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Did financial frictions stifle R&D investment in Europe during the great recession? ☆

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ABSTRACT

We investigate the role of financial frictions in R&D spending in a large sample of European firms. Our identification strategy exploits the contraction in credit supply that followed the 2008–09 global financial crisis and 2012 Euro area sovereign debt crisis, together with differences in financial frictions across firms and industries to identify a causal effect of financial constraints on investment in innovation. We show that firms that are more likely financially constrained, in industries more dependent on external finance, invest disproportionally less in R&D during periods of tight credit supply. Smaller, private firms with weaker balance sheets also have a lower share of R&D in total investment, suggesting R&D drops more than total investment during these crisis episodes. These results are robust to different proxies of financial constraints and fixed-effects identification strategies.

1. Introduction

European countries have experienced two crisis episodes in rapid succession: the first corresponding to the 2008–09 global financial crisis and the second to the 2012 Euro area sovereign debt crisis. Both episodes were accompanied by large contractions in bank credit, as depicted in Fig. 1, which shows the evolution of two indicators of credit supply from the ECB's Bank Lending Survey (Becker and Ivashina, 2018; Scopel et al., 2016). In this paper, we examine whether these periods of tight credit supply caused European firms to cut back on their investments in innovation.

The importance of bank credit for financing innovation is not straightforward. A long-standing argument in the finance literature is that, due to their uncertain outcome, informational problems and lack of collateral value, investments in innovation are best financed through equity or internal funds (see Hall et al., 2010).[1] Yet, bank credit might matter in periods of

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[1] A large literature looking mainly at listed firms supports this claim. For example, Brown et al. (2009) show that young, high-tech, publicly-traded firms in the United States finance their R&D investment almost entirely through internal cash flows and external equity markets. Similarly, Brown et al. (2012) look at European listed firms and highlight the sensitivity of R&D to stock issuance after controlling for internal funds. Acharya and Xu (2017) underline the importance of public equity markets in financing innovation in a sample of listed US firms. Brown et al. (2017) show that stock market development is associated with faster growth in high-tech industries that are more R&D intensive, while credit markets only matter for the growth of industries that rely extensively on external finance to fund their fixed capital investments.

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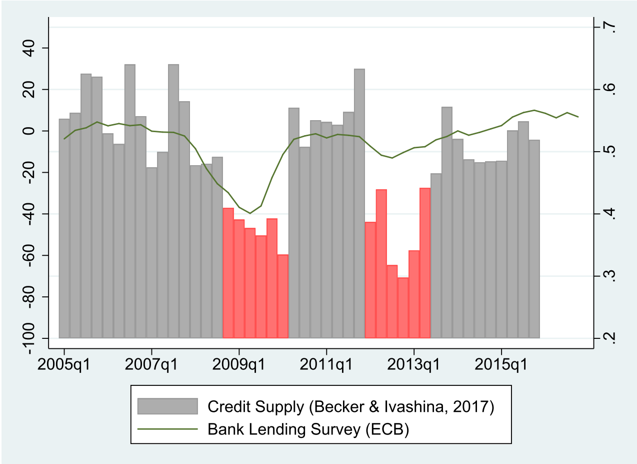

Fig. 1. Contractions in credit supply in Europe. The bar lines (right axis) show a measure of credit supply constructed by Becker and Ivashina, 2018 as the fraction of firms receiving new bank loans among all firms that raise new debt in a given quarter. A lower fraction of firms issuing bank loans as compared to bond financing is indicative of a contraction in credit supply, after controlling for the demand for credit. The line (left axis) is an index based on a survey of banks conducted by the European Central Bank that shows the difference between the share of banks reporting easing of credit standards and the share reporting tightening. Both measures indicate a contraction in bank credit supply during 2008Q4-2010Q1 and 2012Q1-2013Q2, respectively.

tight credit supply, even if firms do not directly finance innovation through debt. The argument is that, when bank credit supply is low, firms that are unable to access other sources of external finance will divert any available funds towards more "essential" investments (see Nanda and Nicholas, 2014). We sketch this argument theoretically by exploring the idea that firms' reliance on external financing is a technological characteristic intrinsic to the production process that is stable across time at the industry level as in Rajan and Zingales (1998). We show that, when R&D investment cannot be collateralized, tighter credit constraints will cause firms in industries that generally depend more on external finance to invest disproportionally less in innovation.

We then employ the 2008–09 global financial crisis and the 2012 Euro area sovereign debt crisis as natural experiments to investigate the effect of contractions in credit supply on investments in Research and Development (R&D). We combine various sources to construct a large firm-level dataset of European companies that report data on R&D spending over the period 2006–2016. The particularity of our data is that it contains both privately-held, small firms, as well as large publicly listed firms across 12 European countries.

Our identification strategy exploits three sources of variation in financial conditions. At the firm-level, we employ several proxies of financial constraints including differences among private and publicly listed firms and small and large firms.[2] We argue that the extent to which firms' financial constraints matters for R&D spending depends on how reliant firms are on obtaining external financing, in general. We capture this latter characteristic using the Rajan and Zingales (1998) industry-level index of dependence on external finance. Finally, at the aggregate level, we employ the time and cross-country variation in credit conditions in Europe as an exogenous shock to credit supply. The main argument is that, if bank credit matters for investments in innovation, then, in periods when credit supply is low, firms that face tighter financial frictions will invest disproportionally less in innovation.

Our results point to a strong effect of contractions in credit supply on firm investment in innovation. In a difference-in-difference framework, we find that firms that are more financially constrained invest less in R&D during periods of tight credit supply, in particular in industries that have an above the median dependence on external finance. Our main measure of financial constraints is a firm's ability to obtain external financing from other sources when the banking sector is in distress, which we proxy by its status as a private or publicly listed company. Alternatively, we employ other proxies such as firm size or its financial position captured by liquidity or leverage ratios prior to the crisis episodes.

We capture investment in innovation using three measures: the growth rate of R&D spending, the growth rate of R&D to sales and the share of R&D in total investment. The disruption in credit supply had an economically significant impact along all these measures. For example, private firms in industries highly dependent on external finance have a 2% lower growth rate of R&D spending, a 3% lower R&D intensity growth rate and a 12% lower share of R&D in total investment during periods of tight credit supply. These differential effects come from comparing financially constrained and unconstrained firms in the same country and industry cell, i.e., by controlling for fixed effects at the country-industry level.

[2] Farre-Mensa and Ljungqvist (2016) show that differences between private and public firms, as well as very small and large firms, are better at capturing financial constraints at the firm level, as compared to five widely-used proxies, such as the Kaplan and Zingales (1997) index or the ability to pay dividends. They show that when increases in taxes create an exogenous demand for bank credit, even firms that are classified as financially constrained according to these proxies are, in fact, able to borrow as a response to increases in corporate taxes. Privately-held small firms or listed firms close to default were the only ones unresponsive to the tax changes, suggesting that they indeed have difficulties raising external finance.

These results are robust to a wide-array of model specifications. First, we further control for aggregate demand conditions by saturating the model with industry-year, country-year, as well as three-way fixed effects at the country-industry-year level. We also include several firms characteristics that can be correlated with the investment behavior as well as the treatment condition, i.e., differences in financial constraints. This wide-array of fixed effects and controls reduces concerns of omitted variable bias and confounding demand-side conditions, allowing us to isolate the causal impact of financial frictions on firm investment in innovation. Next, we account for the cross-country variability in the contraction in credit supply across Europe, particularly during the 2012 Euro area sovereign debt crisis. We find that the drop in innovation spending was disproportionally larger in countries more affected by the crisis. Finally, we perform propensity score matching to ensure that firms in the treated and control samples are comparable, and we check the robustness of our results to several falsification strategies.

The remainder of this paper is organized as follows. Section 2 discusses the relation with previous literature, while Section 3 presents a stylized theoretical argument that guides our empirical strategy. Section 4 discusses the identification strategy and data. Section 5 presents the results and Section 6 concludes.

2. Relation to literature

Our work is related to several strands of the literature. First, a number of works study the consequences of the contraction in credit supply in Europe following the 2008–09 financial crisis and the 2012 Euro area debt crisis. For instance, Bentolila et al. (2018) and Cingano et al. (2016) look at samples of Spanish and Italian firms and document that firms borrowing from banks heavily exposed to the financial crisis experienced significantly larger drops in employment and investment (see also Balduzzi et al., 2017; Bofondi et al., 2018). Huber (2018) shows that this drop in credit also had important aggregate effects, by linking the lending cuts by a large German bank to persistent drops in productivity at the county level. We complement these findings by providing the first cross-country study of how these two European crises have impacted not only the volume, but, more importantly, the composition of corporate investment, by documenting a disproportional drop in R&D spending. Similar evidence is presented in Garicano and Steinwender (2016) who look at a sample of Spanish firms and find a shift from long to short-term investments.

Second, this paper is related to a growing literature that suggests that bank credit is an important source of funding, even for firms engaged in innovation. Classical arguments, discussed extensively in early surveys such as Hall et al. (2010), view a limited role of banks in financing innovation due to the high uncertainly and low collateral value of this type of investment. However, more recent surveys, such as Kerr and Nanda (2015), argue that recent work provides more nuanced evidence supporting a role for debt financing. For example, Cornaggia et al. (2015) and Chava et al. (2013) show that exogenous increases in credit supply, such as those that followed the interstate deregulations in the US during the 1980s, increased innovation output by small, private firms, who are also likely to depend more on bank financing (see also Benfratello et al., 2008; Robb and Robinson, 2014). Closely related to our work is Aghion et al. (2012) who use a sample of French firms over 1994–2004 to show that R&D investment is, in general, negatively related to sales, i.e., it is countercyclical. However, in periods when firms face tighter credit constraints (captured by a failure to pay trade creditors), R&D investment becomes procyclical. We focus on less stringent cross-sectional measures of financial constraints and show that they can explain the drop in R&D investment in periods of low aggregate credit supply. Ridder (2017) also shows that large US firms, who borrowed on the syndicated loan market from banks exposed to the 2008–09 financial crisis, have invested less in R&D. Our work complements these results in a wider cross-section of firms across several countries and crises episodes.

Another approach in linking access to finance to innovative behavior is to look at differences between private and listed firms. The argument is that access to equity markets should facilitate spending on R&D as this is a better source of external financing for such risky, uncollateralized investment (Brown et al., 2009). Indeed, Acharya and Xu (2017) and Feldman et al. (2018) find that going public increases R&D spending and patent output. Bernstein (2015), on the other hand, finds that the transition to public equity markets leads firms to reposition their R&D investments toward more conventional projects. In a difference-in-difference set-up similar to the one in this paper, Nanda and Nicholas (2014) find that private firms operating in US counties with higher bank distress during the 1930's Great Depression were less innovative than public ones, suggesting that periods of tight credit supply can affect innovation.

Finally, our work is also related to recent research that looks at the causes of the sustained drop in productivity that follows episodes of systemic bank distress (Reinhart and Rogoff, 2014). While persistent demand shortfalls have undoubtedly played an important role, the leading theoretical argument points to supply-side factors. For instance, Anzoategui et al. (2017) build a macroeconomic model of the US economy, and show that the productivity slowdown following the 2008–09 financial crisis was caused by a drop in R&D investment and technology adoption. (Duval et al., 2020) show that financially fragile firms experienced a lower total factor productivity growth and cut back more on intangible investment in a sample of eleven countries hit by the 2008–09 financial crisis. Their main measure of balance sheet fragility is the level of debt prior to the crisis. We also employ this measure together with several other proxies of financial constraints. Moreover, our results explicitly link financial conditions to firms' incentives to engage in R&D spending, which is the most common proxy for spending on innovation and is generally recorded as an expense and not always capitalized as an intangible investment.

3. Theoretical argument

This section sketches a simple theoretical argument that is used to guide our subsequent empirical exercise. The model is based on Aghion et al. (2010) and Aghion et al. (2012) and makes a distinction between two types of investment projects available to a firm, i.e., physical capital and R&D investments.

Set-up. The economy is populated by a continuum of entrepreneurs (firms) who live two periods and maximize their end-of-life wealth. We assume entrepreneurs have no initial wealth, and some amount of external financing I is required to initiate investment projects. Under the usual assumption of information asymmetries, we model credit market imperfections as a simple credit multiplier, such that if a firm wants to invest I it must have assets of at least vI, with $v \in (0, 1)$.[3] Given this initial level of borrowing, the firm can invest in two types of capital. Physical capital, denoted by k, yields a short-run profit $a_t k$ at the end of the first period and has an irreversible adjustment cost of $\frac{1}{2}k^2$. Investment in R&D, denoted by z, takes longer to become productive and yields an output $E(a_{t+1})z$ in period $t+1$ at cost $\frac{1}{2}z^2$. Investment in R&D differs from physical capital in two ways. First, its output is uncertain as it depends on the expected productivity at time $t = 1$, denoted by $E(a_{t+1})$. Second, in line with empirical arguments, we assume that R&D investment cannot be easily pledged as collateral, as its output is generally an uncertain intangible asset (Hall et al., 2010). As such, the firm's borrowing constraint is determined by its investment in physical capital:

$$I \leqslant \tau a_t k, \tag{1}$$

where $\tau \equiv \frac{1}{v} \geqslant 1$ is the credit multiplier.

Assuming entrepreneurs are risk-neutral and do not discount the future, they choose the optimal investment in physical capital and R&D to maximize their profits as follows:

$$\begin{aligned} \text{Max}_{k,z} \quad & a_t k + E(a_{t+1})z - \tfrac{1}{2}k^2 - \tfrac{1}{2}z^2 \\ & \text{subject to}: \ k + z \leqslant \tau a_t k. \end{aligned}$$

Depending on whether the borrowing constraint binds or not, the optimization problem above yields two cases. First, consider firms for which the constraint is not binding, i.e., firms whose reliance on external finance is generally low. We interpret this case as firms in industries that generally have a low dependence on obtaining external finance.[4]

Low dependence on external finance. The firm's optimization problem when the constraint is not binding yields the first-best allocation of investment projects as follows:

$$\begin{aligned} k &= a_t, \\ z &= E(a_{t+1}). \end{aligned}$$

Thus, in the case of firms that have a low dependence on external finance, the optimal level of investment in R&D only depends on the expected productivity of the project and not on the credit constraint.[5]

High dependence on external finance. Consider now the case of firms that rely extensively on obtaining external finance, for which the borrowing constraint is more likely to bind. In this case, we can write the borrowing constraint as $z = (a_t\tau - 1)k$ and the firm's constrained maximization problem yields:[6]

$$z = \frac{(a_t\tau - 1)[a_t + E(a_{t+1})(a_t\tau - 1)] + 1}{1 + (a_t\tau - 1)^2}, \tag{2}$$

which implies that:

$$\frac{\partial z}{\partial \tau} = \frac{a_t(a_t\tau - 1)(2E(a_{t+1}) - a_t^2\tau)}{\left(1 + (a_t\tau - 1)^2\right)^2} > 0, \tag{3}$$

which is positive as $a_t\tau - 1 > 0$, by construction, and $2E(a_{t+1}) - a_t^2\tau > 0$ if the credit constraint is binding. This implies that tightening credit constraints - that is, a reduction in τ - will lower investment in innovation among firms that rely heavily on external finance to finance their investment projects. Moreover, the tighter these constraints are, the lower will be, both the level, as well as the share of R&D in total investment.[7]

[3] See Aghion et al. (1999) for a rationalization of this result under costly state verification and moral hazard.

[4] Rajan and Zingales (1998) argue that, for technological reasons innate to the production process, firms in certain industries incur higher up-front costs and require more external capital, making them more dependent on obtaining external financing.

[5] Under additional assumptions about the dynamics of the productivity process, Aghion et al. (2012) show that a similar model can generate countercyclical R&D dynamics, i.e., unconstrained firms invest more in R&D during recessions. As our identification strategy exploits differences between constrained and unconstrained firms, this possibility only reinforces the effect we aim to uncover empirically.

[6] The credit constraint is binding whenever the equilibrium value of R&D investment is higher than $(a_t\tau - 1)k$, i.e., $E(a_{t+1}) > (a_t\tau - 1)a_t$.

[7] The share of R&D in total investment is $\frac{z}{k+z} = \frac{(a_t\tau - 1)k}{k + (a_t\tau - 1)k} = 1 - \frac{1}{a_t\tau}$, which is increasing in τ. This implies that changes in credit conditions have a larger impact in investments in innovation. The intuition for this result follows naturally from the binding borrowing constraint, $z = (a_t\tau - 1)k$, whereby an increase in τ increases z for the same level of k.

Empirical implications. Based on the simple theoretical model argument presented in this section, we expect that contractions in credit supply will lower investment in R&D among credit constrained firms, in particular in industries that depend more on external financing.

4. Data and identification strategy

Our identification strategy exploits differences in financial constraints across firms and industries, as well as the variation in aggregate credit supply. As such, isolating movements in loan credit *supply* in Europe over the period 2006–2016 is crucial to our analysis. We use the 2008–09 global financial crisis and 2012 Euro area sovereign debt crisis as natural experiments. There is, by now, extant evidence that these two episodes were accompanied by sharp contractions in credit supply.[8]

One approach to identifying credit supply shocks is proposed in Becker and Ivashina (2014). They identify movements in loan supply in a time-series context by examining the substitution between bank credit and public debt for firms that raise external finance. The argument is that, conditional on firms raising external finance, a substitution from bank credit to bond financing is evidence of a shift in bank credit supply. Using this methodology for a large sample of European firms, Becker and Ivashina, 2018 identify two time frames that correspond to a contraction in corporate credit supply in Europe, namely 2008Q4-2010Q1 and 2012Q1-2013Q2, respectively. These periods also coincide with the contraction in credit supply identified by the survey conducted by the European Central Bank, which directly asks banks whether they tightened their lending standards. Fig. 1 in the Introduction presents the evolution of both these measures between 2005 and 2015. Similarly, Ferrando et al. (2017) use firms' self-reported measures of financial constraints collected by the ECB SAFE survey to show that firms in countries severely affected by the 2012 Euro area sovereign debt crisis faced lower access to credit. Based on this evidence, we define a dummy variable called $Crisis_t$ that takes the value 1 in the years 2008–2010 and 2012–2013, in order to capture periods of contraction in credit supply across the European countries considered.[9]

Given this variation in credit supply over the period considered, we then exploit the cross-firm severity of financial constraints and cross-industry dependence on external finance to highlight a causal impact of bank credit on firm investment in innovation. Our baseline model is as follows:

$$Y_{i,t} = \beta_0 + \beta_1 FinConst_i \times Crisis_{t-1} + \beta_2 FinConst_i + \beta_3 Crisis_{t-1} + \theta' X_{c,i,j,t} + \epsilon_{it} \quad (4)$$

where $Y_{i,t}$ is the measure of innovation activity for firm i in industry j in country c at time t, $FinConst_i$ is a firm-level proxy of financial constraints and $Crisis_{t-1}$ is a dummy variable taking the value one for periods of low credit supply as defined above. We consider the effect of a contraction in credit supply in year t on investment one period ahead, as R&D spending is well-known to be more persistent than capital investment and to respond to macroeconomic conditions with a lag (Bloom, 2007). $X_{c,i,j,t}$ is a vector of control variables that includes firm-specific accounting measures and an array of fixed effects.

Our baseline estimation includes country-industry and year fixed effects. This implies that identification comes from the differences among financially constrained and unconstrained firms within the same industry in the same country. Year fixed effects also eliminate Europe-wide patterns in aggregate investment in a given year. We also gradually saturate the model with other two-way fixed effects such as country-year fixed effects that shut down macroeconomic conditions in a country, in a given year, as well as industry-year fixed effects to account for industry-specific fluctuations in, for example, demand or technological advancements. Finally, our most conservative specification also includes country-industry-year fixed effects, which shut down any aggregate demand conditions that affect firms in the same country-industry in a given year. This wide-array of fixed effects reduces concerns of omitted variable bias and confounding demand side conditions, allowing us to isolate the impact of financial frictions on firm investment in innovation.

We estimate the model in Eq. (4) separately for industries that have a below and above the median dependence on external finance. As suggested by the theoretical argument in the previous section, firms in industries with a high dependence on external finance are more likely to rely heavily on borrowing to finance their investment projects, and, as such, will respond more to a drop in credit supply.

4.1. Data

We obtain data from various databases provided by Bureau van Dijk to construct a unique dataset composed of firm-level observations on R&D spending for a sample of European countries. Most of the data obtained comes from the ORBIS Europe database, which we complement with country-specific datasets, such as AIDA for Italy, DIANE for France and FAME for the UK.[10] These datasets include information on both listed and unlisted firms collected from various country-specific sources, such

[8] Several works using credit registry data show that distressed banks decreased credit supply and this affected firm investment. Identification employing credit registry data is obtained from firms that borrow from multiple banks over a short period of time, which is generally a very small percentage of firms. Moreover, the availability of such data is limited to a few countries (see, for example, Cingano et al. (2016) and Balduzzi et al. (2017) for evidence for Italy, Iyer et al. (2014) for Portugal, or Garicano and Steinwender (2016) and Bentolila et al. (2015) for Spain.

[9] As the non-Eurozone countries in our sample were less affected by the Sovereign debt crisis, the dummy takes the value of zero in the 2012–2013 period for Denmark, Sweden and the UK.

[10] As discussed in Kalemli-Ozcan et al. (2015), the coverage of ORBIS Europe and the various country-specific databases does not perfectly overlap, with the latter containing a larger and more complete firm coverage.

as national registries and annual reports. While the ORBIS dataset contains data for many European countries, its coverage is extremely uneven, with most countries reporting information on very few firms (see Kalemli-Ozcan et al., 2015). After extensive checking of the data, we retain a sample of 12 countries with sufficiently good coverage and data quality for the main variable used in our analysis, namely, Research and Development spending. We collect information for the time frame 2006–2016. We include a sample of both manufacturing and service industries corresponding to the two-digit industry codes 10–82 in NACE Rev.2. This excludes farming, extraction and financial sectors, as well as non-market services. We also exclude Scientific R&D industries (NACE Rev.2 code 72). All variables are deflated by applying local currency deflators at the industry level obtained from OECD STAN (ISIC 4 version). We restrict our analysis to firms that consistently report R&D data (including a value of zero) for at least nine years, such that they are present in the sample during both crisis episodes.[11]

Table 1 presents the resulting sample of countries along with some summary statistics and checks on the quality of the data. Overall, while the number of firms reporting R&D expenditure varies across countries, the representativeness of the sample in terms of R&D coverage is rather high. Column 1 reports the total number of firm-year observations in each country, while column 2 shows the percentage of private firms in an average year. There is a large variation in data coverage even in our restricted sample, with some countries mainly reporting data on listed firms. Italy and France have the highest coverage of firms, with a large percentage of private firms, while Denmark has the lowest percentage of private firms in the sample. There is a total of close to 85,000 firm-year observations, with an average of 31% private firms across countries. To gauge the representativeness of this sample, Column 3 reports the ratio of total sales in the sample of ORBIS firms to total output at the country level reported by the OECD, while Column 4 relates the total R&D expenses of the firms in our sample to the total R&D at the country level from the OECD ANBERD database. Our sample covers, on average, 20% of the output produced in a given country in 2013, but as high as 61% of the total R&D. As such, the ORBIS data in our sample captures the bulk of aggregate R&D as reported by the OECD.

We construct three measures that capture the degree of investment in innovation of a firm. The first one is the growth rate of R&D investment defined as: $g^{R\&D}_{i,t} = \frac{R\&D_{i,t} - R\&D_{i,t-1}}{\frac{1}{2}(R\&D_{i,t} + R\&D_{i,t-1})}$. This definition is widely used in the firm dynamics literature, as it delivers a growth rate bounded between -2 and 2, and it accommodates the possibility of an investment of 0 in a given year (see Haltiwanger et al., 2013; Schmitz, 2017). The second measure captures R&D intensity and is computed as the growth rate of R&D to Sales in year *t*, using the same definition of growth rates shown above. Finally, we also look at the share of R&D in Total investment, where Total investment is defined as the annual increase in gross fixed assets plus R&D spending. In line with the theoretical argument in the previous section, investments in R&D are more sensitive to credit conditions and we expect that credit constrained firms cut down more on this type of investment as compared to capital investment. This definition will also allow us to understand the effect of the crunch in credit supply on the composition of firm investment.

We employ proxies for financial constraints at the firm, industry and country level. As discussed above, we exploit the variation of credit supply at the country level using the indexes constructed by Becker and Ivashina, 2018 and the ECB Bank Lending Survey. At the industry level, we classify industries according to their dependence on external finance following Rajan and Zingales (1998). This measure is constructed on a sample of US Compustat firms by measuring the level of capital expenditures in excess of firm cash flows. The use of external finance by large listed US firms should reflect their financial needs and, to a lesser extent, frictions in the supply of finance, as the US has one of the most developed financial systems in the world. Industry-level measures are obtained by taking the median of the firm-level dependence on external finance in an industry over time. The ranking of US industries then represents a good proxy for ranking industries in all countries. Moreover, the hierarchy of sectors by external finance dependence has been shown to be quite stable over time and countries, and has been widely employed in the literature (see, among others, Claessens and Laeven, 2003; Kroszner et al., 2007; Chor and Manova, 2012; Manova and Yu, 2016). We obtain this measure from Peia (2017) who reconstructs the index of financial dependence for a large set of industries (see Online Appendix for details).

Identifying financial constraints at the firm level is more confounded. Farre-Mensa and Ljungqvist (2016) show that firms that are classified as financially constrained according to five widely-used proxies such as the Kaplan and Zingales (1997) or Whited and Wu (2006) indices are, in fact, able to borrow when they have the incentives to do so. They use staggered increases in corporate taxes to capture firms' increased demand for debt given the tax benefit of raising additional financing. They show that privately-held, small or listed firms close to default were the only ones unresponsive to the tax increases, suggesting that they indeed have difficulties raising external finance. Our main measure of financial constraints at the firm-level is a dummy that distinguishes between private and publicly listed firms.[12] We also employ several other measures of financial constraints based on firm size, liquidity and leverage.

Table 2 presents some descriptive statistics of the main firm balance-sheet variables employed, whose definition is detailed in Appendix Table A. We split the sample into private and listed firms. As expected, listed firms tend to be larger and invest more in R&D, however R&D to total assets is, on average, comparable across the two samples. Average R&D intensity is nonetheless higher among public firms. Interestingly, private firms tend to be more leveraged, while both groups of

[11] This ensured that our analysis focuses on a sample of innovating firms that consistently invest in R&D. In robustness tests, we employ different attrition rules to show that our main results are not affected by the potential survival bias in our main specification.

[12] Saunders and Steffen (2011) and Gao et al. (2013), among others, also show that privately held firms, particularly those that are relatively small, are substantially more likely to be financially constrained then listed firms.

Table 1
Sample and data coverage.

Country	Firm-year observations	Percentage of private firms	Ratio of sample revenue to total revenue	Ratio of sample R&D to total R&D
Austria	266	5.26	0.08	0.08
Belgium	210	3.3	0.08	0.26
Denmark	217	1.4	0.13	0.56
Finland	532	4.3	0.35	1.06
France	31,561	95.2	0.26	0.72
Germany	2774	36.7	0.32	0.99
Greece	330	4.5	0.02	–
Italy	44,729	99.2	0.14	0.44
Netherlands	294	3.1	0.23	0.73
Spain	214	4.2	0.09	0.3
Sweden	2973	80.4	0.41	1.02
UK	1178	4.9	0.12	0.57
Total	85,012	30.65	0.2	0.61

The table shows the set of countries used in the analysis. It reports the total number of firm-year observations by country in Column 1, the percentage of private firms in each country in an average year and the ratios of Total sales and R&D expenses in our sample to total output and total R&D at the country level, as reported in the ANBERD dataset from the OECD.

firms have similar levels of liquidity, defined as the difference between current assets and current liabilities scaled down by total assets.

These statistics suggest that listed and private firms differ along a set of characteristics, which might be correlated with their investment behavior. This is confirmed in Fig. 2 that shows simple cross-sectional estimations of a dummy equal to one if a firm is private regressed on a set of firm characteristics in 2007 and 2015, respectively. As expected, private firms tend to be significantly smaller, where size is measured by the log of total assets. They also have significantly lower levels of investment and liquidity, but they are more leveraged. As such, we control for these firm characteristics in all subsequent estimations.

As a first look at the data, Fig. 3 presents a simple split sample analysis where we look at the share of R&D to total investment in private versus listed firms in crisis and non-crisis years, respectively. First, as expected, listed firms have a larger share of R&D in total investment in both time frames. Second, both groups of firms see a drop in the share of investment in innovation during crisis years, but this drop is significantly larger among private firms (the t-statistic of a t-test on the equality of means between non-crisis and crisis periods for private firms is t = 11.72, p-value$<$0.001). For listed companies, the drop in R&D investment is smaller and not statistically different in the two sub-periods (t = 1.45, p-value = 0.15). This suggests that the impact of the credit contraction on investment in innovation is stronger in more financially constrained firms.

Another way to validate our identifying assumptions, is to check that the differential decrease in R&D investment is not present before or after the periods classified as having tight credit supply. This will also allow us to (indirectly) test for the parallel trend assumption and to assess the dynamics of the treatment effect in each year in our sample. To do so, we estimate a difference-in-difference model where we include an interaction of the $Private_i$ dummy with year dummies and control for country-industry fixed effects, as follows:

$$Y_{i,t} = \alpha_{jc} + \beta_q \sum_{q \neq 2008} 1_{t=q} \times Private_i + \theta Private_i + \epsilon_{it}, \tag{5}$$

where $Y_{i,t}$ is the growth rate of R&D investment. We expect the coefficients of β_q in the years not corresponding to a contraction in credit supply not to be statistically different from zero once we take into account the overall difference in R&D spending captured by θ. Fig. 4 plots the coefficients of β_q from the regression above. It shows a significantly lower growth rate of R&D investment among private firms during two distinct periods: 2010–11 and 2013–14. All other years do not show a statistically significant difference. The coefficient is significant, but positive, in 2012 suggesting a higher bounce-back in R&D investment among private firms as credit conditions improved in 2011. At the same time, Fig. 4 reinforces the idea that investment in innovation responds with a lag to aggregate macroeconomic conditions as the drop in spending generally occurs one or two years after the start of a contraction in credit supply as identified by the Becker and Ivashina, 2018 and BLS indices in Fig. 1.

5. Results

The results from our baseline model in Eq. (4) are presented in Table 3. Panel A shows the estimations for industries with an above the median dependence on external finance, while Panel B for those below. The measure of financial constraints at the firm level is the distinction between private and listed firms, captured by the dummy variable $Private_i$. We look at the

Table 2
Summary statistics.

	Private Firms			Listed Firms		
	Mean	Median	Std. Dev.	Mean	Median	Std. Dev.
R&D (euro1000s)	655	78	2132	101,066	8059	356,556
Total Assets (euro1000s)	35,378	11,166	89,126	5,118,652	331,454	14,521,768
R&D/Total Assets	0.05	0.01	0.12	0.05	0.02	0.08
Sales (euro1000s)	34,399	11,668	82,661	3,359,718	318,034	8,888,976
R&D/Sales	0.06	0.01	0.18	0.11	0.03	0.37
Investment (euro1000s)	9504	1963	26,329	456,788	27,892	1,400,456
Investment/Total Assets	0.35	0.29	0.29	0.1	0.07	0.09
Investment/Sales	0.43	0.21	0.71	0.16	0.08	0.28
Liquidity	0.3	0.25	0.23	0.37	0.34	0.19
Leverage	0.88	0.93	0.36	0.33	0.32	0.19

Table presents average values of firm-level variables employed in the analysis over the period 2006–2016. Liquidity is the difference between Current Assets and Current Liabilities divided by Total Assets. Leverage is the ratio of Total Liabilities to Total Assets.

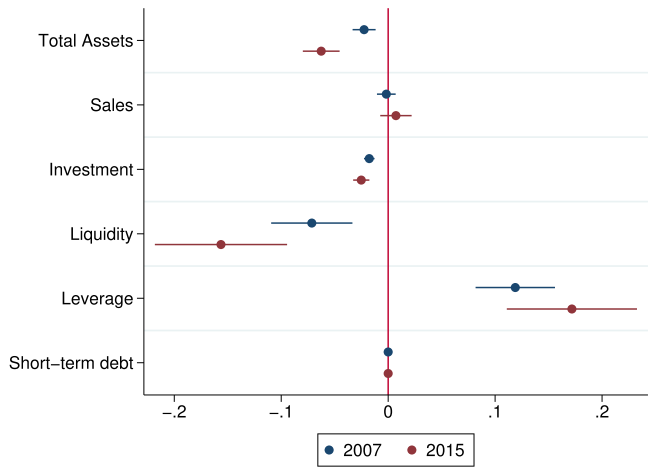

Fig. 2. Correlations between treatment condition and firm characteristics. The figure shows coefficient estimates of two cross-sectional OLS regressions in the years 2007 and 2015. The dependent variable is $Private_i$, a dummy equal 1 if the firm is private. Total Assets is the log of total assets, Sales is the log of sales, Investment is the ratio between investment, measured as the gross change in fixed assets, and total assets. Liquidity is defined as the difference between current assets and current liabilities scaled down by total assets. Leverage is the ratio of liabilities to total assets. 95% confidence intervals are shown.

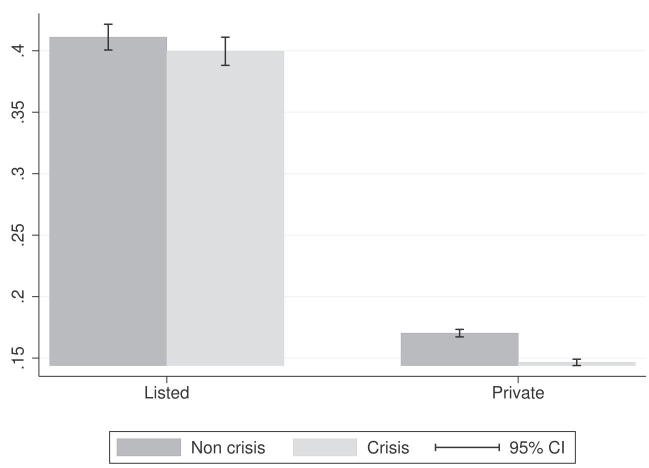

Fig. 3. Differences in the share of R&D in total investment. The figure shows the average R&D in total investment in private versus listed firms. Non-crisis/Crisis refers to the years where the Crisis dummy is zero/one. 95% confidence intervals are shown.

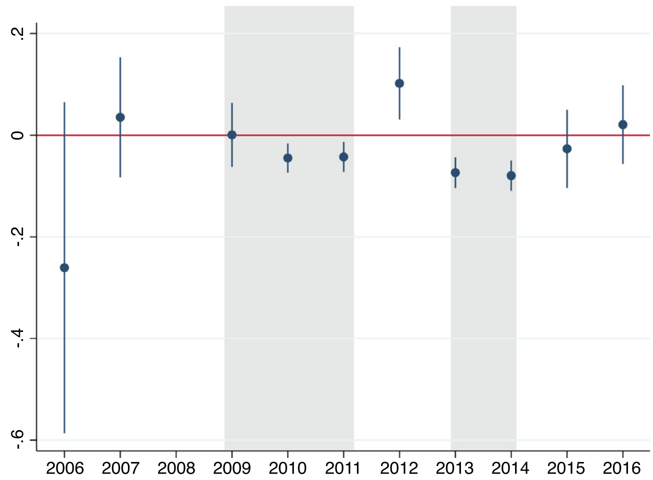

Fig. 4. Time-varying effects of credit tightening for private vs listed firms. The figure reports coefficients and standard errors of the interaction term between the private and annual dummies in Eq. (5). Country-industry fixed effects are included. Standard errors are clustered at the country level. Coefficients are measured relative to 2008. 95% confidence bands are reported. The shaded grey areas correspond to the years 2009–2011 and 2013–2014, i.e. one year after the beginning and the end of the 2008 global financial crisis and the 2012 sovereign debt crisis, respectively.

growth rate of R&D investment in columns (1)–(2), the growth rate of R&D intensity in columns (3)–(4) and the share of R&D in total investment in columns (5)–(6). Across all specifications and measures of innovation spending, we find that private firms invest disproportionately less in R&D during periods of tight credit supply, and this difference is significant in industries that are highly dependent on external finance and not in those below the median level of financial dependence. Moreover, as all estimations include country-industry fixed effects, these differences account for factors that are specific to a certain industry in a country, such as tax benefits for investing in R&D, and imply that identification is obtained from differences between firms in narrowly defined country-industry cells. We also include year fixed effects to account for a slowdown in investment in all the countries in our sample in a given year, such as the one that followed the 2008–09 financial crisis.

Columns (2), (4) and (6) add firm specific controls, which include the log of total assets, the log of sales, liquidity, leverage and investment scaled down by total assets. This baseline specification is also robust to alternative fixed effects identification strategies. Specifically, Appendix Table A2 includes industry-year and country-year fixed effects, which shut down any industry-specific demand or technological factors, as well as macroeconomic conditions at the country level in a given year. Our most stringent specification in Appendix Table A2 includes three-way fixed effects at the country-by-industry-by-year level. This implies that identification comes from firms in the same country-industry cell in a given year and allows us to control for time-varying demand side factors or investment opportunities that affect firms in the same country and industry. The results for R&D growth are less precisely estimated in this last specification, however, we find that R&D intensity and R&D to total investment are still significantly lower among private firms.

This wide array of fixed effects reduce concerns of omitted variable bias or confounding aggregate demand-side conditions, suggesting that the disproportionally lower investment in R&D among financially constrained firms is caused by the tightening in credit supply. The effects are also economically relevant. The coefficient estimates in Table 3 suggest that private firms have a 2% lower growth rate of R&D spending (column (1)), a 3% lower R&D intensity growth (column (3)) and a 12% lower share of R&D in total investment (column (5)).

5.1. Accounting for the cross-country variation in credit supply

The severity of the credit crunch, especially following the 2012 Euro area sovereign debt crisis, was different among the sample of European countries considered. For example, the measure of changes in credit standards collected by the ECB shows that 43% more banks tightened credit supply in Italy in 2012 as compared to those that relaxed them, while the difference was only 3% in the same year in Germany. To account for this heterogeneity in the tightening in credit supply across countries, we augment the model in Eq. (4) as follows:

$$\begin{aligned} Y_{i,t} = \beta_0 + \beta_1 Private_i \times Crisis_{t-1} \times BLS_{c,t} + \beta_2 Private_i + \beta_3 Crisis_{t-1} + \\ + \beta_4 BLS_{c,t} + \theta' X_{c,i,j,t} + \epsilon_{it}, \end{aligned} \tag{6}$$

where the coefficient of interest is now the triple interaction term between $Private_i$, the time dummy $Crisis_{t-1}$ and the country level index of credit standards, $BLS_{c,t}$. The latter is a survey-based variable collected by the European Central Bank across a large sample of banks operating in Euro area countries. This measure is computed as the difference between the share of

Table 3
Baseline results: Investment in innovation and credit constraints.

Dependent variables:	R&D		$\frac{R\&D}{Sales}$		$\frac{R\&D}{Investment}$	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Firms in industries with high dependence on external finance						
$Private_i \times Crisis_{t-1}$	−0.063**	−0.071**	−0.085***	−0.091***	−0.025***	−0.026***
	(0.025)	(0.029)	(0.028)	(0.035)	(0.009)	(0.009)
Observations	41,801	40,614	41,294	40,119	29,838	28,773
R-squared	0.023	0.033	0.018	0.025	0.37	0.40
Panel B: Firms in industries with low dependence on external finance						
$Private_i \times Crisis_{t-1}$	−0.029	−0.026	−0.026	−0.020	−0.002	−0.005
	(0.026)	(0.024)	(0.028)	(0.023)	(0.008)	(0.008)
Observations	43,980	42,938	43,629	42,592	28,610	27,642
R-squared	0.016	0.024	0.016	0.024	0.39	0.42
Controls:						
$Private_i$, $Crisis_{t-1}$	Yes	Yes	Yes	Yes	Yes	Yes
Country-industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm-level controls		Yes		Yes		Yes

Table presents the estimates of Eq. (4). The dependent variable in columns (1)–(2) is the growth rate of R&D investment in year t, in columns (3)–(4) is the growth rate of the ratio of R&D to sales, while in columns (5)–(6) it is the share of R&D to total investment. Panel A includes industries with an above the median dependence on external finance, while Panel B those with below the median dependence. $Private_i$ is a dummy equal 1 if a firm is private in 2007 and zero otherwise. $Crisis_t$ is a dummy taking the value one in 2008–2010 and 2012–2013. Firm level controls include: the log of total assets, the log of sales, liquidity, leverage and investment to total assets. Standard errors are clustered at the country level. */**/*** represents significance at 10, 5 and 1% level.

banks that have tightened credit standards and those that have relaxed them. As such, higher values imply that more banks have tightened their credit conditions than eased them. Recent work shows that this measure is highly informative of the aggregate credit conditions in an economy (see Becker and Ivashina, 2018; Bondt et al., 2010). The empirical strategy in Eq. (6) allows us to exploit both the time-series, as well as the cross-sectional variation of the credit crunch across Euro area countries. Our sample is nonetheless slightly reduced, as not all countries in our sample are included in the BLS survey.

The results are presented in Table 4, where we perform the same split sample analysis depending on the industry-level dependence on external finance. Results are consistent across all specifications: private firms invest disproportionately less in R&D during crisis periods, in particular in countries where the contraction in credit supply was more severe. We also find that in countries more affected by the two crises, financially constrained firms invest less in innovation across all industries (as the coefficients in the Panel B regressions in Table 4 are now strongly statistically significant).

One important identifying assumption in our analysis is that firms in our sample mainly rely on bank credit as a source of external financing. While this is the case in bank-based economies which characterize most European countries, it is also possible that some firms have access to other sources of external financing in periods when bank credit supply is low. For instance, Adrian et al. (2012) show that, in the US, bond financing spiked as banks tightened credit supply during the 2008–09 financial crisis. To assess the importance of other sources of external financing, we construct a country-level measure that captures the size of bank credit as compared to financing through corporate bonds or venture capital. These measures are obtained from the World Bank Global Financial Development Database and the OECD (See Appendix Table A for variables' definitions). Specifically, we construct the ratio of domestic credit to the private sector by banks to the sum of the volume of corporate bond issuance and venture capital investment. As these alternative sources of financing are also endogenous to the business cycle, we fix them at their 2007 level. Hence, the variable *Bank credit intensity*$_c$ is fixed at the country level, with higher levels implying that countries are more reliant on bank credit as opposed to other sources of financing. We then repeat the empirical exercise in Eq. (6), where we replace the BLS index with this alternative country-level index. The results are presented in Appendix Table A3, and show that the drop in R&D investment is significantly larger among private firms in countries with a relatively higher reliance on the banking sector as opposed to the two other sources of financing. This confirms the importance of bank credit for financing investments in innovation among firms whose access to alternative sources of external finance is limited.

5.2. Alternative measures of financial constraints

Our identification strategy thus far has been based on the premise that publicly traded firms face similar aggregate demand shocks as unlisted firms, but less financial constraints, as they can rely on other sources of financing when bank credit is tight. A concern is that the variation in aggregate demand shocks might still impact some industries more than others, in a way that it leads private firms to be systematically less likely to invest in innovation. Although segmenting our sample by more or less financially dependent industries and using country-by-year and industry-by-year fixed effects does help to address this particular issue, we present additional results where we employ alternative proxies for financial

Table 4
Accounting for the cross-country heterogeneity in credit supply.

Dependent variables:	R&D		$\frac{R\&D}{Sales}$		$\frac{R\&D}{Investment}$	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Firms in industries with high dependence on external finance						
$Private_i \times Crisis_{t-1} \times BLS_{c,t}$	−0.229***	−0.194***	−0.263***	−0.239***	−0.062***	−0.062***
	(0.045)	(0.044)	(0.028)	(0.027)	(0.017)	(0.017)
Observations	38,797	37,615	38,540	37,367	25,903	25,903
R-squared	0.022	0.033	0.018	0.025	0.33	0.33
Panel B: Firms in industries with low dependence on external finance						
$Private_i \times Crisis_{t-1} \times BLS_{c,t}$	−0.274***	−0.223**	−0.310***	−0.282***	−0.085**	−0.084**
	(0.092)	(0.092)	(0.074)	(0.083)	(0.039)	(0.040)
Observations	41,021	39,981	40,851	39,814	25,791	24,823
R-squared	0.016	0.024	0.016	0.024	0.28	0.31
Controls:						
$Private_i$, $Crisis_{t-1}$, $BLS_{c,t}$	Yes	Yes	Yes	Yes	Yes	Yes
Country-industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm-level controls		Yes		Yes		Yes

Table presents the estimates of Eq. (6). The dependent variable in columns (1)–(2) is the growth rate of R&D investment in year t, in columns (3)–(4) is the growth rate of the ratio of R&D to sales, while in column (5)–(6) it is the share of R&D to total investment. Panel A includes industries with an above the median dependence on external finance, while Panel B those with a below the median dependence. $Private_i$ is a dummy for private firms. $Crisis_t$ is a dummy taking the value one in 2008–2010 and 2012–2013. $BLS_{c,t}$ is the difference between the share of banks that have tightened their credit standards and those that have loosened them, in country c, during year t. Firm level controls include: the log of total assets, the log of sales, liquidity, leverage and investment to total assets. Standard errors are clustered at the country level. */**/*** represents significance at 10, 5 and 1% level.

constraints at the firm level. These alternative classifications of firms should further mitigate the concern that private firms systematically face different aggregate demand conditions that can explain their investment behavior.

First, we consider firm size. Farre-Mensa and Ljungqvist (2016) show that size correlates to the extent of financial constraints, particularly among private firms. Moreover, the relationship between size and investment in R&D is confounded. In an important work, Klette and Kortum (2004) show that R&D intensity is independent of firm size. On the other hand, Seru (2014) finds that smaller firms are more innovative and produce a larger number of patents. In a general equilibrium framework, Akcigit and Kerr (2017) model the interactions between firm size and two types of R&D investment: exploration (product) and exploitation (process). In a sample of US firms, they show that smaller establishments have higher R&D intensity and a higher rate of product innovation. Larger firms, on the other hand, tend to invest more in process R&D.

Whether or not small firms invest less in innovation will nonetheless only affect the level and not the trend of R&D spending. It is reasonable to assume that the trend of R&D investment and its intensity are not systematically related to our measure of firm size. We thus construct a dummy variable called $Small_i$ that takes the value of 1 if a firm is in the 25th percentile of the distribution of firms by total assets in a given industry and 0 if it is in the 75th percentile. We classify firms according to this criteria in 2007 and include them in the treatment or control group based on this definition in all the other years in the sample.

While the classifications into private and small firms are arguably the most exogenous to business conditions, we also construct two additional standard balance sheet measures of firms' financial health (see, among others, Duval et al., 2020; Fazzari and Petersen, 1993; Giroud and Mueller, 2017; Manova and Yu, 2016). Firms with low liquidity have more financial obligations outstanding in the short run and less freedom in managing cash flows or raising additional external capital. Similarly, firms with high leverage are less able to raise additional short- and long-term debt in response to aggregate demand conditions or to fund new investment opportunities. As a result, we construct two dummy variables that capture firms with low liquidity and high leverage, which we expect to be less financially healthy and more constrained. $Liquidity_i$ is a dummy equal to 1 for firms in the 25th percentile of the distribution of firms in the same industry and 0 for those in the 75th percentile in 2007. $Leverage_i$ is a dummy equal to 1 for firms in the 75th percentile of the distribution of firms in the same industry and 0 for those in the 25th percentile in 2007.[13] Since these two measures are more sensitive to credit market frictions, for each firm we compute its leverage and liquidity ratios in 2007 and fix the classification in treatment and control groups throughout the sample in order to capture pre-crisis balance sheet vulnerabilities.

We then repeat the empirical exercise in Eq. (4), where we replace $Private_i$ with the three alternative measures of financial constraints. We perform the same split sample analysis according to the industry level of external finance dependence. The results are summarized in Fig. 5 that plots the coefficient of the interaction term between the crisis dummy and each of the measures of financial constraints (see the Online Appendix for the details of the estimations). Results are consistent for the $Small_i$ proxy for all definitions of the dependent variable. We find that small firms have a lower growth rate of R&D and R&D intensity, as well as a lower share of R&D in total investment during periods of tight credit supply. Moreover, these dif-

[13] Our results are consistent if we employ the actual ratios, as opposed to the dummy variables.

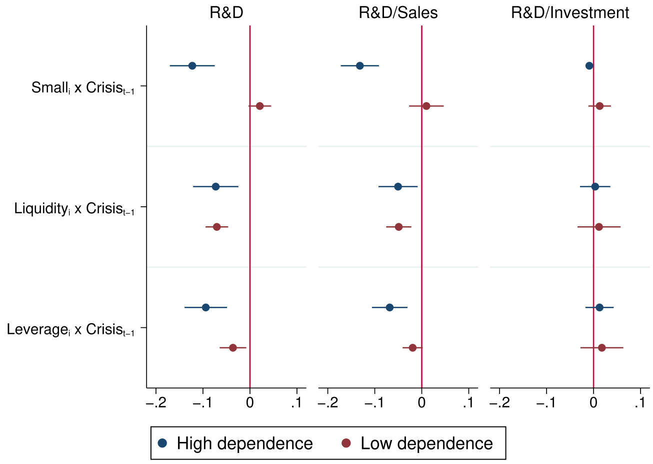

Fig. 5. Alternative measures of financial constraints. The figure presents the estimates of Eq. (4) where the firm-level proxy of financial constraints is (1) $Small_i$, (2) $Liquidity_i$ and (3) $Leverage_i$. The figure reports the coefficients and standard errors of the interaction term between the crisis dummy and the three measures of financial constraints. Eq. (4) is estimated separately for industries with high and low dependence on external finance. The Online Appendix presents the details of these estimations. 95% confidence bands are reported.

ferential effects are present only in industries with an above the median dependence on external finance. For leverage and liquidity, we find that firms that were less liquid or more leveraged in 2007 have a lower R&D growth rate and R&D intensity during crisis periods, as compared to more liquid or less leveraged firms. However, these differential effects are observed in both industries with a high and low dependence on external finance. This is not surprising since, for example, more liquid firms are less likely to be dependent on external financing and can smooth R&D spending as a result. The estimates for the share of R&D in total investment are not robustly estimated for the measures of liquidity and leverage as proxies for financial constraints.

5.3. R&D intensive industries and financial constraints

R&D investment often faces higher adjustments costs, which makes it expensive for firms to adjust the flow of R&D spending in response to transitory financial shocks. As a result, firms sometimes hoard cash in order to smooth their R&D expenditures (Brown and Petersen, 2011; He and Wintoki, 2016). This should be particularly the case among firms that generally invest a lot in R&D, or, in other words, firms with a higher R&D intensity. We test this hypothesis next.

As our analysis so far shows that R&D intensity at the firm level is highly sensitive to financial constraints, we circumvent any endogeneity concerns by employing an industry level classification of R&D intensity. The OECD provides a ranking of industries based on their R&D intensity, which is measured as the percentage of R&D in gross value added at the industry level (see Galindo-Rueda and Verger, 2016). The classification of industries is country-specific and at the 2-digit industry level in the year 2014. We thus perform a split sample analysis, where we estimate the model in Eq. (4) for industries with a below or above the median level of R&D intensity, where the median is computed for each country in 2014. The results are presented in Table 5 for various proxies of financial constraints at the firm level. Consistent with the idea that firms with a high R&D intensity might build up cash reserves to smooth R&D investment, we find that private firms invest disproportionately less in R&D, in particular in industries with low R&D intensity. The coefficient of the interaction term $Private_i \times Crisis_{t-1}$ is negative and statistically significant in industries below the median of R&D intensity, and not above. This result is also consistent across all measures of innovation spending.

The interaction terms employing the other measures of financial constraints are also negative and significant, but mainly in high R&D intensity industries. This suggests that small, highly leveraged and low liquidity firms reduce investment in innovation even in industries that generally invest a lot in R&D.

The results above suggest that even private firms might be able to smooth R&D investment, if they generally engage a lot in this type of spending. This can be due to the fact that R&D intensive firms hoard more cash. Brown and Petersen (2011) and He and Wintoki (2016), among others, document this tendency of R&D intensive firms to hoard cash among listed US firms. While hoarding cash is indicative that financial frictions matter for R&D investment, we nonetheless test whether our results are sensitive to the inclusion of changes in cash holdings. We thus replicate the baseline model in Eq. (4) including the change in cash holdings in a given year alongside other firm level characteristics. The results are presented in Appendix Table A4. Our sample is smaller in this case, as fewer firms report data on cash holdings, however we obtain consistent estimates.

Table 5
R&D intensive industries and financial constraints

Dependent variables:	R&D				$\frac{R\&D}{Sales}$				$\frac{R\&D}{Investment}$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel A: Firms in industries with high R&D intensity												
$Private_i \times Crisis_{t-1}$	−0.017				−0.029				−0.014			
	(0.016)				(0.022)				(0.010)			
$Small_i \times Crisis_{t-1}$		−0.078**				−0.086***				0.001		
		(0.036)				(0.032)				(0.007)		
$Liquidity_i \times Crisis_{t-1}$			−0.087***				−0.067***				0.015	
			(0.018)				(0.022)				(0.018)	
$Leverage_i \times Crisis_{t-1}$				−0.078***				−0.057***				0.021
				(0.010)				(0.016)				(0.020)
Observations	51,217	13,906	19,108	20,524	50,769	13,719	18,933	20,265	30,965	8,028	8,739	9,684
R-squared	0.0235	0.0203	0.0193	0.0173	0.0230	0.0211	0.0215	0.0204	0.425	0.437	0.601	0.576
Panel B: Firms in industries with low R&D intensity												
$Private_i \times Crisis_{t-1}$	−0.118***				−0.130***				−0.035*			
	(0.040)				(0.032)				(0.018)			
$Small_i \times Crisis_{t-1}$		−0.045				−0.065				0.004		
		(0.159)				(0.164)				(0.023)		
$Liquidity_i \times Crisis_{t-1}$			−0.023				0.006				−0.001	
			(0.081)				(0.095)				(0.036)	
$Leverage_i \times Crisis_{t-1}$				−0.090				−0.081*				0.015
				(0.057)				(0.045)				(0.026)
Observations	8,345	2,976	3,213	3,609	8,183	2,907	3,124	3,497	6,221	2,095	2,166	2,483
R-squared	0.0420	0.0551	0.0510	0.0554	0.0300	0.0448	0.0365	0.0390	0.447	0.471	0.502	0.458
Controls:												
$Credit_{t-1}$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country-industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm-level controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table presents the estimates of Eq. (4). The dependent variable in columns (1)–(4) is the growth rate of R&D investment in year t, in columns (5)–(8) is the growth rate of the ratio of R&D to sales, while in columns (9)–(12) it is the share of R&D to total investment. $Private_i$ is a dummy for private firms. $Crisis_t$ is a dummy taking the value one in 2008–2010 and 2012–2013. $Small_i$ is a dummy that takes the value of 1 if a firm is in the 25^{th} percentile of the distribution of firms by total assets in a given industry and 0 if it is in the 75^{th} percentile. $Liquidity_i$ is a dummy equal 1 if a firm is in the 25^{th} percentile of the distribution of firms by liquidity in a given industry in 2007 and 0 if it is in the 75^{th} percentile. $Leverage_i$ is a dummy equal 1 for firms in the 25^{th} percentile of the distribution of liquidity in an industry in 2007 and 0 for those in the 75th percentile. Firm level controls include the treatment condition in each interaction term as well as the log of total assets, the log of sales, liquidity, leverage and investment to total assets. Standard errors are clustered at the country level. */**/*** represents significance at 10, 5 and 1% level.

Table 6
Propensity score matching.

Dependent variable	R&D		$\frac{R\&D}{Sales}$		$\frac{R\&D}{Investment}$	
	High (1)	Low (2)	High (3)	Low (4)	High (5)	Low (6)
Panel A: Matching based on Total Assets						
$Private_i \times Crisis_{t-1}$	−0.079**	−0.030	−0.098**	−0.027	−0.031*	−0.019
	(0.030)	(0.027)	(0.038)	(0.027)	(0.014)	(0.016)
R-squared	0.033	0.024	0.025	0.024	0.424	0.437
Panel B: Matching based on Sales						
$Private_i \times Crisis_{t-1}$	−0.083**	−0.033	−0.101**	−0.029	−0.033**	−0.018
	(0.032)	(0.027)	(0.039)	(0.027)	(0.015)	(0.016)
R-squared	0.033	0.024	0.025	0.024	0.422	0.437
Other Controls:	*Private, Crisis, Country-industry FE, Year FE, Firm-level controls*					
Observations	40,567	42,865	40,073	42,519	28,727	27,569

Table presents the estimates of Eq. (4). The dependent variable in columns (1)–(2) is the growth rate of R&D investment in year t, in columns (3)–(4) is the growth rate of the ratio of R&D to sales, while in columns (5)–(6) it is the share of R&D to total investment. $Private_i$ is a dummy for private firms. $Crisis_{t-1}$ is a dummy taking the value one in 2008–2010 and 2012–2013. Firm level controls include: total assets, sales, liquidity, leverage and investment to total assets. High/Low refer to industry with an above/below the medium dependence on external finance. Standard errors are clustered at the country level. */**/*** represents significance at 10, 5 and 1% level.

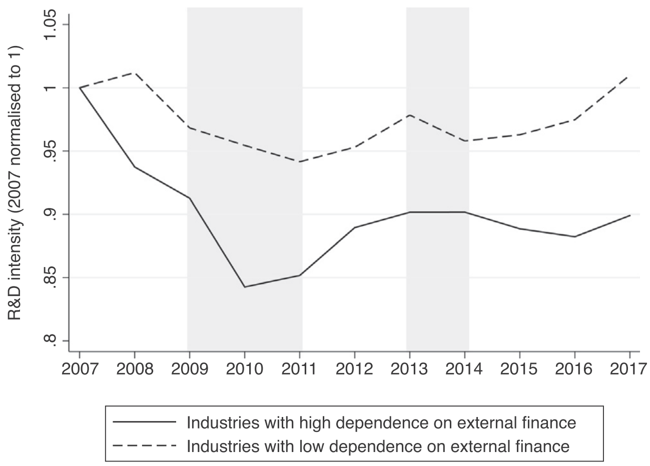

Fig. 6. Evolution of R&D intensity (2007–2017). The figure shows the evolution of the average R&D intensity at the industry level computed as the ratio between R&D expenses obtained from the OECD ANBERD database and the industry level of production obtained from the OECD STAN Industrial Analysis. R&D intensity is normalised to 1 in 2007. The full line corresponds to industries with an above the median dependence on external finance, while the dashed line to those below the median. The shaded grey areas correspond to the years 2009–2011 and 2013–2014, i.e. one year after the beginning and the end of the 2008 global financial crisis and the 2012 sovereign debt crisis, respectively..

5.4. Other robustness tests

In this section we consider a set of additional robustness tests for our main results. First, while we show that private smaller firms are less likely to engage in spending on innovation when credit supply is low, this does not imply that aggregate investment in innovation is affected, especially if the bulk of R&D spending is concentrated among listed firms that are less likely to be affected by a contraction in credit supply. To control for observable differences between public and private firms we use a matching procedure that matches our treated and control groups by firm size, measured by either total assets or sales. Firms are matched using propensity scores based on a logit model in 2007 that relates the probability of being assigned to the treated group to firm size. We then employ this propensity score to re-weight treatment and control groups such that the distribution of firm size is similar in both groups. This is done using the conditional probability of being in the treated group, $\hat{\lambda}$, to compute a weight as the odds ratio $\hat{\lambda}/(1-\hat{\lambda})$ (see Nichols, 2007). We then re-estimate the model in Eq. (4) using the weighted data based on propensity scores. The results are presented in Table 6 and show consistent estimates.

Another way to gauge the aggregate effects of our results is to look at the evolution of R&D spending at the industry level. If the drop in R&D investment among our treated firms is large enough, then we can expect that industries with a high dependence on external finance will see a larger drop in R&D investment as well. Fig. 6 confirms this patterns by plotting the evolution of the average R&D intensity in industries below (dashed line) and above (full line) the medium level of dependence on external finance. R&D intensity is computed as the ratio between R&D expenses at the industry level obtained from the OECD ANBERD database and the industry level of production obtained from the OECD STAN Industrial Analysis. We normalize the level of R&D intensity to 1 in 2007 such that we show the difference in the growth rates of this ratio across the two industry types. Fig. 6 highlights a larger drop in R&D intensity among industries with high dependence on external finance following the 2008 financial crisis, which does not recover to the pre-crisis level in subsequent years. For industries with a low dependence on external finance, the drop is not as large and R&D intensity bounces back towards the end of the sample to its pre-crisis level. This evidence is in line with Peia (2017) who also finds a significantly lower spending on R&D among financially dependent industries in a larger sample of countries that have experienced sharp contractions in credit supply following systemic banking crises.

Second, we perform a series of falsification strategies commonly employed in difference-in-difference estimations. Specifically, we repeat the empirical exercise in Eq. (4) by randomly changing the crisis year. Next, we randomize the treatment and control assignment, by setting the dummy $Private_i$ to 1 in a random sample of firms. The results are presented in Appendix Table A5. The coefficient of the interaction term $Private_i \times Crisis_{t-1}$ is no longer significant, except for one estimation among low dependent industries. These results strengthen our identification strategy and show that the disproportionally lower investment in R&D is specific to firms that are more credit constrained, during periods of tight credit supply, and not just an artifact of the data.

Third, we use different attrition rules in selecting the sample of firms. Our sample contains firms with at least 9 years of R&D data (including those reporting a zero). This ensures that we investigate the behavior of innovative firms that consistently invest and report R&D expenditures. However, this attrition rule might introduce survivorship bias. Although this bias should weaken our results, as less financially healthy firms should have even lower investment rates, our baseline results are consistent across a larger sample of firms by including those reporting R&D data for at least 5 years (see the Online Appendix).

Fourth, we show that our results are robust to different variable definitions. We estimate the split sample analysis in Table 3 by classifying industries with a high dependence on external finance as those in the 75th percentile of the distribution of the Rajan and Zingales (1998) index, while those in the 25th percentile as low dependent. Furthermore, some countries, such as Germany, were less affected by the 2012 Sovereign Debt Crisis. While this is accounted for in Table 4 when we employ the BLS measure of financial constraints, we also show that our results are robust to classifying Germany as a non-crisis country in 2012–2013.

Lastly, in all specifications error terms were clustered at the country level. We show that our main results are robust to clustering at the country-industry level, which accounts for the cross-sectional correlation between firms in the same industry and country. The results for these robustness tests are included in the Online Appendix.

6. Conclusion

A longstanding argument in the finance and innovation literature views a limited role for bank credit in financing investments in innovation such as R&D spending. This is because these investments generally face more severe informational problems, highly uncertain returns and, most importantly, cannot be easily collateralized. In this paper, we show that bank

Table A1
Variables employed.

Variable	Definition	Source
R&D	Growth rate of R&D spending at time t, calculated as $g^{R\&D}_{i,t} = \frac{R\&D_{i,t} - R\&D_{i,t-1}}{\frac{1}{2}(R\&D_{i,t} + R\&D_{i,t-1})}$	Bureau van Dijk
$\frac{R\&D}{Sales}$	Growth rate of R&D spending to sales at time t, calculated as above.	Bureau van Dijk
$\frac{R\&D}{Investment}$	Ratio of R&D to total investment, where total investment is computed as the sum of R&D spending to fixed investment.	Bureau van Dijk
Investment	$\max \{\frac{\text{FixedAssets}_t - \text{FixedAssets}_{t-1} + \text{Depreciation}_t}{TotalAssets}, 0\}$	Bureau van Dijk
Private	Dummy equal to 1 if firm is private.	Bureau van Dijk
Crisis	Dummy equal to 1 in years 2008–2010 and 2012–2013 for all countries. UK, Denmark and Sweden have a value of zero in 2012–2013.	Bureau van Dijk
Small	Dummy equal to 1 if a firm is in the 25th percentile of the total assets distribution in an industry.	Bureau van Dijk
ExtDep	An industry-level measure of external dependence proposed by Rajan and Zingales (1998).	Peia (2017)
BLS	Index based on a survey of banks conducted by the European Central Bank that shows the difference between the share of banks reporting tightening of credit standards and the share reporting easing.	ECB Statistics
Liquidity	Difference between current assets and current liabilities divided by total assets.	Bureau van Dijk
$Liquidity_i$	A dummy equal to 1 for firms in the 25th percentile of the distribution of firms by liquidity in the same industry and 0 for those in the 75th percentile in 2007.	Bureau van Dijk
Leverage	Ratio of liabilities to total assets.	Bureau van Dijk
$Leverage_i$	Dummy equal to 1 for firms in the 75th percentile of the distribution of firms by leverage in the same industry and 0 for those in the 25th percentile in 2007.	Bureau van Dijk
Bank credit intensity	Ratio of domestic credit to the private sector by banks (FD.AST.PRVT.GD.ZS) and other sources of external finance, i.e. the amount of outstanding private debt securities (GFDD.DM.05), the volume of corporate bond issuance volume (GFDD.DM.13) and venture capital investments (OECD).	World Bank Global Financial Development Database and OECD

Table A2
Baseline results: including country-by-year, industry-by-year and country-by-industry-by-year fixed effects

Dependent variables:	R&D				$\frac{R\&D}{Sales}$				$\frac{R\&D}{Investment}$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel A: Firms in industries with high dependence on external finance												
$Private_i \times Crisis_{t-1}$	−0.068**	−0.044	−0.058**	−0.054	−0.091***	−0.094**	−0.073**	−0.094***	−0.027***	−0.039***	−0.029***	−0.041***
	(0.028)	(0.043)	(0.024)	(0.038)	(0.033)	(0.042)	(0.030)	(0.032)	(0.009)	(0.012)	(0.010)	(0.013)
Observations	40,614	40,614	40,614	40,614	40,119	40,119	40,119	40,119	28,773	28,773	28,773	28,773
R-squared	0.0306	0.0335	0.0374	0.0594	0.0224	0.0252	0.0297	0.0511	0.379	0.388	0.383	0.433
Panel B: Firms in industries with low dependence on external finance												
$Private_i \times Crisis_{t-1}$	−0.024	−0.056*	−0.020	−0.051	−0.017	−0.061	−0.017	−0.049	−0.004	−0.004	−0.010	−0.007
	(0.023)	(0.029)	(0.024)	(0.032)	(0.024)	(0.043)	(0.024)	(0.047)	(0.008)	(0.012)	(0.008)	(0.012)
Observations	42,938	42,938	42,938	42,938	42,592	42,592	42,592	42,592	27,642	27,642	27,642	27,642
R-squared	0.0223	0.0248	0.0272	0.0459	0.0220	0.0245	0.0279	0.0465	0.381	0.397	0.389	0.484
Controls:												
$Private_i$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$Crisis_{t-1}$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes		Yes		Yes		Yes		Yes		Yes	
Industry FE	Yes	Yes			Yes	Yes			Yes	Yes		
Year FE	Yes				Yes				Yes			
Country-year FE		Yes				Yes				Yes		
Industry-year FE			Yes				Yes				Yes	
Country-industry-year FE				Yes				Yes				Yes
Firm-level controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table presents the estimates of Eq. 4. The dependent variable in columns (1)–(4) is the growth rate of R&D investment in year *t*, in columns (5)–(8) is the growth rate of the ration of R&D to sales, while in columns (9)–(12) it is the share of R&D to total investment. Panel A includes industries with an above the median dependence on external finance, while Panel B those with a below the median dependence. $Private_i$ is a dummy for private firms. $Crisis_{t-1}$ is a dummy taking the value one in 2008–2010 and 2012–2013. Robust standard errors are presented. */**/*** represents significance at 10, 5 and 1% level.

finance matters for investments in innovation during periods of tight credit supply, such as the ones that followed the 2008–09 global financial crisis and 2012 sovereign debt crisis in Europe.

We exploit three sources of exogenous variation in financial conditions in our identification strategy: the time and cross-country variation in credit standards; the cross-firm heterogeneity of financial constraints; and a cross-industry variation in dependence on external finance. Controlling for firm characteristics and a wide array of fixed effects, we show that firms that are more likely credit constrained, in industries more dependent on external finance, invest disproportionately less in innovation during periods of tight credit supply. These results are consistent across different measures of spending on innovation, such as the growth rate of R&D investment, the growth rate of R&D intensity and the share of R&D investment in total investment. Moreover, our findings are also robust to various measures of financial constraints at the firm-level including the difference between private and listed firms, small and large, more or less liquid/leveraged firms.

Our results point to a significant disruption in investment in innovation in Europe as a result of the drop in credit supply that followed the distress in its banking sector. Given the importance of R&D investment in long-run growth, this disproportionally lower investment in innovation can have implications that go beyond the episode of credit market disruption. As such, policy interventions should be directed towards supporting R&D spending, especially among private, smaller firms during periods of tight credit supply.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A

See Tables A1–A5.

Table A3
Accounting for the cross-country heterogeneity in reliance on banks.

Dependent variables:	R&D		$\frac{R\&D}{Sales}$		$\frac{R\&D}{Investment}$	
	High (1)	Low (2)	High (3)	Low (4)	High (5)	Low (6)
$Private_i \times Crisis_{t-1} \times$ $\times$ *Bank credit intensity*$_c$	−0.092*** (0.030)	−0.084*** (0.019)	−0.099*** (0.029)	−0.081*** (0.019)	−0.017*** (0.005)	−0.009* (0.005)
Controls:						
Small$_i$, Crisis$_{t-1}$	Yes	Yes	Yes	Yes	Yes	Yes
Country-industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	41,342	43,487	40,841	43,136	29,497	28,185
R-squared	0.0132	0.0101	0.0108	0.0103	0.134	0.146

The dependent variable in columns (1)–(2) is the growth rate of R&D investment in year *t*, in columns (3)–(4) is the growth rate of the ratio of R&D to sales, while in columns (5)–(6) it is the share of R&D to total investment. Columns (1), (3) and (5) include industries with an above the median dependence on external finance, while columns (2), (4) and (6) those with a below the median dependence. $Private_i$ is a dummy for private firms. $Crisis_t$ is a dummy taking the value one in 2008–2010 and 2012–2013. *Bank credit intensity*$_c$ is the ratio between domestic credit to private sector by banks and other sources of external finance, i.e. the amount of outstanding private debt securities, the volume of corporate bond issuance volume and venture capital investments. Standard errors are clustered at the country level. */**/*** represents significance at 10, 5 and 1% level.

Table A4
Controlling for cash holdings.

Dependent variables:	R&D		$\frac{R\&D}{Sales}$		$\frac{R\&D}{Investment}$	
	High (1)	Low (2)	High (3)	Low (4)	High (5)	Low (6)
$Private_i \times Crisis_{t-1}$	−0.031* (0.018)	−0.022 (0.023)	−0.048*** (0.019)	−0.026 (0.022)	−0.024*** (0.008)	−0.012 (0.008)
$\Delta Cash_t$	−0.276 (0.207)	−0.770*** (0.181)	−0.391* (0.237)	−0.850*** (0.246)	0.324*** (0.091)	0.236* (0.128)
Other Controls:	*Private$_i$, Crisis$_{t-1}$, Country-industry FE, Year FE, Firm-level controls*					
Observations	23,690	30,642	23,250	30,337	12,392	15,646
R-squared	0.0267	0.0182	0.0183	0.0195	0.519	0.497

Table presents the estimates of Eq. (4). The dependent variable in columns (1)–(2) is the growth rate of R&D investment in year *t*, in columns (3)–(4) is the growth rate of the ratio of R&D to sales, while in columns (5)–(6) it is the share of R&D to total investment. Columns (1), (3) and (5) include industries with an above the median dependence on external finance, while columns (2), (4) and (6) those with below the median dependence. $Private_i$ is a dummy for private firms. $Crisis_t$ is a dummy taking the value one in 2008–2010 and 2012–2013. Firm level controls include: Total Assets, Sales, Liquidity, Leverage and Investment. ΔCash is the change in cash holdings between year *t* and $t-1$. Standard errors are clustered at the country level. */**/*** represents significance at 10, 5 and 1% level.

Table A5
Falsification strategies.

Dependent variable	R&D		$\frac{R\&D}{Sales}$		$\frac{R\&D}{Investment}$	
	High (1)	Low (2)	High (3)	Low (4)	High (5)	Low (6)
Panel A: Randomised crisis dates						
$Private_i \times Crisis_{t-1}$	0.028	0.035	0.044	−0.011	−0.001	−0.059***
	(0.043)	(0.036)	(0.054)	(0.042)	(0.013)	(0.010)
R-squared	0.0329	0.0240	0.0245	0.0238	0.399	0.415
Panel B: Randomised private firms						
$Private_i \times Crisis_{t-1}$	0.023	0.026	0.010	0.005	−0.024	−0.062**
	(0.021)	(0.027)	(0.029)	(0.022)	(0.030)	(0.026)
R-squared	0.0329	0.0239	0.0246	0.0236	0.393	0.414
Other Controls:	*Private, Crisis, Country-industry FE, Year FE, Firm-level controls*					
Observations	40,614	42,938	40,119	42,592	28,773	27,642

Table presents the estimates of Eq. 4. The dependent variable in columns (1)–(2) is the growth rate of R&D investment in year *t*, in columns (3)–(4) is the growth rate of the ratio of R&D to sales, while in columns (5)–(6) it is the share of R&D to total investment. Columns (1), (3) and (5) include industries with an above the median dependence on external finance, while columns (2), (4) and (6) those with a below the median dependence. Panel A includes randomised crisis dates dummies. Panel B includes randomised private firms dummies. Standard errors are clustered at the country level. */**/*** represents significance at 10, 5 and 1% level.

Appendix B. Supplementary material

Supplementary data associated with this article can be found, in the online version, at https://doi.org/10.1016/j.jimonfin.2020.102263.

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