a handful of countries in the analysis (see section 3.2 for details). Yet, insufficient data quality in the ORBIS database impedes us from including Cyprus, Malta, Ireland, and the Netherlands. Other studies either focus on one country, or cover the biggest euro area countries, or, in rare cases, include 10 to 15 EU Member States in the analysis.

[8] For data availability reasons, Cyprus and Malta are excluded from the analysis. As the quality of the ORBIS data for Ireland and the Netherlands is poor, these countries are excluded as well.

In the *second step*, we produce a nowcast and prediction of monthly industrial turnover until the end of 2021 by combining the estimated coefficients with available information on the explanatory variables in 2021, and their projected values until the end of the year. These projections help to shed light on the differences among countries in the dynamics of the pandemic and of its differential effects on the industries. In particular, there is variation in the speed of the rebound in industrial activity as restrictions are loosened. While monthly turnover figures are published with a lag of several months, information for the explanatory variables is available almost in real time. As such, we can rely on the information on workplace mobility, containment measures currently in place etc., along with the estimated coefficients, to obtain a prediction for the evolution of turnover in each country-industry for the months yet to be covered by official statistics. Moreover, projections for the values of the regressors (e.g. a gradual return to the workplace and the lifting of containment measures) provide a first basis for predicting the evolution of industrial turnover in the months still to come.

In the *third step*, we feed the series of monthly turnover shocks, together with information on time-varying factor-specific cost elasticities, into corporate financial statements, to obtain the distribution of profitability shocks in each month of 2020 and 2021.[9] Public support incorporated in the analysis includes tax deferrals, loan moratoria, as well as labour cost reductions linked to the implementation of short-time work schemes. By combining these profitability shocks with information on pre-existing liquid assets, we deduce the cumulative liquidity needs in the EU non-financial corporate sector. We quantify the magnification of the insolvency risk and the associated number of jobs at risk by combining information on liquidity-constrained firms with their pre-crisis likelihood of default and post-crisis solvency status.[10]

The paper proceeds as follows. Section 2 describes the empirical model used to obtain the series of monthly shocks to turnover. Section 3 describes the methodology used to obtain the set of firm-level profitability shocks. Section 4 presents the results on the projected evolution of industrial turnover, the quantification of the associated liquidity shortfall and increased risk of insolvency by the end of 2021. Section 5 concludes and discusses how further work could build upon this methodology to evaluate the effectiveness of public support programs and to improve policy in the recovery phase.

2. AN EMPIRICAL MODEL TO EXPLAIN FLUCTUATIONS IN INDUSTRIAL TURNOVER

This section describes the empirical model used to obtain the pattern of monthly turnover in each industry and country of the European Union. The methodology comprises three steps. First, we combine Eurostat data on monthly turnover in each industry until April 2021 with multiple data sources that capture the state of the pandemic, the associated containment measures, business and

[9] We are indebted to Paloma Lopez-Garcia for sharing with us information on industry-specific cost elasticities that she estimates on ORBIS data for a subset of EU Member States. The actual cost elasticities that we use may deviate from Bodnár et al. (2020) because of specific assumptions on short-term adjustment factors and speed of convergence to long run values.

[10] Ebeke et al. (2021) is closest to this paper in terms of the sample of countries used and the approach taken to assess the magnitude of corporate distress. The main contribution of Ebeke et al. (2021), relatively to Demmou et al. (2021), is to incorporate detailed information on support policies. Ebeke et al. (2021) and Demmou et al. (2021) extend to a multiple country setting the approach of Carletti et al. (2020) who evaluate the likelihood of insolvency based on equity erosion. The main contribution of this paper is to refine the modelling of turnover shocks, to extend the analysis to cover 2021, and to propose a more comprehensive approach to assessing the risk of default. We differ from Gourinchas et al. (2020) in that we place the focus on nowcasting of industry-specific shocks and on quantifying the magnitude of distress under imperfect operational flexibility, while leaving the evaluation of the appropriate policy mix for the recovery phase for future work.

consumer sentiment, as well as standard indicators of domestic macroeconomic activity and global activity captured via demand and supply linkages. The raw data are available at different frequency, from daily to quarterly, so the information is harmonised to obtain a database at monthly frequency for each industry.[11] In the second step, this database is used to estimate industry-specific coefficients of turnover with respect to a comprehensive set of explanatory variables. In the third step, nowcasts and predictions of monthly turnover are obtained by extending the data series of the explanatory variables until the end of 2021. This cut-off is chosen to evaluate the financial health of the corporate sector after two years of activity in the context of the pandemic, while not making any assumption or assertion as regards the end of the pandemic. Real time data on the explanatory variables is used up to Q2-2021 which were the available data at the time of writing. For the second half of 2021, projections for the evolution of the pandemic and for the explanatory variables are obtained based on past information in different phases of the pandemic. The combination of the estimated coefficients with the projected path of the explanatory variables delivers predicted monthly turnover until the end of 2021.[12] The estimated coefficients are also used in combination with the explanatory variables to impute missing data points in Eurostat data.

2.1. THE DATABASE USED TO EXPLAIN INDUSTRIAL ACTIVITY OVER 2020 AND 2021

For monthly turnover data, we rely on Eurostat's short-term business statistics (STS). These are the earliest statistics released to track the evolution of economic activity at the industry level.[13] For the majority of EU countries, information on seasonally and calendar adjusted turnover figures is available for a range of industries, covering manufacturing at NACE 2-digit level and services at NACE 1-digit level. Table A.1 in the Annex presents the classification of industries covered in the analysis.

The main source of information behind STS data are national business surveys. Therefore, the first batch of data published by Eurostat corresponds to estimations and is subject to revisions, while the actual turnover data becomes available at a later stage. Another caveat are the systematically missing country-industry cells, in particular in services, because reporting obligations may be quarterly rather than monthly. Table A.2 in the Annex describes the coverage of monthly turnover by country and industry. Missing cells include for instance the German transport industry and the Italian accommodation and food industry.[14] For the purposes of this exercise, we take the full set of monthly information available at a given point in time and consider it a reliable approximation for actual turnover. At the time of data download, monthly turnover data were available until April 2021 for the majority of country-industry cells. In the case of systematically missing cells, monthly turnover figures are obtained by assuming that the estimated industry-specific coefficients are common to all Member States. Our method thus allows us to provide monthly turnover figures for all EU countries and industries. In the case of missing observations in the first months of 2021, i.e. cases where Eurostat does not yet provide an estimation, the advantage of our approach is its reliance on data sources that become available with a very short delay (max. several weeks). Hence, we are able to fill in these data gaps with nowcasts of monthly turnover.

[11] We opt for monthly frequency to better capture the rapidly evolving dynamics of the pandemic. In multiple instances, restrictions were imposed and lifted again in a matter of weeks, leading to significant fluctuations in monthly economic activity. Quarterly indicators would fail to capture such variation.

[12] Using real time data for additional quarters of 2021 – as it has become available in the meantime – has a minor incidence on the path of turnover in the second half of 2021 (results available upon request). Yet, these discrepancies have no incidence on the results reported on the liquidity and solvency of the corporate sector by the end of 2021. These findings demonstrate that our model works well, in particular for nowcasting (i.e. when information on explanatory variables is available).

[13] Data on industrial production are published with a 2-month delay while data for some service industries, such as retail, are published with a 1-month delay. For some countries, data for certain services are provided at quarterly frequency only.

[14] Monthly data is missing for around 1 out of 4 country-industries. Coverage tends to be better for manufacturing industries (ca. 20% missing) compared to services (ca. 30% missing).

For the set of explanatory variables (see Table 2.1), we rely on standard macroeconomic and industrial indicators, complemented with data that have become available to track the state of the pandemic. The main epidemiological variables that we use are the confirmed COVID-related deaths per million and the reproduction rate (R naught) of COVID-19. Government restrictions are captured directly through the stringency index and indirectly through mobility indicators. A third group of variables consists of economic and business indicators such as domestic GDP growth, domestic economic support provided to households, business and consumer sentiment, as well as exposure to global growth through supply and demand linkages.[15] Additional control variables capture industry-specific exposure to global value chains (GVC). A final set of variables captures the vulnerability of the industry to the pandemic by controlling for physical proximity of employees at the workplace and their ability to work from home.

The explanatory variables are available at different levels of aggregation (industry, country) and frequency (daily, monthly, quarterly, annual). In particular, GDP growth, epidemiological variables, government stringency and economic support indicators are all country-level variables, whereas GVC exposure and business confidence are available at the industry level. As the model explains sectoral turnover, the variation in the regressors across countries and/or time is exploited in the regressions. As regards frequency, certain variables such as GVC exposure or proximity of employees at work is constant over the period under study, while GDP growth rates are available on a quarterly basis. Other variables, such as business and consumer sentiment surveys, are available with monthly frequency while epidemiological variables and containment measures are available on a day-by-day basis. We take simple monthly averages for the variables with daily frequency. Table 2.1 provides the full set of regressors and describes their characteristics in terms of frequency and dimension of variation.

Table 2.1. **Set of explanatory variables, together with source, data frequency and extent of variation**

Variable	Description	Source
Epidemiological information	Daily number of new confirmed deaths per million and daily reproduction rate (R naught) ► varies across countries and time	Our World in Data
Government stringency	Daily stringency index recording the strictness of "lockdown style" policies that primarily restrict people's behaviour ► varies across countries and time	University of Oxford's Blavatnik School of Government
Mobility	Daily mobility at workplaces, retail and recreation places, groceries and pharmacies and transit stations ► varies across countries and time	Google Community Mobility Reports
Domestic macroeconomic growth	Quarterly GDP, volume in USD, constant PPP, indexed at 100 in Q4 of 2019 ► varies across countries and time	DG ECFIN Winter Forecast OECD Economic Outlook, Dec 2020
Foreign macroeconomic growth	Foreign quarterly GDP indices weighted by international supply and demand linkages ► varies across countries, industries and time	Idem as above OECD Inter-Country I-O Tables
Economic support	Daily indicator capturing the extent of income support for households and debt relief ► varies across countries and time	University of Oxford's Blavatnik School of Government

[15] The variable of economic support impacts industry turnover through its support to consumer income and does not account for the direct support provided to corporates.

Government expenditures	Annual non-healthcare related expenditures (% of GDP) ► varies across countries	DG ECFIN country desk estimates
Confidence	Monthly indicators covering consumer confidence, Economic Sentiment and sectoral business confidence based on order-book levels, stocks and production expectations for the months ahead ► varies across countries and time ► business confidence also across industries	DG ECFIN Business and Consumer Survey
Control variables	GVC exposure indicators: reliance of industry on foreign inputs and foreign demand Occupational physical proximity and teleworkability in the industry ► varies across countries and industries	OECD Inter-Country I-O Tables Calculations based on LFS and O*NET (2018 data)

Note: The Description column specifies the frequency (daily, monthly, quarterly, yearly) as well as the level (country, industry) at which the variables are observed. The start of data collection for each variable is January 2020.

2.2. ESTIMATION OF AN INDUSTRY-SPECIFIC MODEL ON POOLED DATA

We pool country-industry data on monthly turnover for all EU Member States over the period Q1-2020 to Q2-2021 and run basic OLS regressions *by industry* on a subset of explanatory variables.[16] Instead of including country fixed effects in the industry-specific regressions, we opt for the inclusion of control variables that are country-(industry) specific but invariant over time.[17] These variables capture the role that country-specific characteristics play in determining the impact of the pandemic on specific industries. For example, measures of teleworkability and physical proximity at the workplace vary at the country-industry level, as do the indicators of exposure to global value chains (GVCs), while government expenditures vary at the country-level only. We include a broad set of explanatory variables that track the evolution of the pandemic over time (months), rather than including time fixed effects which would capture the lion's share of the variation in turnover. For each *industry*, we run the following regression:

$$Turnover_{c,s,t} = \alpha_0 + X'_{c,s,t}\beta + Y'_{c,t}\gamma + Z'_c\delta + \varepsilon_{c,s,t} \quad (1)$$

where $Turnover_{c,s,t}$ is a measure of turnover (indexed at 100 in Jan 2020) in sector *s* in country *c* in month *t*. The explanatory variables can be grouped according to their extent of variation, as detailed in Table 2.1. Variables that vary across countries, industries and time (e.g. sectoral business confidence) are denoted by *X*. Variables at the country-time level (e.g. number of COVID-19 deaths) are denoted by *Y*, while the country-level regressors (e.g. government expenditures as % of GDP) are in included

[16] The subset of explanatory variables included in the regressions is selected with two criteria in mind. First, only significant regressors are taken on board, as the aim of the approach is to provide us with a tool that allows filling data gaps as accurately as possible, rather than estimating the causal relationship between turnover and the explanatory variables. Second, the smallest set of variables that explain most of the variation in the dependent variable (i.e. industry turnover) are included in the industry-level regressions. This approach ensures the best fit between observed and predicted turnover, while revealing interesting differences between industries in the subset of relevant explanatory variables. It also mitigates the risk of multicollinearity, as the included variables typically capture one distinct aspect of the supply and demand sides. We thus identify for each industry the subset of explanatory variables that most accurately helps us to fill data gaps.

[17] Regression results including fixed effects are available upon request.

in *Z*.[18] While we do not specify it in Equation (1) for expositional purposes, some explanatory variables are lagged and others, when relevant, are interacted with a "first wave" dummy to account for structural breaks in their explanatory power.

The main objective of this exercise is to provide us with a predictive statistical tool that allows filling data gaps and nowcasting industry trajectories, rather than estimating the causal relationship between turnover and the explanatory variables. Consequently, we give more weight to the overall explanatory power of the model and its ability to capture the impact of the different waves of the pandemic while worrying somewhat less about endogeneity and possibly biased coefficient estimates.

The performance of the empirical model for explaining turnover fluctuations in the hardest hit industries is documented in Table 2.2.[19] It illustrates how the subset of relevant explanatory variables varies by industry. Macroeconomic growth has the expected positive impact on turnover in these industries. Mobility at the workplace is an important determinant of turnover in manufacturing, albeit only during the first wave for transport equipment. Exposure to GVCs played an ambiguous role during the crisis, as indicated by the differing signs of the coefficients estimated for reliance on foreign supply and reliance on foreign demand. In textiles, stronger reliance on foreign demand mitigated the decline in sales due to a reduction in domestic demand. In contrast, the disruption of global supply chains as well as shortages in foreign inputs affected turnover in the transport equipment industry more in countries that depend more on foreign supply. Stringency has a strong adverse effect on turnover in accommodation and food services.

The empirical model tends to have a good fit (as captured by the coefficient of determination R^2), in particular in the industries hardest hit by the pandemic. The set of regressors that effectively explains variation in turnover tends to be industry-specific in a way that is consistent with production and demand features. For instance, the state of the economy, as captured by the quarterly GDP index, plays an important role in determining turnover in most (heavy) manufacturing industries. Yet, such industries are relatively less sensitive to government restrictions. In turn, demand-sensitive manufacturing activities, such as manufacturing of textiles, retail, or transport equipment, are highly sensitive to fluctuations in consumer confidence and economic sentiment. The epidemiological variables have little or no explanatory power in the majority of regressions. Our hypothesis is that turnover fluctuations are mainly attributable to the reaction function of firms, consumers, and public authorities to the dynamics of the epidemic, rather than to the epidemic itself. The latter is picked up by the set of explanatory variables (e.g. stringency, mobility, confidence) that are strongly correlated with the epidemiological situation.

Further, we pick up structural breaks in some coefficients, documenting that certain explanatory variables gained and others lost importance after the first wave of the COVID-19 outbreak. To give an example, evidence of a structural break in July 2020 is found in several manufacturing industries for the indicator that measures mobility at the workplace.[20] This variable is highly significant in the first half of 2020 but loses significance thereafter. As the indicator is provided at the country level, this loss of significance could be due to the worse performance of this variable in capturing mobility at the workplace in manufacturing. However, it could also be indicating that manufacturers adjusted the organisation of production (e.g. by working in shifts) and learned to cope with physical distance requirements.

[18] Note that the distinction between the set of country-sector-time variables X and the country-time variables Y is purely semantic. As the regressions are specified at the level of the industry, the variation of the two sets of variables in the regressions is the same (namely country-time).

[19] Results for the less-hit industries are available upon request.

[20] Following Turner et al. (2021), the structural break is assumed in July 2020 and its significance is confirmed by means of a Chow test.

Table 2.2. **Results of the regressions for a subset of hard-hit industries**

	Monthly turnover		
	Manufacturing of textiles	**Manufacturing of transport equipment**	**Accommodation and food services**
Domestic GDP	0.470**		0.754***
Foreign GDP		0.542	
Workplace mobility	0.184**		
• First wave		0.949***	
• After first wave		0.125	
Retail and recreation mobility			0.460***
• First wave	0.274***		
• After first wave	-0.0148		
Stringency			-0.244***
Economic support (lagged)	0.0394*		0.0787**
Consumer confidence	0.306***		
Business confidence			0.258***
Economic Sentiment Indicator		0.385***	
Reliance on foreign supply		-0.181**	
Reliance on foreign demand			
• First wave	0.128***		
• After first wave	0.139***		
Constant	70.24	22.03	17.83
Observations	298	303	202
R-squared	0.566	0.604	0.786

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

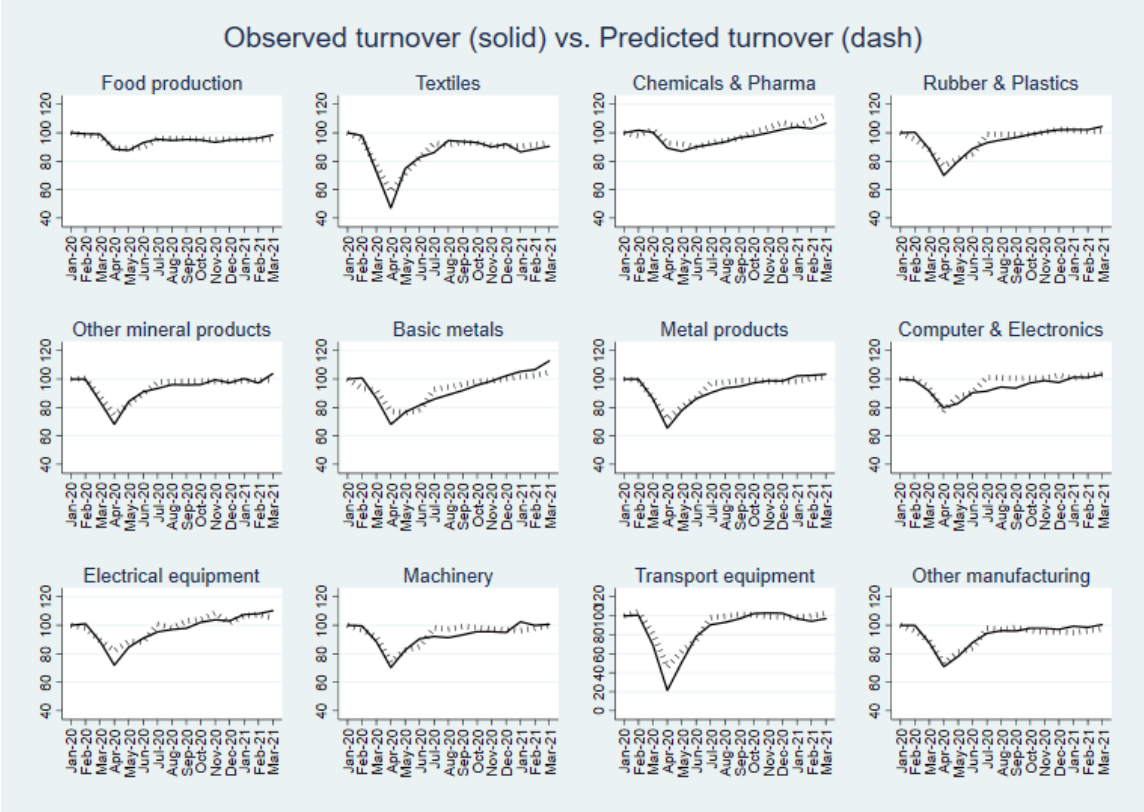
Source: Authors' own calculations.

Overall, the correlation between observed and predicted industrial turnover is quite high, especially at the aggregate EU level. A visual representation of the fit for the EU is provided in Graphs 2.1 and 2.2 while Graphs A.1-A.4 in the Annex illustrate that the model performs rather well at predicting turnover patterns for individual countries and industries.[21] On average, the set of explanatory variables

[21] The examples of the model fit for Spain and Portugal are provided in the Annex for illustrative purposes, as coverage in Eurostat for these countries is comprehensive. The full set of country-industry results is available upon request.

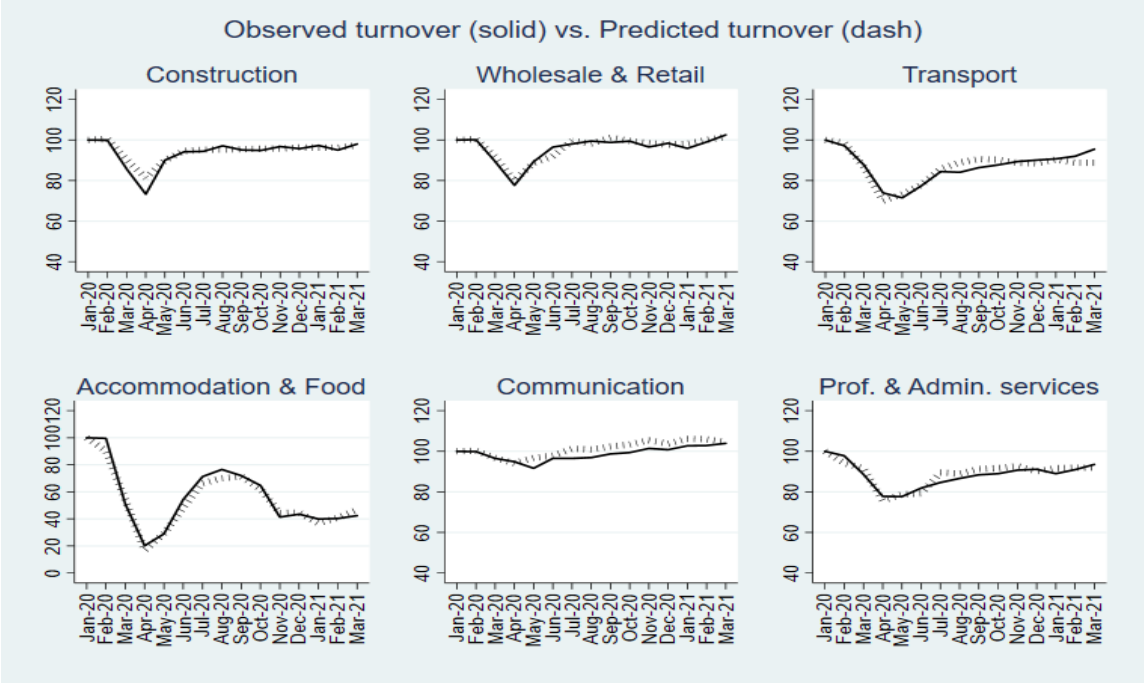
accounts for 50% to 60% of the variation in turnover, although there are significant differences across countries and industries.

Graph 2.1. **EU turnover in manufacturing[22] (weighted average of country indices, Jan 2020 = 100)**



Source: Eurostat Short-term Business Statistics (STS) and authors' own calculations.

Graph 2.2. **EU turnover in services (weighted average of country indices, Jan 2020 = 100)**



Source: Eurostat Short-term Business Statistics (STS) and authors' own calculations.

[22] For readability, the industry "Wood and Paper" (C16-C18) was omitted. The omitted results are available upon request.

It is immediate from Graphs 2.1 and 2.2 that the empirical model does a reasonable job at picking up the dynamics of the pandemic, i.e. the magnitude of the initial shock and the subsequent recovery. A rebound is indeed visible in virtually all industries in the second half of 2020 (*solid* line), with turnover exceeding pre-crisis levels in some industries. This rebound comes to a halt in the autumn of 2020, as COVID-19 diffusion picks up and brings back containment measures. These novel surges in infection rates had a visible impact on economic activity in several industries, although the contraction tended to be less pronounced than during the first wave in early 2020.

The fine-tuning of the model whereby we allow for structural breaks in the coefficients after the first wave (July 2020) strongly contributes to improving the predictive power of the model in the second half of 2020 and in early 2021. Indeed, while the epidemiological situation and lockdown measures were of similar magnitude during the subsequent surges of infection rates, the economic contraction has been less pronounced. The dampened impact of these subsequent waves of the pandemic on economic activity suggests that firms, workers, and consumers were better able to adapt to the containment measures, implying that e.g. the working from home obligation may have a weaker impact on turnover in 2021 relatively to April 2020 in most industries. The ability of our model to pick up the improvement in the adjustment capacity of the European economy plays an important role in delivering credible predictions of industrial activity in Q2-Q4 of 2021.

2.3. IMPUTATION OF MISSING DATA AND PREDICTIONS FOR 2021

The framework developed in this paper enables us to:
(1) fill in the systematically missing industry-country cells in the Eurostat STS data (see Table A.2) with help of the estimated industry-specific model;
(2) produce nowcasts of monthly turnover in Q2 of 2021, using the observed values of the explanatory variables and incorporating structural breaks in the estimated coefficients where relevant;
(3) produce predictions of monthly turnover in Q3-Q4 2021, using the predicted trajectory of the explanatory variables and incorporating structural breaks in the estimated coefficients where relevant.

A critical advantage of the set of explanatory variables that we use is the timeliness with which they become available. Many of the daily variables are published with a lag of just a few days. Moreover, the coverage for these measures is almost perfect, with hardly any gaps for a country, sector, or period. Consequently, to address (1) and (2), the set of the estimated industry-specific coefficients is combined with the set of explanatory variables to impute the evolution of turnover for countries, sectors and months that are not (yet) reported in Eurostat. To address (3), the trajectory of the explanatory variables is simulated for the recovery phase in Q3-Q4 of 2021. The set of assumptions used to obtain this trajectory are shown in Table 2.3. In order to have a cut-off data for the analysis, we assume that the loosening of restrictions observed in Q2 of 2021 is pursued, so that pre-crisis levels are reached by the end of 2021. Essentially, this implies that our simulations do not account for the new wave of infections in the autumn of 2021.

As discussed in section 2.2, the empirical model estimated separately for each industry picks up a structural break in the coefficients for a subset of explanatory variables in some industries, with this break situated in July 2020. These structural breaks likely pick up an improvement in the adjustment capacity of the industry and strongly contribute to improve the fit of the model over the period under study. Imputations and predictions of monthly turnover fully incorporate information on such breaks.

Table 2.3. **Predictions for the explanatory variables**

Variable	Prediction
Epidemiological information	Interpolation to reach zero in Dec 2021 (this is a cut-off point of the analysis and does not indicate an end of the COVID-19 pandemic)
Government stringency	Interpolation to reach zero in Dec 2021 (cfr. above)
Mobility excl. workplaces	Interpolation to reach zero in Dec 2021 (cfr. above)
Mobility at workplaces	Status quo over Jun-Aug 2021, then interpolation to reach zero in Dec 2021 (cfr. above)
Domestic and foreign macroeconomic growth	Spring Forecast and OECD outlook predictions
Economic support	Status quo over Jun-Sep 2021, then interpolation to reach zero in Dec 2021 (cfr. above)
Government expenditures	Expenditures like 2020 over Jan-Sep 2021, then interpolation to reach zero in Dec 2021 (cfr. above)
Confidence	Status quo over May-Jun 2021, then interpolation to reach, by Dec 2021, the level of the country's best month since the start of the crisis

Source: Authors' assumptions.

3. QUANTIFYING THE IMPACT OF COVID-19 ON THE NON-FINANCIAL CORPORATE SECTOR

Having established the pattern of industrial turnover for each month of 2020-2021 in all EU Member States, we implement an accounting approach that has become widespread in the literature to simulate the impact of this sequence of revenue shocks on the profitability, liquidity, and solvency of the EU non-financial corporate sector.[23] We obtain the distribution of firm-specific monthly profitability shocks by combining information on industry-specific shocks, applied proportionally to corporate revenues of all firms within a country-industry, with information on the firm-specific structure of variable and fixed costs. Our choice of a more granular approach to the identification of industry-specific revenue shocks allows us to strike a better balance between the need to include multiple countries in the analysis and the need to achieve greater precision in quantifying the cumulative profitability shocks associated with the pandemic. We demonstrate the relevance of industry-level nowcasting at monthly frequency by showing that we are better able to capture the *variability* of the effects of the pandemic while *covering a longer time horizon* than previous studies. The methodology and the data used in the analysis are described in this section.

3.1. METHODOLOGY

Below we describe the methodology used to assess the impact of the COVID-19 pandemic on corporate distress. We start from evaluating the effect of the pandemic-related shocks on firm profitability. Then we quantify the magnitude of corporate distress using three criteria: *liquidity*, based on two definitions of liquid assets: cash and demand deposits, as well as working capital; *solvency*,

[23] See Schivardi and Romano (2020), Bodnár et al. (2020), Ebeke et al. (2021), and Demmou et al. (2021).

based on two criteria related to leverage: negative equity and debt burden (interest coverage ratio); while controlling for *pre-pandemic financial vulnerability*, based on the Altman Z-score model.

3.1.1. Profitability

Adverse shocks to corporate revenues translate into adverse profitability shocks whenever the firm is unable to reduce costs in the same proportion. Thus, sufficiently strong adverse revenue shocks combined with imperfect operational flexibility translate into corporate losses. We follow Schivardi and Romano (2020) and use a simple accounting identity[24] to determine each firm *i*'s Profit or Loss ($PL_{i,t}$) in euros in month *t* as:

$$PL_{i,t} = \frac{(1-d_{s,c,t})S_i}{12} - \frac{(1-\varepsilon_{Ms,t}d_{s,c,t})M_i}{12} - \frac{(1-\varepsilon_{Ws,t}d_{s,c,t})W_i}{12} - \frac{(1-\varepsilon_{Fs,t}d_{s,c,t})F_i}{12} - \frac{I_i}{12} - \frac{T_i}{12} \quad (2)$$

where $d_{s,c,t}$ is the shock to turnover in industry s, country c, and month t; S_i, M_i, W_i, F_i, I_i and T_i are, respectively, firm *i*'s annual revenue, material expenses, labour expenses, overhead costs, interest payments, and taxation payments (assumed strictly exogenous to the profit generation process) in the most recent available financial statement. The parameters $\{\varepsilon_{Ms,t}, \varepsilon_{Ws,t}, \varepsilon_{Fs,t}\}$ are, respectively, the elasticity of material costs, labour costs, and overhead costs with respect to revenue. These parameters are of critical importance in our application as they represent the degree of operational flexibility of the firm in a particular industry and month, with respect to a particular type of costs.

The parameters in Equation (2) determine the pattern of a firm's monthly profits or losses. The key contribution of the methodology described in Section 2 is to equip us with the set of country-industry shocks $\{d_{s,c,t}\}$ to turnover, as compared to the baseline level of January 2020. For the material and labour cost elasticities, we rely on the work in Bodnár et al. (2020), where estimates of the cost elasticities are obtained by panel regressions run on firm-level data for the period 2006-2016.[25] These elasticities vary by industry, as shown in Table 3.1. They represent the ability of firms to adjust variable costs to the level of production, assessed over a rather long time horizon (as the estimations rely on annual data). Given the frequency of data used in our simulations (monthly shocks to firm sales and costs) and the exceptional nature of the COVID-19 pandemic (an unanticipated sizeable shock that distorts the normal input adjustment process), we scale down these elasticities with an adjustment factor. As shown in Table 3.2, the adjustment factor increases over time to account for higher operational flexibility that we expect firms to acquire as the COVID-19 shock is revealed to be persistent.[26] The elasticity for the fixed factor is set at 0.1 in the first half of 2020. It is assumed to

[24] Gourinchas et al. (2020) propose an alternative approach whereby the firm's cost minimisation problem in COVID times is solved to determine the optimal choice of inputs, given sectoral productivity and demand shocks. This approach minimises data requirements on actual sectoral shocks and builds in near-perfect operational flexibility, by assuming optimal input choice, conditional on sectoral labour supply constraints, together with a relatively high substitutability of labour with material inputs. We opt for the Schivardi and Romano (2020) approach because our main contribution is precisely the construction of the monthly sectoral shock series and a more nuanced approach to modelling imperfect operational flexibility.

[25] The elasticities are estimated using the ORBIS database. Annual changes in input costs are regressed on changes in sales while controlling for firm characteristics, notably the age and the initial employment of the firm, and for time dummies to absorb the impact of aggregate shocks. The equation is estimated with a fixed-effect estimator, i.e. exploiting the within-firm variation, and errors are clustered at the firm level. These elasticities are used in Bodnár et al. (2020) to quantify corporate distress in five euro area countries. However, Bodnár et al. (2020) differ in the assumptions on short-term adjustment factors. Therefore, we scale down the elasticities with an adjustment factor as explained in the text.

[26] The initial value of the adjustment factor is somewhat arbitrary. Schivardi and Romano (2020) use .56, whereby the material cost elasticity in their study equals .5 and the labour cost elasticity equals .15. Demmou et al. (2021) set the two elasticities to .8 and .2, respectively. We opt for .6 as the initial value of the adjustment factor by rounding the elasticity used in Schivardi and Romano. We cap the adjustment factor to .8 in 2021 to ensure that the material cost elasticity remains strictly below 1.

increase to 0.2 in the second half of 2020 and to remain at this level in 2021, to factor in some flexibility in adjusting this type of costs as well (possibly via provision of policy support).

We also allow for an asymmetric response of costs to a positive revenue shock, as opposed to the adverse COVID-related shocks. The assumption is that a firm will need to adjust its material inputs if it wants to expand its production in response to an increase in demand. The need for an asymmetric elasticity can be illustrated with the example of a car producer. If the firm produces 10% less cars, it might still have to pay for part of the inputs that it already ordered. If it wants to produce more cars, however, it will need to purchase those extra inputs in a proportionate manner. To reflect this asymmetry and to account for the impact of potential shortages in the supply of inputs,[27] we do not scale down the long run material cost elasticity for positive turnover shocks in 2021 in the manufacturing and construction industries. For labour costs we do not introduce any asymmetry as there is likely some slack in the labour market.

Table 3.1. **Estimates of the sectoral elasticities**

	Material costs	Labour costs
Manufacturing	1.09	0.43
Construction	1.17	0.41
Wholesale and Retail	1.03	0.41
Transport	1.00	0.59
Accommodation and Food services	0.89	0.79
Information and Communication	1.04	0.53
Professional and Administrative services	1.01	0.42

Source: Bodnár et al. (2020).

Table 3.2. **Adjustment factors applied to the cost elasticities over 2020-2021**

	Material costs	Labour costs	Fixed costs
Jan-Jun 2020	0.60*estimated elasticity	0.60*estimated elasticity	0.10
Jul-Aug 2020	0.65*estimated elasticity	0.60*estimated elasticity	0.20
Sep-Oct 2020	0.70*estimated elasticity	0.60*estimated elasticity	0.20
Nov-Dec 2020	0.75*estimated elasticity	0.60*estimated elasticity	0.20
Jan-Dec 2021	0.80*estimated elasticity	0.60*estimated elasticity	0.20

Source: Bodnár et al. (2020) and authors' own calculations.

For comparability with previous studies, public support is modelled in a stylised way.[28] Support to operational costs takes the form of short-time work (STW) schemes. As in the work by Schivardi and Romano (2020) and Demmou et al. (2021), it is modelled as an increase in the elasticity of labour costs to revenue shocks (ε_{Wst}). With policy support, this elasticity is assumed to equal 0.8 in all industries and months, from March 2020 until December 2021 despite the fact that in reality in some Member States labour cost support might have been more tightly linked to activity. This support enables firms to reduce labour costs almost proportionately to the reduction in revenue, as governments relieve them of a significant part of their wage bill. This way of modelling policy support provides a relatively bigger boost in terms of operational flexibility to industries where the long run elasticity is low (e.g. construction, wholesale and retail). Yet, even in the Accommodation and Food services industry, the boost to flexibility is significant as the elasticity increases from .47 to .80.

[27] Evidence of such shortages (and concomitant price increases) has been documented in 2021 in semiconductors as well as basic inputs such as wood, plastics, and steel.

[28] See Ebeke et al. (2021) for a country-specific approach to modelling policy support over a shorter timespan (i.e. 2020).

Three scenarios are simulated to evaluate the impact of policy support. The first variant assumes no policy intervention. The second variant allows for higher operational flexibility in adjusting the wage bill through STW schemes ("*STW*"). The third variant incorporates the deferral of tax and interest payments, on top of STW schemes ("*STW+*"). In the latter case, corporate tax and interest payments are not paid throughout the period under study, thereby temporarily reducing the liquidity needs of firms. In practice, $I_i/12$ and $T_i/12$ due each month are subtracted from equity and added to the liabilities of the firm in each month between March 2020 and December 2021.[29] In the core of the paper, we focus on the results obtained with the *STW* and the *STW+* scenarios, as they best correspond to the policy package effectively implemented in the EU Member States.[30]

3.1.2. Liquidity

Equation (2), along with the parameter values in Tables 3.1 and 3.2, allows quantifying the impact of the pandemic in terms of corporate profitability. To translate the impact of this profitability shock on corporate liquidity, the calculation is complemented with an assessment of the extent to which firms can absorb the incurred losses with help of previously accumulated liquidity buffers. We posit that firms can rely on either their most liquid asset (cash) or a broader definition of liquid assets (working capital). The *narrow* liquidity buffer simulations allow firms to deplete their cash reserves to cover losses. The *broad* liquidity buffer simulations allow firms to deplete their working capital to cover losses, i.e. firms can draw on all current assets to the extent that these assets exceed current liabilities. To correct for legacy problems, if a firm's starting position in terms of cash or working capital is negative, it is set to zero.[31] The liquidity buffer simulations take this form:

$$LIQ^b_{i,t} = LIQ^b_{i,t-1} + PL_{i,t} \tag{3}$$

where $PL_{i,t}$ is defined as in Equation (2) and *b* stands for the buffer: {cash, working capital}.

The losses described by Equation (2) dent the two liquidity buffers ($LIQ^b_{i,t}$) as described in Equation (3). The liquidity buffer simulations allow us to establish the liquidity position of each firm in every month *t*. Hence, we can compute the share of firms in a given country and industry estimated to have become illiquid at a particular point of the crisis. Notice that firms are said to be illiquid or, equivalently, in *liquidity distress*, when the adverse shock to revenue, combined with an imperfect ability to adjust costs, translates into losses that cannot be covered with previously accumulated liquidity buffers. Because of liquidity buffer depletion, the liquidity shortfall is smaller than the total corporate losses.

The approach taken in this paper is to cumulate, month after month, the corporate profits or losses incurred in the month, with the associated liquidity buffer replenishment or depletion. The objective is to quantify the fraction of firms that face liquidity shortages at any point in time over the crisis. While we will account for the firm's access to fresh funding when assessing its risk of insolvency (cfr. infra), we do not account for its ability to borrow or raise equity when simulating its liquidity status. Rather,

[29] Deferred interest payments should increase current liabilities, and this approach would logically imply that the cash buffer of the firm is unchanged while its working capital buffer is reduced in the *STW+* scenario. Yet, as it is not clear when these deferred payments would actually be due, we incorporate them in *long-term* debt, leaving current liabilities unchanged.

[30] Our modelling of emergency support may be underestimating the role played by support measures akin to equity injections (e.g. grants) received through other channels than wage support schemes (e.g. support to overhead costs). Further, we do not allow for private equity injections in addressing financing needs. Instead, although we do not directly model public loan guarantees, we assume that all firms have access to credit financing when they exhaust liquidity buffers. Hence, we may be overestimating the fraction of firms that fully depleted equity over the course of 2020-2021.

[31] Around 0.3% of all firms in the sample had a negative cash position at the onset of the crisis. Current liabilities exceeded current assets for 22% of the companies, leading to a negative working capital position for these firms.

we aim to track the prevalence of intrinsic illiquidity as the crisis unfolds, while allowing firms to compensate for the initial liquidity shortfall in the months when industrial activity rebounds, thereby documenting the extent of country and industry heterogeneity in the persistence of the pandemic's impact on corporate liquidity.[32] The *STW* scenario is our preferred approach to modelling policy support when assessing the intrinsic liquidity status of the firm. Indeed, the deferral of interest payments and corporate tax payments is a temporary liquidity preserving measure, which may lead us to underestimate the intrinsic liquidity needs of the firm.

3.1.3. Risk of insolvency

The *illiquidity* status signals that at a given point in time the firm had financing needs that required either additional borrowing or an injection of equity. It does not imply that firms were unable to address these liquidity needs with fresh funding. Rather, the available evidence suggests that the liquidity shortfall in non-financial corporations has been has at least to some extent met by the provision of credit, mostly by banks; the latter facilitated by emergency support measures such as public loan guarantees[33]. Consequently, we carry out a complementary exercise to assess the magnification of financial vulnerability in the EU non-financial corporate sector, while explicitly modelling the implications of adverse profitability shocks on equity depletion and of additional financing needs on corporate borrowing, together with the ensuing increase in interest payments.

We assume that the generous public support package and the temporary measures aiming to suspend bankruptcy filings are fully effective in that all incumbent firms survive until December 2021. For simplicity, we assume that all existing debt is rolled over, and that the monthly interest payments *I_i/12* associated with pre-pandemic debt are unchanged. This approach allows focussing on additional borrowing stemming from novel financing needs.

New borrowing needs in quarter *Q={1,..,8}* where 1 stands for Q1-2020 and 8 stands for Q4-2021 are given by the difference between cumulative losses (if any) suffered until the end of that quarter and the pre-pandemic liquidity buffer $LIQ^{b}_{i,0}$ (if any).[34] We make three assumptions. First, we posit that firms cannot raise equity, so additional financing is obtained through borrowing. Second, we posit that the firm is reluctant to fully deplete liquidity, so it starts borrowing once its cumulative losses exceed half of its liquidity buffer. Third, we posit that firms operate in the *STW+* scenario in the sense that deferred interest payments are accumulated as liabilities and do not generate new financing needs over the period under study. New borrowing $B^{b}_{i,q}$ in quarter *q* generates new interest payments to be paid in the next quarter, $I^{b}_{i,q}$.[35] [36] Equation (2) is adjusted to keep track of quarterly corporate losses, while accounting for the cost of additional borrowing:

$$PL^{b}_{i,q+1} = \sum_{t \in q+1} PL_{i,t} - I^{b}_{i,q} \qquad (2b)$$

[32] The prevalence of intrinsic illiquidity is expected to be highest at the end of each cycle of the pandemic, when most losses have been accumulated and buffers depleted.

[33] See European Banking Authority (2020) and European Systemic Risk Board (2021).

[34] Borrowing needs are assessed per quarter, for computational purposes. This choice has little impact on the results and merely involves a summing (of three months) within each quarter.

[35] Available evidence, see European Central Bank (2021) suggests that over the period under study, credit conditions were relatively lenient, so it is an open question which interest rate should be applied to new debt. We opt for internal coherence. Hence, we run a series of regressions to determine interest payments as a function of firm, industry, and country characteristics. For each firm, we apply the minimum among the resulting set of estimated implied interest rates. Details on the approach and on the resulting distribution of interest rates are available upon request.

[36] Interest is accumulated for debt contracted in period q, that is why the subscript of debt and interest coincide, the payment is completed when the period is over.

where losses (gains) in the first quarter are equal to the expression in (2), i.e. $PL^{b}_{i,1} = \sum_{t \in Q=1} PL_{i,t}$

Equation (3) for the liquidity buffer that the firm considers when determining new borrowing is adjusted to take into account that all interest payments, including those associated with new borrowing, as well as corporate tax payments are deferred:

$$LIQ^{b}_{i,q+1} = LIQ^{b}_{i,q} + \left[PL^{b}_{i,q+1} + \frac{I_i}{4} + \frac{T_i}{4} + I^{b}_{i,q}\right]\left[PL^{b}_{i,q+1} + \frac{I_i}{4} + \frac{T_i}{4} + I^{b}_{i,q}\right] \quad \text{(3b)}$$

New borrowing is given by the difference between cumulative losses and ½ the pre-pandemic buffer:

$$B^{b}_{i,q} = -\min\left\{\frac{LIQ^{b}_{i,0}}{2} + \sum_{\tau=1}^{T}\left[PL^{b}_{i,\tau} + I^{b}_{i,\tau-1}\right] + T\left(\frac{I_i}{4} + \frac{T_i}{4}\right); 0\right\}, \text{ where T=q and } q \in \{1;8\} \quad (4)$$

Interest payments associated with new borrowing in any given quarter irreversibly deplete equity and increase total indebtedness. However, we allow the firm to decide at the end of each subsequent quarter whether it rolls over new debt, according to equation (4). If the sequence of adverse revenue shocks is reversed, additional borrowing may be quickly terminated. Yet, for precautionary motives, the firm seeks to preserve liquidity and does not start paying back any of the deferred interest payments until the end of the period under study.

The evolution of equity ($E^{b}_{i,q}$) and of total debt ($D^{b}_{i,q}$) is given by resp. (5) and (6):

$E^{b}_{i,q+1} = E^{b}_{i,q} + PL^{b}_{i,q+1}$ with equity by the end of March 2020 given by $E^{b}_{i,1} = E^{b}_{i,0} + PL^{b}_{i,1}$ (5)

$$D^{b}_{i,q+1} = D^{b}_{i,0} + B^{b}_{i,q+1} + \sum_{\tau=1}^{T}\left[I^{b}_{i,\tau}\right] + (T+1)\left(\frac{I_i}{4} + \frac{T_i}{4}\right), \text{ where T=q and } q \in \{1;7\} \quad (6)$$

with total debt by the end of March 2020 given by $D^{b}_{i,1} = D^{b}_{i,0} + B^{b}_{i,1} + \left(\frac{I_i}{4} + \frac{T_i}{4}\right)$.

The evolution of total assets is co-determined by corporate profits, the deferred costs, and the eventual additional borrowing in the quarter:

$$A^{b}_{i,q+1} = A^{b}_{i,q} + \left[PL^{b}_{i,q+1} + \left(\frac{I_i}{4} + \frac{T_i}{4}\right) + I^{b}_{i,q}\right] + \left(B^{b}_{i,q+1} - B^{b}_{i,q}\right), \text{ where } q \in \{1;7\} \quad (7)$$

with total assets by the end of March 2020 given by $A^{b}_{i,1} = A_{i,0} + PL^{b}_{i,1} + \left(\frac{I_i}{4} + \frac{T_i}{4}\right) + B^{b}_{i,1}$.

Thus, corporate losses affect the financial health status of the firm through two channels. The direct effect is through the *depletion of equity*, as described in (5). The indirect effect is through the *increase in indebtedness*, as described in (6), driven by the incentive to preserve liquidity and the need to continue financing the operational needs of the firm. This is achieved through deferring payments, which accumulate as future liabilities, and through new borrowing, to avoid the full depletion of liquidity buffers. Depletion of equity and accumulation of liabilities increase *leverage*, while new borrowing increases the *debt burden* of the firm, by increasing interest payments. The *interest coverage ratio*, i.e. the ratio of operating profits to interest payments, is reduced because its numerator falls while its denominator increases.

We take into account both channels in defining the *risk of insolvency post-crisis*. A firm is said to be insolvent if it fulfils at least one of the following criteria by the end of 2021: [37]

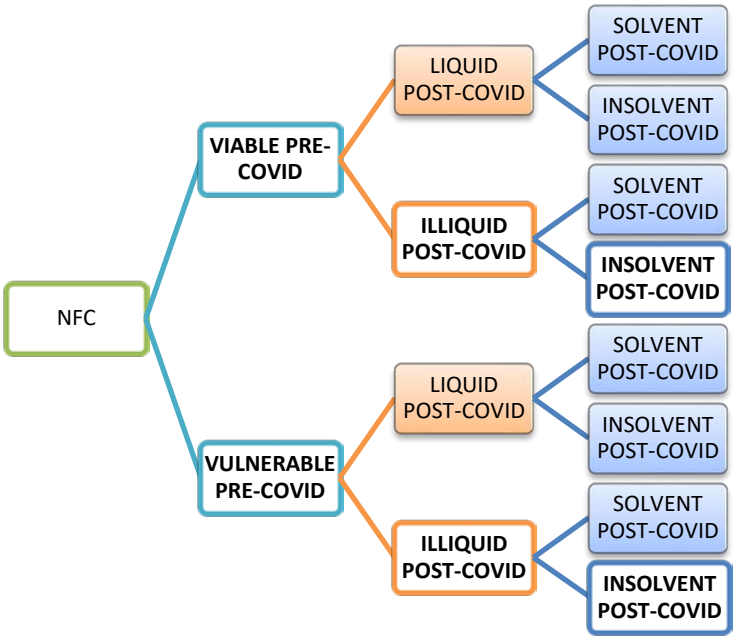
(i) the firm is predicted to have negative equity (implying that the firm is in the top quartile of the pre-pandemic distribution of leverage in the country-industry by the end of 2021);

(ii) the firm is unable to cover accumulated interest payments with operating profits, and the firm finds itself by the end of 2021 in the top quartile of the pre-pandemic distribution of leverage in the country-industry.

3.1.4. Financial vulnerability pre- and post-pandemic

The final step is to quantify the extent of financial vulnerability in the non-financial corporate sector by the end of 2021. The aim is to pin down the fraction of firms in each country and industry, which are most likely to face difficulties in getting access to additional funding once emergency support measures are removed. This thought experiment consists of combining the liquidity and the solvency criteria, to identify firms that are most likely to require additional funding *and* may be deemed unable to pay back expenses on debt once emergency support measures are withdrawn. Among such firms we further distinguish those that were already financially vulnerable before the pandemic from those deemed financially healthy - or *viable* - before the pandemic and which appear to have shifted into insolvency status by the end of 2021. The latter group is identified with the magnification of financial vulnerability associated with the COVID-19 outbreak. Figure 3.1 illustrates how the grouping works. The decision tree shows the classification of firms that motivates which firms are considered for the analysis below. Specifically these are firms that fall in the white background cells in the rightmost section of the decision tree – firms that are illiquid post-COVID and at the same time insolvent. Some of them were viable pre-COVID, while some of them were already financially vulnerable.

Figure 3.1. **Grouping of firms in the non-financial corporate (NFC) sector by liquidity and solvency criteria**



Source: Authors' own calculations.

[37] The use of this definition of insolvency is also motivated by the fact that in the EU the obligation to file for insolvency may hinge on a liquidity test (inability to pay financial obligations as they become due and/or on a solvency test (negative equity). See McCormick et al. (2016). Previous studies rely only on the negative equity criterion (see Carletti et al. (2020); Ebeke et al. (2021); Demmou et al. (2021)).

The *first* criterion groups firms according to their pre-pandemic financial health status. In line with the literature, we use a scoring model that assesses the likelihood that a firm files for bankruptcy based on its performance before the pandemic (Altman Z-score model).[38] Specifically, the risk of filing for bankruptcy is assessed based on the firm's liquidity, profitability, and capital structure as documented in the most recent financial statement before the pandemic. The assumption is that firms that were already financially vulnerable before the pandemic may face difficulties in getting access to additional sources of funding after the withdrawal of emergency support. Yet, if such firms are revealed to be liquid and solvent due to the pandemic, it is likely that they continue to operate. Consequently, the pre-pandemic financial health criterion is combined with post-pandemic liquidity and solvency criteria to identify post-pandemic vulnerable firms.

The *second* criterion groups firms according to their liquidity status at the end of 2021. As explained in 3.1.2, we define as *illiquid* or in *liquidity distress* the firms that exhaust their liquidity buffers and therefore face higher liquidity needs as a result of the pandemic. Specifically, these firms were unable to compensate the sequence of adverse profitability shocks with previously accumulated liquidity buffers and (potential) profits generated in the recovery phase. This characterisation does not mean that these firms were unable to access additional financing over the course of the pandemic. Rather, it aims to capture the fraction of firms that faced the need for external funding to cover their liquidity needs at the end of 2021. Such firms have additional borrowing needs and are thus more likely to face liquidity distress once emergency support is withdrawn. The likelihood that such firms obtain additional financing in post-pandemic circumstances depends on their observable characteristics pre- and post-pandemic. Therefore, we apply a *third* criterion, namely the risk of insolvency post-pandemic, as defined in 3.1.3. The assumption is that firms in liquidity distress and with observable characteristics pointing at risk of insolvency may be unable to access additional funding after the withdrawal of emergency support.

To sum up, we combine information on corporate liquidity needs with information on the financial vulnerability of the firm pre-pandemic and its insolvency status post-pandemic to quantify the fraction of firms most likely to face difficulties in getting access to additional funding once emergency support is removed. We have no prediction as to the fraction of these firms that will effectively file for bankruptcy, as the latter depends on the dynamics of the recovery and the criteria that banks will rely upon to assess firm viability. Yet, we see this quantification as a useful exercise to assess the extent of financial vulnerability in the European corporate sector by the end of 2021.

3.2. DATA

Translating industry-level turnover shocks into their cumulative impact on profitability and liquidity of a given firm over 2020-2021 requires information on corporate balance sheets and profit and loss statements in the European non-financial corporate sector. Clearly, the first best is to work with real data on corporate costs and revenues in each month of 2020. To the best of our knowledge, such data are not available on a cross-country basis.[39] Consequently, in line with the literature,[40] we work with the most recent comprehensive set of corporate financial statements available pre-pandemic. These cover corporate activity in 2018. Although these statements do not account for the shocks experienced

[38] The assessment uses the scoring model pioneered by Altman (1968), which has been shown to perform well in predicting bankruptcy in a sample of countries and sectors (see Altman et al. (2017)). Two variants of the Altman Z-score model are used, as one puts more weight on liquidity while the other puts relatively more weight on profitability. The firm is said to be at the high risk of default when both variants of the Z-score model identify the firm to be at high risk of default pre-shock. In relation to the COVID-19 pandemic, the Z-score model was used in European Commission (2021).

[39] Country-specific data is gradually becoming available (Tielens et al. (2020), Hadjibeyli et al. (2021), Altomonote et al. (2021)). The study by Tielens et al. (2020) uses actual data on costs and revenues of Belgian firms in 2020. This paper provides evidence of imperfect operational flexibility, whereby the reduction in corporate revenues is not matched by the reduction in operating costs, and this finding characterises the whole year. These findings are consistent with the hypothesis of imperfect operational flexibility chosen here for simulations.

[40] Romano & Schivardi (2020), Gourinchas et al. (2020), Ebeke et al. (2021), Demmou et al. (2021), among others.

by firms in the course of 2019, they adequately capture the distribution of firm characteristics at the start of the pandemic under the assumption that the shocks in 2019 are idiosyncratic, and thus wash out in the aggregate. The set of financial statements is taken from the ORBIS database. This data source, made available by Bureau Van Dijk (a Moody's Analytics Company), has the advantage of providing better coverage for most of the EU Member States than other sources.

We work with unconsolidated accounts of firms deemed *active* at the date on which they deposited their most recent financial statement. We restrict the sample to unconsolidated accounts because of our interest in the impact of the COVID-19 pandemic on establishments that carry out effective activity in a particular location. The drawback of this approach is that we may be underestimating the ability of affiliates to rely on headquarters for provision of liquidity and equity injections. Yet, as our focus is on intrinsic illiquidity, rather than on the ease with which illiquid firms can access additional funding, this drawback does not affect our results.

Extensive cleaning is carried out on the set of financial statements to (1) fill in missing variables using the full set of financial information made available by the firm; (2) impute missing information by leveraging available information on moments that characterise firms in this country-industry; (3) discard observations with implausible values. To illustrate the importance of step (1), note that out of the 5.6 million observations in the raw dataset, 95% lack direct information on overhead costs, 50% lack information on material costs, and 43% lack information on labour costs. Yet, information made available by the same firm in its financial statement - used in step (1) - allows reducing the share of missing observations to just 28% for overhead costs, and to 38-39% for material and labour costs.

To illustrate the importance of step (2), note that frequently partial information on variable costs is available, i.e. either only the total variable cost is known or only one component of variable costs is filled (e.g. only material costs). Information on industry-level cost shares (α_s^f, where {f=M,W}) is computed based on firms that report the split of variable costs among materials and labour. Firm-specific cost shares α_i^f for firms that do not report this split are obtained by combining information on the firm-specific cost share of total variable costs ($\alpha_i^C = (M+W)/REVENUE$) with information on industry-level cost shares: $\alpha_i^M = \frac{\alpha_s^M}{\alpha_s^M + \alpha_s^W}\alpha_i^C$. The share of missing observations is reduced to 20-21% for material and labour costs in this step.[41]

Step (3) ensures that we reduce the impact of outliers on our estimates. Several quality controls are implemented. Firstly, we eliminate observations where full consistency of financial accounts could not be established and where some variables could not be plausibly filled. This step eliminates observations with negative value added as well as observations for which information on total costs is inconsistent with information on revenue and operating profits. Secondly, we eliminate observations where either the ratio of total costs to revenue or the ratio of total variable costs to revenue is in the top or bottom 2.5 percentiles of the EU-wide distribution. In practice, this approach restricts the ratio of total variable costs to revenue (α_i^C) in the sample to the 3-128% range.[42]

At the end of step (3), we have a sample of 2.86 million observations, i.e. 51% of the original dataset, with fully consistent financial accounts and no missing variables. 61% of the sample corresponds to firms with 0-4 employees, and a further 17% to firms with 5-9 employees. As our focus is on keeping as many EU Member States in the sample as possible, and given that coverage of the very small firms is particularly bad in the ORBIS database for countries such as Austria, Germany and Greece, we

[41] Additional steps are undertaken to replace implausible or missing observations for the variables that report corporate taxation expenses and debt servicing costs. Details are available upon request.

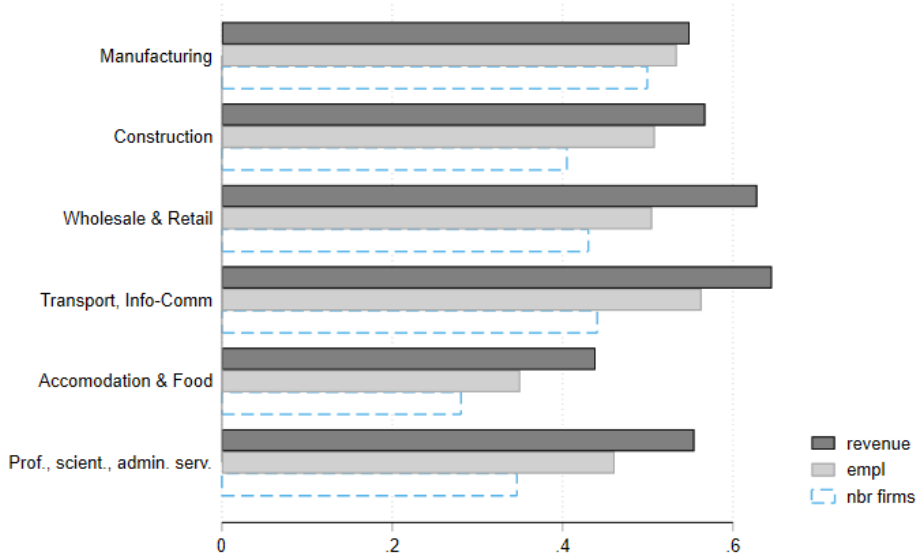
[42] Results are not strongly sensitive to alternative approaches. Cropping on total variable costs restricts α_i^C to the 7-122% range while cropping on total variable costs within NACE 1-digit industries restricts α_i^C to the 3-150% range.

restrict the sample used in the simulations to firms with 10+ employees. As we are left with less than 100 firms in Cyprus and Malta, we let go of these two countries. Further, we let go of Ireland (2047 firms) and the Netherlands (2427 firms) because the distribution of these firms among the remaining size classes diverges significantly from the distribution reported in the Eurostat SBS database. Finally, we discard observations where information on cash or working capital could not be computed.

The final dataset used in the simulations contains 611,810 firms, of which 48% have 10-19 employees, 31% have 20-49 employees, 17% have 50-249 employees, and 4% have 250+ employees. Graph 3.1 illustrates how coverage in our sample compares to the Eurostat SBS data[43]. In manufacturing, our sample covers about half of all firms. In construction, wholesale & retail, transport, as well as in information and communication services, the sample covers 40+% of firms. Coverage is closer to 1/3 in the other service industries. Revenue coverage is similar across industries, between 50-65%, with the exception of the accommodation & food services where it remains above 40%. Employment coverage is close to 50%, with the exception of accommodation & food services, where it is about 1/3. As documented in previous studies, the ORBIS sample thus tends to consist of relatively large firms, in terms of employment and revenue (see Bajgar et al. (2020)).

To sum up, coverage is relatively homogeneous across industries and the key variables of interest. Yet, variability in coverage is more pronounced at the country-industry (and size class) level. Thus, SBS data for the variables of interest (number of firms, employment and revenue) are used to construct a weighting scheme for each country-industry-size class cell. Results at the firm level are reweighted within each cell to deliver aggregate results that mimic the evolution in the full population of firms.

Graph 3.1. **Coverage of the ORBIS data, compared to Eurostat SBS, firms with 10+ employees, EU23**



Source: Bureau van Dijk Orbis database, Eurostat Short-term Business Statistics (STS) and authors' own calculations.

[43] This compares to 2.5 million firms from Advanced Europe in Ebeke et al. (2021), however almost 2.48 million of them are SMEs. Demmou et al. (2021) uses a more restricted approach to very small firms, discarding those that have less than 3 employees and thus has a sample of around 690 000 firms, which is comparable to ours.

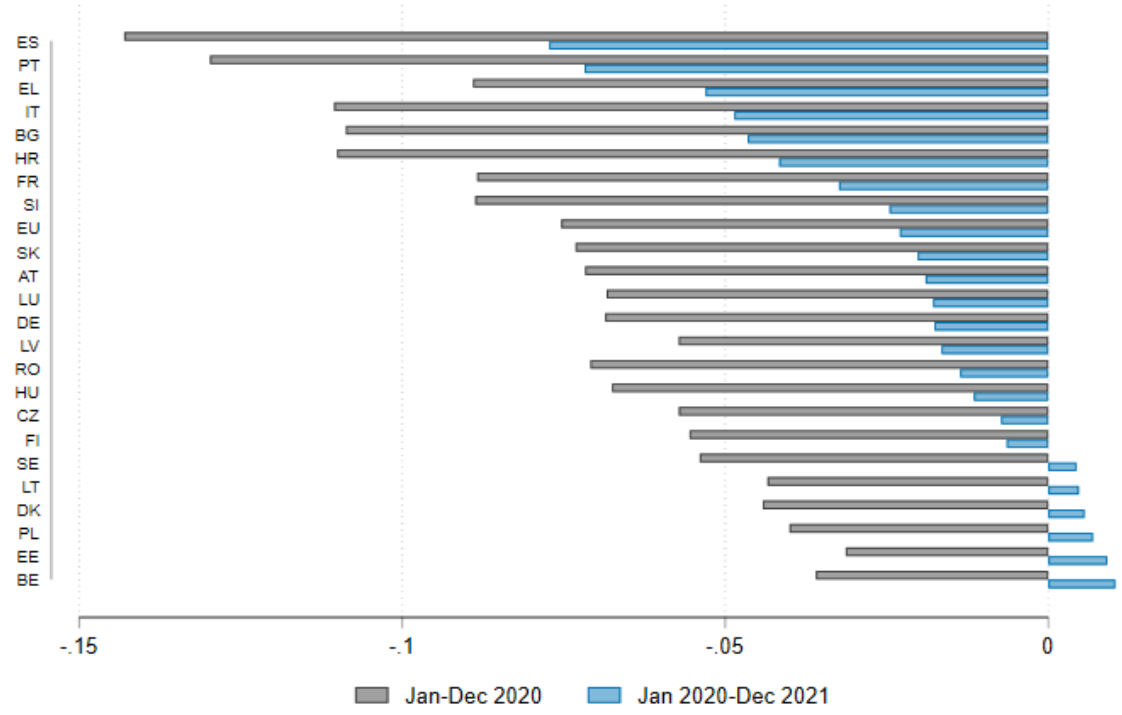
4. RESULTS

This section presents our results on the impact of the COVID-19 pandemic on monthly industrial turnover in the EU as well as on the profitability, liquidity, and solvency in the European non-financial corporate sector.

4.1. IMPACT ON INDUSTRIAL TURNOVER

Graph 4.1 summarises the results of our model on the cumulative impact of the COVID-19 pandemic by country over 2020-2021. Two results stand out. First, countries have been affected in a strongly heterogeneous way. Based on the industries included in our analysis,[44] the hardest hit countries were Spain, Portugal, Italy, Croatia and Bulgaria, each losing 10% or more of total output in 2020, relatively to the pre-pandemic level. The least hit countries were Belgium, Denmark, Estonia, Lithuania, and Poland, as these countries lost less than 5% of total output in 2020. Second, all countries recovered in 2021, whereby output losses for 2020-2021 are situated in the {-8%; 1%} range (vs. {-14%; -3%} range in 2020). Yet, the ranking of the hardest hit countries over 2020-2021 is roughly similar to the 2020 ranking.[45]

Graph 4.1. **Cumulative turnover impact across countries (industry impact weighted by the share of the industry in the country's total revenue)**



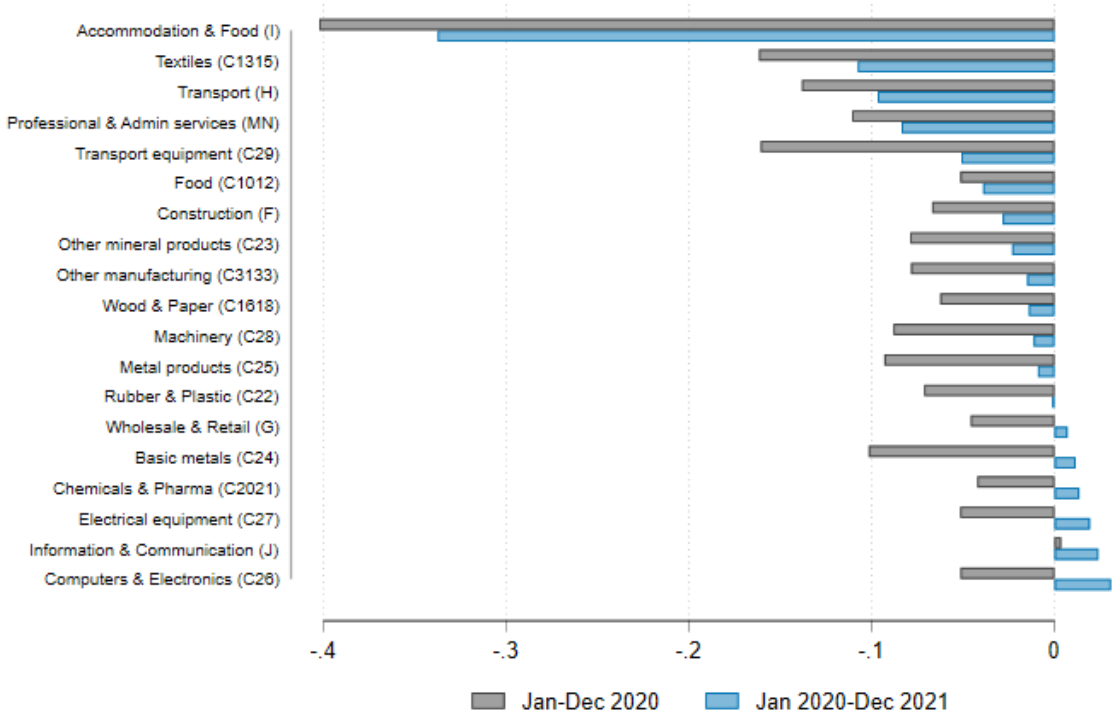
Source: Eurostat Short-term Business Statistics (STS) and authors' own calculations.

[44] These industries are manufacturing (C) and a subset of services (F-J; M-N). The energy industry (D-E), finance and insurance (K) and the real estate industry (L) are omitted from the analysis. For 2020, the results are mainly based on the published turnover data at the industry level.

[45] Greece and Latvia recover slower than the other EU countries, meaning that their position in terms of the severity of the shock over 2020-2021 is less favourable than for the 2020 shock. According to the same metric, Belgium and Denmark recover relatively fast in 2021.

A pattern of strongly pronounced heterogeneity is also documented at the industry level (Graph 4.2). The range of the cumulative output shock, i.e. {-40%; 0%} in 2020 and {-34%; 3%} in 2020-2021, indicates that the COVID-19 pandemic is primarily an industry-specific phenomenon. The *Accommodation and food services* industry stands out with a -40% output loss in 2020, and a -34% output loss over 2020-2021. The other strongly hit industries are *Textiles* (-16 and -11%, respectively), *Transport equipment* (-16 and -5%, resp.), *Transport services* (-14 and -10%, resp.) and *Professional and administrative services* (-11 and -8%, resp.). Yet, the salient fact at the industry level is that the pattern of recovery in 2021 is also strongly heterogeneous. Most industries in manufacturing recover quickly, with some, such as *Basic metals*, *Electrical equipment*, *Computers and Electronics*, recording output growth over 2020-2021, relatively to pre-pandemic levels. Certain other activities, such as *Food production*, *Wood and paper*, *Construction* and *Wholesale and retail*, recover relatively slowly.

Graph 4.2. **Cumulative turnover impact across industries (country impact weighted by the share of the country in the industry's total revenue)**



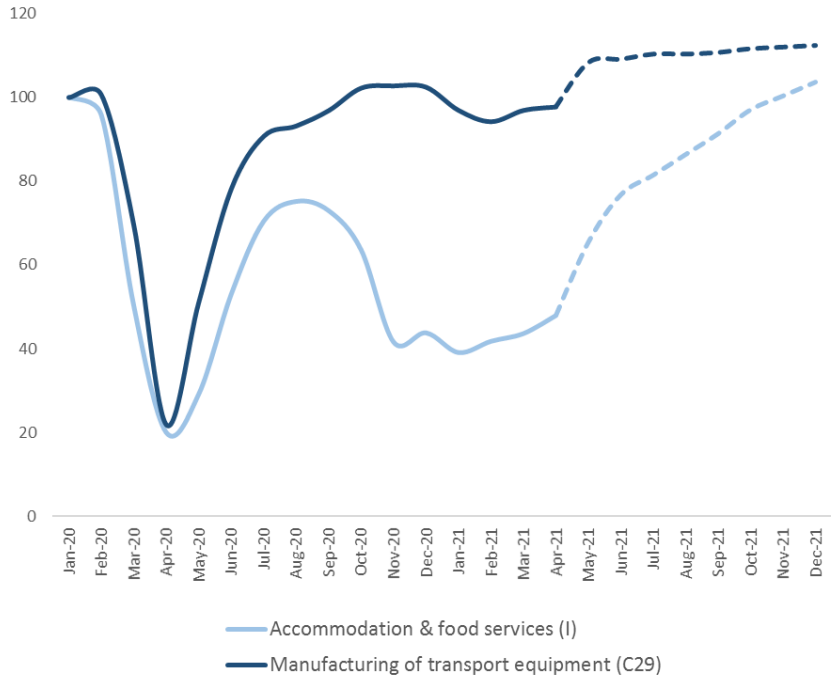
Source: Eurostat Short-term Business Statistics (STS) and authors' own calculations.

To illustrate this strongly pronounced heterogeneity in the impact of the pandemic on turnover over the course of 2020 and 2021, we zoom in on two industries, namely *Transport equipment* (hereafter referred to as the *automotive* industry) and the *Accommodation and food services* (hereafter referred to as the *hospitality* industry). Both industries carry significant economic importance for multiple Member States and the EU economy as a whole. Both industries experienced a strong adverse shock in the first half of 2020 and recovered to various degrees in the third quarter of 2020. Graph 4.3 presents the pattern of turnover in the EU automotive and hospitality industries over 2020 and 2021, obtained by weighting country turnover with its share in total EU turnover in this industry. In this graph, as well as in all subsequent graphs in this section, *solid* lines correspond to the period of observed monthly turnover shocks while *dashed* lines correspond to the period of estimated turnover shocks. In the automotive industry, production was strongly affected by factory shutdowns, supply chain disruptions, and social distancing requirements. At the same time, sales took a hit as consumers postponed their purchases. The swift rebound observed in the third quarter of 2020 likely corresponds to a period when pent-up demand was unleashed. The resurgence of the pandemic that started in the early autumn of 2020 had a much more muted impact on turnover in this industry, likely resulting from the

adjustment to the pandemic by businesses and consumers (as picked up by our empirical model, see Section 2.2).

The hospitality industry relies heavily on intensive contact and intra/international mobility. It suffered comparable losses of about 80% of pre-pandemic output in the second quarter of 2020, but experienced a less pronounced recovery when restrictions were eased in the third quarter of 2020. Moreover, the resurgence of the pandemic in Q4-2020 again caused a sizeable reduction in turnover. Owing to possibly better-targeted measures and some adjustment by businesses and consumers, the industry retained around 40% of monthly turnover. Yet, its sales stagnated at this level for several months as subsequent surges of infections impeded or slowed down the lifting of restrictions. Nowcasts suggest a gradual recovery in the spring of 2021 with the re-opening of the hospitality industry, though a return to pre-crisis levels of monthly turnover is unlikely before the end of 2021.

Graph 4.3. **Monthly turnover in the hospitality and the automotive industries in the EU (Jan 2020 = 100)**



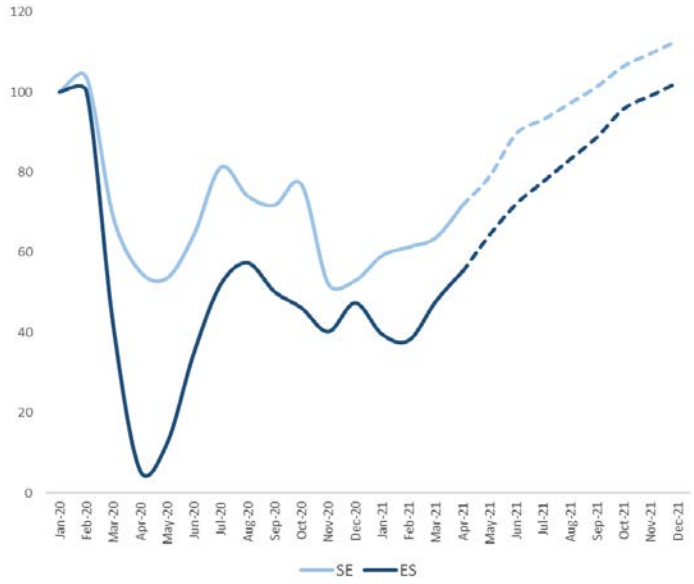
Source: Eurostat Short-term Business Statistics (STS) and authors' own calculations.

The evolution of turnover in these two industries at the EU level hide considerable heterogeneity among the EU Member States. Some countries were hit harder and sooner than others in the first half of 2020, took longer to recover over Q3-2020 and experienced very different subsequent shocks to turnover. Further, Member States have differed and continue to differ in the approach taken to contain the spread of the virus, while at the same time trying to dampen the adverse impact of the pandemic on economic activity. Nowcasts produced for each industry allow us to capture these differences, delivering country-industry specific recovery dynamics over 2021.

Taking the example of the hospitality industry, Graph 4.4 illustrates the differential sensitivity of turnover in European countries, with the example of Sweden and Spain. Clearly, these two countries differed not only in the dynamics of the pandemic, but also in the approach taken by the government to contain the spread of the virus. In Spain, the industry experienced an extremely pronounced drop in turnover in Q2-2020, falling to nearly zero, while the resurgence of the pandemic at the end of 2020 had a more modest impact. In Sweden, the hospitality industry experienced a less dramatic reduction

of turnover in Q2-2020. The hospitality industry experienced a relatively sharper reduction in turnover towards the end of 2020, as the resurgence of the pandemic led the government to adopt relatively stricter containment measures than in the first half of 2020. Following the pandemic scenario specified in Table 2.3, our simulationspredict a recovery to pre-pandemic levels by the end of summer 2021 in Sweden while in Spain the industry is likely to recover its pre-pandemic activity level by the end of 2021.

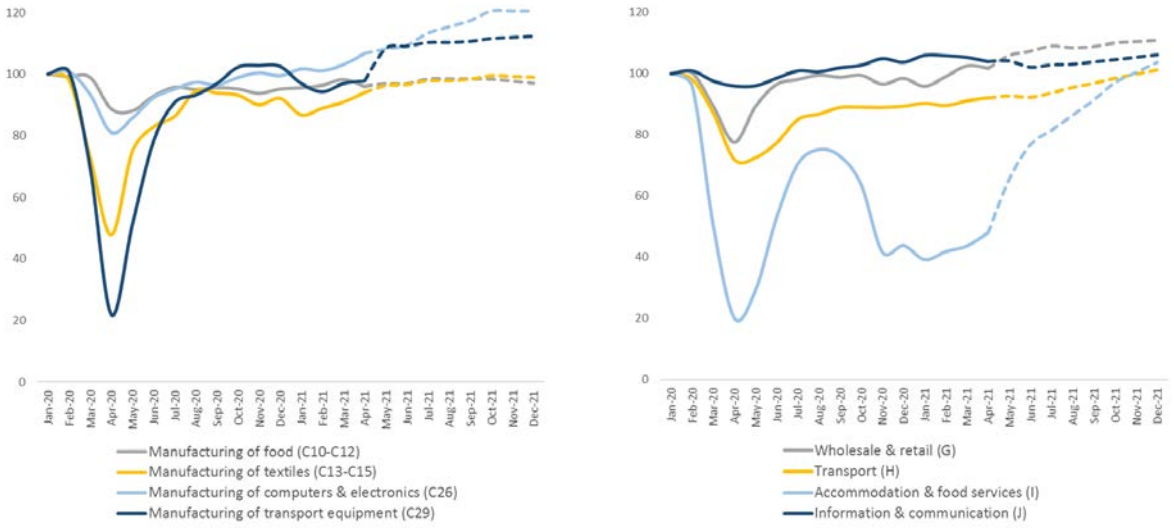
Graph 4.4. **Pattern of turnover in the Spanish (ES) and Swedish (SE) hospitality industry (Jan 2020 = 100)**



Source: Eurostat Short-term Business Statistics (STS) and authors' own calculations.

Yet, differences in the impact of the pandemic within a given industry among EU countries are much less pronounced than differences in its impact across industries. Graph 4.5 illustrates the latter heterogeneity by plotting monthly turnover in the EU in a subset of manufacturing and services.

Graph 4.5. **Monthly turnover in a subset of EU manufacturing and services' industries (Jan 2020 = 100)**



(a) Manufacturing

(b) Services

Source: Eurostat Short-term Business Statistics (STS) and authors' own calculations.

Industries differ in the extent to which they were hit during the first half of 2020. Industries also differ in the speed of rebound in Q3-2020 and in their sensitivity to the subsequent surges in infection rates. Demand-sensitive manufacturing industries, such as transport equipment and textiles, experienced the most pronounced impact of the first wave, due to reduced demand in addition to supply-side restrictions. (Graph 4.5 panel (a)). These industries rebounded quickly after the first wave, due to the easing of supply-side restrictions as well as pent-up demand. Industries that produce essential or digital goods, such as food or computers and electronics, experienced a relatively modest drop in sales (-15% at the trough; -5% over 2020) and tended to maintain turnover close to pre-pandemic levels. Yet, recovery was much stronger in the manufacturing of computers and electronics (+3% of turnover over 2020-2021) than in food production (-4% of turnover over 2020-2021).

Turning to services (Graph 4.5 panel (b)), the hardest hit industries, which are also shown to experience a relatively slow recovery, are transport services and the hospitality industry. Both activities are projected to barely reach pre-crisis levels by the end of 2021. This result is in part attributable to the persistence of restrictions, in particular on international travel, and in part to consumer behaviour, namely less likelihood of pent-up demand in services than in goods. To give an example, it is unlikely that visits to restaurants will overshoot sufficiently to compensate for some of the lost demand once restrictions are lifted, in particular because pent-up demand of some consumers may be compensated by permanently reduced demand of other consumers. In contrast, essential services (e.g. part of wholesale and retail activity) and teleworkable or digital services (e.g. information and communication services) experienced a rather muted impact on turnover. Overall, turnover in the wholesale and retail sector is predicted to remain at the pre-pandemic level in 2020-2021, while turnover in the information and communication services is predicted to exceed the pre-pandemic level by 2.4% in 2020-2021.

4.2. DEPLETION OF CORPORATE LIQUIDITY BUFFERS AS A RESULT OF COVID-19

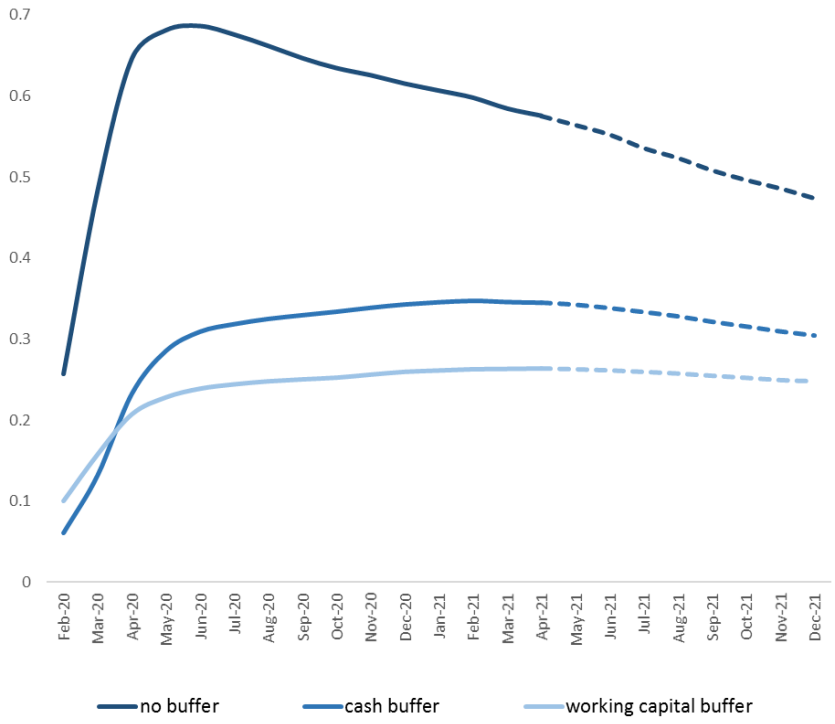
Equipped with the series of monthly shocks to industry turnover over 2020-2021 in all EU Member States, we implement the accounting approach described in section 3.1 to obtain the distribution of profitability shocks and corporate liquidity needs in each month of 2020-2021. Our simulations document substantial depletion of corporate liquidity buffers over the course of 2020, and point to a very partial replenishment of these buffers by the end of 2021. Consistently with the heterogeneity of disturbances to economic activity, we find substantial differences in the magnitude and persistence of liquidity distress across industries and Member States.

Graph 4.6 plots the share of firms in the EU that suffer losses (*no buffer*) together with the share that fully deplete the narrow (*cash*) or the broad (*working capital*) liquidity buffer. Profitability shocks are accumulated over time, meaning that the slope of the curve in 2021 indicates the speed with which firms recover from adverse shocks incurred at the peak of the first wave. The simulations rely on observed monthly shocks to turnover over 2020 and Q1-2021 (*solid* line) and on nowcasts thereafter (*dashed* line). Graph 4.6 documents that previously accumulated liquidity buffers were instrumental in shielding European firms from liquidity distress. At the peak of the first wave, 70% of firms incurred losses while 30 to 40 percentage points fewer firms became illiquid.

The second salient fact documented in Graph 4.6 is the slow replenishment of liquidity buffers. Specifically, the fraction of firms that suffer a loss is monotonically decreasing in the second half of 2020 and throughout 2021, whereby about 50% of firms report a cumulative loss over 2020-2021. Yet, the fraction of firms unable to absorb the cumulative loss with the liquidity buffer peaks much later, i.e. at the end of Q1-2021 at about 1/3 of all firms (in the *narrow* buffer scenario). Subsequently, the fraction of illiquid firms is only weakly decreasing until the end of 2021. It follows that, due to the COVID-19 pandemic about 30% of firms need additional liquidity to fill in their liquidity buffer. This fraction is reduced to about 25% of firms in the full policy scenario, i.e. when labour cost support schemes are complemented also with tax and debt servicing cost deferrals (not shown here).

These results underline the importance of broad-based emergency support measures provided at both the national and the EU level to prevent business failures attributable to liquidity distress. Such broad-based support helped to avoid a surge in unemployment and the associated loss of human capital, while reducing switching costs that would have been incurred by illiquid firms laying off workers in viable jobs, only to look again for competent workers in the recovery phase.

Graph 4.6. **Share of EU firms suffering losses and/or becoming illiquid (accounting for STW schemes)**



Source: Bureau van Dijk Orbis database and authors' own calculations.

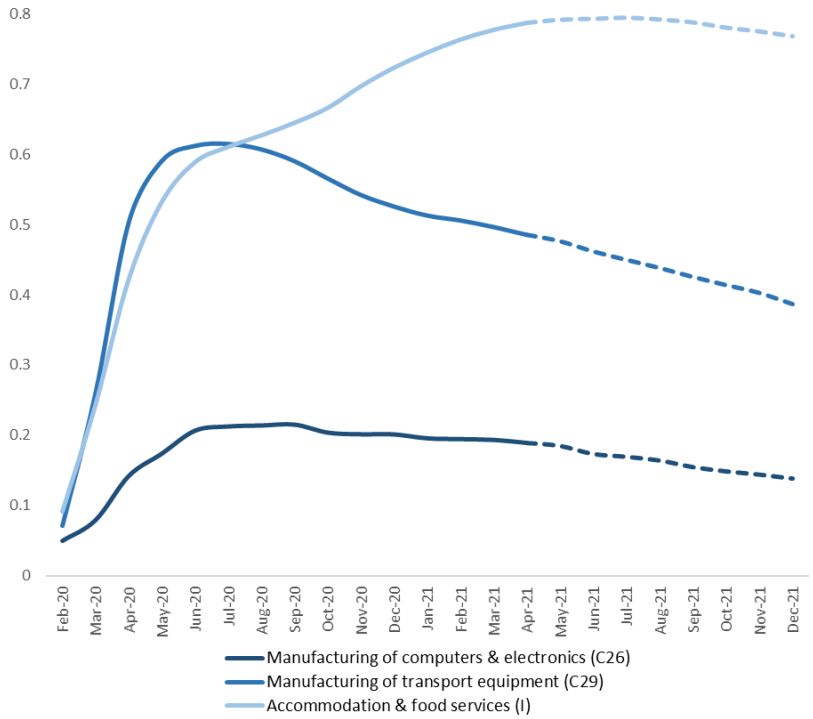
Results for the total economy hide considerable heterogeneity in the magnitude and persistence of liquidity distress in different industries. Graph 4.7 illustrates this heterogeneity by plotting the fraction of firms in liquidity distress in the *narrow* buffer scenario in the hospitality industry (accommodation and food services), the automotive industry (manufacturing of transport equipment), and in the manufacturing of computers and electronics in each month of 2020-2021.

The substantial and persistent adverse profitability shocks in the first wave in the automotive and hospitality industries translate into broad-based liquidity distress, with about 60% of firms becoming illiquid in the first half of 2020. Liquidity distress was much more contained in the manufacturing of computers and electronics, with just 20% of firms becoming illiquid in the first half of 2020. Subsequently, liquidity distress dynamics mimic the pattern of recovery in the industry, documented in section 4.1. In the automotive industry, owing to the pace of recovery in the summer of 2020 and the muted impact of subsequent pandemic surges on turnover, we observe some absorption of previously accumulated losses. The fraction of illiquid firms is reduced to 40% by the end of 2021.[46] In contrast, in the hospitality industry, the accumulation of additional adverse shocks leads to more widespread

[46] The share of illiquid firms in Graph 4.7 corresponds to firms that depleted pre-shock cash buffers. The reduction in the fraction of illiquid firms in the automotive industry indicates that subsequent positive profitability shocks allowed some firms to recover initial losses, resulting in a positive liquidity position. This finding does not imply that cash buffers were restored to their pre-shock levels.

liquidity distress, peaking at about 80% of all firms by the end of the first half of 2021. The two industries diverge: while one fifth of firms in the automotive industry restore their liquidity position, over the same period about one fifth of firms in the hospitality industry shift into illiquidity status.

Graph 4.7. **Share of EU firms becoming illiquid in a subset of industries (cash buffer, accounting for STW schemes)**



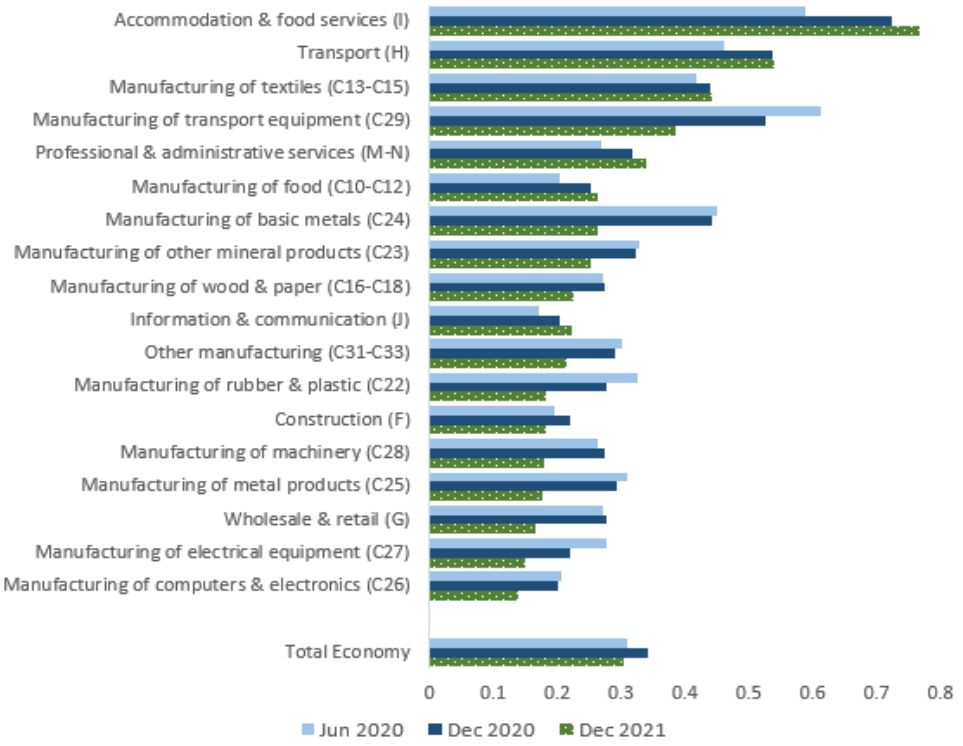
Source: Bureau van Dijk Orbis database and authors' own calculations.

Graph 4.8 plots the share of illiquid firms in each of the industries in the sample at the peak of the impact of the first wave (end of June 2020), at the end of 2020, together with the projected liquidity position by the end of 2021. The incidence and persistence of liquidity distress mimics the pattern of profitability shocks in the industry.[47] Although the fraction of companies unable to absorb the cumulative profitability shock with previously accumulated liquidity buffers decreases in most industries in 2021, between 10 and 50% of firms have higher liquidity needs due to the pandemic[48]. This share peaks at almost 4/5 of all firms in the hospitality industry.

[47] Graph 4.8 provides a visual illustration. In section 4.3 we document this relationship with help of a simple regression.

[48] It is beyond the scope of this paper to estimate to what extent these needs were met by provision of additional finance and/or public support.

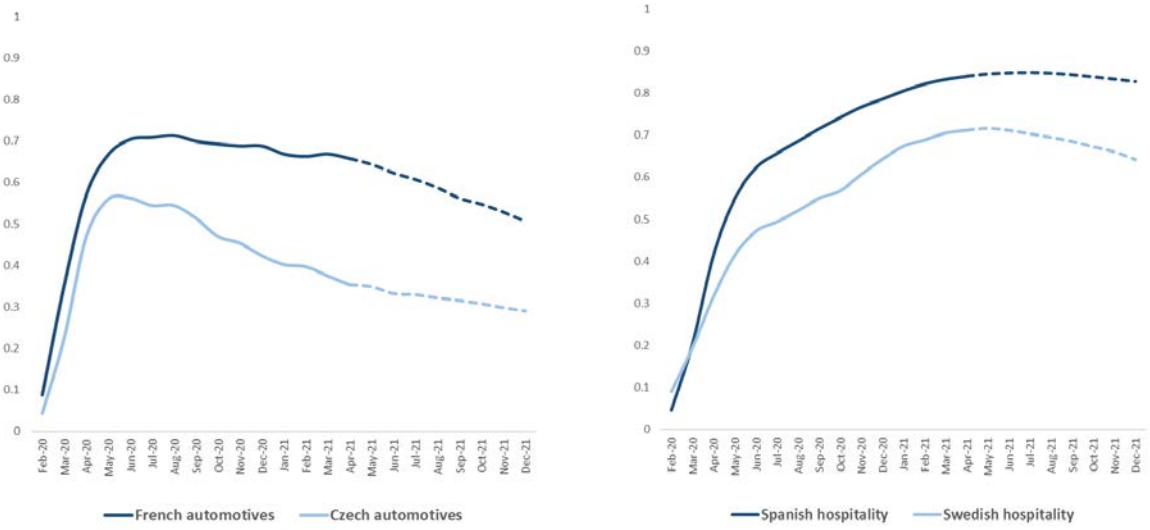
Graph 4.8. **Share of EU firms becoming illiquid, by industry (cash buffer, accounting for STW schemes)**



Source: Bureau van Dijk Orbis database and authors' own calculations.

Further unpacking the incidence and dynamics of liquidity distress within the industry among Member States, we also document some heterogeneity. Graph 4.9 shows that the evolution of the pandemic led to more widespread liquidity distress in the French automotive industry and in the Spanish hospitality industry, relatively to their Czech and Swedish counterparts, respectively. Such differences are attributable to the combination of several factors: the timing and the severity of the pandemic in the country, the government response in terms of containment measures, the specificities of the industrial structure, together with the pre-shock liquidity and solvency of the corporate sector.

Graph 4.9. **Share of illiquid firms in a subset of countries and industries (cash buffer, accounting for STW schemes)**

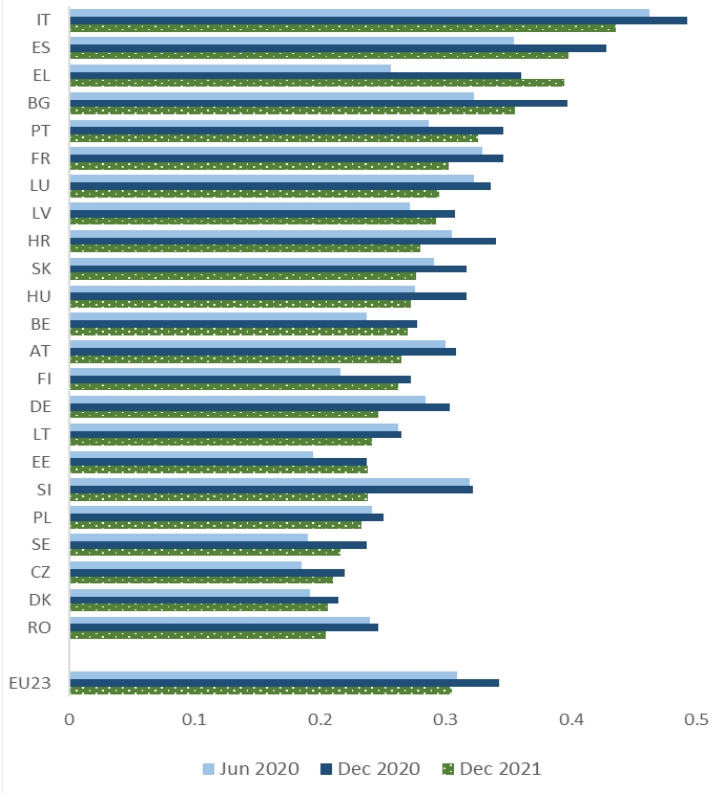


Source: Bureau van Dijk Orbis database and authors' own calculations.

Graph 4.10 documents the incidence of liquidity distress across all EU Member States. Country differences are mainly attributable to the combination of the cumulative adverse profitability shock in the industry with the importance of the industry in the economy. The weight of the hospitality industry in countries such as Greece, Italy, Portugal, and Spain contributes to the magnitude of the aggregate adverse shock (see Graph 4.1), leading to more widespread liquidity distress throughout 2020-2021. Another contributing factor is variation in the magnitude of turnover shocks within the industry (as illustrated by Graph 4.9). To give an example, the cumulative turnover shock in the textiles industry amounts to -14 to -16% in Greece, Italy, Romania, and Spain while best described as stable at pre-shock levels in Finland or Poland. In the construction industry, aggregate turnover shocks range between -10% (Luxembourg) to +5% (Denmark). Pre-shock profitability and liquidity buffers complete the picture.

The higher liquidity needs that we document for 25 to 30% of European firms by the end of 2021 underscore the need to rely on real time data in designing and fine-tuning policy support measures in the recovery phase. The relevance of the methodology proposed in this paper consists in providing a forward-looking perspective on the ability of firms to absorb the cumulative COVID-19 shock, as a function of the magnitude and persistence of the adverse shock as well as of the strength of the projected recovery in the industry. In the next subsection, we complement the analysis of liquidity distress with the build-up of liabilities and equity depletion, underpinning how support measures in the recovery phase could be better targeted to firms that are intrinsically viable, though appearing financially vulnerable due to the pandemic. The gradual shift towards more targeted support measures will be crucial to anticipate and tackle non-performing loans and possible spillover effects to the financial sector, while limiting increases in public debt and facilitating the reallocation of resources towards more productive uses.

Graph 4.10. **Share of EU firms becoming illiquid, by country (cash buffer, accounting for STW schemes)**



Source: Bureau van Dijk Orbis database and authors' own calculations.

4.3. PROFILING OF FIRMS IN DISTRESS – FINANCIAL VULNERABILITY

Corporate losses affect corporate balance sheets and capital structure by depleting equity and increasing indebtedness whenever previously accumulated liquidity buffers are insufficient to absorb losses. Corporate liabilities further increase because firms are expected to make use of moratoria to defer the payment of eligible expenses, such as corporate taxes due in 2020 and 2021, to preserve liquidity. The combined effect of reduced equity, higher leverage, higher future expenses on debt, and reduced profitability magnifies the fraction of firms that appear financially vulnerable due to the pandemic, relatively to the fraction of firms that could already be characterised as financially vulnerable at its outset. Although some of these firms would have been intrinsically viable without the COVID-19 shock, their financial vulnerability and higher liquidity needs by the end of 2021 imply that they may be at risk of not obtaining sufficient funding to continue operating when support measures are withdrawn. A degree of recapitalisation may be required to restore, at least partially, the financial position prevailing before the shock, and to facilitate the absorption of losses incurred during the downturn.[49]

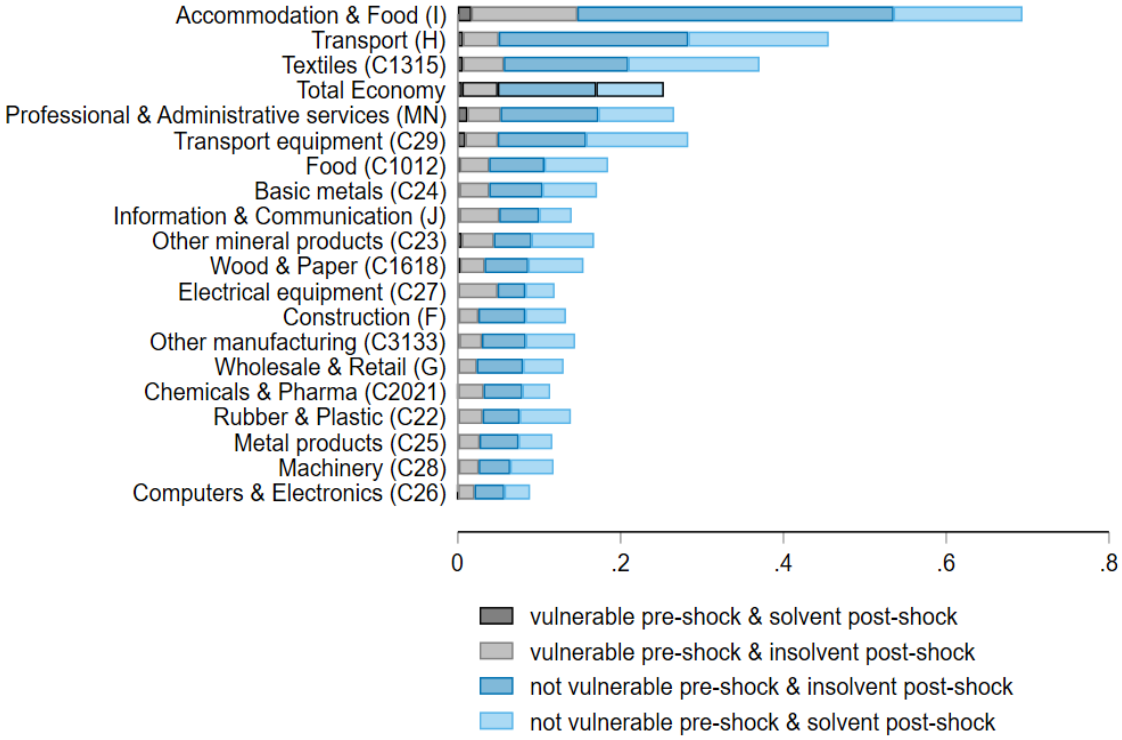
In this section, we make use of the three criteria described in 3.1.4, namely *pre-pandemic financial health*, *post-pandemic liquidity*, and *post-pandemic risk of insolvency*, to quantify the extent of financial vulnerability in the non-financial corporate sector by the end of 2021.[50] In a similar vein to the analysis presented so far the choice of end-2021 is motivated by the need of a practical cut-off date rather than an assumption or assertion of a definitive date of the pandemic. The three criteria are based on the observable characteristics of the firm pre- and post-pandemic. The goal is to identify the fraction of firms that may have difficulty getting access to additional funding once emergency support measures are withdrawn. We posit that this group can be circumscribed to *illiquid* firms, whenever these firms also face *solvency* concerns due to the pandemic. The combination of these two criteria is useful in that the liquidity criterion indicates that the firm effectively needs additional funding to operate while the solvency criterion – based on observable characteristics post-pandemic – may make banks reluctant to provide funding. The final criterion, namely the *financial health status of the firm pre-pandemic*, is helpful to disentangle between firms already vulnerable at the outset from those which financial vulnerability appears more directly associated with the adverse profitability shocks suffered over the course of 2020-2021.

For the EU economy as a whole, about ¼ of all firms appear to face higher liquidity needs by December 2021. These firms are most likely to require external funding in 2022-2023 to cover their operational needs. Figures 4.11 and 4.12 report - respectively by industry and by country – how these firms with higher liquidity needs can be classified in terms of their pre-pandemic and post-pandemic financial health. This split gives four groups. The illiquid firms most likely to face difficulties in obtaining the necessary funding are those that were financially vulnerable before the shock and are at risk of insolvency by the end of 2021 (4%, light grey bar). Another 12% of firms is at risk of insolvency due to the pandemic even though these firms were deemed financially healthy before the pandemic (dark blue bar). Together, these two groups make up 16% of EU firms and correspond to our quantification of financial vulnerability due to the pandemic. The two remaining groups (9%) are unlikely to face funding concerns in connection to their increased liquidity needs. These two groups consist of firms that remain solvent. The bigger of the two groups (8% of total, light blue bar) encompasses firms that were not financially vulnerable before the pandemic and remain solvent after it started. The smaller group (1% of total, dark grey bar) was deemed vulnerable pre-pandemic but remains solvent after it started.

[49] See for example discussion in Carletti et al. (2021) and Demmou and Franco (2021).

[50] As explained in 3.1.4, we present the results for the *STW+* scenario throughout this section.

Graph 4.11. **Illiquid firms by end of 2021, grouped by pre-pandemic financial vulnerability and post-pandemic risk of insolvency (share of total in industry)**

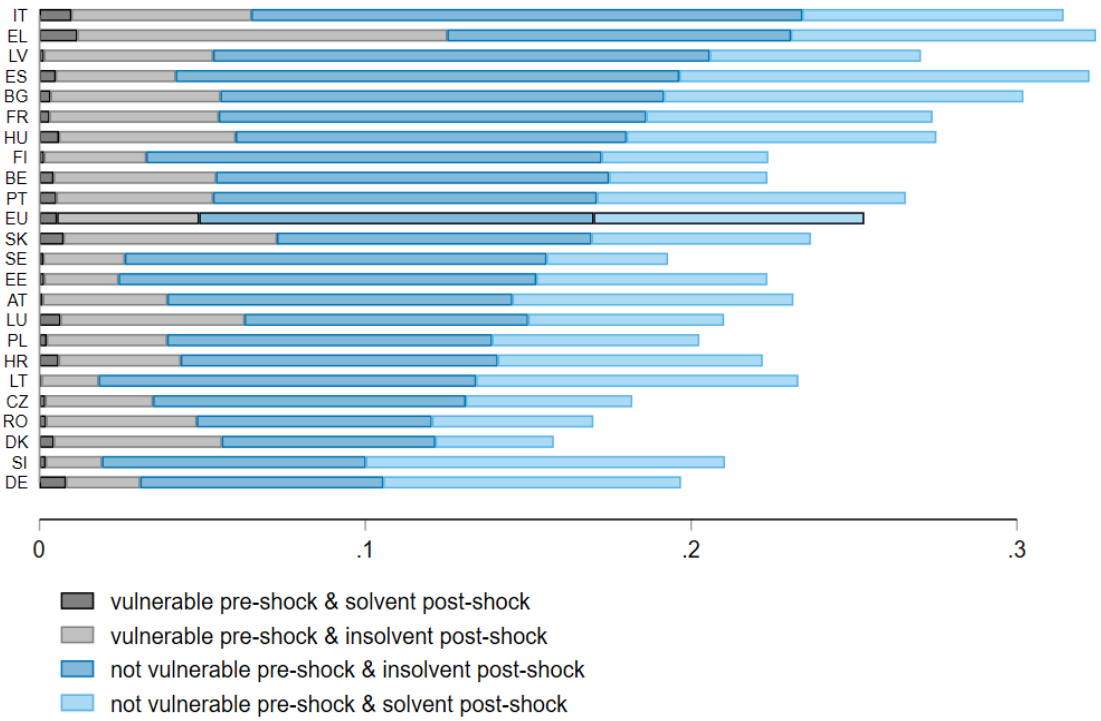


Source: Bureau van Dijk Orbis database and authors' own calculations.

Post-pandemic solvency concerns contribute strongly to more widespread financial vulnerability. This magnification is illustrated by the size of the *dark blue* bar, relatively to the size of the *light grey* bar in Graphs 4.11 and 4.12. The prevalence of pre-pandemic financially healthy but post-pandemic at-risk-of-insolvency firms varies from less than 4% in several manufacturing sectors (Metal products; Machinery; Computers & Electronics) to 23% in Transport services and 38% in the Accommodation & Food services (dark blue bar in Graph 4.11). At the country level, the fraction of such firms varies from about 7% in Denmark, Romania, and Germany to 15% in Latvia and Spain; reaching 17% in Italy (dark blue bar in Graph 4.12).

As explained in section 3.1.3, the firm may appear at risk of insolvency due to the pandemic through two channels. On the one hand, it may have fully depleted its equity. On the other hand, it may have an excessive debt burden in the sense of having interest payments in excess of operating profits, i.e. an interest coverage ratio (ICR) inferior to 1, on top of being highly leveraged. Finally, the firm may be at risk of insolvency because it verifies both criteria.

Graph 4.12. **Illiquid firms by end of 2021, by pre-pandemic vulnerability and post-pandemic risk of insolvency (share of total in country – NB: the scale differs from Graph 4.11)**



Source: Bureau van Dijk Orbis database and authors' own calculations.

Graph 4.13 provides additional information on the pre-pandemic financially healthy firms that have liquidity needs in excess of their liquidity buffers and appear at risk of insolvency by the end of 2021 (the *dark blue* bar for the Total Economy in Graph 4.11). Specifically, we plot the evolution of the size of this group over the course of the pandemic, while splitting it by *risk of insolvency* criterion. All firms in this group satisfy the *high leverage* criterion: firms with negative equity (NE) are automatically considered highly leveraged, while firms with an excessive debt burden are considered at risk of insolvency if and only if they are also highly leveraged (see section 3.1.3).[51] As regards the excessive debt burden (DB), it can materialise in two ways. Either the firm had negative operational profits already before the pandemic (EBIT<0) and, mechanically, has a negative interest coverage ratio after it started. Or the firm had positive operational profits before the pandemic (EBIT>0), which are no longer sufficient to cover the interest payments after it started. To provide more intuition as to the impact that pre-pandemic profitability has on the excessive debt burden (DB) criterion, we further split firms that verify the DB criterion by their pre-pandemic profitability (EBIT).

Three salient facts are visible in Graph 4.13. First, if we look at the split of firms by insolvency criterion by the end of 2021 (the dark blue bar of Graph 4.11 is split in its 5 components in Graph 4.13), equity depletion is the main explanatory factor of insolvency. Indeed, the bulk of the *at-risk-of-insolvency* firms (11%) has negative equity and about half of firms with negative equity also verify the criterion of excessive debt burden (6%). Firms with negative profitability pre-pandemic are prevalent in the latter subgroup. Less than 2% of firms are at risk of insolvency because they verify the excessive debt criterion only.

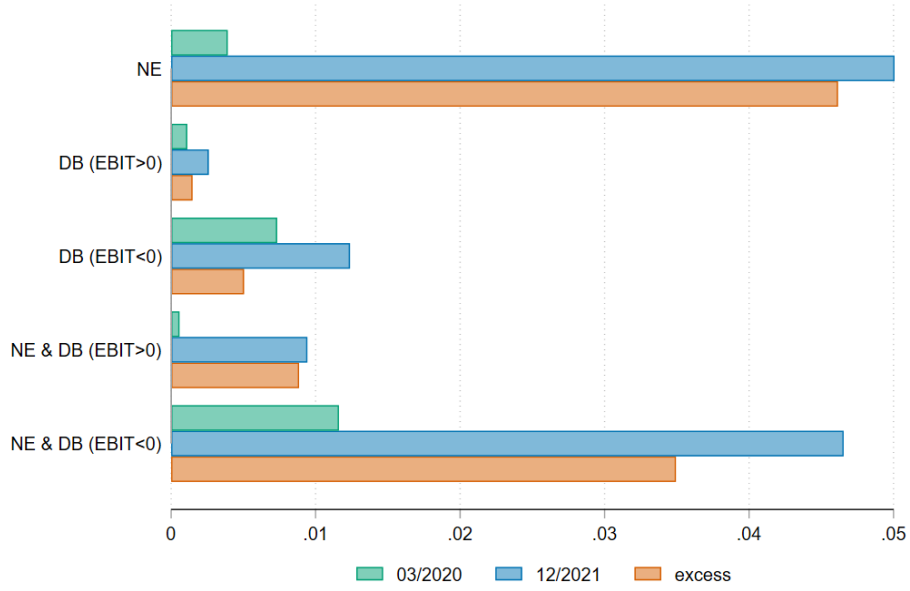
Second, the picture is quite different at the onset of the pandemic, i.e. by the end of March 2020 (green bars in Graph 4.13). About 3% of firms are at risk of insolvency, with 2/3 of these firms verifying the criterion of excessive debt burden, and 1/3 verifying both criteria. Thus, negative profitability pre-

[51] Leverage is computed as the ratio of liabilities to equity. Whenever equity is negative, we classify the firm (by convention) as being in the top quartile of the pre-pandemic distribution of leverage in the country-industry.

pandemic plays an important role in explaining the risk of insolvency that materialises in the early stages of the COVID-19 outbreak for firms deemed viable pre-pandemic.

Third, if we use the difference in the fraction of firms at risk of insolvency by the end of 2021 and those at risk of insolvency already by the end of March 2020 as a proxy of the group which solvency concerns are most likely to be specifically attributable to the COVID-19 outbreak (orange bars in Graph 4.13), pure equity depletion characterises 4.6% of firms. Another 4.3% of firms verifies both criteria, i.e. equity depletion *and* excessive debt burden. Negative pre-pandemic profitability is again prevalent in the latter subgroup. The pure accumulation of an excessive debt burden corresponds to a negligible share of the total (.6%). Overall, 9.5% of firms are estimated to have solvency concerns which may be linked to the pandemic (dark blue bar in Graph 4.12). In terms of employment at risk, 8.5% of employment is attributable to such firms (not shown).

Graph 4.13. **Split of non-vulnerable pre-shock but post-shock at-risk-of-insolvency firms, by criterion (share in total EU firms)**



Note: "NE" stands for "negative equity"; "DB" stands for "debt burden"; "EBIT" stands for "operating profits".

Source: Bureau van Dijk Orbis database and authors' own calculations.

Yet, it could be argued that firms recording negative operational profits (i.e. EBIT<0) prior to the pandemic have legacy issues that may lead to solvency concerns, even in the absence of the additional adverse profitability shock linked to the pandemic. Adopting this more restrictive view circumscribes the group of firms with solvency concerns specifically attributable to the pandemic to 5.5% of all firms.[52] The risk of insolvency for 84% of these firms is identified through the negative equity criterion only. The prevalence of equity depletion in determining post-pandemic solvency concerns suggests a role for targeted recapitalisation, to prevent the exit of pre-pandemic viable firms.

Table 4.1 demonstrates that the magnitude of the adverse shock to industrial activity (i.e. total output loss relatively to the pre-pandemic baseline) is strongly correlated with the fraction of firms that face higher liquidity needs by the end of 2021 (column 1). The magnitude of the shock is also strongly correlated with solvency concerns (columns 2-3) and with the prevalence of the negative equity

[52] This result is obtained by summing the three *excess* bars in Graph 4.13 that correspond to negative equity, debt burden with EBIT>0, as well as negative equity & debt burden with EBIT>0 (i.e. discarding the two bars with EBIT<0).

criterion in determining *post-pandemic risk of insolvency* in the industry (column 4; see Graph A.5 in the Annex for a visual illustration of this link). Specifically, a 1 percentage point additional loss of turnover in the industry translates into a 0.8 percentage point increase in the fraction of firms that shift into *at risk of insolvency* status because of equity depletion. The coefficients obtained for the cumulative 2020-2021 shock tend to be higher than for the 2020 shock, indicating that the persistence of the shock helps to explain the shift of intrinsically viable firms into insolvency. All of the regressions include the economy-wide shock (i.e. the aggregate loss of turnover in the economy relatively to the pre-pandemic baseline) as a control variable. We pick up a positive coefficient on this variable. This result underpins that conditional on the set of industry-specific shocks, the corporate sector in the hard-hit economies is – if anything - relatively resilient, i.e. it is really the idiosyncratic industry shock that matters for explaining magnified corporate vulnerability.

These findings underline the risk brought about by predominant reliance on credit in addressing corporate liquidity needs in the hardest hit industries.[53] As the COVID-19 shock becomes protracted, excessive reliance on credit may result in widespread financial vulnerability among intrinsically viable firms, if one defines intrinsic viability through the financial health status of the firm at the onset of the pandemic. Graph A.6 in the Annex provides additional evidence on the strength of the linkage between magnified financial vulnerability in the hardest hit industries and in the country overall.

Table 4.1. **Impact of the cumulative loss of turnover in the industry and in the economy on liquidity distress & solvency status in the EU corporate sector by the end of 2020 and by the end of 2021**

	Illiquid (1)		**Insolvent (2)**		***Newly* insolvent (3)**		**Negative equity (4)**	
	2020	**2020-2021**	**2020**	**2020-2021**	**2020**	**2020-2021**	**2020**	**2020-2021**
Industry shock	-1.559[a]	-1.545[a]	-0.735[a]	-0.865[a]	-0.617[a]	-0.748[a]	-0.772[a]	-0.827[a]
Aggregate shock	0.487[a]	0.775[a]	0.616[a]	0.747[a]	0.429[a]	0.520[a]	0.432[a]	0.711[a]
Observations	435	435	435	435	435	435	266	220
R-squared	0.68	0.68	0.61	0.62	0.62	0.62	0.70	0.57

Notes: The dependent variable is the share of firms in the country-industry that verify a particular criterion of distress, with each subsequent criterion narrowing down the sample of firms that verify it. (1) Illiquid: firms with higher liquidity needs. (2) Insolvent: firms with higher liquidity needs and at risk of insolvency. (3) Newly insolvent: firms with higher liquidity needs and at risk of insolvency, with solvency concerns linked to the pandemic. (4) Negative equity: firms with higher liquidity needs and at risk of insolvency, with solvency concerns linked to the pandemic; and for which the risk of insolvency materialises through the negative equity criterion.

Standard errors clustered by industry; [a] $p<0.001$. The aggregate country-level shock is included as a control variable; it explains <1% of total variation. The number of observations is reduced in (4) because it is run on the intensive margin, i.e. on the subsample of country-industry observations where the fraction of firms is strictly positive. Results stand when zeros are included, but the estimation becomes less precise (significant at 5%).

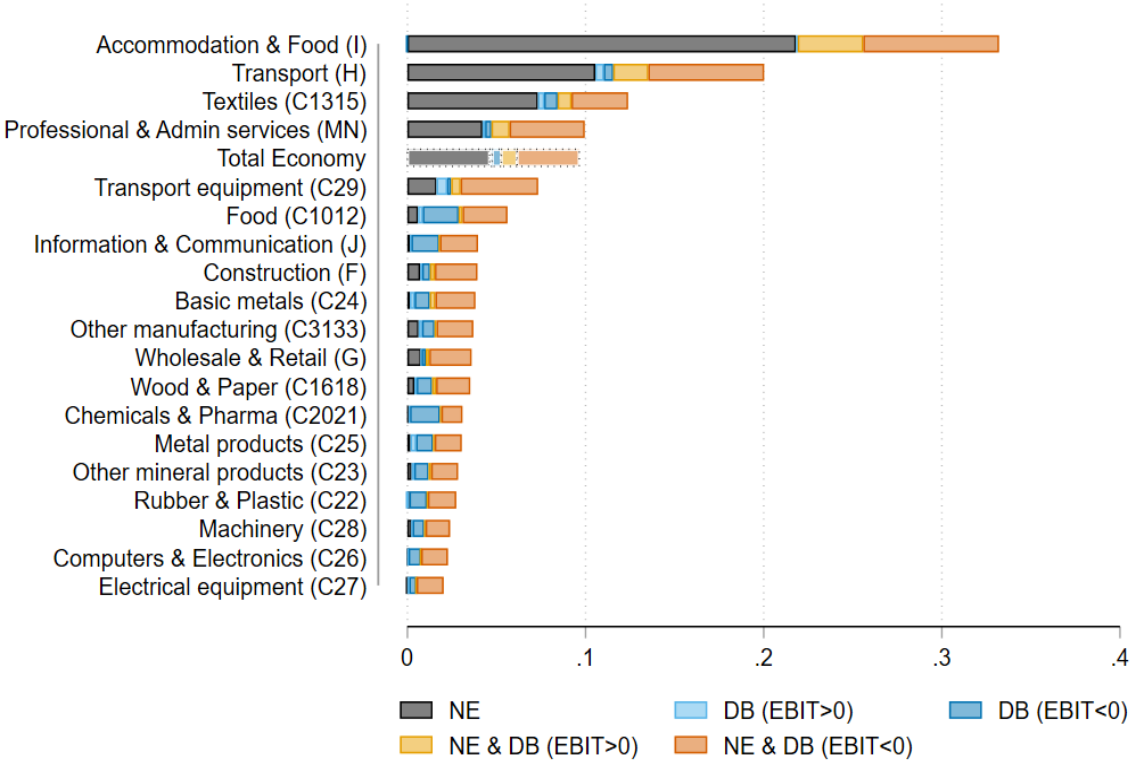
Source: Bureau van Dijk Orbis database and authors' own calculations.

[53] In the simulations, liquidity needs in excess of 50% of previously accumulated liquidity buffers are addressed via additional borrowing. This borrowing generates additional expenses on debt in the following quarters. This approach can be seen as providing an upper bound to additional borrowing, as some firms may have been able to rely on equity injections. To calculate the interest coverage ratio in 2022, it is assumed that the firm recovers its pre-shock operational profits but starts paying expenses on its pre-shock debt and on its additional borrowing. This approach can be seen as providing a lower bound to financial expenses in 2022 as it does not incorporate payment of deferred financial expenses.

Graph 4.14 illustrates this point at the industry level. The *hardest hit* industries are characterised by the prevalence of newly insolvent firms which did not suffer from negative profitability and did not have an excessive debt burden before the pandemic (as illustrated by the size of the dark grey+yellow+light blue bars relatively to the size of the dark blue + orange bars). These intrinsically viable firms depleted their equity in the course of the pandemic, because of the sequence of strongly adverse profitability shocks. The *least hit* industries are characterised by the prevalence of newly insolvent firms that were already suffering losses before the pandemic and further increased their borrowing and/or fully depleted their remaining equity over 2020-2021. In the latter group of industries the adverse profitability shocks experienced by firms in 2020 were more than compensated in the subsequent recovery period. It follows that the intrinsic characteristics of the firm, such as its negative profitability prior to the pandemic, explain its shift into insolvency status, rather than the cumulative shock to industrial activity that can be associated with the COVID-19 outbreak.

These findings underpin the need to fine-tune the criteria used to assess firm viability due to the pandemic. It is preferable to identify sectors which are hit less and where most of the firms that are affected were already suffering losses. In such sectors, the costs of untargeted support start to outweigh the benefits, and viability assessment is very important. In the most affected sectors, on the other hand, even without targeting, support will still rescue a large proportion of viable firms that would not survive otherwise.

Graph 4.14. **Split of firms at risk of insolvency post-pandemic, with solvency concerns attributable to the pandemic, by insolvency criterion (share of total in industry)**



Note: "NE" stands for "negative equity"; "DB" stands for "excessive debt burden"; "EBIT" stands for "operational profits".

Source: Bureau van Dijk Orbis database and authors' own calculations.

CONCLUSION

This paper develops a novel approach to track the effects of the COVID-19 pandemic in real time on industrial activity and, consequently, on the liquidity and solvency of the non-financial corporate sector. We demonstrate that the empirical model performs well in tracking monthly variation in industrial turnover, capturing not only the impact of the first wave of the pandemic and the subsequent rebound, but also the dampened effect of the later surges in infection rates on economic activity, i.e. the adjustment capacity of the economy. Following the accounting approach adopted in the recent literature, the obtained series of monthly shocks to industrial turnover are fed into the profit-generating process derived from financial statements at the firm level to obtain the distribution of profitability shocks in each country and industry over 2020-2021. We document that in the period March 2020 – December 2021, between 25 and 30% of European firms faced higher liquidity needs. Further, about 10% of pre-pandemic viable firms are estimated to shift into insolvency status by the end of 2021. The estimations take into account part of the policy support, which helped to contain the impact of the shock.

We document that the depth and persistence of turnover shocks associated with the pandemic explain about 2/3 of variation in liquidity distress and in the magnification of financial vulnerability across countries and industries. These findings underpin the risk brought about by predominant reliance on credit in addressing corporate liquidity needs. As the COVID-19 shock became protracted, excessive reliance on credit may result in a more widespread risk of insolvency in the hardest hit industries among firms deemed financially healthy at the onset of the pandemic. This paper also contributes to improve our understanding of financial vulnerability by broadening the solvency status considerations to include debt overhang, measured through the inability of the firm to cover its interest payments with its operational profits. The paper's findings underpin a potential need to fine-tune the policy criteria for providing targeted support, i.e. by employing viability criteria in sectors that are less affected and where firms in distress tend to be the ones with legacy problems.

We see this work as a first step on the path to developing richer empirical models for producing industrial nowcasts, explicitly taking into account domestic and international supply and demand linkages and incorporating the multitude of novel indicators that allow tracking economic activity in real time.[54] Although the use of such novel data sources is rapidly progressing at the national level, we hope that this paper, by adopting an EU-wide perspective, contributes to make the case for the emergence of an EU-wide platform that would enable tracking economic activity in real time by relying on anonymised data from private and public sources alike.

Furthermore, we see this work as proof of concept of a framework that allows simulating the micro-level effects and the macro-level implications of specific policies. The approach developed and implemented in this paper can be used to further investigate the characteristics of financially vulnerable firms in terms of their position in the productivity distribution and viability going forward. This would also be important in light of the discussions on phasing out of broad-based support and considerations to have more targeted support measures in place for the sectors that are affected more severely and persistently by the pandemic. For comparability with previous studies, in this paper we adopted a stylised approach to modelling emergency support policies over the course of the pandemic. In future work we aim to refine the modelling of policies while adopting a forward-looking approach, to underpin how specific aspects of policy design may affect the recovery of the non-financial corporate sector over the medium term.

[54] Specifically, we illustrate how information available at different levels of granularity can be connected, made mutually consistent, and fed back to refine macroeconomic forecasts. Chetty et al (2020) convincingly show the potential of real time data for monitoring the economic impact of the pandemic and fine-tuning the policy response for the US at a granular spatial level. Landais et al. (2021) document the distributional effects of the crisis in France using anonymised bank and transaction data. Durante et al. (2021) quantify the extent to which income support in Spain helped low-income households smoothen their consumption over the course of the health crisis.

REFERENCES

Altman E., Iwanicz-Drozdowska M., Laitinen E., and Suvas A. (2017). Financial distress prediction in an international context: A review and empirical analysis of the Altman Z-score model. *Journal of International Financial Management and Accounting*, 28:2.

Altman, E.I. (1968). Financial Ratios, Discriminant Analysis and the Prediction of Corporate Bankruptcy. *Journal of Finance*, 23: 589-609.

Altomonte, C., M. Demertzis, L. Fontagné and S. Mueller (2021). COVID-19 financial aid and productivity: Has support been well spent? *Policy Contribution* 21/2021, Bruegel.

Aspachs O., Durante R., Montalvo J.G., Graziano A., Mestres J., and Reynal-Querol M. (2021). Tracking the Impact of COVID-19 on Economic Inequality at High Frequency. Forthcoming *PLOS ONE*.

Bajgar M., Berlingieri G., Calligaris S., Criscuolo C., and Timmer J. (2020). Coverage and representativeness of ORBIS data. *OECD Science, Technology, and Industry working papers*, 06.

Balduzzi P., Brancati E., Brianti M., Schiantarelli F. (2020). The Economic Effects of COVID-19 and Credit Constraints: Evidence from Italian Firms' Expectations and Plans. *Unpublished manuscript*.

Bańbura M., Giannone D., Modugno M. and Reichlin L. (2013). "Now-casting and the real-time data flow" in *Handbook of Economic Forecasting* vol. 2A, chapter 4 (ed. Elliott G. and Timmermann A.).

Banerjee R., Illes A., Kharroubi E. and Serena J.-M. (2020), COVID-19 and Corporate Sector Liquidity. *BIS bulletin* 10 (April).

Bodnár K., Le Roux J., Lopez-Garcia P. and Szörfi B. (2020). The impact of COVID-19 on potential output in the euro area. Published as part of *ECB Economic Bulletin*, issue 7 (September).

Carletti E., Oliviero T., Pagano M., Pelizzon L. and Subrahmanyam M. (2020). The COVID-19 Shock and Equity Shortfall: Firm-level Evidence from Italy. *CEPR Discussion Paper* 14831.

Chetty R., Friedman J., Hendren N. and Stepner M. (2020). The Economic Impacts of COVID-19: Evidence from a new public database built using private sector data. *NBER Working Paper* 27431.

Connell Garcia W. and Ho V. (2020), What Types of Firms become Illiquid as a Result of COVID-19? A Firm-Level Perspective using French Data. *ECFIN Discussion Paper* 136.

Cros M., Epaulard A. and Martin, P. (2021). Will Schumpeter Catch Covid-19? *CEPR Discussion Paper* 15834.

Deb P., Furceri D., Ostry J. and Tawk N. (2020). The Economic Effects of COVID-19 Containment Measures. *IMF Working Paper* 158 (August).

Demmou, L., Calligaris, S., Franco, G., Dlugosch, D., McGowan, A. and Sakha, S. (2021). Insolvency

and Debt Overhang Following the COVID-19 Outbreak: Assessment of Risks and Policy Responses. *Covid Economics*, Issue 69.

Demmou L. and Franco G. (2021). From hibernation to reallocation: loan guarantees and their implications for post-COVID-19 productivity. *OECD Economics Department Working Papers* 1687.

De Vito A. and Gomez J.-P. (2020). Estimating the COVID-19 cash crunch: Global evidence and policy. *Journal of Accounting and Public Policy*, volume 39, issue 2 (March-April).

Dingel J. and Neiman B. (2020). How Many Jobs Can be Done at Home? *NBER Working Paper* 26948.

Durante R., Guiso L., Gulino G. (2021). Asocial capital: Civic Culture and Social Distancing during COVID-19. *Journal of Public Economics*, 194.

Ebeke C., Jovanovic N., Valderrama L. and Zhou J. (2021). Corporate liquidity and solvency in Europe during COVID-19: the role of policies. *IMF Working Paper* 2021/056 (March).

European Banking Authority (2020). First Evidence on the Use of Moratoria and Public Guarantees in the EU Banking Sector. EBA/Rep/2020/31

European Central Bank (2021). Survey on the Access to Finance of Enterprises in the Euro Area. November 2021.

European Commission (2021). The Sectoral Impact of the COVID-19 crisis. *Technical note for the Eurogroup* (March).

European Commission (2021). Corporate Solvency of European Enterprises – state of play. *Note to the Eurogroup Working Group* (February).

European Commission (2021). European Economic Forecast – Winter 2021. *Institutional Paper* 144.

European Commission (2020). Identifying Europe's recovery needs. *Staff Working Document* 98.

European Systemic Risk Board (2021). Financial Stability Implications of Support Measures to Protect the Real Economy from the COVID-19 Pandemic. February 2021.

Foroni C., Marcellino M. and Stevanović D. (2020). Forecasting the Covid-19 recession and recovery: lessons from the financial crisis. *ECB Working Paper* 2468 (September).

Giannone, D., Lenza, M. and Primiceri G. (2017). Economic Predictions with Big Data: The Illusion Of Sparsity. *CEPR Discussion Paper* 12256.

Gourinchas, P.-O., Kalemli-Özcan S., Penciakova, V., and Sander, N. (2020). COVID-19 and SME Failures. *NBER Working Paper* 27877.

Guerrieri V., Lorenzoni G., Straub L. and Werning I. (2020). Macroeconomic implications of COVID-19: Can Negative Supply Shocks Cause Demand Shortages? *NBER Working Paper* 26918.

Hadjibeyli B., Roulleau G. and A. Bauer (2021). Live and (don't) let die: the impact of COVID-19 and of public support on French firms. *Direction Générale du Trésor Working Papers* #2021/2 (April).

Landais C., Bounie D., Camara Y., Fize E., Galbraith J., Lavest C., Pazem T. and Savatier B. (2020). Consumption Dynamics in the COVID Crisis: Real-Time Insights from French transaction and Bank data. *CEPR Discussion Paper* 15474.

Maurin L. and Pal R. (2020). Investment vs. debt trade-offs in the post-COVID-19 European economy. *EIB working paper* 2020/09 (November).

McCormick G., Keay A., Brown S., and Dahlgreen J. (2016). Study on a new approach to business failure and insolvency: Comparative legal analysis of the Member States' relevant provisions and practices. *DG JUST: European Commission Tender No. JUST/2014/JCOO/PR/CIVI/0075*.

Schivardi F. and Romano G. (2020). A simple method to estimate firms' liquidity needs during the COVID-19 crisis with an application to Italy. *Covid Economics*, Issue 35, p. 51-69.

Tielens J., Piette C. and De Jonghe O. (2020). Belgian corporate sector liquidity and solvency in the COVID-19 crisis: a post-first-wave assessment. *NBB Economic Review* (December).

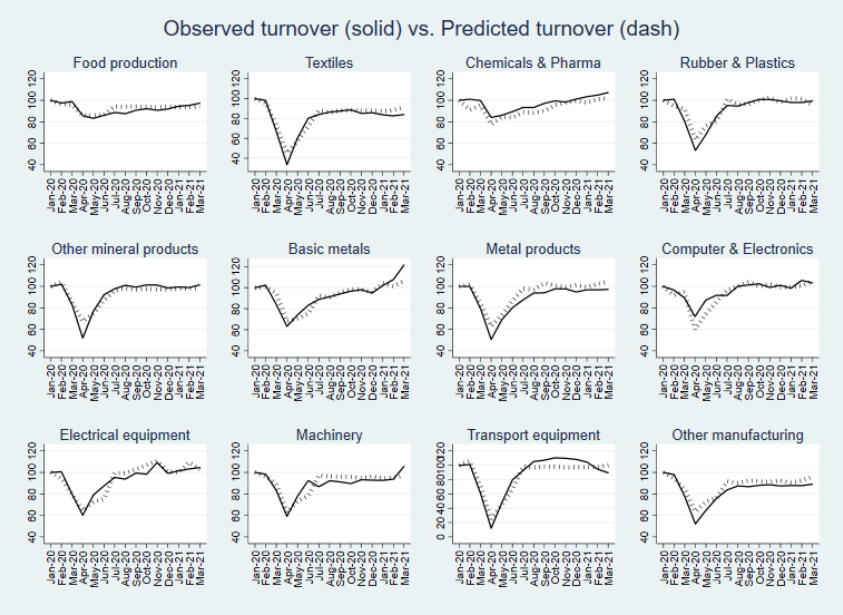
Turner D., Égert B., Guillemette Y., and Botev J. (2021). The tortoise and the hare: The race between vaccine rollout and new COVID variants. *OECD Economics Department Working Papers*, #1672.

ANNEX

Table A.1. **List of industries covered in the analysis**

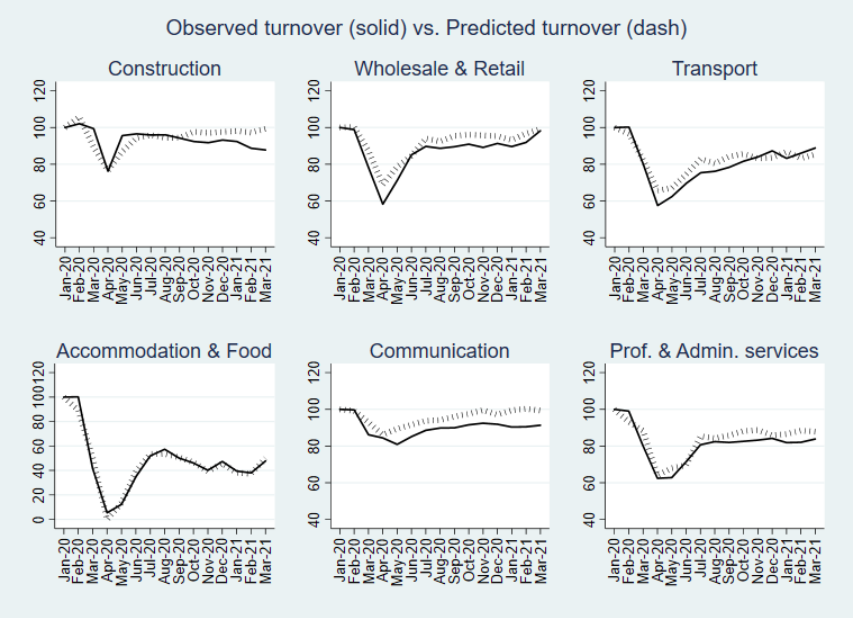
Industry code	Industry description
C10-C12	Manufacturing of food
C13-C15	Manufacturing of textiles
C16-C18	Manufacturing of wood and paper
C20_C21	Manufacturing of chemicals and pharmaceuticals
C22	Manufacturing of rubber and plastics
C23	Manufacturing of other mineral products
C24	Manufacturing of basic metals
C25	Manufacturing of metal products
C26	Manufacturing of computers and electronics
C27	Manufacturing of electrical equipment
C28	Manufacturing of machinery
C29	Manufacturing of transport equipment
C31-C33	Other manufacturing
F	Construction
G	Wholesale and Retail
H	Transport
I	Accommodation and Food services
J	Information and Communication
M_N	Professional and Administrative services

Graph A.1. **Turnover in manufacturing in Spain**



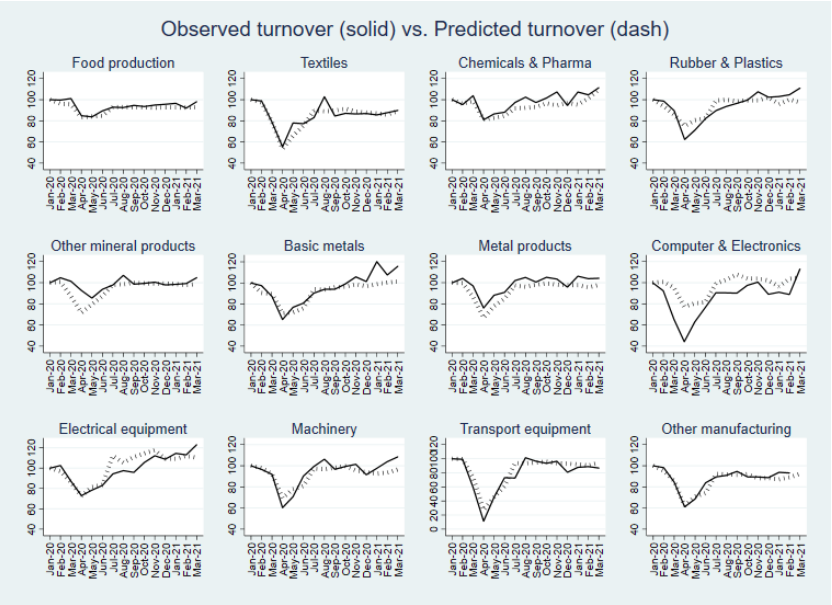
Source: Eurostat Short-term Business Statistics (STS) and authors' own calculations.

Graph A.2. **Turnover in services in Spain**



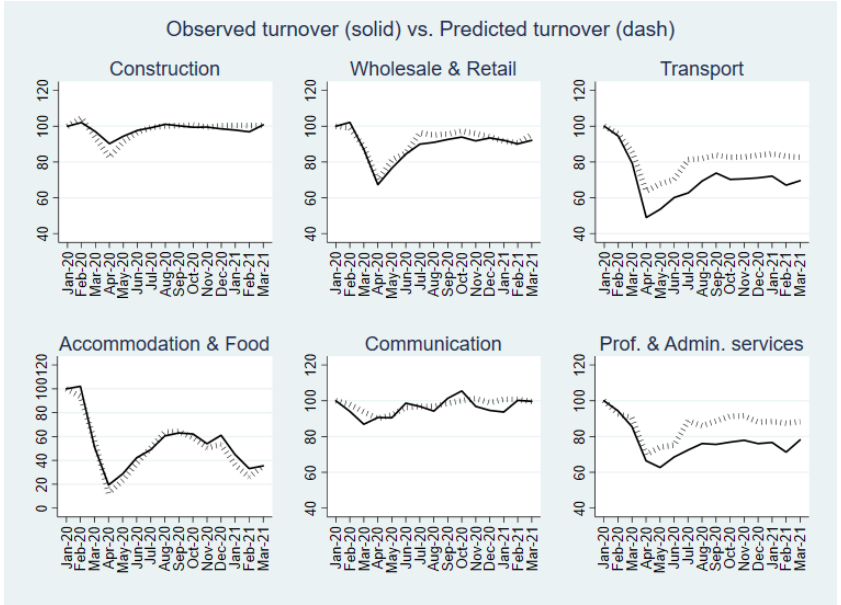
Source: Eurostat Short-term Business Statistics (STS) and authors' own calculations.

Graph A.3. **Turnover in manufacturing in Portugal**



Source: Eurostat Short-term Business Statistics (STS) and authors' own calculations.

Graph A.4. **Turnover in services in Portugal**



Source: Eurostat Short-term Business Statistics (STS) and authors' own calculations.

Table A.2. **Coverage of monthly turnover in Eurostat STS by country and industry**

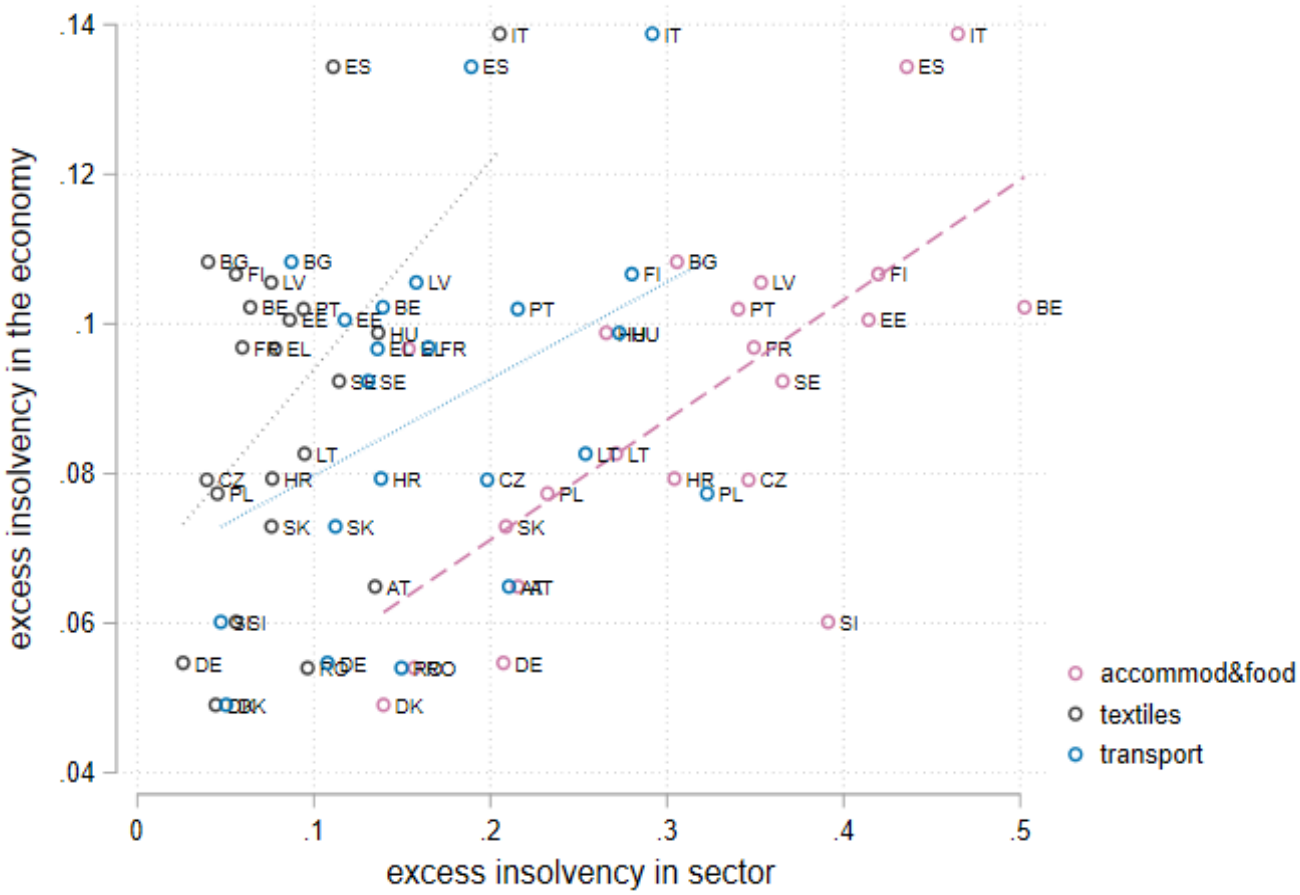
	C10-C12	C13-C15	C16-C18	C20_C21	C22	C23	C24	C25	C26	C27	C28	C29	C31-C33	F	G	H	I	J	M_N
AT	V	V	V	V	V	V	V	V	V	V	V	V	V	V	V	-	-	-	-
BE	V	V	V	V	V	V	V	V	V	V	V	V	V	V	V	-	-	-	-
BG	V	V	V	V	V	V	V	V	V	V	V	V	V	V	V	V	V	V	V
CY	-	-	-	-	-	-	-	-	-	-	-	-	-	-	V	-	-	-	-
CZ	V	V	V	V	V	V	V	V	V	V	V	V	V	V	V	V	V	V	V
DE	V	V	V	V	V	V	V	V	V	V	V	V	V	V	V	-	V	-	-
DK	V	V	V	V	V	V	V	V	V	V	V	V	V	V	V	V	V	V	V
EE	V	V	V	V	V	V	V	V	V	V	V	V	V	-	V	-	-	-	-
EL	V	V	V	V	V	V	V	V	V	V	V	V	V	-	V	-	-	-	-
ES	V	V	V	V	V	V	V	V	V	V	V	V	V	V	V	V	V	V	V
FI	V	V	V	-	-	V	V	V	-	-	V	V	V	-	V	V	V	V	V
FR	V	V	V	V	V	V	V	V	V	V	V	V	V	V	V	V	V	V	V
HR	-	-	-	-	-	-	-	-	-	-	-	-	-	V	V	V	V	V	V
HU	V	V	V	V	V	V	V	V	V	V	V	V	V	V	V	-	-	-	-
IE	V	-	V	-	V	V	-	V	-	V	-	V	-	-	V	-	-	-	-
IT	-	V	V	V	V	V	V	V	V	V	V	V	V	V	V	-	-	-	-
LT	V	V	V	V	V	V	V	V	V	V	V	V	V	-	V	-	-	-	-
LU	-	-	-	-	-	-	-	-	-	-	-	-	-	V	V	V	V	V	V
LV	V	V	V	V	V	V	V	V	-	V	V	V	V	-	V	V	V	V	V
MT	-	-	-	-	-	-	-	-	-	-	-	-	-	-	V	-	-	-	-
NL	V	V	V	V	V	V	V	V	-	V	V	V	V	V	V	-	-	-	-
PL	V	V	V	V	V	V	V	V	V	V	V	V	V	V	V	-	-	-	-
PT	V	V	V	V	V	V	V	V	V	V	V	V	V	V	V	V	V	V	V
RO	V	V	V	V	V	V	V	V	V	V	V	V	V	V	V	V	V	V	V
SE	V	-	V	V	V	V	V	V	V	V	V	V	V	V	V	V	V	V	V
SI	-	-	-	-	-	-	-	-	-	-	-	-	-	V	V	V	V	V	V
SK	-	-	-	-	-	-	-	-	-	-	-	-	-	V	V	V	V	V	V

Source: Eurostat Short-term Business Statistics (STS).

Graph A.5. **Firms at risk of insolvency in services by end of 2021, with risk of insolvency 2021, attributable to the pandemic, plotted against the cumulative turnover shock in industry over 2020-2021 (variables standardised with respect to industry means)**

Source: Bureau van Dijk Orbis database and authors' own calculations.

Graph A.6. **Firms at risk of insolvency in country by end of with risk of insolvency attributable to the pandemic, plotted against excess insolvency in the hardest hit industries**



Source: Bureau van Dijk Orbis database and authors' own calculations.

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