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COVID-19, Innovative Firms and Resilience

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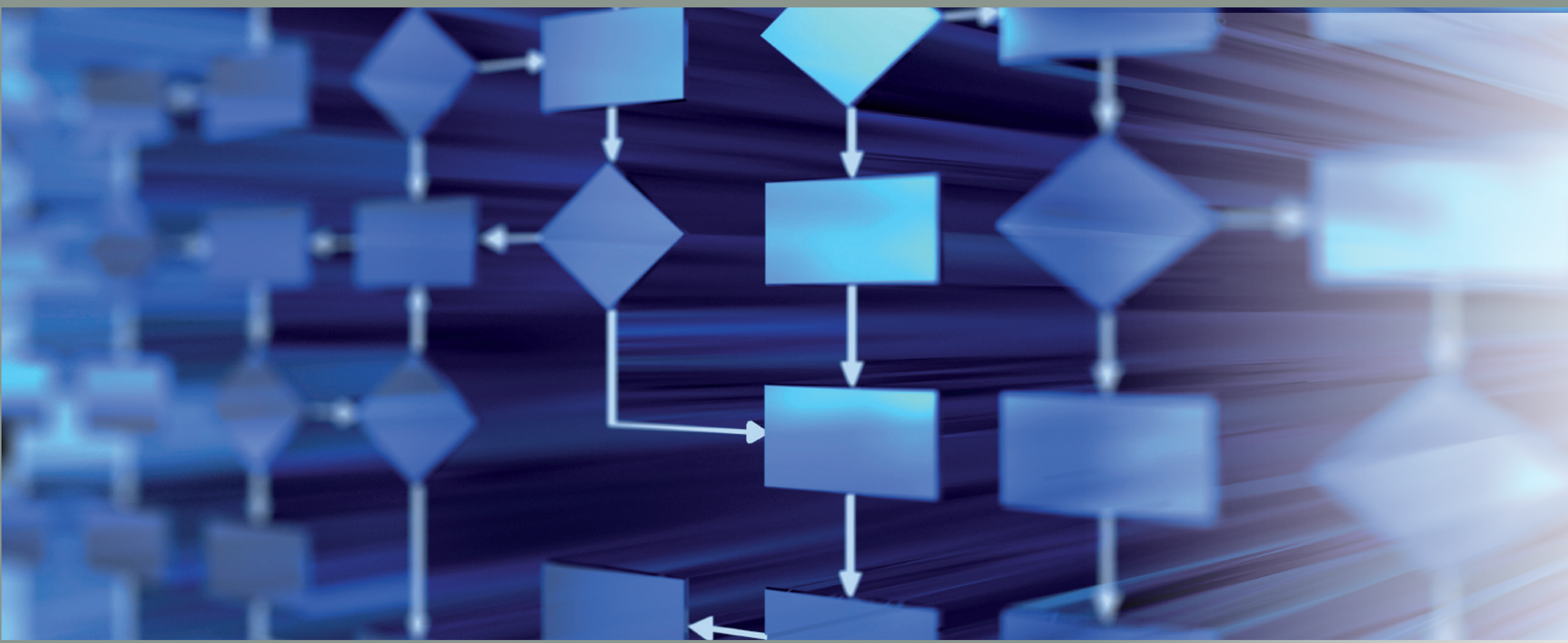

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COVID-19, Innovative Firms and Resilience

Michele Battisti[1], Filippo Belloc[2], Massimo Del Gatto[3]

Abstract:

This paper explores the empirical association between patents and various indicators of firm resilience during the COVID-19 pandemic with worldwide firm-level data from manufacturing industries. The study shows that patent-intensive firms have a reduced probability of exit, in particular if they are larger and if engaging with complementary investments in R&D and other intangibles. Additional estimates show that firm productivity has been an important transmission channel. Taken together, the results presented in the paper offer evidence-based findings pointing to patents as an important potential factor contributing to firm resilience during the COVID-19 pandemic. Policy insights are discussed.

JEL Classification: D20 L60 O30

Keywords: *firm resilience, patents, productivity, COVID-19*

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Executive summary

Over the last two years, the COVID-19 outbreak has had a major impact on businesses nearly in all countries and industries. In the context of the broader debate about the effects of innovation on firm resilience, a key question is how patent portfolios have affected the patterns of firm exit and the market performance of firms across the pandemic.

This report contributes to this discussion, by exploring the empirical association between patents and various indicators of firm resilience during the COVID-19 pandemic with worldwide firm-level data from manufacturing industries.

The report provides several takeaways.

- Patent-intensive firms and firms with larger patent portfolios showed a reduced probability of exit, both within industries and within countries. The effects of patents on improved firm resilience were greater for firms that engaged in R&D and invested in intangibles.

- Firm size is associated with a higher probability of survival across the pandemic, mostly driven by the improved ability of large businesses to benefit from patents. Indeed, small firms show a weaker association between patents, firm survival and sales volumes.

- Patents have played a less relevant role in sectors that faced increasing demand as a result of the health emergency and in sectors with high asset specificity, particularly in the pharmaceutical industry. Instead, patents have had a major effect on both survival and sales performance for firms operating in less innovation-intensive sectors.

- Firm productivity has been an important transmission channel. On average, innovative firms show productivity levels about 40% higher than non-innovative firms. Moreover, across the pandemic, firms holding one or more patents raised their productivity by about 3.7 percentage points more than firms without patents.

Taken together, the results presented in this report offer evidence-based insights pointing to patents as an important potential factor contributing to firm resilience during the COVID-19 pandemic. Although the empirical analysis does not allow to isolate unambiguously the mechanisms behind the effects of patents, arguably patent-filing firms have been able to exploit their positional advantage and their improved technologies to adapt to the new market conditions, with some differences across sectors and regions.

Importantly for policy makers, the empirical findings help identify several areas for policies aiming at improving firm resilience across negative macroeconomic shocks. First, when designing such policies, it is important to help firms close the gap with the technological frontier by facilitating their investments in product and process innovations. Second, innovation polices should be accompanied with technology diffusion policies and with industrial policies addressing the obstacles typically faced by small firms. In fact, patents themselves, taken in isolation, may sustain firm resilience only moderately if not associated with other complementary activities, such as investments in intangible assets and R&D, which are more difficult to undertake by smaller businesses. Third, innovation policies should be primarily directed to alleviate the heterogeneous costs from the pandemic, by ensuring that innovation opportunities are shared more widely both across and within countries.

This report fits into a relatively new literature on firm resilience across the COVID-19 outbreak, which has so far overlooked the role of patents. While the impact of the pandemic on patent activity and new technology adoption has been investigated by some studies (see, e.g., Riom and Valero (2020), Valero and Van Reenen (2021), and more generally Fink et al. (2022)), only Cirera et al. (2022) attempted to measure the link between pre-determined technology characteristics of firms and their resilience during the COVID-19 pandemic, but for a small sample of developing countries and without focusing on patents. In this literature, a systematic empirical work about the firm-level effects of patents on various margins of resilience (including firm exit, sales performance and total factor productivity) is still missing. This report tries to contribute filling this gap, with the widest possible international coverage.

1. Introduction

The effects of the COVID-19 pandemic on the economic performance of firms, industries and countries have received an increasing attention by economists, policy makers and the public opinion in general. Yet, the mechanisms through which these effects have taken place are still poorly understood. In particular, there is a substantial dearth of evidence on how new technology adoption, innovativeness, IP (Intellectual Property) intensity and R&D investments have shaped the ability of firms and industries to face the first two years of the COVID-19 pandemic. A better understanding of how technology differences across firms cause differences in their economic resilience has important economy-wide implications, because microeconomic heterogeneity may lead to fluctuations in the macroeconomic performance well beyond the effect of the initial COVID-19 shock.

There is a small body of literature investigating how firm technology may mitigate the effects of external shocks (Doms et al., 1995; Colombo and Delmastro, 2001; Hsu et al., 2018; Cefis and Marsili, 2019; Barontini and Tagliatela, 2022). In this line of literature, the impact of technology sophistication and innovativeness on the performance of firms in the years of the COVID-19 outbreak has not been systematically explored yet. Among others, Riom and Valero (2020), Valero and Van Reenen (2021), Lamorgese et al. (2021) and Valero et al. (2022) analyze from different angles the patterns of technology adoption during the pandemic. In particular, Cirera et al. (2022) study how the innovation abilities of firms may have helped to offset some of the initial negative impact of the COVID-19 pandemic, for a small sample of firms in developing countries. There are no studies with worldwide international coverage (including from high- to low-income countries) and/or looking at a broad spectrum of firm technological dimensions, including patent intensity, reliance on R&D and innovativeness.

This report aims at filling this gap by documenting the empirical relationship between the technological infrastructure of firms and their economic resilience during the first years of the COVID-19 pandemic, with a specific focus on patents.

In particular, the analysis takes advantage of a very large international sample of firms, covering more than 213000 firms over 121 countries and 307 (4-digit) sectors observed both before and during the COVID-19 pandemic, to systematically address the relationship between patent-filling activities and firm resilience, also taking into account a broad set of other firm characteristics such as age, size, asset composition, sector and country of activity. Within this general objective, the study explores the details of the relationship along different dimensions of resilience and different dimensions of firms' technologies. Specifically, the resilience effect is investigated along the extensive margin (i.e., survival rates) and the intensive margin (i.e., sales volumes), and several dimensions of firms' technology, such as patenting activity, reliance on R&D and intangible assets are considered, focusing on the possible complementarities between these dimensions and their differentiated effects across different countries, sectors and types of firms (e.g., small firms compared to larger ones).

Finally, the report delivers insights for industrial policy and in particular to help in the design of targeted innovation polices. The main empirical results show that patent-filling firms showed a reduced probability of exit during the pandemic. While this result seems to hold in general, the positive effect of patents on firm resilience appears stronger in less innovative sectors (where arguably improved innovation outcomes produce larger performance differentials between patenting and non-patenting firms). Interestingly enough, the effect of patents on resilience has been weaker in the pharmaceuticals sector, where the increased product demand during the pandemic has benefited both more and less innovative firms. In terms of firm-level characteristics, moreover, the analysis shows that larger innovative firms have greater margins of resilience than their smaller counterparts, possibly due to the higher ability of large businesses to benefit from patents. On the other side, small firms show a weaker association between patents, firm survival and sales volumes. As a complementary asset, R&D activities tend to improve the positive influence of patents on resilience.

Although it is difficult to interpret the causal mechanisms behind these empirical correlations, further steps of the analysis seem to point to firm productivity as an important transmission channel. Innovative firms, on average, have total factor productivity levels about 40% higher than non-innovative firms. Furthermore, patent-filling firms raised their productivity in the first two years of the pandemic by about 3.7 percentage points more than firms without patents. This may suggest that the size of patent portfolios to some extent reflects an underlying productivity advantage of more innovative businesses.

The analysis presented in this report delivers policy insights for the design of targeted innovation-oriented industrial polices. In particular, innovation policies should help smaller businesses to overcome the obstacles that they typically encounter when dealing with innovation activities. Most of these obstacles seem to relate to the difficulties in raising external finance to fund R&D programs and other complementary investments. Related to this, policy initiatives facilitating innovation networks of small firms (e.g. cross-licensing) may be of some help. More in general, in addition to pushing forward the technological frontier (e.g. by means of R&D subsidies), innovation policies should also facilitate the within-country and within-sector diffusion of innovation-related knowledge, innovation practices and new technologies across firms. Indeed, as emphasized in several contexts (see, e.g., OECD, 2015) the productivity growth of the globally most productive firms remained robust in the 21st century, while the gap between high productivity firms and the rest has been rising. Absent such types of policies, the productivity gap between innovative and non-innovative firms may persist, with important aggregate consequences in terms of productivity dispersion and macroeconomic stability.

The report proceeds as follows. Section 2 summarizes the related literature. Section 3 describes the data used in the analysis. Section 4 explores the data, looking at the main characteristics of patent-filling firms and how they changed in the first two years of the COVID-19 pandemic. Section 4 analyzes systematically the relationship between patenting outcomes and firm resilience, as measured in terms of survival (extensive margin) and sales volumes (intensive margin). Section 5 explores the productivity dynamics as a possible transmission channel. Section 6, finally, concludes with a brief policy discussion.

2. Previous literature on firm resilience during the COVID-19 pandemic

The COVID-19 pandemic had a massive impact on the business economy all over the world, leading to an unprecedented recession in many countries and industries.

Recent studies show that the negative effects of the COVID-19 outbreak on firms’ activities have been particularly strong in countries that were beaten by the pandemic the most (including both highly industrialized and developing countries). In these countries, the pandemic-induced recession has raised concerns about business closures as a possible trigger of aggregate productivity loss. While firm exit may be productivity enhancing at an aggregate level in certain circumstances (e.g. when it induces the selection of the most productive firms), during the COVID-19 pandemic the dynamics of firm exit has been driven by the geographical and industrial patterns of infection diffusion and lockdowns rather than by the productivity characteristics of firms, thereby leading to a process of firm closures which also involved healthy and productive firms. In its turn, this caused large employment losses and widespread destruction of firm-specific human and intangible capital, potentially limiting the speed of the recovery (Crane et al., 2021).

A small but growing body of literature offers empirically grounded quantifications of the impacts of the COVID-19 outbreak on production interruptions, permanent firm exit and firm resilience more in general.

In one of the first analyses of the impacts of the COVID-19 pandemic on business activity, Riom and Valero (2020) show that, as to July 2020, 40% of firms in UK have had to stop production activities or to close business sites and offices, while nearly 80% of firms switched to some form of remote working in response to the introduction of the social distancing measures. Riom and Valero (2020) also report that, in the same period, more than 70% of UK firms experienced a change in demand for products or services and that about 50% of firms suffered from supply chain disruptions and delays.

With a focus on business closures, Fairlie (2020), using data from the US Current Population Survey on small businesses, finds that the number of active firms dropped by 22% between February and April 2020, with nearly all US industries being affected to some extent. Many of those firm closures were temporary, but in May and June 2020 the number of active firms remained lower by 15% and 8%, respectively, compared with the situation just before the outbreak. More precisely, Fairlie et al. (2022), using data from the California Department of Tax and Fee Administration, estimate that, in the second quarter of 2020, business closures were 2.7 percentage points higher due to COVID-19, which implies a relatively large effect if one considers that the average closure rate in 2019 was 4.6%. They also report that the increase in closures rates in the first half of 2020 was only partly compensated by a reversal of the trend in the second half of 2020. Interestingly enough, Fairlie et al. (2022) show that the increase in closure rates in the first half of 2020 was largely driven by small businesses closures, with a consequential increase in concentration of market shares among large firms.

That small businesses suffered from COVID-19 relatively more than large firms is confirmed by other studies. For Spain, Pedauga et al. (2022) find that small and medium firms were responsible for about the 40% of the income decline and more than the 60% of the employment decline caused by the pandemic. The weaker resilience of small firms across the COVID-19 shock is showed also by Liu et al. (2022) for China, where in particular the adverse effects on business activity were showed to be relatively more pronounced for non-State-owned enterprises. For the US, Dua et al. (2020) find that the rate of small businesses reporting negative effects was larger in those sectors that were touched by government's social distancing restrictions the most (e.g. accommodations and food services, educational services, recreation, entertainment and social assistance). For UK, however, Riom and Valero (2020) caution that the effect of firm size on resilience during the pandemic is not significant after controlling for firm age and sector of activity.

In terms of employment consequences, Barrero et al. (2020) find that, in the first months of the pandemic in the US, gross staff reductions were equal to about 15% of March 2020 employment. They measure that temporary layoffs and furloughs accounted for 77% of gross staffing reductions and that 42% of those layoffs were resulted in permanent job loss. Based on these measures, Barrero et al. (2020) estimate the reallocation effects of the pandemic in the labour market and find that the COVID-19 shock caused about 3 new hires in the near term for every 10 layoffs.

Going behind country-level averages, a handful of studies has tried to look at what specific firm characteristics made some firms more resilient than others. As we have already mentioned, firm size, geographical location and the sector of activity have been identified as important aspects. What is less clear is why firms with similar size and operating in a same market and location have shown in several instances very different abilities to deal with the outbreak, with some exiting the market and some others managing to survive or even to grow. According to the data collected through the Centre for Economic Performance (CEP) and the Confederation of British Industry (CBI) surveys and analyzed by Riom and Valero (2020) and Valero and Van Reenen (2021), the most resilient firms appeared to be those more capable to introduce new digital technologies (e.g. remote working technologies, automated machinery, advanced analytics and other AI applications) and product innovations in response to the COVID-19 shock. Indeed, over a quarter of firms covered by the CEP-CBI survey reported that new technology adoption led to an increase in both hiring of specialized workers and hiring from a broader geography than before the pandemic.

The process of digitalization and process/product innovation, however, was uneven. For instance, while Bloom et al. (2021) show the diffusion of patent applications to increase remote distance jobs, Lamorgese et al. (2021) find that changes in the organization of labour and the use of tools for remote working during the lockdown period were associated with managerial quality, with the result that firms with more structured management practices experienced lower declines in expected sales after the lockdown (in particular, a one standard deviation increase in an index of managerial quality reduces the drop in expected sales during the pandemic by 30%). In addition, Valero et al. (2022) find that firms that were already using digital technologies before the outbreak were more innovation-prone during the pandemic and more capable to increase the productivity of the workers involved with digital tasks, arguably because they were more flexible and endowed with improved absorptive capacity.

The only study using international firm-level data to analyze how and to which extent the predetermined technology characteristics of firms influenced firm resilience during the COVID-19 pandemic is Cirera et al. (2022), based on a sample of around 1000 firms from Brazil, Senegal, and Vietnam. It explores how pre-pandemic technology sophistication affected firm sales during the first months of the pandemic, where technology sophistication (or readiness) is measured by means of an index ranging from 1 to 5 according to the level of digitalization of the technologies used for general business functions, such as business administration, production and marketing planning, quality control and supply chain management. The estimation results show that pre-pandemic technology readiness exerted both direct and indirect effects on firm resilience, respectively by facilitating interactions with workers, customers and suppliers and by facilitating the introduction of additional digital technologies in the production process during the outbreak. The resulting total effect measured by Cirera et al. (2022) is economically significant, with an increase of one standard deviation in technology sophistication resulting in an increase of 3.8 percentage points in sales (with a pick of 14 percentage points for firms at the bottom of the distribution, i.e. the least sophisticated).

Surprisingly, the role of pre-pandemic patents portfolios, R&D intensity and intangible assets has been overlooked so far, although prior literature showed that patents may be an important driver of firm resilience across economic crises (see, e.g., Barontini and Tagliatela, 2022). This is what the present study focuses on.

3. The data used in this study

The analysis presented in the present work is based on international firm-level data covering time periods before and during the COVID-19 pandemic. The basic firm-level variables used to perform the empirical study include information on: whether the firm closed its activity during the COVID-19 pandemic (between 1.1.2020 and 31.12.2021); market performance (as reflected in the pattern of revenues); the technological structure (as measured by patent intensity), intangibles portfolios, R&D activity, size (i.e., number of employees), age, fixed capital assets, exposure on the stock market, as well as about location and sector of activity of the firm. The source of data is the database Orbis Intellectual Property[4], by Bureau van Dijk, which contains balance-sheet information on an annual basis for a very large sample of firms, with worldwide coverage, plus information on the patents portfolio for each firm in the sample provided through the IP extension of the database. After data cleaning, the sample used in the analysis covers more than 213000 firms over 121 countries and 307 (4-digit) sectors, observed both before and after the arrival of the COVID-19 pandemic. Note that the use of aggregate data (e.g., at a country-sector level) instead of firm-level data, would not allow to address within-country and within-sector heterogeneity across different types of firms, thereby introducing an omitted variable bias in the estimation of the effects of interest.

[4] https://www.bvdinfo.com/en-gb/our-products/data/international/orbis-intellectual-property

4. Firm innovativeness and firm exit during the COVID-19 pandemic

4.1. The main correlates of patent-filling

Before exploring the relationship between patenting activities and firm resilience during the COVID-19 outbreak, this Section briefly documents the main correlates of patent-filling.

While the literature on technology adoption is huge and growing, few works analyze the firm-level drivers of patent-filling. Among them, Da Silva et al. (2019) review 22 case studies on Brazilian firms and find evidence of a positive correlation between patents and firm size and R&D, thereby suggesting some complementarities between patenting and the firm capacity to deal with large and risky investments. Similar results are showed by Licht and Zoz (2000) on German firms.

The present Section briefly complements this literature, by assessing how patents correlate with a set of variables linked to various characteristics of the firm, including the capital stock, whether the firm is listed on the stock market, age, liquidity ratio, proxies for other technology-oriented activities (R&D and share of tangible over intangible assets), and a proxy for the market structure, namely an Herfindal-Hirschman Index measuring the concentration of firms at the country-sector (2-digit) level.

Table 1 reports the results of the cross-sectional correlation between the natural log of patents and the mentioned set of potential correlates. The analysis is cross-sectional because uses the average of values of all the variables over the pre-pandemic period (2011-2019).

All the estimated coefficients have the expected sign. In particular, older, larger and listed firms show a greater patent activity as well as firms undertaking R&D. Moreover, it emerges that the liquidity ratio is positively correlated with patent-filling, suggesting that firms with lower financial constraints may be more likely to invest in patenting activities but also that firms with more patents may be more profitable, thereby increasing their liquidity ratio.

The negative association between patents and market concentration may be consistent with the view of oligopolist firms becoming less innovative. Finally, the negative sign of the share of tangible capital points towards the possibility that patenting activities are complementary to the availability of intangible assets.

Table 1. Patent-filling and firm-level characteristics

	(1)	(2)	(3)	(4)	(5)	(6)
Explanatory variables	**Estimated effect (Std. Err.)**	**Estimated effect (Std. Err.)**	**Estimated effect (Std. Err.)**	**Estimated effect (Std. Err.)**	**Estimated effect (Std. Err.)**	**Estimated effect (Std. Err.)**
Age (years since incorporation)	0.022*** (0.000)	0.021*** (0.000)	0.009*** (0.000)	0.009*** (0.000)	0.009*** (0.000)	0.007*** (0.001)
Listed firm (versus non-listed one)			1.845*** (0.025)	1.846*** (0.025)	1.835*** (0.025)	1.568*** (0.084)
Log of total assets			0.174*** (0.002)	0.174*** (0.002)	0.179*** (0.002)	0.305*** (0.010)
HH Index				-0.431*** (0.060)	-0.430*** (0.061)	-0.229 (0.171)
Liquidiy ratio					0.006*** (0.000)	0.013* (0.007)
Share of tangible assets					-0.000*** (0.000)	-0.269*** (0.064)
Ln R&D						0.445*** (0.011)
Constant term (linear coefficient)	0.638*** (0.007)	-0.745*** (0.049)	-2.180*** (0.046)	-1.761*** (0.074)	-1.842*** (0.072)	-4.441*** (0.223)

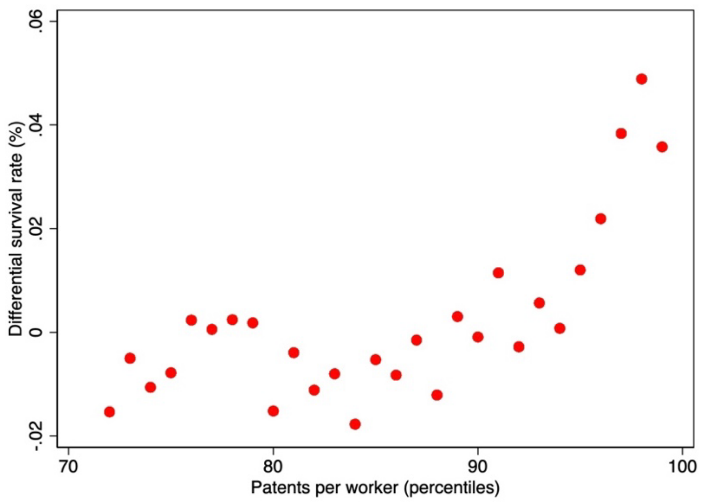
Note. The dependent variable is the hyperbolic transformation of the natural log of patents. Overall sample: ~213000 firms. All the variables are averaged over the 2011-2019 period. Legend: *** = statistical significance at the 1%, ** = statistical significance at the 5%, * = statistical significance at the 10%. Country and sector fixed effects are added in columns (2)-(6). Other regression details are omitted in the Table for simplicity (the constant term is the linear coefficient, not the marginal effect). OLS estimates.

4.2. The differential survival rate of patent-filling firms

In order to analyze the relationship between patents and resilience during the COVID-19 outbreak, the analysis starts by looking at the crude association between the survival rates of firms and patent portfolios. Specifically, the analysis considers the survival rate during the first two years of the pandemic (i.e., between 1.1.2020 and 31.12.2021) and observes how it differs across firms with empty patent portfolios and firms with at least one patent in their portfolios in 2019. It emerges that the rate of survival between 1.1.2020 and 31.12.2021 of firms with at least one patent in their portfolios in 2019 was about 5.5% higher than the rate of survival for firms without patents.

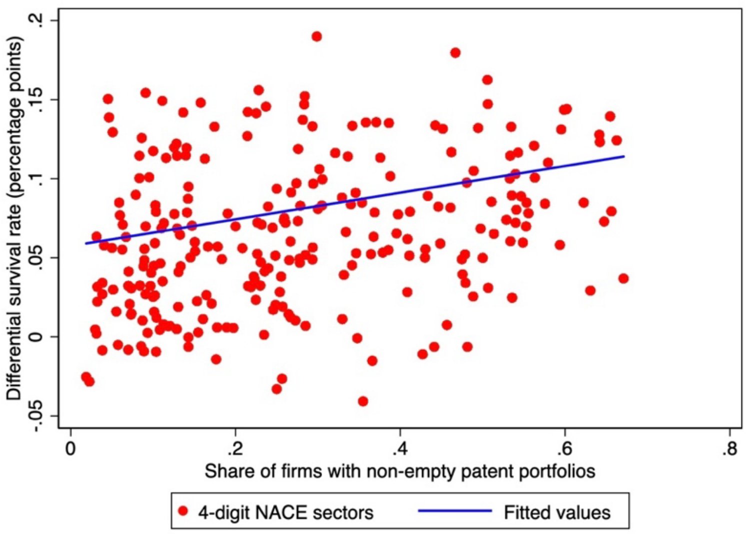
Figure 1 displays the differential percentage rate of survival of firms with at least one patent with respect to firms with empty patent portfolios during the first two years of the COVID-19 pandemic (2020-2021) along the distribution of the number of patents per worker (i.e., the average differential rate of survival of patenting firms versus firms without patents, for each percentile of the distribution of the number of patents per worker). This figure helps understanding what has been, in average terms, the gross relationship between survival rates and the relative size of patents portfolios scaled by firm size. Figure 1 displays only the values referring to percentiles above the 70th, as below this threshold the number of patents per worker is always zero (i.e., about 70% of firms in the sample have empty patent portfolios). It is evident the overall positive association between the rate of survival and the relative size of patents portfolios, particularly above the 90th percentile of the distribution, which is the group of firms with the most consistent stock of patents. In particular, firms in the top-3 percentiles of the distribution of patents per worker show a rate of survival to the COVID-19 pandemic higher than that of firms without patents by about 50% or more.

Figure 1. Differential survival rates (%) with respect to firms with empty patent portfolios during the COVID-19 shock (2020-21)



A positive differential survival rate between patenting and non-patenting firms emerges also across sectors. Figure 2 shows the differences between the average survival rates by 2-digit NACE and the overall survival rate of non-patenting firms plotted against the average share (by 4-digit NACE) of firms with non-empty patent portfolios. It emerges that sectors (narrowly defined) with a higher share of patenting firms have lower survival rates for non-innovative firms.

Figure 2. Differences between the average survival rates by 4-digit NACE and the overall survival rate of non-patenting firms plotted against the average share by 4-digit NACE of firms with non-empty patent portfolios



4.3 The characteristics of firms during the first two years of the COVID-19 pandemic

The above descriptive analysis reveals that firms with non-empty patents portfolios showed a better survival performance with respect to firms without patents. At the same time, it is reasonable to expect that the COVID-19 pandemic has hit firms asymmetrically also within the group of innovative firms. Phrased differently, firms with different characteristics, besides patents portfolios, may have reacted to the COVID-19 shock in different ways, with the result that the pandemic may have changed to some extent the average characteristics of the firms that survived to the first two years of COVID-19. In a more technical language, this effect is called “selection”, intended as the effect of an exogenous shock on the composition of a population of firms.

Table 2 reports some average characteristics of innovative and non-innovative firms before and after the first two years of the COVID-19 pandemic. It is easy to see that the pandemic changed the characteristics of the two groups in a different way. In the group of firms with empty patent portfolios, the share of firms engaged in R&D has slightly increased while the share of firms with intangibles was reduced during the pandemic; in the group of firms with at least one patent in 2019, the effect of the pandemic on the shares of firms making R&D and having intangibles was the opposite. This suggests that, among firms without patents, the COVID-19 shock has beaten more intensively those without R&D activity, thereby inducing the “selection” of a higher share of firms with R&D. In the group of firms with patents, the selection effect was at the expenses of the firms without other intangible assets besides patents. Among firms with patents, moreover, during the first two years of COVID-19 there was a lower survival rate for younger and smaller firms (arguably the most fragile), indeed both average firm age and size have increased during the pandemic. Among firms without patents, instead, larger firms seem to have been the weakest, in terms of survival performance. Finally, in both groups of firms, companies listed on the stock market showed a greater resilience.

Table 2. Characteristics of firms before and after the first two years of the COVID-19 shock (2020-21)

	Dimension (variable)	**Before the pandemic - 31.12.2019 - (All firms)**	**After the first two years of the pandemic - 31.12.2021 - (Only survived firms)**
Firms with empty patent	Share of firms making R&D	4.4	7.7
	Share of firms having	58.4	50.5
	Firm size (average n. of	165	113
	Firm age (average n. of	17	25
	Share of firms listed on the	3.1	5.1
Firms with at least one patent in	Share of firms making R&D	71.7	56.8
	Share of firms having	93.2	96.3
	Firm size (average n. of	1519	3993
	Firm age (average n. of	29	46
	Share of firms listed on the	21.2	31.5

Figures from 3 to 5 show the Lorentz curves of patents referring, respectively, to the entire population of firms in the sample and to sub-groups of firms distinguished by aggregations of countries and sectors of activity, calculated in the two years before and after the COVID-19 outbreak. It is interesting to observe that the pandemic seems to have left the inequality in the distribution of patents substantially unchanged, both globally and by geographical area and sector.

Figure. 3. Lorentz curve of patents before and after the COVID-19 shock (2018-19 vs 2020-21)

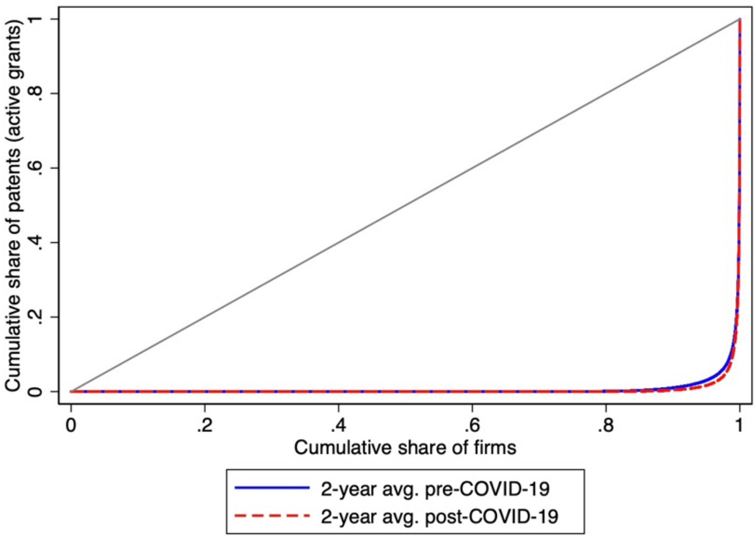


Figure. 4. Lorentz curve of patents by macro-region before and after the COVID-19 shock (2018-19 vs 2020-21)

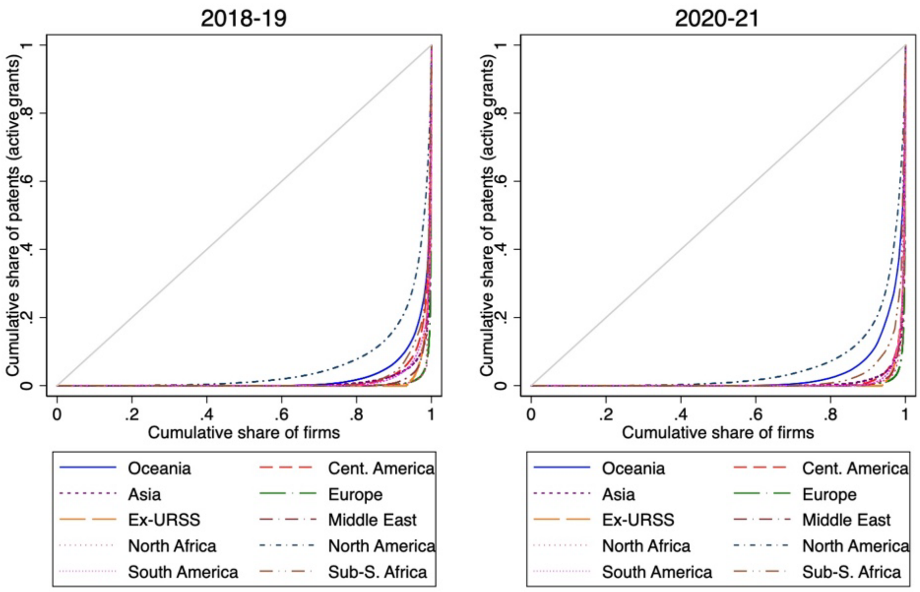
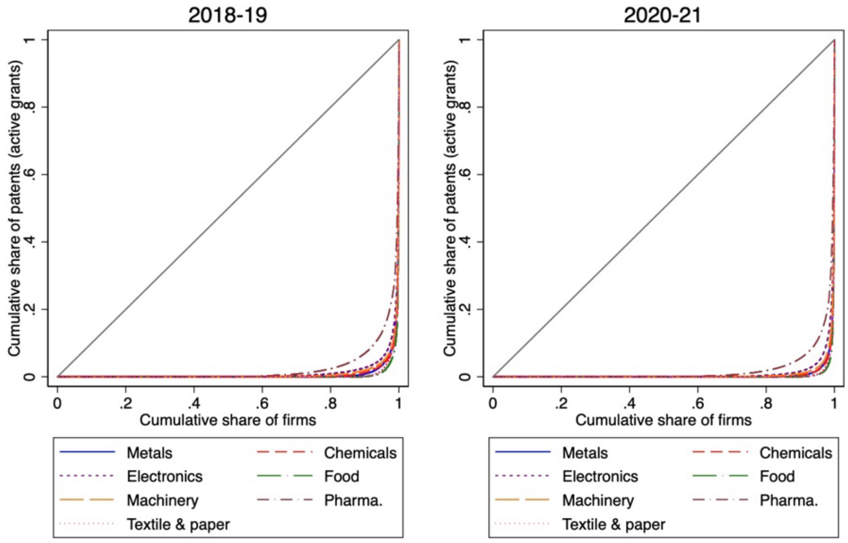


Figure. 5. Lorentz curve of patents by macro-sector before and after the COVID-19 shock (2018-19 vs 2020-21)



4.4 The direct effect of being innovative on firm resilience

To isolate the direct effect of firm innovativeness on resilience during the COVID-19 pandemic, this report follows the empirical strategy of Cirera et al. (2022), who model firm resilience as a function of the pre-pandemic characteristics of the firm. In other words, firms' innovativeness, in the form of patent-filling, R&D and investment in intangible assets, before the COVID-19 pandemic supposed to affect the extent of resilience during the COVID-19 shock (the dependent variable of the model). Formally, the following regression model is estimated:

$$\text{Resilience}_i = \square + \square\ \text{Innovativeness}_i + \text{Control variables}_i \qquad \text{[Eq. 1]}$$

where the subscript "i" denotes the firm, "Resilience" is an indicator of firm resilience (here, a firm closure dummy which equals 1 if the firm exits the market between 1.1.2020 and 31.12.2021, and 0 otherwise), "Innovativeness" is a dummy variable which equals 1 if the firm has a non-empty patent portfolio as to 31.12.2019 (and 0 otherwise), and where the term "Control variables" refers to a set of control variables capturing other relevant firm-level characteristics (R&D activity, intangible assets, firm size, firm age, fixed capital assets, presence on the stock-market, location (i.e. geographical macro-region) of the firm and sector of activity, as to 31.12.2019). Finally, □ is the model's constant and □ is the parameter of interest, reflecting the marginal effect of having at least one patent in 2019 on the probability of firm exit, all else being equal (i.e., net of other observable firm-level characteristics and country and sector specificities). If having patents implies a higher probability of survival during the first two years of the COVID-19 pandemic (i.e., it implies a lower probability of firm closure), then the coefficient □ is expected to have a negative sign. The equation is estimated by means of a logit model in a “cross-section” specification (observations relative to the same firm in different years are dealt with as independent observations). The results from different model specifications are collected in Table 3.

Table 3. Estimated direct effect of innovativeness on firm exit during the COVID-19 pandemic

	Whole	Whole	Whole	Whole
Explanatory variables	**Estimated**	**Estimated**	**Estimated**	**Estimated**
Innovativeness (non-empty patent	-	-		-
R&D intensity (R&D investments per		-0.001*		-0.001**
Intangibles intensity (intangible capital		-0.000		-0.000
Total assets (tangible + intangible				-
Size (# of employees)			0.001**	-0.000
Age (years since incorporation)			-	-
Listed firm (versus non-listed one)			-	-
Constant term (linear coefficient)	1.773***			5.670**

Note. The dependent variable is a drop-out dummy, which equals 1 if the firm left the market between Jan 1 – 2020 and Dec 31 – 2021 and 0 otherwise. All the control variables are measured as to 31.12.2019. Geographical area and sectoral fixed effects are included. Overall sample: ~213000 firms. Legend: *** = statistical significance at the 1%, ** = statistical significance at the 5%, * = statistical significance at the 10%. Other regression details are omitted in the Table for simplicity (the constant term is the linear coefficient, not the marginal effect).

In the full model version, the direct marginal effect of having a non-empty patent portfolio on the reduced probability of firm exit is about 2.6 percentage points, i.e. on average a firm with at least one patent as to 31.12.2019 shows a probability of exit during the first two years of the COVID-19 pandemic lower by 2.6 percentage points than a similar counterpart with no patents.

A dummy variable for empty/non-empty patent portfolios is clearly a crude measure of innovativeness. However, its estimated coefficient, in the sign and statistical significance, is in line with previous empirical evidence about new technologies and survival. For example, Doms et al. (1995) find that the adoption of advanced production technologies reduces the probability of firm closures in “good times”, for a sample of US establishments. Similar results are shown by Colombo and Delmastro (2001) on Italian data. Other studies report a survival advantage of more technologically sophisticated firms also during “bad times”, i.e. when firms are hit by exogenous negative shocks. Hsu et al. (2018), looking at the impact of natural disasters, find that firms with diversified patent portfolios are significantly less subject to the negative consequences of negative shocks, suggesting that patent-based technology diversity may improve firm survival. Cefis and Marsili (2019) find a survival advantage of innovative firms in the Netherlands during and after the global financial crisis of 2008. Similarly, Barontini and Tagliatela (2022) show that patent-filing firms in Italy have been more resilient during the 2008 crisis. With reference to the COVID-19 outbreak, Cirera et al. (2022), as already mentioned, find that technology sophistication exerted positive effects on firm resilience during the pandemic.

From a theoretical point of view, the negative correlation between patenting performance and firm exit, detected in the present analysis, is not obvious. On the one hand, firms with an improved patenting activity may be more fragile than their non-patenting counterparts due to several reasons. Patenting firms may have undertaken costly investments in R&D and in new equipment, thereby increasing their financial exposure on the capital market. Furthermore, investments aimed at improving the innovation capacity of the firm are typically firm-specific, have a large fixed-cost component and show a relatively low resale price. Hence, highly innovative firms may be associated with a higher risk of insolvency. In addition, innovative firms tend to operate more frequently in product-sectors at the technological frontier, where the market environment is more turbulent and characterized by higher uncertainty both on the supply and the demand sides. On the other hand, patenting firms may enjoy a positional advantage resulting from the adoption of novel production processes and from the commercialization of new products. This selection process leads the most innovative firms to have stronger market positions at the expenses of their less innovative competitors. Patents, moreover, give to the patent-owner a monopolistic power in the specific product-markets associated with the patents themselves, because the usage or the reproduction of the innovative technology is prevented by the associated intellectual property rights. By definition, such monopolistic power insulates patent-filing firms from competitive forces. Phrased differently, patenting firms may be relatively more resilient both because of their underlying (preexisting) technological advantage and because patents may reinforce this advantage.

The reduced probability of exit of patenting firms estimated in this analysis suggests that the advantages of an improved patenting activity more than compensate the possible disadvantages. In particular, the results reveal the greater ability of patenting firms to survive to the COVID-19 outbreak. This points to the patenting performance as an important aspect for explaining the differential in the survival rates between firms during the pandemic, even within the same sector or country. Arguably, during the pandemic, patenting firms have been able to exploit their positional advantage and their improved technologies to adapt to the new market conditions and to the restrictions imposed by governments. As highlighted by the so-called “evolutionary theory” of the firm (Nelson and Winter, 1982), innovative firms have a greater capacity to introduce new routines and practices, thereby being better suited to go through “bad times” with respect to non-innovative firms. This is in line with the argument put forward by Cirera et al. (2022), who find that the consolidated use of advanced technologies prior to the COVID-19 pandemic helped firms to introduce additional digital technologies during the pandemic, which were useful to maintain production lines in activity during the lockdown.

As shown in Table 3, it also emerges a lower probability of exit for highly capitalized, listed and older firms and for firms making R&D investments. However, even if statistically significant, the effects of R&D intensity and firm age and the effect of the size of the capital structure are small in economic terms.

It is interesting to observe that firm size, as measured by the number of employees, does not correlate significantly with firm exit during the pandemic, once the other firm-level characteristics are controlled for in the regression. This latter finding corroborates previous results obtained by Riom and Valero (2020), who find a statistically insignificant correlation between firm size and resilience after controlling for firm age and sector of activity. In light of the literature on resilience of small businesses, the statistically insignificant effect of size on firm exit is interesting, because it highlights that the higher rate of firm closures observed among small firms during the pandemic is not due to firm size *per se*, but it is arguably associated with other characteristics that small firms typically show (e.g. smaller or empty patent portfolios, lower R&D intensity, lighter capital structure, lower age and lower likelihood of being on the stock market). Once these characteristics are considered in the econometric model, smaller firms, in statistical terms, are showed to be as much resilient as their larger counterparts. In line with such finding, previous literature on firm survival in "good times" shows that the correlation between firm size and exit is statistically insignificant in econometric models that control for other relevant firm-level characteristics, including the level of technological sophistication (Colombo and Delmastro, 2001). Related to this, among others, Klepper and Simons (2000) show that larger firms tend to survive longer principally because they are more likely to introduce technological changes into the production process and to innovate. Similarly, Agarwal and Audretsch (2001) find that the relationship between firm size and the likelihood of survival depends on the technological conditions of the product-sector and on the stage of the industry life cycle.

5 Patent intensity and the margins of firm resilience during the COVID-19 pandemic

This Section enriches the analysis in two ways. First, it exploits the granularity of the data about the firm-level number of patents and estimate the effect of "patent intensity" (see below) of firms. Second, it complements the analysis of the effects of patents on firm exit (i.e., the extensive margins of firm resilience) with the study of the effects of patents on the economic performance of the firms that survived (i.e., the intensive margin of resilience).

The use of patent intensity (measured as number of patents divided by number of workers), as a firm-level measure of innovativeness, is intended to provide with a more in-depth analysis of the firm-level relationship between resilience and innovation, in which the extent of innovativeness, and not only the circumstance that the firm has been patenting at least once before the breakdown, is taken into account. The more natural measure of the innovation effort of the firm, in terms of patenting, would be the size of the patent portfolio (i.e., number of patents). However, this is strongly correlated with the size of the firm (as measured by the number of employees or by the capital stock). Indeed, larger firms tend to show larger patent portfolios than their smaller counterparts, simply because of a firm-size effect. As a result, a direct comparison between the resilience of firms with larger patent portfolios and the resilience of firms with smaller portfolios would not provide a meaningful identification of the role of patents because of conflating patent and size effects. For this reason, this empirical study uses patents per worker, referred to as "patent intensity", as a measure of patent-filling effort, instead of the crude number of patents per firm.[5] In more formal terms, Eq. [1] is estimated by measuring "Innovativeness" as a variable computed as the number of patents per worker, at the firm-level.

5.1 The extensive margin of firm resilience during the COVID-19 pandemic

The analysis of the extensive margin of firm resilience focuses on the role of patents in terms of their influence on the ability of firms to survive to the pandemic. This type of analysis refers to the extensive margin of resilience in the sense that it looks at "whether" firms with a higher patent

[5] Table A2 in the Appendix reports the results of a similar analysis conducted by considering the absolute (unweighted) number of patents as the main regression of interest. The qualitative results remain unchanged (i.e. both the sign and the statistical significance of the coefficients of interest do not change with respect to the use of the number of patents per worker). In terms of magnitude, clearly, the size of the coefficient associated with the unweighted number of patents is lower with respect to the weighted version of the patent variable.

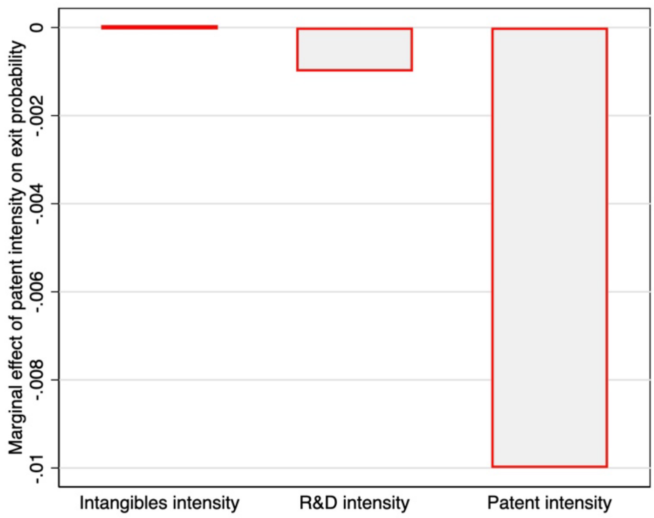
intensity have been more likely to survive to the COVID-19 shock and not at “how” they survived (i.e., it does not look at the market, or performance conditions of the firm during the shock). In different words, the analysis of the extensive margin of resilience focuses on the cross-sectional extent to which firms survived, conditional to having larger patent portfolios per worker.

Different regressions are run, discussed next.

5.1.1 Direct effects of patent intensity on the extensive margin of firm resilience

The analysis starts from the baseline version of Eq. [1], where “Innovativeness” takes the form of patent intensity as the main regressor of interest on the right-hand-side of the equation. A measure of R&D intensity (i.e., R&D investments per worker) and a measure of intangible assets intensity (i.e. intangible assets per worker) are included in the set of control variables, together with firm size, firm age, fixed capital assets, presence on the stock-market, location (macro-region) of the firm and sector of activity. The direct effect on the extensive margin of resilience (i.e., the firm closure dummy) is estimated, with the coefficients of interests reported in graphical terms in Figure 6 (point estimates are collected in Table A1 in the Appendix, together with other details regarding the estimation analysis).

Figure 6. Direct effects of innovation variables on firm closure during the COVID-19 shock (2020-21)



The estimation results show that patent intensity is associated with a negative and significant coefficient, which means that a higher patent intensity reduces the probability of firm closure in a statistically significant way. More precisely the magnitude of the estimated coefficient is -0.010.

Since patent intensity is measured as the number of patents per worker, such coefficient suggests that a one-point increase in patent intensity (i.e., one patent more per worker with respect to the average in the sample) is associated with a reduction in the probability of firm closure by 1 percentage point. It is worth emphasizing again that this effect is net of other firm-level characteristics that may impact on both patent portfolios and firm resilience, particularly the concomitant presence in the same firm of R&D activities and intangible assets.

Similarly to the results reported in Table 3, these estimates can be interpreted as suggesting that richer patent portfolios are both a “signal” of the better ability of the firm to introduce additional technologies during the pandemic and a strategic instrument that patenting firms may have used to protect their market position thanks to the monopolistic powers associated with patents themselves.

Figure 6 also reports the separate, direct effects of R&D intensity and intangible assets intensity on resilience, in their turn obtained as net of the effect of patent intensity. Both are negative and statistically significant. The effect of R&D intensity (measured as thousands of Euros invested in R&D per worker in 2019) is associated with a reduction in the probability of firm closure by 0.1 percentage point. The effect of intangible assets intensity (measured as thousands of Euros of intangible assets per worker in 2019) is much lower and barely distinguishable from zero.

This first step of the analysis points to patent intensity as an important aspect for firm resilience during the first two years of the COVID-19 pandemic. It is important to notice, however, that such effect is an estimated “average” effect, as it is obtained as the effect of a one-point increase in patent intensity for the “average” firm in the sample. Nevertheless, it is hard to think to firms, particularly in such a large and heterogeneous sample, as close enough to their “average”, in terms of capital structure, size or sector of activity, among other dimensions. It is likely that the effect of patent intensity is more important for firms that also engage in R&D activity, or have portfolios with other intangible assets, or are larger, or operate in certain sectors or regions. From this point of view, the size of the direct effect of patent intensity as reported in Figure 6 may mask rather different effects across firms with different characteristics and, as an average effect, it may be downsized by the fact that a large proportion of the firms in the sample are small, do not engage in R&D and do not show those characteristics that are most important to boost the effect of patent intensity. The analysis presented next digs into these aspects.

5.1.2 Conditional effects of patent intensity on the extensive margin of firm resilience

Here the report looks at the “conditional” effects of patent intensity on the extensive margin of firm resilience. In simple words, the analysis disentangles the effect of patent intensity for firms with different characteristics, in order to identify more precisely what could be the effect of patent intensity for specific types of firms, so going beyond the “average” effect reported in the previous sub-Section of the report.

Formally, the specification of Eq. [1] is modified, by introducing a set of interaction terms, one-by-one in different regressions. In particular, the patent intensity variable is interacted with a set of other relevant variables considered one-by-one. Besides contributing to improve granularity in the estimation of the effect of patent intensity across different types of firms, this type of analysis can be seen also as a way to measure possible complementarities between patent intensity and R&D activities[6], intangible assets, economies of scale (as reflected by the size of the firm) and contextual factors referring to the sector and region of activity.

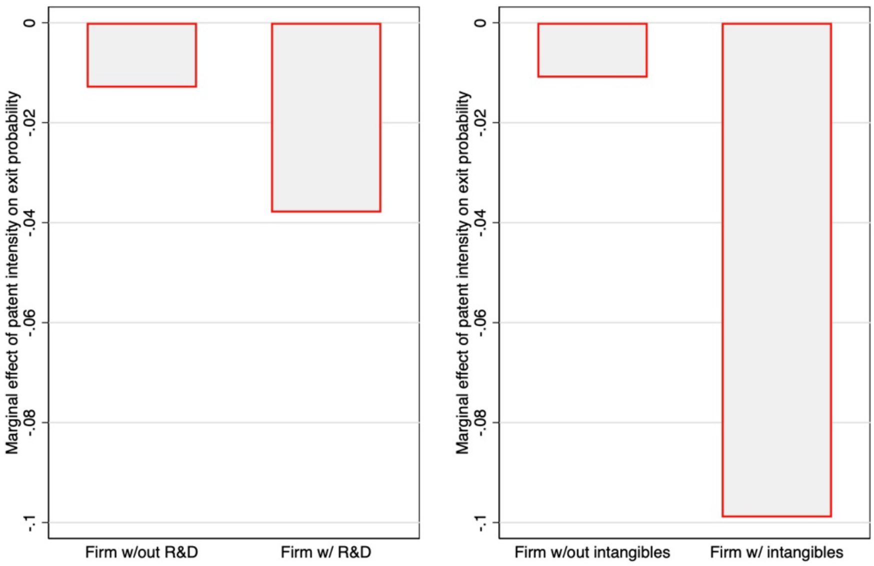
Complementarities between patents, R&D and intangibles on the extensive margin

The analysis here starts by considering the effects of patent intensity conditional to R&D activities and intangible assets. It is well-known that investments in R&D and in various types of intangibles are important inputs for generating patentable innovations. At the same time, a higher patent intensity may be more powerful in helping firms to resist to the COVID-19 shock in firms that are more innovation-prone also besides their patenting performance. In particular, firms engaging in R&D activities and that have other intangible assets may be more capable to exploit their patents as a leverage to protect their market position during a systemic shock, such as the COVID-19 pandemic. This may be driven by the fact that R&D and intangible assets include several factors which are complementary to patents, and which make patents a more valuable resource to cope with exogenous economic turmoil. As an example, a patent may have a higher market value for a firm that is able to provide complementary technology assets to its customers (even if these assets are not patented) or that has more sophisticated know-how in terms of marketing strategy. To investigate this aspect with reference to the extensive margin of resilience, Eq. [1] is extended by interacting the patent intensity indicator with, respectively, a dummy variable taking value one

[6] For instance, Schmiedeberg (2008) finds, by using German data for the manufacturing sector, that the probability of patenting is positively correlated with internal and external R&D activities.

when the firm is engaged in R&D activity and a dummy variable taking value one when the firm owns other intangible assets besides patents. The results are represented in Figure 7 below.

Figure 7. Effects of patent intensity on firm closure during the COVID-19 shock (2020-21) conditional to R&D and intangibles

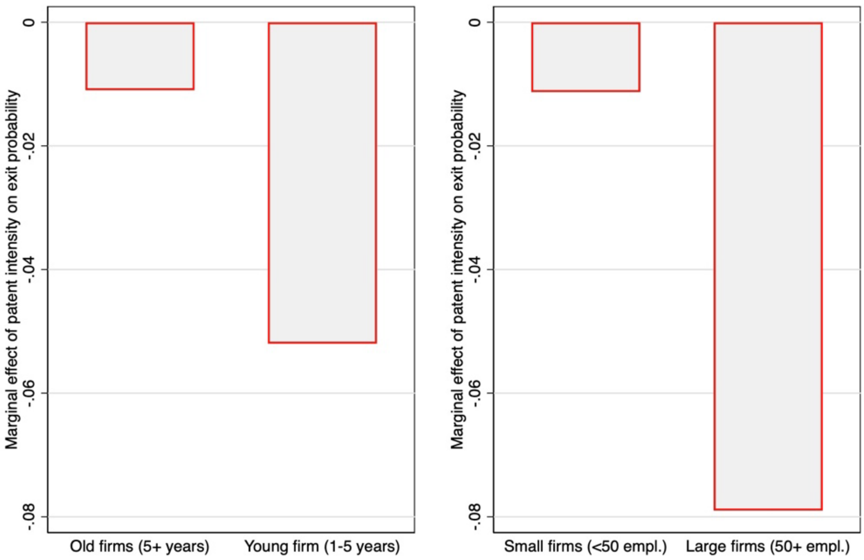


It is interesting to observe that the estimated effect of patent intensity is much higher, in absolute value, for firms making R&D and having intangible assets, with respect to their counterparts without R&D activity and intangibles. In more quantitative terms, a one-point increase in the patent intensity indicator is associated with a reduction in the likelihood of firm closure of 3.8 percentage points when the firm makes R&D and 9.9 percentage points when the firm has an intangible assets portfolio. In a firm which both makes R&D and has intangibles, one patent more per worker is associated with an estimated decrease in the firm closure probability of about 13.7 percentage points.

Complementarities between patents, firm size and age on the extensive margin

By adopting the same empirical strategy, based on interacting the patent intensity indicator with other selected firm-level variables, the analysis proceeds by measuring the specific effect of patent intensity for large firms (> 50 employees) with respect to small ones and for old firms (> 5 years since the year of the incorporation) with respect to young ones. The results of this empirical exercise are displayed in Figure 8.

Figure 8. Effects of patent intensity on firm closure during the COVID-19 shock (2020-21) conditional to firm age and size



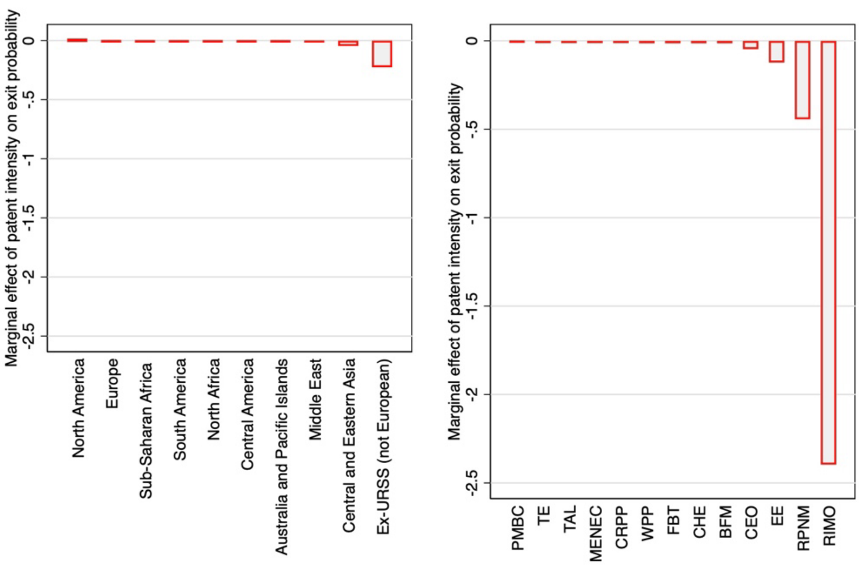
The effect of patent intensity on the extensive margin of resilience for young firms is found to be about five times higher than for old firms. In particular, one patent more per worker is associated with a reduction in the closure probability of 5.9 percentage points. This finding is consistent with the argument that young firms are typically more fragile than their older counterparts and in such types of firms patenting performance is therefore more likely to count relatively more for firm resilience. In other terms, a young firm with a significant patent portfolio is much more likely to survive to the COVID-19 shock than a young firm without patents, with this differential being larger than the same differential calculated between old firms with and without patents.

Moving to consider the marginal effect of firm size, the results of the analysis show that large firms, all else being equal, are more capable to benefit from a higher patent intensity, in terms of survival probability, than small companies. It is worth noting that this effect is calculated as net of the firm age affect. Specifically, the regression analysis produces a patent intensity coefficient for large firms equal to -0.079 (i.e., one patent more per worker reduces the firm closure probability by 7.9 percentage points), while the patent intensity effect for medium and small firms is about 1 percentage point. This result points to the fact the larger firms may have larger markets where they can benefit from larger patent portfolios, and they are hence better suited to exploit a higher patent intensity as an ingredient for resilience. Small firms arguably deal with smaller markets, have less consolidated market positions and deal with more uncertain and unstable demand. As a consequence, for small firms may be more difficult to benefit from more patents per worker in terms of survival probability. Related to this, very recent empirical literature shows that average invention value rises with firm size, whereas average invention quality declines (Arora et al., 2022). This may be suggesting that the larger firms may have a superior ability to extract value from patents, arguably due to their greater commercialization capabilities, but they do not necessarily have superior inventive capability.

Complementarities between patents, geographical area and sector of activity on the extensive margin

Finally, the analysis looks at the relationship between patent intensity and the extensive margin of resilience conditional on the geographical area (i.e., the macro-region) and the sector of activity. The coefficients are graphically reported in Figure 9.

Figure 9. Effects of patent intensity on firm closure during the COVID-19 shock (2020-21) conditional to area and sector of activity



The negative effect of patent intensity on drop-out rates is weaker in Europe and North America than in other regions. This pattern could be explained by the fact that the institutional response to the COVID-19 pandemic was highly asymmetric across countries, with a higher impact for the business activity in innovative, manufacturing sectors in more industrialized countries with respect to the rest of the world. This may have reduced the ability of firms with a higher patent intensity in Western countries to exploit patents as a key to better tackle the pandemic comparatively to less innovative firms. Moreover, competition levels in the EU and the US are typically higher than in other regions of the world, hence the pandemic in Western countries might have hit firms more evenly (i.e., to some extent independently of patent portfolios) with respect to firms in other regions.

As for the sector of activity, the effects of patent intensity on firm resilience are stronger in the repair sector (sectoral abbreviations are reported in Table A3) and in activities related to the installation of machinery and weaker in the pharmaceuticals. This suggests that, on the one hand, patenting firms benefited more from their innovative potential in what typically are counter-cyclical activities (installation and repair sectors), and that, on the other, the pharmaceutical industry is somewhat a particular case, where firm technology characteristics, as reflected into patent intensity, counted less in front of the COVID-19 shock. This might be because most of the firms in the pharmaceuticals benefited from a surge in the demand during the pandemic, thereby generating externalities for both more innovative and less innovative firms in the sector (indeed, aggregate statistics show that pharmaceuticals faced increasing demand as a result of the health emergency; see, e.g., UN (2022)). Moreover, as predicted by previous theoretical literature (e.g. Dixit, 1989), the heterogeneity among sectors in the amount of sunk costs may lead to different patterns of firm exit, with industries characterized by a lower salvage value of the production equipment showing a lower probability of firm closure. In the pharmaceuticals, in particular, a high project-specificity of the assets used in production prevents the possibility to fully re-sell them in case of failure, with the results that firms may refrain to stop their activity, even across negative macroeconomic shocks like the COVID-19 pandemic, regardless of their innovative outcomes.

To dig more specifically into the granularity of the sectors of activity, it is also measured the effect of patent intensity on the extensive margin of resilience by classifying the 4-digit NACE sectors of activity in terms of share of firms with non-empty patent portfolios. In particular, the 4-digit NACE sectors are divided based on whether the within-NACE share of patenting firms is above or below the overall average as calculated over the whole sample (any sector). The two groups of 4-digit NACE sectors so identified are called “broad patenting sectors” and “narrow patenting sectors”, respectively. The results are displayed in Figure 10. The estimated negative effect of patent intensity on the firm closure probability is relatively higher in absolute terms in the narrow patenting sectors with respect to the broad patenting sectors. In quantitative terms, the effect of one patent more per worker in the narrow patenting sectors equals a 14% reduction in the firm closure probability. This suggests that patents make more difference for the firm survival in the sectors where the population of patenting firms is smaller. This is coherent with the sector-specific findings showed above and in particular with the weaker effect of patents in the pharmaceuticals industry.

Figure 10. Effects of patent intensity on firm closure during the COVID-19 shock conditional to the patenting rate by 4-digit NACE

5.2 The intensive margin of firm resilience during the COVID-19 pandemic

The previous sub-Section analyzed the extensive margin of firm resilience, intended as the cross-sectional heterogeneity in the ability of firms to survive to the COVID-19 shock. It did not look at “how” the pandemic affected the comparative market performance of innovative and non-innovative firms. This sub-Section presents an analysis that follows a similar empirical strategy as the one implemented for studying the extensive margin of resilience, but, rather than focusing on firm closure, here the analysis digs into the pattern of the market performance (sales volumes) of firms that survived the first two years of the pandemic.

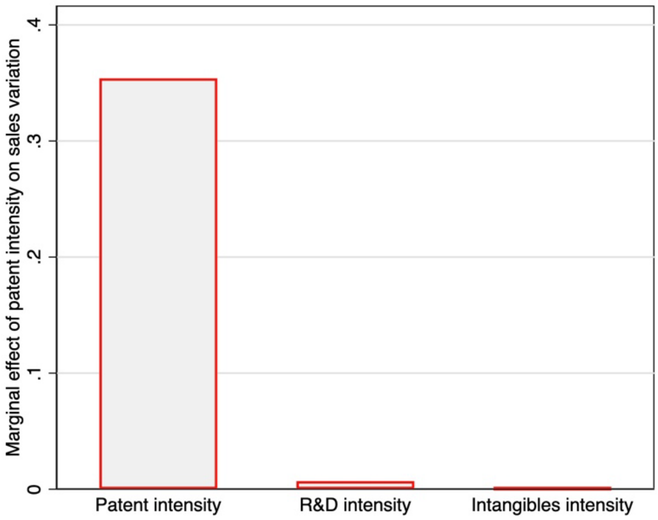
This empirical investigation of the intensive margin of firm resilience is based on a specification of the regression model in Eq. [1] in which the percentage change of the firm total revenues for the years 2020-2021, with respect to the firm total revenues for the years 2018-2019, is used as dependent variable. Clearly, the sample under study, in this case, is composed only by firms that survived the shock as to 31.12.2021.

5.2.1 Direct effects of patent intensity on the intensive margin of firm resilience

The same battery of regressions run for the extensive margin analysis is followed, based on the baseline version of Eq. [1], where the dependent variable measures the change in the revenues and where patent intensity is the main regressor of interest on the right-hand-side of the equation.

Since the dependent variable is a continuous variable, the regression method in this case is an Ordinary Least Squares (OLS). As in the extensive margin analysis, the right-hand-side of the regression equation includes a measure of R&D intensity (i.e., R&D investments per worker) and a measure of intangible assets intensity (i.e., intangible assets per worker) among the control variables, together with firm size, firm age, fixed capital assets, presence on the stock-market, macro-region of the firm and sector of activity. The main results are reported in Figure 11 (point estimates are relegated to the Appendix, in Table A1).

Figure 11. Direct effects of innovation variables on firm revenues during the COVID-19 shock (2020-21)



The estimated coefficient associated with the number of patents per worker is about 0.35, which means that a one-point increase in the patent intensity indicator results in an increase in the revenues of about 0.35 percentage points. This may appear as a small effect in economic terms. Nevertheless, it is worth noting that this effect is the differential effect calculated with respect to the average change in the revenues observed in the sample, i.e. the most successful firms during the pandemic, which did not close their activity before 31.12.2021. Indeed, only firms that survived are included in the intensive margin analysis. This is equal to saying that the estimated effect of patent intensity reported here is a lower bound of the "true" effect on revenues, because it measures only the additional, or incremental effect among survived firms, which arguably showed the best market performance during the pandemic compared to those firms that closed their activity before 31.12.2021 thereby withdrawing from the sample.

Figure 11 also shows that the effect of R&D activities and the effect of the size of the intangibles assets portfolios on the intensive margin of resilience have been modest at best, they being estimated with a magnitude below 0.1 percentage point. However, the same considerations about the sample selection effects mentioned above apply also to the interpretation of the effects of R&D and intangibles (i.e., these effects should be interpreted as lower bounds).

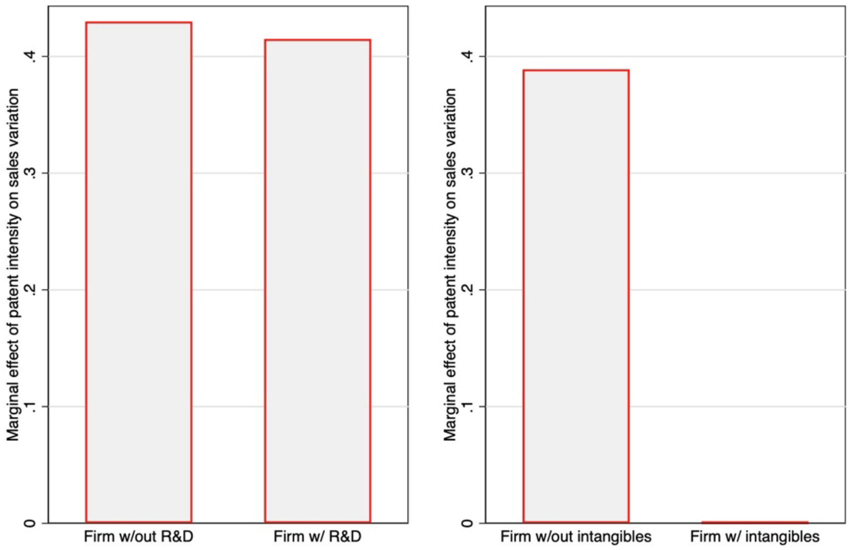
5.2.2 Conditional effects of patent intensity on the intensive margin of firm resilience

The analysis now looks at the "conditional" effects of patent intensity on the intensive margin of firm resilience. As already explained for the extensive margin analysis, this type of analysis digs into the granularity of the effect of patent intensity across firms with different characteristics.

Complementarities between patents, R&D and intangibles on the intensive margin

The interaction analysis between patent intensity, R&D and other intangible assets, as graphically reported in Figure 12, reveals that, differently from what has been observed in the extensive margin of resilience, patent intensity acts as a substitute with respect to R&D activities and other intangibles. In particular, the coefficient associated with the patent intensity indicator is disproportionately higher for firms that do not have other intangibles and slightly higher for firms that do not engage in R&D activity. This result might be interpreted as suggesting that patents are associated with a great ability of firms to survive to external shock (this is the main insight from the extensive margin analysis), but, among the firms that survived, the market performance, as reflected in revenues, can be sustained in somewhat alternative ways by patenting activities, R&D investments and sizeable portfolios of intangible assets. In retrospective terms, this may suggest that, during the pandemic, firms that survived followed different innovation strategies (among patentable and non-patentable investments) to safeguard their market position.

Figure 12. Effects of patent intensity on firm revenues during the COVID-19 shock (2020-21) conditional to R&D and intangibles



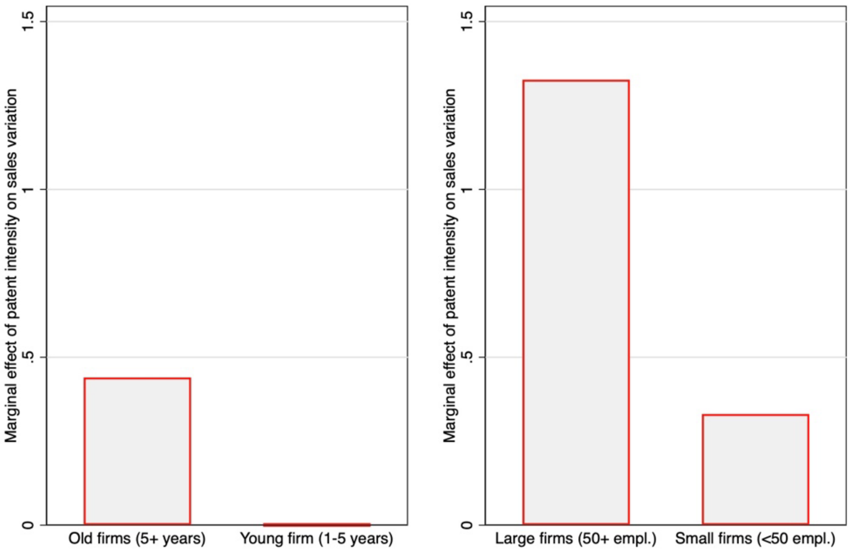
Complementarities between patents, firm size and age on the intensive margin

When considering the interaction between patents and firm size, it is possible to see that, besides their better resilience on the extensive margin, large firms are also better equipped to monetize their patenting activity in revenue performance with respect to small firms. This may be driven by factors associated with economies of scale in large firms as well as with the better-established market position that large firms typically have. Consistently with this empirical finding, Cohen and Klepper (1996), among others, argue that larger firms are better able to extract value from an innovation, because they can sell more output embodying the innovation itself.

Firm age is another important moderating factor on the intensive margin of resilience. In particular, as the larger firms also older firms showed a greater ability to translate a better patenting performance in a better market performance during the pandemic, provided that they survived the shock. Taken together with the results from the extensive margin of resilience, this finding suggests that young firms are typically more fragile, hence patents are for them an important asset for reducing the risk of closure, but they are also less able to make profits from patents than older firms.

See Figure 13.

Figure 13. Effects of patent intensity on firm revenues during the COVID-19 shock (2020-21) conditional to firm age and size



Complementarities between patents, geographical area and sector of activity on the intensive margin

Similar to the analysis on the extensive margin, also on the intensive margin the effect of patent intensity is lower for firms located in Europe and North America, while it is stronger for firms in Central and Eastern Asia (including China). It might be that in Asian countries (and the other countries with less developed institutional infrastructures) the pandemic had more unequal effects across firms, with those in a monopoly position (e.g., because patent-intensive) being somehow more insulated. In addition, industrial specialization may have played a role in this respect. Therefore, it is important to look also at the differential effect of patent intensity across sectors. Again, patent intensity was less important for firms in the pharmaceutical sector, as compared to other sectors (e.g., the chemical industry). One more time, this may suggest that the pharmaceutical industry as a whole was less negatively exposed to the pandemic, thereby making the cross-firm heterogeneity in patenting activities less crucial also for the intensive margin of resilience. On the other side, the chemical industry seems to be the sector where the effect of patents on sales volumes across the pandemic has been most powerful. This points to an important role of patents in broader sectors, like the chemicals, where there is a high heterogeneity across firms in terms of goods produced and technological sophistication of the production. In such heterogeneous and relatively less frontier contexts, the innovation performance of producers is more likely to make a difference among firms during negative aggregate shocks. The results are displayed in Figure 14.

Figure 14. Effects of patent intensity on firm revenues during the COVID-19 shock (2020-21) conditional to area and sector of activity

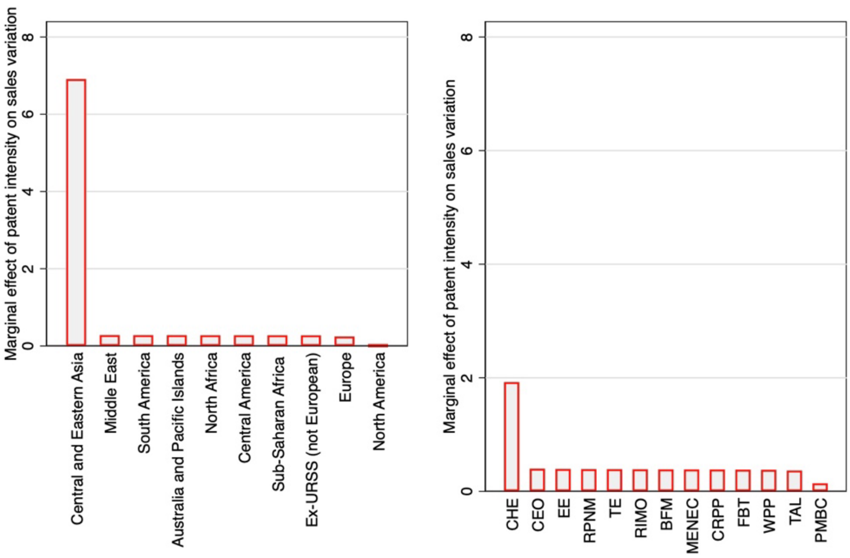
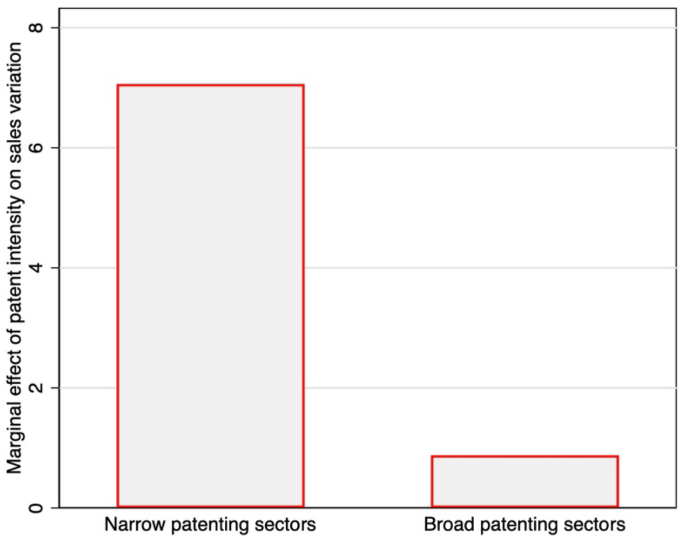


Figure 15. Effects of patent intensity on firm revenues during the COVID-19 shock conditional to the patenting rate by 4-digit NACE



Also the analysis of the intensive margin of resilience looks at the effect of patent intensity by distinguishing broad and narrow patenting 4-digit NACE sectors. The estimated coefficients are reported in Figure 15. Patent intensity is shown to matter more in narrow patenting sectors than in broad patenting sectors, with the effect of one patent more per worker on the increase of revenues being equal to about 7% in narrow patenting sectors and to about 0.9% in broad patenting sectors.

6 The productivity of innovative firms during the COVID-19 pandemic

In Section 4, a number of possible transmission channels connecting patents with firm resilience have been mentioned, including the ability to use more productive processes and to introduce and commercialize new products. A simple way to explore whether this interpretation has some validity is to look at the productivity performance of innovative firms. In particular, if innovative firms were more resilient during the COVID-19 pandemic because they were more efficient in production, then innovative firms should also show some productivity advantage across the outbreak.

This Section investigates this issue by measuring the variation in the productivity of innovative firms in the first two years of the COVID-19 outbreak (2020 and 2021). The analysis here focuses on the so-called Total Factor Productivity (TFP), as a measure of the comparative productivity performance of firms with respect to the average (i.e. predicted) within-sector performance. By construction, a firm's TFP is a measure of output differential between with respect to the average firm in the same sector, inputs level being equal. In this sense, TFP is a measure of the “relative” performance of the firm, because it reflects if and to what extent a firm performs better (or worse) than an ideal counterpart employing the same amount of capital and labour in the same product-sector. At its heart, TFP growth captures variations in output not explained by variations in the levels of the inputs used in production.

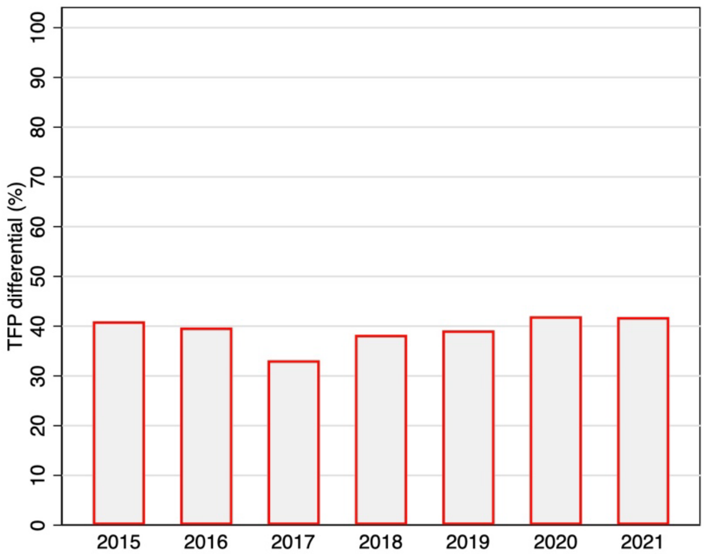
A broad literature has documented large TFP differences across firms, even within narrowly defined industries (e.g. Syverson (2004) and Hsieh and Klenow (2009)). A strand of empirical studies has identified many possible drivers of such TFP differentials (see Syverson (2011) for a survey), including human capital, input quality, technological innovation, trade patterns and competition levels. Here, the role of firm innovativeness during the COVID-19 pandemic is explored. This empirical exercise is a simple one, nevertheless it is the first attempt to explore the relationship between innovativeness and TFP in the years of the COVID-19 outbreak.

TFP is measured following Olley and Pakes (1996), which is one of the most widely used method to estimate TFP with firm-level data, as it allows addressing the so called “simultaneity bias” highlighted by recent literature on production function estimation. The simultaneity issue stems from the circumstance that information on actual productivity, although unknown to the econometrician, is arguably known to the firm when the decision on the amount of inputs is taken. This induces potential correlation between regressors (i.e., inputs) and error term that is likely to bias the production function estimation in a standard OLS setting. The semi-parametric approach put forward by Olley and Pakes (1996) consists of recovering the productivity term from the traces it leaves in the observed behavior of the firm. This is done by identifying a (proxy) variable that reacts to the changes in TFP observed by the firm and is thus a function of such changes. Insofar as this function is invertible, its inverse may be calculated and plugged into the production function estimating equation. In particular, Olley and Pakes (1996) suggest resorting to investment as a proxy.[7]

Figure 16 reports the TFP differential (in percentage points) between innovative and non-innovative firms, for each year in the 2015-2021 period. In simple terms, the numbers reported in Figure 16 can be interpreted as the yearly average of the productivity premium of innovative firms. Innovative firms are those with non-empty patent portfolios. The figure reveals a stable TFP advantage of innovative firms both before and after the pandemic. If any, in the first two years of the COVID-19 outbreak, the TFP premium of innovative firms has become larger than before the pandemic, raising from 39.1% in 2019 to around 42% in 2020 and 2021.

Figure 16. Average TFP differential (%) between innovative and non-innovative firms

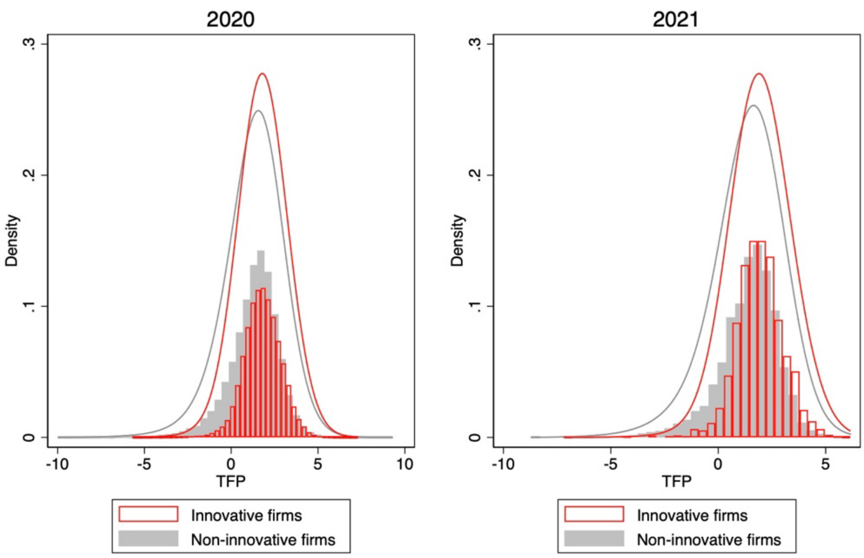
[7] Other key contributions to this approach, commonly referred to as the “proxy variable” method, include, Levinsohn and Petrin (2003), and Ackerberg et al. (2006) as well as the GMM estimation adopted by Wooldridge (2009).



Note. Innovative firms are firms with non-empty patent portfolios as to 31.12 of each year. TFP is measured as in Olley and Pakes (1996).

Figure 17 zooms on the TFP distribution in 2020 and 2021. The TFP advantage of innovative firms emerges clearly from the figure, with the TFP distribution of innovative firms being more concentrated around a higher average value with respect to non-innovative firms. This suggests that non-innovative firms, taken together, may introduce instability into the system: indeed, in response to negative shocks, microeconomic heterogeneity (like TFP dispersion) may amplify macroeconomic dynamics thereby leading to fluctuations in the aggregate productivity beyond the effect of the initial shock (e.g. Fiori and Scoccianti, 2021).

Figure 17. TFP distributions of innovative and non-innovative firms during the COVID-19 pandemic (2020 and 2021)



Note. Innovative firms are firms with non-empty patent portfolios as to 31.12.2019. TFP is measured as in Olley and Pakes (1996). The histogram (fractional) and the density function have different y-scale.

Finally, a simple regression analysis is run to estimate the effect of firm innovativeness on the variation of TFP performance across the COVID-19 pandemic. The strategy in Eq. [1] is followed, with firms' percentage change of the average TFP in 2020-2021 with respect to the average TFP in 2018-2019 now used as the dependent variable. As one may intuit, the sample under study is composed only by firms that survived the outbreak as of 31.12.2021.

The results are collected in Table 4.

Table 4. Estimated direct effect of innovativeness on TFP % changes before/after the COVID-19 pandemic

Explanatory variables	**Estimated**	**Estimated**	**Estimated**	**Estimated**
Innovativeness (non-empty patent		3.864*		3.751*
R&D intensity (R&D investments per		0.018		0.012
Intangibles intensity (intangible capital		-0.000		-0.000
Total assets (tangible + intangible			0.000	0.000
Size (# of employees)			0.000	0.000
Age (years since incorporation)			0.006	-0.069**
Listed firm (versus non-listed one)				2.502
Constant term	-13.175**	-7.327***	-14.267**	-5.670**

Note. The dependent variable is the % change of TFP between 2018-2019 and 2020-2021. All the control variables are measured as to 31.12.2019. Macro-region and sectoral fixed effects are included. Overall sample: ~213000 firms (with only firms survived as to 31.12.2021 used in the regression). Legend: *** = statistical significance at the 1%, ** = statistical significance at the 5%, * = statistical significance at the 10%. Other regression details are omitted in the Table for simplicity.

Different model specifications are considered. In the full model version, the estimated effect of having non-empty patent portfolios is about 3.7 percentage points, meaning that innovative firms experienced a variation in their TFP that was 3.7 percentage points higher than non-innovative firms. To grasp the sense of scale of this premium, it is useful to observe that the constant term of the model is equal to -5.6, i.e. during the first two years of the pandemic the average TFP (calculated over the entire sample of innovative and non-innovative firms) was -5.6 percentage points lower than in the two years before the pandemic. These results confirm that the productivity advantage of innovative firms has been an important transmission channel in the link between pre-determined innovation activity of firms and their greater resilience during the pandemic.

7 Policy implications

The analysis presented in this report delivers important policy insights. Taken together, the empirical results show that firms with improved patenting performance and R&D activity have been more resilient, on average, than less innovative firms, both on the extensive and intensive margins. This leads to consider patent portfolios (and innovation abilities more in general) a significant support for business stability during macroeconomic shocks. It follows that, at an aggregate level, industrial systems more largely populated by innovative firms should be more likely to have greater stability during macroeconomic turmoil. In terms of policy, a direct implication is that policies aimed at improving the innovation performance of firms are good not only for economic growth, as already highlighted by extensive literature, but also for macroeconomic stability and business resilience, with important consequences on various sectors of the economy (including the labour market). As a main policy conclusion, hence, the results of this report point to the importance of innovation-oriented industrial policies, ranging from supply side initiatives (e.g., R&D subsidies) to demand side measures (e.g., incentives and other supports for new technology adoption).

Looking at the specific firm characteristics that reinforce the link between patents and resilience, it is found that during the COVID-19 pandemic larger firms appeared better equipped than smaller firms to reap the benefits of patents. At the same time, it is not firm size *per se* that matters. Larger firms seem to make a better use of patents (both on the extensive and intensive margins of resilience) because they are better able at undertaking larger complementary investments in R&D and in intangible inputs, are older and typically show consolidated market positions. While this leads to see larger innovative firms as a crucial asset for macroeconomic resilience, it also suggests that industrial policies should help smaller businesses to overcome the obstacles that they typically encounter when dealing with innovation activities, in particular the difficulties in raising external finance to fund R&D programs and other complementary investments. Also policy instruments helping small firms to build innovation networks (e.g. through cross-licensing) may be of help in this respect.

More in general, the great divergence in terms of market resilience between innovative and non-innovative firms documented in the report highlights the importance of policies for innovation diffusion. It has been showed that an excessive dispersion in microeconomic productivity and in other measures of business health may have important economy-wide consequences in periods of turmoil because cross-firm heterogeneity may amplify the effects of macroeconomic shocks (e.g. Fiori and Scoccianti, 2021). It follows that, in addition to pushing forward the technological frontier, innovation policies should also aim at diffusing new technologies and innovation practices more broadly. Innovation diffusion policies are particularly important considering the strong concentration of patents (both globally and within regions and sectors) documented at the beginning of the report. Indeed, the persistence of such high concentration levels during the years of the pandemic is the consequence of the self-reinforcing dynamics in the patterns of patenting activities, which progressively increases the cost of catching-up for laggard firms.

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Appendix

A1. A simple description of the baseline empirical strategy

In this study, the econometric analysis of the relationship between firm resilience during the COVID-19 pandemic, patent portfolios and other firm characteristics is conducted through a regression study. In simple terms, the analysis exploits the heterogeneity across firms over several dimensions to identify systematic correlations between different measures of resilience and patent assets. This means looking at how and to which extent the ability of firms to be resilient is associated with the patenting activity of the firm and with other possibly relevant dimensions, including R&D, intangible assets, the size of the firm and its age, the capital structure, the presence of the firm on the stock market and the sector and region of activity.

The multivariate regression analysis is the standard, most simple econometric technique to investigate the sign and the magnitude of a relationship between two or more variables, as it provides a correlation coefficient (in this case, between resilience and patent portfolios) which is obtained by taking into account also other observable, possibly relevant characteristics of firms. For example, in a descriptive analysis firms with patents may appear to survive the COVID-19 pandemic more frequently. However, firms with patents may also have more consolidated market positions, thereby being more typically older and larger. Suppose that firm age and size are themselves two important drivers both of resilience and of successful innovation activities and suppose that patent portfolios do not have significant direct effects on resilience. Without considering differences in age and size, it might be observed that firms with patents are associated with a higher survival frequency, but this association would be a “spurious” association, in the sense that it would be driven by some omitted factors (i.e., firm age and size). It is only by accounting for the other possibly relevant drivers of firm resilience (drivers which in their turn may also be correlated with the patenting activity) that the analysis helps understanding the direct effects, if any, of patents on resilience.

At the same time, it is also the case that firms with patents engage more frequently with R&D activities, have other intangible assets more likely, and in general show other typical characteristics (e.g., in terms of capital structure). These variables may correlate both with firm resilience and with the size of patent portfolios. Hence, without controlling for such dimensions, the magnitude of the estimated coefficient □ would be affected by an omitted variable bias, which means a distortion in the size of the coefficient of interest driven by the characteristics shown more frequently by firms with patents to the extent that these characteristics remain omitted (or unobserved) in the estimated model. This issue requires including in the model, as briefly described by Eq. [1], a set of control variables, which account for all these relevant aspects that cannot be omitted in the analysis in order to help the estimation method to approximate the “true” effect of patents as much as possible net of other firm-level variables. In sum, under the assumption that all the aspects (different from patent intensity) relevant for firm resilience are accounted for, the coefficient □ is expected to measure the “net” (or “clean”) direct effect of patents on resilience.

An additional aspect which deserves to be explicitly justified is the time structure of the empirical model. In the specification of Eq. [1], the notation about the time structure is omitted for simplicity. However, it is easy to intuit that the purpose of the model is to capture the effect of patents on firm resilience, without reverse causality forces confounding the identification of the effect of interest. In particular, while on the one hand patents may have an effect on the ability of the firm to be resilient during the pandemic, on the other hand the COVID-19 shock may have altered the ability of the firm to be innovative, to engage in R&D and ultimately to make patent applications. In other words, if firms without patents or with smaller patent portfolios are more likely to suffer during the pandemic, and if the pandemic in its turn tends to harm the ability of the firm to produce new innovations (and to obtain new patents), then the absolute magnitude of estimated coefficient b will be biased upward. In the econometric language, this issue corresponds to the so-called “simultaneity” (or “reverse causality”) problem, i.e. a problem of endogeneity. This problem is well-known in the literature that analyzes the relationship between technology characteristics of firms and resilience to shocks. This issue is tackled by specifying the time structure of Eq. [1] in such a way that the estimation results are not at risk to be affected by the simultaneity problem, as in Cirera et al. (2022).

A2. Methodological description of TFP estimation: Olley and Pakes (1996)

The method used to estimate TFP, along the lines of Olley and Pakes (1996), Levinsohn and Petrin (2003), Ackerberg et al. (2006) and Wooldridge (2009), can be summarized as follows.

The starting point is the following individual production function:

$$Y_{it} = A_{it} \, f\,(K_{it} , L_{it}) \qquad [A1]$$

where “i” and “t” indicate the firm and the year and K_{it} and L_{it} the quantity of capital and labour employed. In Eq. [A1] A_{it} represents TFP, which incorporates the part of productivity not explained by the choices regarding the combination of factors. In particular, A_{it} includes non-measurable components such as R&D assets and other intangible variables such as technological levels and the quality of inputs.

The simplest approach to estimating the parameters of the production function uses a Cobb-Douglass specification of Eq. [A1] and hypothesizes that the parameters do not change from firm to firm. Expressing the variables in logarithmic form, the production function to be estimated becomes:

$$y_{it} = a_{it} + \square\, k_{it} + \square\, l_{it} + u_{it} \qquad [A2]$$

where u_{it} is a stochastic term that takes account not only of measurement error but also of shocks that are unobservable, unexpected and hence uncorrelated with k_{it} and l_{it}, stemming, for example, from environmental or market changes.

For the purposes of measuring the TFP component, it is necessary to note that a_{it} is not observable by the econometrician, while normally it is observable, and observed, by the firm. This means that the choice of k_{it} and l_{it} is influenced by a_{it}. It is customary to say that a_{it} is "transmitted" to the explanatory variables. The consequence is that the error term u_{it} is correlated with k_{it} and l_{it}, generating a simultaneity problem that reduces the quality of the estimate of the coefficients. From an econometric viewpoint, the problem amounts to having omitted variables. This reading makes it easier to understand the solution proposed by Olley and Pakes (1996).

When only cross-section data are available (i.e. data on the various firms in a single year), the parameters of Eq. [A2] are estimated by substituting a constant "a" for the unobservable component of TFP a_{it} and including all its variability in the error term. Once parameters □ and □ have been estimated, TFP is derived as the residual of the difference between the observed value of production and the value estimated on the basis of the parameters. If panel data are available (i.e. data on the various firms for more than one year), one way of refining the estimate is to reduce a_{it} to an effect that is firm-specific but constant over time, treating TFP as an unobservable effect in an estimation based on fixed effects. While this approach takes account of the individual heterogeneity between firms, it still neglects the temporal dimension. The latter can be included by identifying a proxy variable that reacts to the changes in TFP observed by the firm and is therefore a function of it, $m_{it} = m_{it}(a_{it}, \ldots)$. Insofar as this function proves to be invertible, its inverse can be calculated and inserted into Eq. [A2] before proceeding to estimate □ and □.

The key points of the procedure are therefore the identification of the proxy variable m_{it} and the definition of the conditions of invertibility of the corresponding function $m_{it} = m_{it}(a_{it}, \ldots)$. Olley and Pakes (1996) suggest using investment on the basis of the function $m_{it} = m_{it}(a_{it}, k_{it})$, which is invertible provided that, with given capital, investment increases with the growth in TFP as measured by a_{it}. In brief, the strategy for measuring TFP at firm level is to estimate the parameters of Eq. [A2] after substituting the amount of investment for the component a_{it}. This is done through a two-stage estimation procedure in which the labour coefficient estimated at the first stage is then used in a second-stage estimation in which the hypothesis that firms' TFP evolves according to a first-order Markov process is used. The difference between observed output and output so estimated is the measure of productivity.

A2. Additional tables

Table A1. Analysis of the extensive and intensive margins of resilience: regression results.

Interaction variable	Extensive margin of resilience	Intensive margin of resilience
none	-0.010	0.354
The firm does not have intangibles	-0.011	0.389
The firm has intangibles	-0.099	0.001
The firm does not make R&D	-0.012	0.430
The firm makes R&D	-0.038	0.415
The firm is small (<50	-0.011	0.331
The firm is large (50+ employees)	-0.079	1.327
The firm is young (<5 years)	-0.059	0.001
The firm is old (5+ years)	-0.011	0.440
The firm operates in sector FBT	-0.014	0.383
The firm operates in sector TAL	-0.013	0.369
The firm operates in sector WPP	-0.014	0.381
The firm operates in sector	-0.013	0.386
The firm operates in sector CHE	-0.014	1.926
The firm operates in sector	-0.009	0.143
The firm operates in sector	-0.444	0.393
The firm operates in sector BFM	-0.014	0.388
The firm operates in sector CEO	-0.047	0.401
The firm operates in sector EE	-0.123	0.396
The firm operates in sector	-0.013	0.387
The firm operates in sector TE	-0.013	0.392
The firm operates in sector	-2.397	0.390
The firm is located in area API	-0.013	0.281
The firm is located in area CAM	-0.013	0.279
The firm is located in area CEA	-0.046	6.914
The firm is located in area EUR	-0.012	0.247
The firm is located in area	-0.226	0.277
The firm is located in area ME	-0.016	0.283
The firm is located in area NAR	-0.013	0.279
The firm is located in area NAM	0.005	0.016
The firm is located in area SAM	-0.013	0.281
The firm is located in area SSA	-0.013	0.278
The firm is in a low patenting	-0.011	7.065
The firm is in a high patenting	-0.141	0.880

Note. Extensive margin of resilience: dependent variable is a drop-out dummy which equals 1 if the firm left the market between Jan 1 – 2020 and Dec 31 – 2021 and 0 otherwise; estimation method is Logit. Intensive margin of resilience: dependent variable is revenues' percentage change (percentage change of the firm total revenues for the years 2020-2021 with respect to the firm total revenues for the years 2018-2019); estimation method is OLS. Patent intensity is measured as the number of patents per worker, at the firm-level. . Each line in the Table reflects a separate regression. Each regression controls for R&D activity, intangibles portfolio, total assets, number of employees, firm age, presence on the stock market, regional and sectoral fixed effects. All the coefficients reported in the Table are significant at the 10%. Overall sample: ~213000 firms.

Table A2. Estimated direct effects of the unweighted number of patents on firm resilience during the COVID-19 pandemic.

	Dependent variable: Firm	**Dependent variable:**
Explanatory variables	**Estimated effects**	**Estimated effects**
Unweighted number of patents (as to 31.12.2019)	0.001*** (0.000)	0.005*** (0.001)
R&D intensity (R&D investments per worker, th. of Euro)	-0.001*** (0.000)	0.044*** (0.009)
Intangibles intensity (intangible capital per worker, th. of Euro)	0.000 (0.000)	-0.000** (0.000)
Total assets (tangible + intangible capital, th. of Euro)	-0.001*** (0.000)	-0.001* (0.000)
Size (# of employees)	-0.000 (0.000)	-0.000 (0.000)
Age (years since incorporation)	-0.023*** (0.000)	0.655*** (0.028)
Listed firm (versus non-listed one)	-0.646*** (0.045)	68.035*** (1.760)

Note. Firm exit is a drop-out dummy, which equals 1 if the firm left the market between Jan 1 – 2020 and Dec 31 – 2021 and 0 otherwise. Revenues' change is measured as the percentage change of the firm total revenues for the years 2020-2021 with respect to the firm total revenues for the years 2018-2019. All the control variables are measured as to 31.12.2019. Regional and sectoral fixed effects are included. Overall sample: ~213000 firms. Legend: *** = statistical significance at the 1%, ** = statistical significance at the 5%. The constant's coefficient and other regression details are omitted in the Table for simplicity.

Table A3. Legend for sector and area abbreviations.

Sector code	Description
FBT	Food, beverages and tobacco
TAL	Textile, apparel and leather
WPP	Wood, paper and printing
CRPP	Coke and refined petroleum products
CHE	Chemicals
PMBC	Pharmaceuticals, medicinal and
RPNM	Rubber, plastics and non-metallic
BFM	Basic and fabricated metals
CEO	Computers, electronics and opticals
EE	Electrical equipments
MENEC	Machinery and equipments n.e.c.
TE	Transport equipments
RIMO	Repair, installation of machineries
Area (macro-region)	**Description**
API	Australia and Pacific Islands
CAM	Central America
CEA	Central and Eastern Asia
EUR	Europe
EXURSS	Ex-URSS (not European)
ME	Middle East
NAR	North Africa
NAM	North America
SAM	South America
SSA	Sub-Saharan Africa

Table A4. List of countries covered in the study (in alphabetic order by 2-digit code).

Andorra (AD)	Cuba (CU)	Indonesia (ID)	Mauritania (MR)	Svalbard, Jan Mayen (SJ)
United Arab Emirates (AE)	Cabo Verde (CV)	Ireland (IE)	Montserrat (MS)	Slovakia (SK)
Afghanistan (AF)	Curacao (CW)	Israel (IL)	Malta (MT)	Sierra Leone (SL)
Antigua and Barbuda (AG)	Christmas Island (CX)	Isle of Man (IM)	Mauritius (MU)	San Marino (SM)
Anguilla (AI)	Cyprus (CY)	India (IN)	Maldives (MV)	Senegal (SN)
Albania (AL)	Czechia (CZ)	British-Indian Ocean (IO)	Malawi (MW)	Somalia (SO)
Armenia (AM)	Germany (DE)	Iraq (IQ)	Mexico (MX)	Suriname (SR)
Angola (AO)	Djibouti (DJ)	Iran (IR)	Malaysia (MY)	South Sudan (SS)
Antarctica (AQ)	Denmark (DK)	Iceland (IS)	Mozambique (MZ)	Sao Tome, Principe (ST)
Argentina (AR)	Dominica (DM)	Italy (IT)	Namibia (NA)	El Salvador (SV)
American Samoa (AS)	Dominican Republic (DO)	Jersey (JE)	New Caledonia (NC)	Sint Maarten (SX)
Austria (AT)	Algeria (DZ)	Jamaica (JM)	Niger (NE)	Syrian Arab Republic (SY)
Australia (AU)	Ecuador (EC)	Jordan (JO)	Norfolk Island (NF)	Eswatini (SZ)
Aruba (AW)	Estonia (EE)	Japan (JP)	Nigeria (NG)	Turks, Caicos Islands (TC)
Aland Islands (AX)	Egypt (EG)	Kenya (KE)	Nicaragua (NI)	Chad (TD)
Azerbaijan (AZ)	Western Sahara (EH)	Kyrgyzstan (KG)	the Netherlands (NL)	French-Southern Terr. (TF)
Bosnia-Herzegovina (BA)	Eritrea (ER)	Cambodia (KH)	Norway (NO)	Togo (TG)
Barbados (BB)	Spain (ES)	Kiribati (KI)	Nepal (NP)	Thailand (TH)

Bangladesh (BD)	Ethiopia (ET)	Comoros (KM)	Nauru (NR)	Tajikistan (TJ)
Belgium (BE)	Finland (FI)	Saint Kitts and Nevis (KN)	Niue (NU)	Tokelau (TK)
Burkina Faso (BF)	Fiji (FJ)	North Korea (KP)	New Zealand (NZ)	Timor-Leste (TL)
Bulgaria (BG)	Falkland Islands (FK)	South Korea (KR)	Oman (OM)	Turkmenistan (TM)
Bahrain (BH)	Fed. St. Micronesia (FM)	Kuwait (KW)	Panama (PA)	Tunisia (TN)
Burundi (BI)	Faroe Islands (FO)	Cayman Islands (KY)	Peru (PE)	Tonga (TO)
Benin (BJ)	France (FR)	Kazakhstan (KZ)	French Polynesia (PF)	Turkey (TR)
Saint Barthelemy (BL)	Gabon (GA)	Lao People's Dem. R. (LA)	Papua New Guinea (PG)	Trinidad and Tobago (TT)
Bermuda (BM)	United Kingdom (GB)	Lebanon (LB)	Philippines (PH)	Tuvalu (TV)
Brunei Darussalam (BN)	Grenada (GD)	Saint Lucia (LC)	Pakistan (PK)	Taiwan (TW)
Bolivia (BO)	Georgia (GE)	Liechtenstein (LI)	Poland (PL)	Tanzania (TZ)
Bonaire, S. Eustatius, Saba (BQ)	French Guiana (GF)	Sri Lanka (LK)	Saint Pierre, Miquelon (PM)	Ukraine (UA)
Brazil (BR)	Guernsey (GG)	Liberia (LR)	Pitcairn (PN)	Uganda (UG)
Bahamas (BS)	Ghana (GH)	Lesotho (LS)	Puerto Rico (PR)	US Minor Outlying Is. (UM)
Bhutan (BT)	Gibraltar (GI)	Lithuania (LT)	Palestine (PS)	USA (US)
Bouvet Island (BV)	Greenland (GL)	Luxembourg (LU)	Portugal (PT)	Uruguay (UY)
Botswana (BW)	Gambia (GM)	Latvia (LV)	Palau (PW)	Uzbekistan (UZ)
Belarus (BY)	Guinea (GN)	Libya (LY)	Paraguay (PY)	Holy See (VA)

Belize (BZ)	Guadeloupe (GP)	Morocco (MA)	Qatar (QA)	S. Vincent, Grenadines (VC)
Canada (CA)	Equatorial Guinea (GQ)	Monaco (MC)	Reunion (RE)	Venezuela (VE)
Cocos Islands (CC)	Greece (GR)	Moldova (MD)	Romania (RO)	Virgin Islands (British) (VG)
Dem. Rep. of Congo (CD)	S. Georgia, S. Sandwich (GS)	Montenegro (ME)	Serbia (RS)	Virgin Islands (U.S.) (VI)
Central African Rep. (CF)	Guatemala (GT)	Saint Martin (MF)	Russia (RU)	Viet Nam (VN)
Congo (CG)	Guam (GU)	Madagascar (MG)	Rwanda (RW)	Vanuatu (VU)
Switzerland (CH)	Guinea-Bissau (GW)	Marshall Islands (MH)	Saudi Arabia (SA)	Wallis and Futuna (WF)
Cote d'Ivoire (CI)	Guyana (GY)	Rep. N. Macedonia (MK)	Solomon Islands (SB)	Samoa (WS)
Cook Islands (CK)	Hong Kong (HK)	Mali (ML)	Seychelles (SC)	Yemen (YE)
Chile (CL)	Heard Is., McDonald Is. (HM)	Myanmar (MM)	Sudan (SD)	Mayotte (YT)
Cameroon (CM)	Honduras (HN)	Mongolia (MN)	Sweden (SE)	South Africa (ZA)
China (CN)	Croatia (HR)	Macao (MO)	Singapore (SG)	Zambia (ZM)
Colombia (CO)	Haiti (HT)	Northern Mariana Is. (MP)	S. Hel., Ascension, Tr. Cunha (SH)	Zimbabwe (ZW)
Costa Rica (CR)	Hungary (HU)	Martinique (MQ)	Slovenia (SI)	