# Set-up Costs and the Financing of Young Firms*

François Derrien† Jean-Stéphane Mésonnier‡
Guillaume Vuillemey§

March 18, 2025

**Abstract**

Firm births are key drivers of employment growth, productivity gains, and "creative destruction". We show that set-up costs create sizable financial constraints for new firms. When firms face high set-up costs, they can only be established by leveraging up and lengthening debt maturity. We empirically confirm these predictions in a large sample of young French firms. Leverage is higher and debt maturity is longer in high set-up cost industries. Last, we show that, following an exogenous shock that reduces banks' supply of long-term loans, there is relatively lower firm creation in high set-up cost manufacturing industries.

*We are grateful to Denis Gromb and Martin Wagner for insightful discussions and to seminar participants at Banque de France, Bocconi University, BI Oslo, CEMFI, the Econometric Society World Congress 2020, the EIB, Goethe University, HEC Paris, Humboldt University, EUI Florence and the Tinbergen Institute for comments. This research benefited from funding from the Observatoire du Financement des Entreprises par le Marché and the Agence Nationale de la Recherche (F-STAR ANR-17-CE26-0007-01).

†HEC Paris, email: derrien@hec.fr

‡Banque de France & Sciences Po, email: jean-stephane.mesonnier@banque-france.fr

§HEC Paris & CEPR, email: vuillemey@hec.fr

# Introduction

Firm creation is at the heart of the process of "creative destruction". Specifically, firm births contribute disproportionately to net job creation (Haltiwanger et al., 2013) and to productivity gains (Bartelsman and Dhrymes, 1998). The importance of understanding the determinants of firm birth is even greater in a context of mounting concerns about low entry rates and low business dynamism in general, in the US as well as in Europe (Akcigit and Ates, 2021; Decker et al., 2016).

In this paper, we focus on one potential determinant of the constraints that firms face when they are created: the financing of set-up costs. We define set-up costs as the minimum quantity of fixed assets a firm needs to start operating in a given industry. We first show that set-up costs explain important facts about the capital structure of young firms, both across and within industries. Specifically, set-up costs can rationalize the *a priori* surprising fact that young firms have higher leverage and longer-maturity debt than seasoned companies. We then exploit the quasi-bankruptcy of a large bank in France in 2008, which tightened the constraints of a subset of other banks and led them to shorten the maturity of the loans they could supply to firms. We show that, in counties where these constrained banks had large market shares, this financial shock had a negative impact on firm creation in industries with structurally higher set-up costs.

We start by formulating testable predictions based on the theoretical literature, primarily Holmstrom and Tirole (1997) and Albuquerque and Hopenhayn (2004). When firms face set-up costs that are large relative to the entrepreneur's initial net worth, they need to turn to external financiers. In the presence of frictions such as limited commitment or moral hazard, optimal contracts should maximize entrepreneurs' stakes in their own firms, or should aim to increase entrepreneurs' stake as quickly as possible. Therefore, conditional of being created, firms in industries with high set-up costs should have higher leverage and longer debt maturity. For the same reason, within industries, more profitable firms should have lower leverage and lower debt maturity. But limited commitment or moral hazard problems also imply that not all firms will be created: entrepreneurs for which net worth is too low relative to set-up costs may not credibly be financed. In other terms, set-up costs should generate selection in the creation of firms across industries. For example, when the supply of long-term debt drops, there should be heterogeneous effects across industries with different set-up costs.

We take these hypotheses to the data, using several sources, including detailed corporate loan data from the Banque de France and balance sheet data on a random 20% of all firms created in France between 2006 and 2016. These two sources of data allow us to overcome important data limitations that have plagued research on young and private companies so far.

First, we present a set of stylized facts about the debt maturity choices and the capital structure of young firms. At the loan level, the average maturity at issuance of new loans falls from 72 to 54 months on average over the first ten years. In our sample of firms, the ratio of total debt to assets falls from an average of 52% in the first two years of existence of firms to about 37% for 10-year old companies. The maturity of bank debt also decreases significantly with age. We then classify 3-digit industries into terciles based on set-up costs, which we measure using the median value of tangible and intangible assets of newly created firms in each industry. Consistent with our predictions, the above patterns for leverage and debt maturity are almost entirely driven by firms operating in industries with high set-up costs. We then confirm formally these first findings using panel regressions. This allows us to include a variety of controls, as well as firm and time fixed effects. We can therefore rule out the possibility that these stylized facts are driven by selection, which could be the case if firms surviving until age 10 are systematically different from firms surviving only until age 2. We confirm that, young firms borrow at longer maturities, and that leverage and debt maturity decrease with age. These patterns are magnified for firms created in high set-up cost industries. We also find that, within industry, young firms with lower initial profitability borrow longer-term debt.

In the second part of the paper, we then exploit a quasi-natural experiment that exogenously forced some French banks to suddenly shorten the maturity of loans they supply to (small and young) corporations. This event is the failure in 2008 of Dexia, a large French-Belgian bank whose main business was to provide funding to local governments, notably municipalities. Following this shock, municipalities previously relying on loans from Dexia increasingly borrowed from other local banks with whom they had pre-existing relationships. Given that loans to municipalities have very long maturities, the duration mismatch between assets and liabilities increased mechanically for the banks making these loans. To reduce this mismatch, affected banks were constrained to cut the maturity of new loans to corporations, and in particular to small firms. In difference-in-differences regressions, we confirm that treated banks (that is, banks heavily exposed to municipalities that were previously borrowing mostly from Dexia) significantly reduced the maturity of new corporate loans after Dexia's failure. More importantly, we do find that the effect picked up by the difference-in-differences estimation concentrates on firms in high set-up cost industries, for which the demand for long-term financing is greater. As a last step, we find that maturity rationing by treated banks had real effects: in areas with a high concentration of banks affected by the shock, there is subsequently lower firm creation in high set-up cost industries, specifically in manufacturing industries. However, already existing firms in high-set-up-cost industries do not grow less after the Dexia shock, suggesting that the effect of the shortening of debt maturity following the shock affects primarily firms at the time of their creation. This is consistent with the selection patterns predicted by the theory. More broadly, we confirm that industry-specific set-up costs are a source of heterogeneity in the transmission of financial shocks to young firms.

**Related literature.** This paper contributes to three strands of the recent literature in corporate finance. First, it is related to the literature on the financial constraints of young firms. A number of papers study how financial factors, such as wealth (Evans and Leighton, 1989; Hurst and Lusardi, 2004), collateral constraints (Schmalz et al., 2017) or banking competition (Black and Strahan, 2002) affect the decision to become an entrepreneur. However, these papers are not primarily concerned with the capital structure of young firms, because of the lack of balance sheet data on private firms in most countries.[1]

A first exception is the paper by Robb and Robinson (2014), who use the Kauffman Firm Survey to show that young US firms rely heavily on external debt financing, in particular bank loans. Relative to this paper, we rely on panel data, which allow us to focus on time-series variation in the capital structure of young firms, and to use a quasi-natural experiment. Another exception is Dinlersoz et al. (2019), who also document a decreasing relationship between either leverage or debt maturity and age in a sample of young private US firms. They explain their findings based on the model by Albuquerque and Hopenhayn (2004), in which firms start to operate below their optimal scale, and build-up equity as they age, in order to escape financial constraints. While constraints are firm-specific in this model, we show that a large part of the variation in the data can be explained by industry-specific constraints arising from set-up costs. Relative to both Robb and Robinson (2014) and Dinlersoz et al. (2019), a novel message that our analysis conveys is indeed that set-up costs are an important feature for corporate finance researchers to consider in both theoretical and empirical work.

Second, this study relates to the literature on debt maturity choices by firms. A number of theoretical works show how short-term debt can mitigate information asymmetries (Diamond, 1991) and reduce inefficiencies associated with risk-shifting or debt overhang (Myers, 1977), while potentially creating rollover risk. Recent contributions consider these trade-offs in dynamic contexts (Diamond and He, 2014; He and Milbradt, 2016; Huang et al., 2019). The limited amount of empirical work on this topic finds support for the idea that contracting frictions explain part of the variation in firms' debt maturity (Barclay and Smith, 1995; Guedes and Opler, 1996; Custodio et al., 2013). We enrich this literature by showing that set-up costs are an important determinant of firms' debt maturity, at least for young firms.

[1] A different literature focuses on the financing of innovation and innovative firms (Kerr and Nanda, 2015). We instead focus on the entire set of firms in the economy.

Third, the paper also contributes to the literature on the real effects of shocks to financial institutions. A number of papers study how negative shocks to the volume of bank loans supplied to firms impair their ability to invest or grow to reach optimal scale (see, among others, Peek and Rosengren, 2000; Chodorow-Reich, 2014; Cingano et al., 2016; Puri et al., 2011). Instead, we study a new type of shock, by which banks are forced to reduce the maturity, rather than the volume, of loans. The source of heterogeneity that we highlight in the transmission of banking shocks – cross-industry differences in set-up costs – is also novel. We show that such shocks can have substantial effects.

The remainder of this paper is organized as follows. Section 1 derives testable predictions from existing theories. Section 2 describes the data and the measurement of set-up costs. Section 3 presents stylized facts and tests the model's predictions on the role of set-up costs. Section 4 then investigates the real effects of set-up costs using a quasi-natural experiment.

# 1 Theory and testable predictions

We start by building on the existing theoretical literature to derive testable predictions. Throughout, we think of set-up costs as the minimum quantity of equipment, intangible assets or commercial property an entrepreneur needs to start a firm in a given industry. A significant part of set-up costs is arguably industry-specific, and thus exogenous to the entrepreneur. Entrepreneurs may self-select across industries but, upon choosing to operate in a given industry, they must take set-up costs as given, at least to a large extent. For example, to set up a bakery, one needs to invest in some costly physical assets, such as a specialized oven. Instead, a consulting activity may be started with virtually no physical asset.

In models in which new firms face financial frictions, such as limited commitment or moral hazard, a general result is that entrepreneurs need skin-in-the-game, i.e., own funds invested in the project. This prediction arises explicitely in models by Albuquerque and Hopenhayn (2004) or Holmstrom and Tirole (1997). Specifically, Albuquerque and Hopenhayn (2004) explicitely study a model of firm dynamics in the presence of set-up costs. In their model, entrepreneurs need to pay a fixed set-up cost to start a project. To do so, they borrow from a bank. The main friction is that entrepreneurs have limited commitment, and may optimally choose to default at any time. When defaulting, the entrepreneur loses the equity value. Thus, to ensure that the entrepreneur will not default, one must first ensure that she has sufficient equity at stake in the project. In Holmstrom and Tirole (1997), entrepreneurs' skin-in-the-game solves a moral hazard problem: only entrepreneurs with sufficient own funds can create a firm, because they are the only ones who can credibly commit not to shirk. We rely on these mechanisms to formulate testable predictions about the relationship between industry-specific set-up costs and the capital structure of firms. Our hypotheses rely on the idea that, to build equity, entrepreneurs can either provide a sizable amount of own funds initially, or generate profit early on in the life of the firm.

The first prediction pertains to the capital structure of new firms depending on the set-up cost of the industry they operate in.

**Hypothesis 1.** *For a given level of initial resources, conditional on operating the project, young firms in industries with higher set-up costs have higher leverage and borrow with longer-maturity debt.*

The prediction related to leverage is straightforward from the models by Albuquerque and Hopenhayn (2004) or Holmstrom and Tirole (1997). Indeed, since it is always optimal to maximize the amount of own equity invested by the entrepreneur, all else equal, the share of an entrepreneur's equity in the balance sheet of a firm will be larger if she operates in an industry with low set-up costs. Furthermore, while these models do not make explicit predictions about debt maturity, their logic can be extended to introduce a trade-off between short-term and long-term debt. Specifically, for a given level of debt and profitability, short-term debt mitigates limited commitment or moral hazard problems more efficiently. This is because, as soon as some debt is repaid, the equity stake of the entrepreneur increases, and the incentives to either shirk or default drop. This explains why, conditional on operating, firms with limited financing needs – i.e., firms with low set-up costs – will rely more on short-term debt.

The second prediction is about the relation between profitability and debt maturity.

**Hypothesis 2.** *Conditional on operating a project with a given set-up cost, less profitable young firms have higher leverage and longer-term debt.*

This prediction follows from the fact that, in both Albuquerque and Hopenhayn (2004) and Holmstrom and Tirole (1997), it is optimal to build up equity as quickly as possible, to mitigate the impact of financial frictions. Thus, all else equal, young firms with higher early cash flows will deleverage more quickly. In terms of maturity, more profitable young firms will be able to commit to higher short-term debt repayments in the first place, and will thus have lower reliance on long-term debt.

Finally, while Hypotheses 1 and 2 are both conditional on financing the project, Hypothesis 3 is about selection into entrepreneurship.

**Hypothesis 3.** *A negative shock to the supply of long-term financing implies that entrepreneurs facing higher set-up costs are less likely to create firms.*

This prediction follows from the fact that, all else equal, new firms in industries with higher set-up costs face tighter financial constraints. They are thus more reliant on the existence of markets for long-term debt. Indeed, these firms cannot be created without debt markets and, if set-up costs are high enough, cannot be financed only with short-term debt. High set-up costs firms are thus critically reliant on long-term debt markets, and should be affected disproportionately more when supply in these markets is lower.

To summarize, we hypothesize that young firms are likely to be more reliant on long-term debt when they operate in industries with high set-up costs (Hypothesis 1) or when they are less profitable early on (Hypothesis 2). As a consequence, firm creations in industries with high set-up costs are more sensitive to the provision of long-term credit by banks (Hypothesis 3).

# 2 Data and measurement of set-up costs

We now describe the data and the measurement of set-up costs.

## 2.1 Data

Our analysis uses two different samples. First, a firm-level sample, in which we observe a large panel of firms and a wide range of accounting information. Second, a sample of loans, with detailed information at the loan level.

The first main dataset used in subsequent analyses is a firm-level panel, which contains balance sheet and income statement data that we obtain from firms' tax filings. Our main sample is based on a random draw of 20% of the universe of all firms which were created in France between 2006 and 2016, after excluding self-employment and financial firms. We obtain these data from from *Diane* (Bureau van Dijk).[2] After a firm is created, we observe yearly balance sheets and income statements until failure (if any), corresponding to 663,465 firm-year observations (for 168,577 unique firms). The data allow us to measure firms' debt structure (bank debt, other financial debt, and trade credit), broken down by *residual* maturity buckets ($\leq$ 1 year, 1 year $< . \leq$ 5 years, 5 years $<$).

Our second main dataset uses proprietary data from the Bank of France (*M-Contran*) on the detailed characteristics of new bank loans to firms, including their *initial* maturity. This dataset covers all loans granted by a random set of domestic bank branches during the first month of each quarter. While not a panel (since the set of surveyed bank branches rotates over time), these data have advantages over

[2] *Diane* has the drawback that failing firms are removed from the dataset after three years. To ensure that our results are not driven by survival biases, we later test firm-level predictions after including firm fixed effects. Furthermore, In the Online Appendix A.1, we compare our main sample from *Diane* with descriptive statistics on the entire universe of newly-created French firms from the SIRENE, which provides exhaustive data on firl creation by year and industry. We show that our sample is representative in terms of both industry and geography.

standard credit registers. Indeed, credit registers typically aggregate old and new loan exposures at the bank-firm level, so that no information on specific loan terms (initial maturity, interest rate, etc.) is available. We restrict the sample to loans financing corporate investment, which leaves us with 114,703 unique loans between 2006Q1 and 2018Q2 if we consider all firms aged up to 10 years (i.e., the age limit, by construction, of firms in the *Diane* sample above). In most exercises, we however focus on loans issued to young firms, which we define throughout as firms in their first two years of existence (aged strictly less than 24 months). This leaves us with 37,188 investment loans, issued to some 30,000 different firms. We retrieve the complete tax filings of these new firms from *Diane* whenever this information is available.[3] The distribution of young firms across industries in this second dataset comes out as quite close to the one we observe in the first dataset. Descriptive statistics on the two datasets, the firm-level one and the loan-level one, are reported in Table 1.

We complement these two datasets with information from three other sources. First, we use the French credit register to construct additional variables that we use in our quasi-natural experiment (Section 4). The register records all bilateral credit exposures at the bank branch-borrower level (above a small reporting threshold of EUR 25,000, including off-balance sheet guarantees). Whatever the type of borrower, we define total bilateral credit exposures by adding outstanding loans and undrawn credit lines. The credit register collects information on all types of borrowers (except individual borrowers, i.e., households) from banks operating in France, at a monthly frequency. In particular, we exploit information on bank loans to non-financial corporations and to local governments and selected other local administrative entities, which we call throughout "municipalities". Municipalities mostly refer in this paper to the 36,464 French municipalities in a strict sense (representing about 40% of domestic bank lending to all local public entities according to the French credit register in 2007), but we also include the 22 regions (9%) and 96 counties (17%) of mainland France (as of 2007), as well as major groupings of municipalities (*communautés de communes, urbaines, d'agglomération*, about 13% of credit), major types of special purpose entities set up by municipalities (around 8% of credit), as well as municipal social housing entities and chambers of commerce. Together, these local governments and local public administrative entities account for more than 95% of credit by resident banks to local governments and administrative entities in France.[4]

Second, we also use another dataset from the Banque de France, called CEFIT, to

[3]The relevant financial ratios (e.g., leverage, profitability, tangible assets to assets) can be computed for about a fifth of these firms only. This is because firms often do not produce financial statements in the first year of operation.

[4]Excluded legal categories of local public entities (about 30 other types) are either largely irrelevant (e.g., school cashboxes or municipal pawnshops) or do not rely much on bank credit for funding, as they represent each less than 1% of total bank credit to local public bodies. We denote the included local entities as "municipalities" throughout for simplicity.

compute measures of bank competition in local corporate credit markets at the level of the French equivalent of counties (namely, *départements*).[5] The CEFIT database collects the total amount of loans granted by each individual chartered bank in each county, with breakdowns by loan types and borrower types (corporations, households, public administrations). Data is available since 2006 and we compute Herfindhal indexes of concentration in local corporate credit markets using data for 2007, i.e. before the shock we are considering.

Last, we use historical information on firm creations and the geographic location of their establishments in France from the firm register (SIRENE) of the French Statistical Institute (INSEE). The SIRENE database records all companies that received a registration number in France at the time of their creation since 1973 (the official SIREN identifier), be they still active or dead. We use a version of the historical database made of two main files: *SIREN stock*, which provides the unique identifier, industry and creation date of each firm, and *SIRET stock*, which provides the geographic address of each firm's establishments. We exclude sole proprietorship and keep only firms with a creation date between January 2006 and January 2017. We merge the firm and establishment databases and keep only the first created establishment since the creation date of each firm (in general, the two dates coincide). We can then identify the postal address of the firm as the one of its first historical establishment. We then drop firms in Corsica and French overseas territories and collapse the information to compute the number of firm creations in each quarter since January 2006 at the county (*département*) and 3-digit NAF industry level.[6] Since the failure of Dexia took place in the last quarter of 2008, we consistently use event-adjusted years as of the third quarter of the preceding and subsequent years. Last, we complete the panel by filling all missing year-county-industry triplets with zeros. Table A7 in the online appendix provides descriptive statistics on firm creations at the year-county-industry level over the four years surrounding the Dexia shock.

## 2.2 Measuring set-up costs

A key variable of interest in this paper is the fixed set-up cost for firms in a given industry. We estimate set-up costs at the 3-digit industry level as follows. First, in our full sample of young firms (i.e., our main firm-level dataset, based on *Diane)*, we keep firms aged strictly less than 24 months, where firm age in year $t$ is defined as the difference between the reporting year of the balance sheet ($t$) and the year of firm creation ($t_0$).[7] Second, for each firm $f$ in industry $i$, we compute the set-up

[5] We consider all counties in mainland France, excluding Corsica and French overseas counties and territories. Mainland France is partitioned into 96 counties.

[6] Three-digit NAF codes correspond approximately to 3-digit SIC codes in terms of granularity.

[7] For instance, consider a firm created officially in September 2010. In the reporting year 2010, this firm is aged "0 year" in our dataset. In the reporting year 2011, this firms is aged "1 year".

cost $SUC^i_f$, equal to the initial investment needed to set-up the company and start operating. $SUC^i_f$ is the mean value of the sum of property, plant and equipment ($PPE$) and intangible assets ($IA$), in euros, over the first two years of existence of firm $f$ (denoted here years 0 to 1),

$$SUC^i_f = \frac{1}{2}\sum_{t=0}^{t=1}\left[PPE_{ft} + IA_{ft}\right]. \tag{1}$$

Next, for each 3-digit industry $i$, we measure set-up costs as the median of $SUC^i_f$ over all firms $f = 1, ..., F^i$ in industry $i$,

$$SUC_i = \text{median}\left\{SUC^i_1, ..., SUC^i_F\right\}. \tag{2}$$

Taking the median, rather than the minimum, prevents mismeasurement arising from a few anomalous observations (e.g., firms that are legally created but never operate).[8]

We provide descriptive statistics on set-up costs in Table 2. Panel A shows moments of the distribution of set-up costs across the 146 industries for which the measure exists. There is significant cross-sectional variation in set-up costs across industries: the median industry has a set-up cost of 19,000 euros, while the cost jumps to 121,000 euros at the 90th percentile. Panel B reports the 15 industries with the highest and lowest set-up costs. Not surprisingly, industrial activities tend to have high set-up costs (e.g., manufacture of paper products, quarrying of stone, sand and clay), while services relying primarily on human capital have low set-up costs (e.g., translation and interpretation activities, business support service activities).[9] We additionally confirm that set-up costs are very stable over time. For example, the correlation of set-up cost terciles between the first and the last years of the sample period (2006 and 2017) is equal to 73%.

Panel C of Table 2 presents the correlation between key balance sheet characteristics and financial ratios of firms and industry-level set-up costs. We regress these firm characteristics on a constant and on two dummy variables which capture whether the

[8] To further avoid mismeasurement, we restrict the sample to 3-digit industries with at least 15 different firms with non-missing PPE in year 0 or 1. Note that many of these $PPE+IA$ observations are zeros. We treat them as such in our baseline analysis. However, these zeros may arguably stand for non-responses, or missing observations, since young firms generally need some fixed asset to start running their activity. For robustness, we therefore constructed another measure of industry-level set-up costs, whereby we consider all zero $PPE + IA$ observations as missing values, and take the 10th percentile of the within-industry distribution of fixed assets as a measure of the industry-level set-up cost $SUC_i$. Results are qualitatively unchanged when we use this alternative measure of set-up costs, as shown notably in section 4.4.

[9] The rankings of industries look highly similar if we compute set-up costs using tangible assets (PPE) only. Furthermore, while we cannot precisely measure leasing, correlations show that leasing expenses are more common in industries with high tangible assets. Therefore, the omission of leasing is unlikely to revert the ranking of industries. Since our tests never rely on the numerical values of set-up costs, but only on their rankings (by terciles), leasing is unlikely to affect our results.

firm operates in an industry either in the second ($MidCost$) or in the third ($HighCost$) tercile of the set-up cost distribution. Relative to firms in the lowest tercile, firms in high set-up cost industries have significantly higher ratios of PPE/Assets and Intangibles/Assets (by 16.4 and 22.3 percentage points, respectively) when they start operating. Thus, firms in high set-up cost industries not only require a large absolute amount of tangibles and intangibles to operate, but these assets also represent a large proportion of their balance sheets. Firms in these industries also start with a significantly larger size (i.e., more total assets), as one could expect. Besides, these firms are less profitable than their low set-up costs counterparts, whether we measure profitability in terms of gross margin (EBITDA/Assets) of ROA (Net income/Assets). These differences are all persistent when firms age, as can be seen in columns 5 to 10 of the table, which relates to all firms in our sample (up to 10 years old). However, the profitability and size gaps tend to level off quicker than the differences in terms of asset structure. In a similar vein, Online Appendix Figure A1 shows that set-up costs correlate positively with four industry-level characteristics: average capital expenditure, PPE, size, and the RZ index of dependence on external finance, as defined by Rajan and Zingales (1998). To ensure that these correlations with other industry characteristics are not driving our results, we use various combinations of firm controls and fixed effects in our subsequent tests.

# 3 Stylized facts and empirical tests

This section presents stylized facts about the capital structure of young firms and tests the model's predictions on the role of set-up costs.

## 3.1 Stylized facts

We start by plotting several variables of interest to establish stylized facts about the capital structure of young firms. In Figure 1, we display the mean value of several firm characteristics between creation and age 10 years, in the pooled sample of newly-created firms. The top-left panel shows that leverage decreases with age, from an average ratio of total debt to assets of about 52% in the first 24 months of existence, to a ratio of 37% at age 10 years. The top-right panel studies the average maturity of total debt, measured as:

$$Maturity_{it} = 12 \cdot \frac{\text{Debt} \leq 1\text{y}}{\text{Total debt}} + 36 \cdot \frac{\text{Debt} \in (1\text{y}, 5\text{y}]}{\text{Total debt}} + 84 \cdot \frac{\text{Debt} > 5\text{y}}{\text{Total debt}},$$

that is, by assigning maturities of 12, 36 and 84 months to debt in each of the reported buckets. We find that the average maturity of total debt is also decreasing with age, from about 19 months to about 16 months over the first 10 years. This pattern is consistent with the finding (cf. bottom right panel) that the maturity at issuance of new bank loans is longer for start-ups (young firms aged at most one year).

Both patterns on leverage and maturity are surprising from the viewpoint of a number of received theories. Indeed, if young firms are subject to more severe financial frictions (e.g., more information asymmetries or greater commitment problems), they should have a harder access to external finance, and thus borrow less and with shorter-term debt.[10] They are instead consistent with our predictions. The last three panels of Figure 1 show that the decrease in total debt over firms' lifetime is primarily driven by bank debt (which is cut by half, from about 20% to about 10% of total assets), and to a lesser extent by other financial debt (which decreases from about 15% to about 10% of total assets). This fact is also surprising, since bank debt is a priori subject to more severe financial frictions than other financial debt (which is obtained from equityholders, that is, mainly family and friends for young firms), and could thus be expected to grow more over time. However, the fact that bank debt decreases much more with age than other financial debt (obtained from equityholders) is consistent with the predictions, if the latter is subject to milder moral hazard problems than the former. Indeed, when moral hazard problems are not severe (as is arguably the case for family and friends), there is no gain from repaying most of the debt early on. Finally, the ratio of payables to total assets is stable over the lifetime of firms, in line with the view that the general pattern that we document is not related to firms' operations but to the financing of fixed assets.

Next, we provide preliminary evidence in Figure 2 that set-up costs are critical to explain these patterns. We reproduce the same charts as in Figure 1, after breaking down the sample based on whether firms operate in industries with low, intermediate or high set-up costs (based on terciles across industries, as defined previously). For both leverage and maturity, the aggregate patterns are overwhelmingly driven by industries with high set-up costs. For industries in the top tercile of set-up costs, leverage is cut by close to 40% over the first 10 years (from 70% to 43%) while the decrease is much less pronounced for firms in other industries. Regarding maturities, the patterns are even more striking. For firms operating in industries with low or intermediate set-up costs, debt maturity is stable with age. The decrease in maturity is strong only for firms in high-set-up cost industries (from about 24 to about 18 months). Again, loan-level data yield a consistent picture: in their first to years of existence, young firms in high set-up cost industries borrow at longer maturities than young firms in other

[10]This chart is potentially consistent with the pecking order theory (Myers and Majluf, 1984): If equity is more costly to issue than debt due to more severe adverse selection problems, then firms should first issue debt, and issue equity as they age, thus reducing leverage. However, this explanation is unlikely to explain the stylized facts: the small private firms in our sample virtually never issue external equity; the increase in book equity almost entirely comes from retained earnings.

industries.

The three subsequent panels confirm that bank debt is the main driver of this pattern. Finally, Figure 2 also confirms that there is no age pattern in terms of payables regardless of the set-up cost, which is reassuring since the theory does not make any prediction for this specific type of debt.

While all these figures are consistent with our theoretical predictions, they do not provide a formal test. Indeed, they could be driven by differences in firm characteristics, in survival rates across firms with different characteristics, or by time effects. To account for these possibilities, we now turn to explicit tests of our predictions.

## 3.2 Debt maturity, firm age and set-up costs

We start by testing Hypothesis 1: leverage and maturity should be higher for young firms. This relation should also be stronger in industries with high set-up costs. We test these predictions using both our loan-level data, where we observe the initial maturity of new loans to firms, and firm-level accounting data, which provides us with a measure of the average residual maturity of firms' total debt for a larger sample of firms.

We first test the hypothesis that young firms take longer-term loans than more mature firms using our sample of retail corporate loans. Our main specification is as follows:

$$\begin{aligned} Maturity_{libt} &= \beta_0 \cdot Young_{it} + \beta_1 \cdot Young_{it} \cdot HighCost_j \\ &\quad + \beta_2 \cdot Controls_{lt} + \beta_3 \cdot Controls_{it} + \nu_j + \mu_b + \lambda_t + \epsilon_{libt}, \qquad (3) \end{aligned}$$

where $Maturity_{libt}$ is the maturity at issuance of loan $l$ from bank $b$ to firm $i$ in industry $j$ in quarter $t$. $Young_{it}$ is a dummy variable for young firms, i.e. when the age of firm $i$ at $t$ is strictly less than 24 months, while $HighCost_j$ is a dummy variable equal to one the industry $j$ of firm $i$ is in the top tercile of the set-up cost distribution. We include loan-level controls $Controls_{lt}$ (dummies for subsidized, regulated and fixed rate loans), as well as standard firm-level controls $Controls_{it}$ (size, tangibility of assets and profitability of assets). We also include industry and time fixed effects, to absorb industry characteristics and macroeconomic factors, and bank fixed effects.[11] The latter control for unobserved bank-specific lending policies that may matter for setting loan maturities. Finally, to address the concern that industry dynamics may drive some of the effects, we systematically cluster standard errors at the 3-digit industry level.

The regressions in Table 3 confirm the visual evidence from Figure 2, that young

[11] Our sample of loans contains few young firms that receive multiple loans. This prevents us from including firm fixed effects in the tests that rely on loan-level data.

firms in industries with high set-up costs tend to issue longer-maturity debt. In these regressions, we use the same sample of loans made to firms aged up to 10 years as in the figures above. The results in the first two columns show that young firms borrow at longer maturities than more mature firms, by close to 10 months, controlling for the industry. This effect is even larger in high set-up cost industries. Young firms in these industries borrow with longer maturities than their counterparts in other industries (by close to 6 months on average). In columns 3 and 4 of Table 3, we focus on the subsample of firms for which balance sheet data are available, which allows us to control for firm characteristics. Adding these standard firm-level controls yields very similar estimates, although the regression sample is now two and a half times smaller.

We then turn to regressions using firm balance sheet data to confirm these first findings in a set-up with firm fixed effects, although our measure of debt maturity is only indirect and therefore more noisy at firm level. Our main specification is as follows:

$$\begin{aligned} Y_{ijt} \;=\; & \beta_0 \cdot Young_{it} + \beta_1 \cdot Young_{it} \cdot MidCost_j + \beta_2 \cdot Young_{it} \cdot HighCost_j \\ & + \beta_3 \cdot Controls_{it} + \nu_i + \lambda_t + \epsilon_{ijt}, \end{aligned} \tag{4}$$

where $Y_{ijt}$ is either the leverage or the (residual) maturity of the debt of firm $i$ in industry $j$ in year $t$. $Young_{it}$ is a dummy variable equal to 1 if the age of firm $i$ is strictly less than 24 months in year $t$, while $MidCost_j$ and $HighCost_j$ are dummy variables equal to one for firm $i$ when its industry $j$ is in the middle or top tercile of the set-up cost distribution, respectively. Furthermore, a firm fixed effect $\nu_i$ ensures that we are exploiting within-firm variation, that is, our results cannot be explained by differential survival rates of firms across industries or by time-invariant differences across firms. To control for time-varying factors that could vary systematically across industries, we also include standard firm-level controls. Finally, $\lambda_t$ is a time fixed effect. Throughout the tests, we treat the set-up cost as a characteristic of the industry that is exogenous for any individual firm. Based on our predictions, we expect the interaction coefficient $\beta_2$ to be negative: young firms should borrow more and with longer maturities in industries with higher set-up costs.

The estimation results are reported in Table 4. Across specifications, we confirm that in industries with high set-up costs, young firms borrow more debt at longer maturities. This holds after restricting the sample to firms that survive at least 5 years (in columns 2 and 4), which allows us to rule out the concern that survival biases could explain the findings. In the specifications of column 2, debt decreases on average by 7 percentage points between young (strictly less than 24 months) and older firms in industries in the highest tercile of set-up costs. This is in line with the evolution reported in Figure 2, in which we see a clear differential (of about ten percentage points) between the evolution of bank debt over total assets for firms in high set-up cost industries vs. other industries. As for maturity (column 4), the difference between young and older firms is higher by about two months in high set-up cost industries. Again, this is consistent with the effect documented in Figure 2, in which the average debt maturity goes down by about four months on average for young vs. older firms in the highest tercile of set-up costs.

### 3.3 Profitability of young firms and initial debt maturity

We next turn to Hypothesis 2. The prediction is that, within a given industry, young firms that are more financially constrained (that is, firms with lower earnings in their first two years) opt for longer-maturity debt.

We first test this hypothesis using our sample of loans, in which we have a precise measure of the initial maturity of new debt. We estimate the following regression on the sample of loans to young firms (aged strictly less than 24 months):

$$Maturity_{libt} = \beta_0 \cdot \frac{EBITDA_{it}}{Assets_{it}} + \beta_1 \cdot Controls_{lt} + \beta_2 \cdot Controls_{it} + \nu_j + \mu_b + \lambda_t + \epsilon_{libt}, \quad (5)$$

where the dependent variable $Maturity_{libt}$ is the maturity at issuance of new bank loans, and the loan and firm-level controls as well as the fixed effects are the same as in Equation 3 above.

The left panel of Table 5 shows the estimation results. They confirm that young firms that generate more cash flows tend to borrow at shorter maturities. This finding is also robust to the inclusion of a more stringent set of fixed effects, namely, interacted industry and quarter fixed effects, as the underlying data is at the quarterly frequency. Economically, the impact of profitability on the maturity of new loans is large. On average, a young firm at the 25th percentile of profitability issues new loans with a maturity shorter by about three months on average than a young firm at the 75th percentile of profitability.

We then turn to firm-level data for robustness. We estimate the following equation on the sample of young firms (from Diane):

$$Maturity_{ijt} = \beta_0 \cdot \frac{EBITDA_{it}}{Assets_{it}} + \phi_j + \lambda_t + \epsilon_{ijt}, \quad (6)$$

where $Maturity_{ijt}$ is the debt maturity estimated for firm $i$ operating in industry $j$ in year $t$, $\phi_j$ and $\lambda_t$ are industry and year fixed effects, respectively. The main explanatory variable of interest is the ratio of EBITDA over total assets. We restrict the sample to firms in their first two years.

The estimation results are reported in the second panel of Table 5. Consistent with Hypothesis 2, we find a negative and significant correlation of EBITDA with debt maturity, controlling for the average effect of belonging to a given industry and for macroeconomic conditions using year dummies, as well as for standard firm-level ratios. The results are roughly unchanged when we control for interacted industry and year fixed effects in the regression.[12]

### 3.4 Alternative mechanisms

One potential alternative explanation for some of our results is that firms with higher set-up costs buy assets with greater pledgeability, and so can borrow more and with longer-term debt, by using these assets as collateral. Our measure of set-up costs is correlated with firms' fixed assets, as discussed previously. However, although pledgeability obviously bears upon debt capacity, it cannot be the main explanation behind our stylized facts.[13] To begin with, pledgeability can explain differences in the average *levels* of debt and maturity (as seen from the sign of estimated coefficients on tangibility in Table 4), but not the time-series *changes*. Indeed, for tangibility to explain changes in maturity and leverage, it would have to be the case that tangibility decreases with age. We do not observe this to be the case: on average, firms in our sample invest every year to compensate the depreciation of assets. Furthermore, firms in our sample are on average growing with age. Therefore, the monotonic decrease in both leverage and debt maturity with age cannot be explained by tangibility. Furthermore, to alleviate remaining concerns, all our econometric results in Section 3.2 are robust to including measures of asset tangibility (PPE/Assets) as control variables, as seen in Table 4.[14]

Another possible interpretation of our findings is that the longer loan maturity of firms with higher set-up costs reflects the fact that their assets have a longer duration. If so, firms could match the maturity of cash flows from assets and liabilities, which could be valuable for risk management purposes (e.g., if they face financial constraints). This explanation would be consistent with our finding that firms in industries with high set-up costs, which also tend to be industries in which assets have longer duration, borrow at longer horizons. However, this explanation can be rejected for the exact same reason that led us to reject the alternative explanation based on tangibility. Specifically, for this explanation to be true, it would need to be the case that asset duration decreases monotonically with firm age. This is not the case, as firms invest periodically to replace maturing assets with other assets of similar duration. Therefore,

[12]The difference in the magnitude of coefficients between the two panels of Table 5 is due to the fact that maturities are better measured in the first case. In panel B, the residual maturity of total debt on the balance sheet includes some non-financial short-term debt like trade credit).

[13]For evidence on the relation between pledgeability and debt maturity or leverage, see for example Benmelech et al. (2005) and Benmelech (2009).

[14]Additionally, in unreported tests, we replicate Tables 3 and 4 with a measure of set-up costs that only includes intangible assets, which cannot be pledged as collateral. We find qualitatively similar results.

the fact that we highlight does not stem from a property of the assets (which tend to remain similar over the life of a firm), but a property of the first few years. It is an "age effect" that is linked to set-up costs that are paid only once.

A last possibility is that the observed patterns in terms of maturity and leverage across set-up costs are driven by the fact that due to larger initial constarints, firms in high set-up cost industries must be of higher quality to start operating. These firms could thus be more profitable and have a greater ability to repay their initial debt faster than firms in other industries. However, the correlation patterns between set-up costs and profitability reported in Table 2 are inconsistent with this explanation. If anything, firms in hig set-up costs industries have lower EBITDA and ROA, both in their first two years of operation and in subsequent years.

# 4 Set-up costs and the transmission of financial shocks

We now use a quasi-natural experiment to study the impact of set-up costs on the transmission of financial shocks. The shock we study, the failure of Dexia, a large Franco-Belgian bank specialized in funding French municipalities, arguably provides exogenous variation in the ability of some French banks to supply long-term loans to their corporate clients. Our goal is to test whether firms in high set-up cost industries are more affected than other firms by this specific credit supply shock.

## 4.1 A quasi-natural experiment

We exploit in this section the failure of the large Franco-Belgian bank Dexia in October 2008 as a quasi-natural experiment that affected the supply of long-term bank credit to firms in France in 2009-2010.[15] The French retail arm of Dexia was historically specialized in lending to local public administrations and local governments (called here "municipalities" for simplicity), with a market share of 40% in France in 2008. Over the years 1996-2006, Dexia followed an aggressive strategy of rapid external growth, including the acquisition in 2000 of Financial Security Assurance (FSA), a major US monoline insurer. This expansion, against the backdrop of a weak governance inherited from its complex bi-national structure, made the bank quite vulnerable to the outbreak of the subprime financial crisis in the Summer of 2007.

In the first semester of 2008, Dexia was hit by severe credit losses in the US sub-

[15]Dexia Group resulted in 1996 from the merger of the French credit institution *Crédit Local de France* and the Belgian deposit bank *Crédit Communal de Belgique*. The French public finance watchdog (*Cour des comptes*) published in 2013 a detailed report on the failure of Dexia. Statistics reported in this section are taken from this report and from Dexia's annual reports over 2008-2012.

prime market that were unrelated to French municipalities.[16] It also had a fragile capital structure with a heavy reliance on wholesale funding. In October 2008, after the collapse of Lehman Brothers, Dexia became illiquid and was on the verge of bankruptcy, forcing the French and Belgian governments to an emergency bailout of the bank. The two governments injected EUR 6 billion of equity into Dexia. They also agreed to guarantee Dexia's new bond issues (over the period from October 2008 to October 2011) up to a total amount of EUR 150 bns. However, the bank never recovered and was dismantled in the winter 2012-2013.[17] For our purposes, the key fact is that Dexia had to sharply reduce the supply of credit to municipalities starting in early 2008 (before the failure of Lehman Brothers) and until 2012. According to its annual reports, the annual lending volume of Dexia was cut by 50% between the end of 2007 and the end of 2010.

Importantly, the case of Dexia also remained an exception in the crisis years in France. Indeed, the other French banks withstood relatively well the financial turmoil following the Lehman collapse, thanks to their limited direct exposure to Lehman Brothers and the US subprime market. During the subprime crisis, French banks also benefited from the rapid intervention of both the European Central Bank (ECB) and the French government. The ECB had been injecting liquidity massively since July 2007 to mitigate the money market crisis. It then increased its support to European banks in the Fall of 2008 by offering unlimited amounts at its weekly refinancing operations and extending the set of assets taken as collateral. To shield the credit quality of French banks, the French government also took two major initiatives in October 2008: (i) the creation of the SFEF, a special purpose vehicle aimed at providing long-term financing to banks backed by state-guaranteed bonds, and (ii) the creation of another state-owned vehicle, the SPPE, aimed at supporting banks through the purchase of subordinated debt. As early as the Fall of 2009, the main French banking groups had already reimbursed almost all this subordinated debt to the State and the SFEF had stopped issuing new state-guaranteed bonds. According to the French supervisory authority, French banks (other than Dexia) posted at the end of 2009 sound liquidity and capital ratios, and were ready to accommodate the renewed credit demand in the recovery phase.[18]

[16] In addition to direct losses in the US subprime market, losses came from exposures to several European banks that were themselves hit by the collapse of the US subprime market, and to FSA. Over the first semester of 2008, Dexia's equity had shrunk by close to 50%, down to EUR 8.6 bns.

[17] The French part of its loan portfolio was acquired by three state-owned credit institutions, CDC, SFIL and La Banque Postale.

[18] Cf. *Commission bancaire, Rapport annuel 2009*, p. 5.

## 4.2 Identification strategy

We exploit the near-failure of Dexia in 2008 as an exogenous event that affected differentially the ability of other French banks to accommodate the demand of long-maturity loans by firms. Our identification strategy proceeds in three steps. We first use data from the French credit register to identify municipalities that were highly dependent on Dexia before the start of the subprime crisis in August 2007. A municipality is defined in what follows as being Dexia-dependent whenever the share of Dexia in its total stock of bank debt in June 2007 (just before the subprime crisis) is above 50%[19]. This corresponds roughly to municipalities in the top quartile of the distribution of Dexia's market shares across all municipalities at this date.

In a second step, we classify commercial banks based on their share of loans to Dexia-dependent municipalities within their total lending to municipalities, also as of June 2007. Using this ratio, banks above the median are considered as *treated* by the Dexia shock in 2008. The underlying assumption is that municipalities that were relying heavily on Dexia are, after the Fall of 2008, forced to borrow more from other relationship lenders. These banks therefore face a positive loan demand shock, which they largely accommodate as we show below.[20]

The third step of our identification strategy uses the fact that loans to municipalities have significantly longer maturities than loans to non-financial firms. In our data, on average over the sample period, the initial maturity of loans to municipalities is 13 years, as opposed to 6 years for non-financial firms. Therefore, the sudden increase in loans to municipalities by treated banks increases significantly the duration of their assets. Provided these banks have to meet risk management or regulatory limits in terms of asset-liability mismatch, their ability to supply long-term loans to companies should be reduced when they face higher loan demand from municipalities after the Dexia shock.[21] We confirm that this is the case in the next section.

One potential concern about this event is its timing. Since the near-failure of Dexia happens nearly at the time of the failure of Lehman Brothers, one may worry that treated and control banks are affected differentially by events unrelated to Dexia.

[19]To calculate the stock of bank debt of a municipality, we focus on loans greater than 100,000 euros, which are more likely to finance long-term investment.

[20]This identification strategy is reminiscent of Chodorow-Reich (2014). In his paper, a bank is more negatively hit during the financial crisis when it participates in loan syndicates led by Lehman Brothers before the outbreak of the crisis. As shown by Ivashina and Scharfstein (2010), (large) firms that had syndicated credit lines from syndicates where Lehman had a lead role drew down their lines by more following the bankruptcy of Lehman. This led to a liquidity stress for the other participant banks, which were obliged to accommodate this increased demand for funds. In turn, these constrained banks lent less to small firms in the US, which weighed down on firm-level employment during the crisis.

[21]Note that French banks were indeed subject to some national supervisory requirements in terms of their asset-liability liquidity ratios even before the progressive implementation of the Basel III liquidity coverage ratio (LCR) in the 2010s.

However, given the methodology we use to construct the treatment, this is unlikely to be the case. Treated banks are identified by aggregating data from more than 36,000 French municipalities and other local governing councils. For the failure of Lehman Brothers to be a concern, it would need to be the case that some of these municipalities, the ones that depend more on Dexia for their funding, were more affected than others by the failure of Lehman Brothers. This is quite unlikely, especially since we observe no concentration of Dexia-dependent municipalities in specific regions.

To summarize, we exploit the near-failure of Dexia as an arguably exogenous shock to the supply of long-term credit to corporations by commercial banks. We define and use our treatment at three different levels in subsequent tests:

- At the municipality level: Treated (or "Dexia-dependent") municipalities are those for which the share of Dexia in the total stock of bank debt in June 2007 is above 50%;
- At the bank level: Treated banks are those that have a share of loans to Dexia-dependent municipalities within their total lending to municipalities above the median in June 2007;
- At the county level: Treated counties are those in which the share of treated banks (as defined above) in the total lending to corporations in the county is above the median in June 2007.

## 4.3 Relevance of the experiment

In this section, we evaluate the relevance of the near-failure of Dexia as a potential exogenous shock to the supply of long-term credit of commercial banks, which could affect differentially firms in low- vs. high-set-up cost industries that have a different demand for long-term loans.

First, we compare treated and control banks. Table 6 gives reassurance that treated and control banks are not very different from each other: while they differ in terms of their volume of loans to municipalities, they are quite similar in terms of the size of their loan portfolios to corporations. Beyond, both groupings include a significant number of both commercial and cooperative (or mutual) banks, as well as of specialized financial institutions. This suggests that the probability to be hit by the Dexia shock is a function of the geographical distribution of bank branches rather than a function of the type of the bank. Figure 3, which plots total cumulated lending to municipalities by treated vs control banks, confirms that treated banks increase relatively more their lending to municipalities after the shock: they indeed tend to accommodate the demand shock they face from Dexia-dependent municipalities. Specifically, we observe fairly parallel trends in credit to municipalities for the two groups of banks until early 2008, precisely when Dexia enters financial distress. After 2008, the patterns of municipal lending for treated and control banks diverge markedly: between the end of 2007 and the end of 2009, credit to municipalities goes up by more than 10 percent for treated banks, while it increases by less than 5 percent for control banks. Then, it remains approximately flat for control banks, while it keeps growing for treated banks, to reach about 125 percent of the 2008 volume at the end of 2010.

In Table 7, we present regression results that further confirm the intuition behind our instrument. In all four columns, the dependent variable is the growth rate of bank loans to municipalities, as measured at the granular bilateral bank-municipality level. The time dimension is collapsed: we average outstanding bilateral credit amounts over two periods of two years before (2006Q3 to 2008Q2) and after (2008Q3 to 2010Q2) the treatment (the near failure of Dexia). We then compute growth rates between the two periods. These growth rates are regressed on a dummy variable equal to one for Dexia-dependent municipalities, i.e., municipalities with more than half of their bank debt coming from Dexia before the shock. The sample of banks excludes the Dexia group and the state-owned banks that acquired Dexia's municipal loans portfolio. All regressions include bank fixed effects, which allows to identify a demand shock by comparing municipalities borrowing from the same bank. We find that Dexia-dependent local public entities indeed increase their demand for commercial bank credit by about 4.3 percentage points on average after the shock. This extra demand for credit to commercial banks when Dexia reduces its activities is somewhat larger for groupings of cities (column 3) and municipal vehicles (column 4) than for cities strictly speaking (column 2).

For the treatment to affect the supply of long-term credit to corporations, banks affected by the Dexia shock have to reduce the maturity of corporate loans. Figure 4 provides a first indication that this is the case. It compares the average maturity of new loans to young firms (strictly less than 24 months) across treated and control banks. Before 2008, we see no difference between the two groups of banks, while a gap appears around 2008, and closes only in 2012. The magnitude of the maturity difference is about 6 months on average between 2008 and 2012. This first step confirms the relevance of our identification strategy: it is indeed the case that banks that make more long-term loans to treated municipalities following the near-failure of Dexia reduce the maturity of loans to corporations over the same period of time.

Next, we check whether this effect is stronger for firms in high set-up cost industries, which rely more on long-term debt. Figure 5 provides an unambiguous answer: the two upper panels replicate the same exercise as in Figure 4, after breaking down the sample between high and low set-up cost industries. We find that the drop in loan maturities following the Dexia shock affects only firms in industries with high set-up costs, that is, firms that belong to industries in the third tercile of the set-up cost distribution. Additionally, the bottom panels show that no such effect is observed on loan volumes: this means that we have isolated a shock that affects only loan maturity, which is exactly what is needed to test Hypothesis 3.

These effects are confirmed in difference-in-differences regressions at the loan level over the years 2006-2012, as shown in Table 8.[22] In specifications with loan-level controls as well as industry, county and time fixed effects (or even industry and county interacted with time), the treatment effect appears to be statistically significant at the 5% level: maturity-constrained banks indeed reduce the maturity of new corporate loans supplied to young firms by more than 3 months on average. The comparison of columns 3 and 4 shows that this effect is driven by firms in industries with high set-up costs, in which the average maturity drops by about four months for loans made by treated banks after the Dexia shock.

Finally, to better understand the mechanism at play, we additionally break down the sample between counties characterized by levels of bank competition above or below the median (based on the Herfindhal-Hirschmann index computed with local corporate loan shares). This allows us to address the concern that firms in high set-up cost industries can obtain loans from control banks when treated banks cut the maturity of their corporate loans. In fact, this is true only for firms in areas with a high bank competition. In less competitive areas, the maturity constraint imposed by treated banks is likely to be more binding. In line with this intuition, comparing columns 5 and 6 shows that the maturity rationing effect is almost entirely explained by areas in which the level of bank competition is low. In such local markets, the maturity of loans extended by treated banks to young firms in high set-up cost industries goes down by nearly 8 months after the Dexia shock. This is consistent with the intuition that, in areas with less bank competition, local banks are more able to unilaterally change the terms of the loans they make to corporations than when they face fiercer competition. In the Appendix Table A4, we confirm that the same drop in loan maturity is observed in the firm-level sample.[23] As a last check, we ensure that the Dexia shocks affects primarily loan maturities rather than loan volumes. Specifically, in Appendix Tables A5 and A6, we reproduce Table 8, but using the loan size or the loan interest rate as dependent variables, respectively. In Table A5, we do not find any statistically significant effect of the Dexia shock on loan sizes. Table A6 shows that the Dexia shock has no effect on loan rates, even for long-term loans.

[22] Tables A2 and A3 provide statistical evidence that loans supplied by the two types of banks, controls vs. treated ones, are similar in terms of observables, a prerequisite for the validity of such tests.

[23] Since we do not observe lenders in Diane, we construct a county-level measure of the treatment, as the market share of treated banks within the local market for corporate loans.

## 4.4 Real effects of maturity rationing

Using the shock described above, we investigate whether maturity rationing by banks has consequences for young firms. The main prediction is that, if young firms are denied long enough loan maturities by their banks, they may simply not start operating. Therefore, firms in industries that are particularly reliant on long-maturity debt should be more affected by a shock that affects the willingness of banks to make long-term loans. We investigate this prediction using data on the creation of all firms in France in the four years surrounding the Dexia shock of October 2008. We identify firm creations at the county-industry level from the SIRENE register of French firms, which provides a comprehensive coverage of firms registered in France over the last four decades (cf. Data section for details). Specifically, as a dependent variable, we use the number of firms created in a particular 3-digit industry in a given county and a given year. The *Treated* variable is constructed here at the county level, and corresponds to counties above the median in terms of the share of treated banks in local corporate credit. We discard observations related to intermediate set-up cost industries, so as to focus on the comparison of high-cost vs low-cost industries. This auxiliary dataset is still quite large, with about 36,000 observations. Table 9 compares characteristics of treated and control counties before the shock. Based on a two-sample $t$-test, the average of unemployment rate, population count, median income and employment shares by industries, treated and control counties are statistically indistinguishable.

Some 27% of these observations take the value of zero: intuitively, it is indeed unlikely that new firms are created in every county and every 3-digit industry every year. The most common approach in finance when facing count data with many zeros has long been to take logs of one constant (generally one) plus the dependent variable and running OLS regressions. This method is however inappropriate and yields potentially strongly biased estimates (Santos Silva and Tenreyro, 2006). Furthermore, the estimated coefficients have no direct interpretation as semi-elasticities (Cohn et al., 2021). We therefore resort to the alternative Poisson pseudo-maximum likelihood (PPML) estimator, which conveniently deals with zeros, easily accommodates group fixed effects and is becoming the standard method for modeling count data.[24] We control for unobserved shocks at the county and sector levels using fixed effects.

The baseline results are presented in Table 10. The first three columns relate to firm creations in all French counties, while the last three columns present results when we consider only counties with below-median levels of bank competition. In each case, we consider all industries, manufacturing and services industries in turn. In the entire sample of treated counties, we observe a negative effect of the Dexia shock on firm creation in high set-up cost industries, but only for the subset of manufacturing

[24]For comparison, Table A8 in the appendix shows the results if instead the dependent variable is the logarithm of one plus the number of firm creations and the coefficients are estimated using OLS.

industries (column 2). The effect is strong and significant at the 1% level in spite of a relatively low number of observed county-industry cells (less than 6,000). The marginal effect of an independent variable in a Poisson model is equal to $1 - e^{\beta}$. Therefore, the real effect of the Dexia shock in France reads as a drop in the number of high set-up cost, manufacturing firm creations by 30.6% ($= 1 - e^{-0.365}$). We now turn to the subsample of counties where the level of bank competition is relatively low. We find that the effect is still null in services industries but even more negative and significant in manufacturing industries. In these counties, the Dexia shock decreases the number of firm creations in high set-up cost, manufacturing industries, by 66.6% ($= 1 - e^{-1.098}$).[25] Figure 6 shows coefficient estimates of the dummy for treated counties interacted with time, in a dynamic specification of the difference-in-differences regression shown in Table 10, Column 2. The Figure validates the parallel trends assumption, on a 3-year period prior to the shock.

Finally, one may wonder whether the entire effect of maturity shortening by banks goes through firm creation or whether, even for firms that are created, a shorter maturity translates into lower growth in subsequent years (e.g., because some key investment needs to be postponed). To test whether this is the case, we estimate additional difference-in-differences models with measures of firm size after two years as dependent variables. First, we use our loan-level data and test whether borrowing a first loan from a treated bank reduces subsequent firm growth. Second, we use firm-level data and look at the effect on firm size of being located in a treated county. Whatever the specification, we do not find any significant effect of the Dexia shock on firm growth, even when restricting to low-competition counties.[26] Our findings thus suggest that reduced firm creation is the main channel through which set-up costs affect the transmission of shocks in the economy.

# Conclusion

Our main takeaway is that fixed set-up costs are essential to understand young firms. First, they explain otherwise puzzling features of their capital structure, both across and within industries. Most importantly, they explain why young firms borrow more, and with longer-maturity debt. Second, set-up costs explain the heterogeneous response of firms to some financing shocks. When lenders are forced to shrink the maturity of debt contracts, firms in industries characterized by high set-up costs are

[25]Note that these findings are robust to an alternative cutoff for measuring industry-level set-up costs, as explained in the data section. For details, see Table A9 in the online Appendix.

[26]Detailed results are presented in Table A10 in the online appendix, in Panel A for the loan-level regressions and in Panel B for the firm-level regressions, as well as in Table A11. In Table A10, we consider the growth of total assets and fixed assets, while in Table A11 we consider the growth of sales and the wage bill as dependent variables instead.

more affected.

These findings have important implications. First, they can help better design policies to foster firm creation. In particular, one cannot assume that all firms can start with an arbitrarily small size and then grow. There are important "threshold effects" in firm creation. Policies that ignore this fact may end up helping only firms in low set-up cost industries, which are the least constrained. Second, our results can help better understand recoveries following financial crises. If industries with high set-up costs are affected differentially more, then financial crises may be associated with long-lasting changes in industry composition. This prediction remains to be explored.

# References


Akcigit, U. and S. T. Ates (2021). Ten facts on declining business dynamism and lessons from endogenous growth theory. *American Economic Journal: Macroeconomics 13*, 257–298.

Albuquerque, R. and H. A. Hopenhayn (2004). Optimal lending contracts and firm dynamics. *Review of Economic Studies 71*, 285–315.

Barclay, M. J. and C. W. Smith (1995). The maturity structure of corporate debt. *Journal of Finance 50*, 609–631.

Bartelsman, E. J. and P. J. Dhrymes (1998). Productivity dynamics: U.S. manufacturing plants, 1972-1986. *Journal of Productivity Analysis volume 9*, 5–34.

Benmelech, E. (2009). Asset salability and debt maturity: Evidence from nineteenth-century American railroads. *Review of Financial Studies 22*, 1545–1584.

Benmelech, E., M. J. Garmaise, and T. J. Moskowitz (2005). Do liquidation values affect financial contracts? Evidence from commercial loan contracts and zoning regulation. *Quarterly Journal of Economics 120*, 1121–1154.

Black, S. and P. Strahan (2002). Entrepreneurship and bank credit availability. *Journal of Finance 57*, 2807–2833.

Chodorow-Reich, G. (2014). The employment effects of credit market disruptions: Firm-level evidence from the 2008-09 financial crisis. *Quarterly Journal of Economics 129*, 1–59.

Cingano, F., F. Manaresi, and E. Sette (2016). Does credit crunch investment down? New evidence on the real effects of the bank-lending channel. *Review of Financial Stuies 29*, 2737–2773.

Cohn, J. B., Z. Liu, and M. Wardlaw (2021). Count data in finance. unpublished manuscript, University of Texas Austin.

Custodio, C., M. A. Ferreira, and L. Laureano (2013). Why are US firms using more short-term debt? *Journal of Financial Economics 108*, 182–212.

Decker, R. A., J. Haltiwanger, R. S. Jarmin, and J. Miranda (2016). Declining business dynamism: What we know and the way forward. *American Economic Review: Papers and Proceedings 106*, 203–207.

Diamond, D. and Z. He (2014). A theory of debt maturity: The long and short of debt overhang. *Journal of Finance 69*, 719–762.

Diamond, D. W. (1991). Debt maturity structure and liquidity risk. *Quarterly Journal of Economics 106*, 709–737.

Dinlersoz, E., H. Hyatt, S. Kalemli-Ozcan, and V. Penciakova (2019). Leverage over the firm life cycle, firm growth, and aggregate fluctuations. FRB Atlanta Working Paper 2019-18, Federal Reserve Bank of Atlanta.

Evans, D. S. and L. S. Leighton (1989). Some empirical aspects of entrepreneurship. *American Economic Review 79*, 519–535.

Guedes, J. and T. Opler (1996). The determinants of the maturity of corporate debt issues. *Journal of Finance 51*, 1809–1833.

Haltiwanger, J., R. S. Jarmin, and J. Miranda (2013). Who creates jobs? Small versus large versus young. *Review of Economics and Statistics 95*, 347–361.

He, Z. and K. Milbradt (2016). Dynamic debt maturity. *Review of Financial Studies 29*, 2677–2736.

Holmstrom, B. and J. Tirole (1997). Financial intermediation, loanable funds, and the real sector. *Quarterly Journal of Economics 112*, 663–691.

Huang, C., M. Oehmke, and H. Zhong (2019). A theory of multiperiod debt structure. *Review of Financial Studies 32*, 4447–4500.

Hurst, E. and A. Lusardi (2004). Liquidity constraints, household wealth, and entrepreneurship. *Journal of Political Economy 112*, 319–324.

Ivashina, V. and D. Scharfstein (2010). Bank lending during the financial crisis of 2008. *Journal of Financial Economics 97*(3), 319–338.

Kerr, W. R. and R. Nanda (2015). Financing innovation. *Annual Review of Financial Economics 7*, 445–462.

Myers, S. (1977). Determinants of corporate borrowing. *Journal of Financial Economics 5*, 147–175.

Myers, S. C. and N. S. Majluf (1984). Corporate financing and investment decisions when firms have information that investors do not have. *Journal of Financial Economics 13*, 187–221.

Peek, J. and E. S. Rosengren (2000). Collateral damage: Effects of the Japanese bank crisis on real activity in the United States. *American Economic Review 90*, 30–45.

Puri, M., J. Rocholl, and S. Steffen (2011). Global retail lending in the aftermath of the US financial crisis: Distinguishing between supply and demand effects. *Journal of Financial Economics 100*(3), 556–578.

Rajan, R. G. and L. Zingales (1998). Financial dependence and growth. *American Economic Review 88*, 559–586.

Robb, A. M. and D. T. Robinson (2014). The capital structure decisions of new firms. *Review of Financial Studies 27*, 153–179.

Santos Silva, J. and S. Tenreyro (2006). The log of gravity. *The Review of Economics and Statistics 88*(4), 641–658.

Schmalz, M. C., D. A. Sraer, and D. Thesmar (2017). Housing collateral and entrepreneurship. *Journal of Finance 72*, 99–132.

Table 1: Descriptive statistics.

This table shows descriptive statistics in the pooled samples for the variables used in our analysis. Panel A is for the firm-level dataset (i.e., random 20% of the universe of firms created in France between 2006 and 2016). Panel B is for the loan-level dataset (survey of bank branches from 2006 to 2018), restricted to firms aged strictly less than 24 months. Firms' total assets are expressed in thousand euros. The definition of the variables is provided in Appendix A.

Panel A : Firm-level dataset

| | Mean | Std.Dev. | p10 | p25 | Median | p75 | p90 | Nb.Obs. |
|---|---|---|---|---|---|---|---|---|
| Size (log assets) | 4.79 | 1.62 | 2.91 | 3.81 | 4.75 | 5.75 | 6.76 | 663364 |
| Young | 0.48 | 0.50 | 0.00 | 0.00 | 0.00 | 1.00 | 1.00 | 663364 |
| Total debt / Assets | 0.48 | 0.30 | 0.08 | 0.22 | 0.46 | 0.71 | 0.88 | 355600 |
| Financial debt / Assets | 0.30 | 0.28 | 0.00 | 0.04 | 0.22 | 0.52 | 0.75 | 358803 |
| Bank debt / Assets | 0.18 | 0.24 | 0.00 | 0.00 | 0.04 | 0.31 | 0.57 | 656432 |
| Other fin. debt / Assets | 0.13 | 0.20 | 0.00 | 0.00 | 0.04 | 0.18 | 0.41 | 367262 |
| Accounts payables / Assets | 0.16 | 0.18 | 0.01 | 0.04 | 0.10 | 0.23 | 0.41 | 655040 |
| Debt maturity (in months) | 18.11 | 10.50 | 12.00 | 12.00 | 12.60 | 20.46 | 30.47 | 255950 |
| Debt $\leq$ 1y / Debt | 0.58 | 0.42 | 0.00 | 0.00 | 0.72 | 1.00 | 1.00 | 358768 |
| Debt $>$ 1y and $\leq$ 5y / Debt | 0.10 | 0.17 | 0.00 | 0.00 | 0.00 | 0.13 | 0.37 | 377722 |
| Debt $>$ 5y / Debt | 0.03 | 0.10 | 0.00 | 0.00 | 0.00 | 0.00 | 0.03 | 377571 |
| PPE / Assets | 0.15 | 0.21 | 0.00 | 0.01 | 0.06 | 0.21 | 0.46 | 378681 |
| Intangibles / Assets | 0.15 | 0.25 | 0.00 | 0.00 | 0.00 | 0.23 | 0.61 | 342577 |
| EBITDA / Assets | 0.10 | 0.16 | -0.08 | 0.02 | 0.10 | 0.20 | 0.31 | 328806 |

Panel B: Loan-level dataset (firms aged strictly less than 24 months)

| | Mean | Std.Dev. | p10 | p25 | Median | p75 | p90 | Nb.Obs. |
|---|---|---|---|---|---|---|---|---|
| Initial maturity (in months) | 71.14 | 27.56 | 36.00 | 60.00 | 84.00 | 84.00 | 86.00 | 37188 |
| Loan amount (thousand euros) | 191.19 | 982.83 | 12.50 | 25.00 | 51.00 | 140.00 | 326.08 | 37188 |
| Interest rate | 3.27 | 1.49 | 1.17 | 1.97 | 3.40 | 4.40 | 5.15 | 37188 |
| Subsidized loan | 0.09 | 0.29 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 37188 |
| Fixed rate loan | 0.94 | 0.23 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 37188 |
| Regulated loan | 0.08 | 0.27 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 37188 |
| Size (log assets) | 5.79 | 1.42 | 4.27 | 4.85 | 5.57 | 6.47 | 7.52 | 13504 |
| Standalone SME | 0.97 | 0.16 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 37188 |
| Financial debt / Assets | 0.57 | 0.26 | 0.20 | 0.37 | 0.60 | 0.78 | 0.89 | 8294 |
| PPE / Assets | 0.27 | 0.26 | 0.01 | 0.06 | 0.19 | 0.42 | 0.69 | 8788 |
| EBITDA / Assets | 0.05 | 0.18 | -0.13 | -0.02 | 0.05 | 0.15 | 0.26 | 8488 |
| Nb loans by firm | 1.58 | 1.57 | 1.00 | 1.00 | 1.00 | 2.00 | 2.00 | 37188 |

Table 2: Descriptive statistics on set-up costs

This table provides descriptive statistics on set-up costs, measured at the 3-digit industry level. Panel A displays moments of the cross-industry distribution of set-up costs. The measurement of industry-level set-up costs is described in Section 2.2. Panel B shows the 15 industries with the lowest (left panel) and with the highest (right panel) set-up costs. Panel C regresses balance sheet characteristics and financial ratios at the firm-year level on a constant and on two dummies capturing whether the firm operates in an industry in the second ($MidCost$) or in the third ($HighCost$) tercile of the set-up cost distribution. $PPE/A.$ is the ratio of tangible fixed assets to total assets, $Int./A.$ is the ratio of intangible assets to assets, $Size$ is the log of total assets. $EBITDA/A.$ and $ROA$ are the ratios of EBITDA and net income to assets, respectively. The regressions are estimated in the sample of firms with age 0 or 1 (columns 1 to 5) and in the full sample of firms (columns 6 to 10). Heteroskedasticity-robust standard errors are reported in brackets. *, ** and *** denote respectively statistical significance at the 10%, 5% and 1% levels.

Panel A : Descriptive statistics

| | Mean | Std.Dev. | p10 | p25 | Median | p75 | p90 | Nb.Obs. |
|---|---|---|---|---|---|---|---|---|
| Set-up cost (in thousand euros) | 46.47 | 81.85 | 2.31 | 5.55 | 19.23 | 48.38 | 121.01 | 146 |

Panel B: Industries with lowest and highest set-up costs

| Bottom 15 | | Top 15 | |
|---|---|---|---|
| 3-digit industry | Set-up cost | 3-digit industry | Set-up cost |
| Other civil engineering projects | 0 | Fishing | 612.4 |
| Activities of head offices | 0 | Steam and air conditioning supply | 539.8 |
| Translation and interpretation activities | 0.6 | Manufacture of paper products | 255.5 |
| Other human resources provision | 0.7 | Hotels and similar accommodation | 235.2 |
| Management consultancy activities | 0.8 | Hospital activities | 220.4 |
| Office administrative and support activities | 1.0 | Manufacture of concrete products | 204.5 |
| Business support service activities | 1.1 | Bakery | 192.7 |
| Other postal activities | 1.2 | Veterinary activities | 188.1 |
| Wholesale on a fee or contract basis | 1.4 | Sea and coastal passenger water transport | 181.6 |
| Other scientific and technical activities | 1.5 | Medical and dental practice activities | 176.1 |
| Market research and public opinion polling | 1.7 | Quarrying of stone, sand and clay | 155.5 |
| Non-specialised wholesale trade | 1.9 | Dairy productions | 149.4 |
| Computer programming and related activities | 1.9 | Other retail sale in specialised stores | 148.4 |
| Activities of employment placement agencies | 2.3 | Camping grounds and trailer parks | 127.5 |
| Specialised design activities | 2.3 | Other human health activities | 121.0 |

Panel C : Set-up costs and firm characteristics

| | PPE/A. | Int./A. | Size | EBITDA/A. | ROA | PPE/A. | Int./A. | Size | EBITDA/A. | ROA |
|---|---|---|---|---|---|---|---|---|---|---|
| Constant | 0.077*** | 0.066*** | 4.116*** | 0.289*** | 0.242*** | 0.075*** | 0.066*** | 4.616*** | 0.219*** | 0.181*** |
| | [0.001] | [0.001] | [0.006] | [0.002] | [0.001] | [0.000] | [0.000] | [0.004] | [0.001] | [0.000] |
| MidCost | 0.113*** | -0.001 | 0.082*** | -0.052*** | -0.051*** | 0.110*** | 0.001* | 0.042*** | -0.020*** | -0.033*** |
| | [0.002] | [0.001] | [0.009] | [0.002] | [0.001] | [0.001] | [0.001] | [0.005] | [0.001] | [0.001] |
| HighCost | 0.164*** | 0.223*** | 0.649*** | -0.127*** | -0.125*** | 0.138*** | 0.244*** | 0.447*** | -0.058*** | -0.075*** |
| | [0.001] | [0.002] | [0.008] | [0.002] | [0.001] | [0.001] | [0.001] | [0.005] | [0.001] | [0.001] |
| Firms | $< 2$y. | $< 2$y. | $< 2$y. | $< 2$y. | $< 2$y. | All | All | All | All | All |
| Adj. $R^2$ | 0.110 | 0.193 | 0.036 | 0.068 | 0.078 | 0.087 | 0.216 | 0.016 | 0.022 | 0.042 |
| Observations | 105,287 | 97,549 | 204,052 | 71,706 | 129,764 | 378,681 | 342,577 | 663,364 | 276,667 | 453,128 |

Table 3: Firm age and debt maturity across set-up costs – Using loan-level data

This table provides estimates of Equation (3) using loan-level data from *M-Contran*. The dependent variable is the initial maturity of new loans, measured in months. $HighCost$ is a dummy variable equal to one for firms in 3-digit industries that are in the top tercile of the set-up cost distribution. $Young$ is a dummy variable equal to one for firms aged strictly less than 24 months. The estimation is conducted in the sample of firms up to 10 years old. Columns 1 and 2 use the whole sample of borrowing firms, while columns 3 and 4 restrict the estimation sample to firms with available balance sheet data. The definition of the variables is provided in Appendix A. Standard errors, clustered at the 3-digit industry level, are reported in brackets. *, ** and *** denote respectively statistical significance at the 10%, 5% and 1% levels.

| | All firms | | Firms with bal. sh. | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Young × HighCost | 5.831*** | 5.791*** | 5.451*** | 3.829*** |
| | [0.756] | [0.751] | [1.124] | [1.288] |
| Young | 9.697*** | 9.596*** | 8.548*** | 8.756*** |
| | [0.625] | [0.621] | [0.832] | [0.877] |
| Subsidized loan | | 4.883*** | 4.314*** | 4.748*** |
| | | [0.444] | [0.760] | [0.771] |
| Fixed rate loan | | 4.609*** | 3.944*** | 8.319*** |
| | | [1.339] | [1.395] | [1.341] |
| Regulated loan | | -1.966** | -0.401 | -0.422 |
| | | [0.788] | [0.916] | [0.903] |
| Size | | | | 2.466*** |
| | | | | [0.584] |
| PPE / Assets | | | | 22.770*** |
| | | | | [3.332] |
| EBITDA / Assets | | | | -21.047*** |
| | | | | [2.026] |
| Indus. FE | Yes | Yes | Yes | Yes |
| Quarter FE | Yes | Yes | Yes | Yes |
| Bank FE | Yes | Yes | Yes | Yes |
| Firm controls | No | No | No | Yes |
| Nb clusters | 131 | 131 | 129 | 129 |
| Observations | 112,519 | 112,519 | 43,907 | 43,907 |
| Adj. $R^2$ | 0.22 | 0.23 | 0.24 | 0.28 |

Table 4: Firm age and debt maturity across set-up costs – Using firm-level data

This table provides estimates of Equation (4), using either bank debt over total assets or the residual maturity of total debt (measured in months) as dependent variables. *HighCost* is a dummy variable equal to one for firms in 3-digit industries that are in the top tercile of the set-up cost distribution. *Young* is a dummy variable equal to one for firms aged strictly less than 24 months. The estimation is conducted in the pooled sample of Diane firms. The definition of the variables is provided in Appendix A. Standard errors, clustered at the 3-digit industry level, are reported in brackets. *, ** and *** denote respectively statistical significance at the 10%, 5% and 1% levels.

| | Bank debt | Bank debt | Maturity | Maturity |
|---|---|---|---|---|
| Young × HighCost | 0.063*** | 0.071*** | 2.091*** | 2.283*** |
| | [0.009] | [0.010] | [0.506] | [0.570] |
| Young | -0.016** | -0.018** | 0.027 | 0.052 |
| | [0.008] | [0.008] | [0.388] | [0.425] |
| Size | 0.040*** | 0.042*** | 2.221*** | 2.305*** |
| | [0.004] | [0.004] | [0.316] | [0.330] |
| PPE / Assets | 0.396*** | 0.399*** | 14.334*** | 14.659*** |
| | [0.020] | [0.021] | [1.108] | [1.123] |
| EBITDA / Assets | -0.106*** | -0.106*** | -1.994*** | -2.069*** |
| | [0.007] | [0.007] | [0.551] | [0.581] |
| Survival $\geq$ 5y | No | Yes | No | Yes |
| Firm FE | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes |
| Nb clusters | 146 | 146 | 146 | 146 |
| Observations | 327,128 | 227,832 | 223,946 | 158,817 |
| Adj. $R^2$ | 0.252 | 0.269 | 0.131 | 0.140 |

Table 5: Firm profitability and debt maturity

This table provides the estimates of Equation (5) and Equation (6), using the initial maturity of new loans from the loan-level sample (Panel A) and the residual maturity of total debt from the firm-level sample (Panel B) as dependent variables. The estimation is conducted on the sample of firms aged strictly less than 24 months over the 2006-2018 period. The definition of the variables is provided in Appendix A. Time fixed effects refer to quarterly dummies in Panel A, and to yearly dummies in Panel B. Standard errors, clustered at the 3-digit industry level, are reported in brackets. $^{*}$, $^{**}$ and $^{***}$ denote respectively statistical significance at the 10%, 5% and 1% levels.

Panel A: Loan-level. Dep. var.: loan maturity

| | (1) | (2) |
|---|---|---|
| EBITDA / Assets | -15.542$^{***}$ | -19.183$^{***}$ |
| | [2.206] | [3.173] |
| Subsidized loan | 3.630$^{***}$ | 4.758$^{***}$ |
| | [1.298] | [0.934] |
| Fixed rate loan | 6.422$^{*}$ | 3.869 |
| | [3.250] | [2.914] |
| Regulated loan | -2.185 | -2.633 |
| | [1.437] | [1.840] |
| Size | 3.044$^{**}$ | 4.055$^{***}$ |
| | [1.303] | [1.496] |
| PPE / Assets | 5.141 | 3.874 |
| | [4.484] | [5.178] |
| Bank FE | Yes | Yes |
| Industry FE | Yes | Yes |
| Time FE | Yes | No |
| Industry × Time FE | No | Yes |
| Nb clusters | 122 | 108 |
| Observations | 8,469 | 7,482 |
| Adj. $R^2$ | 0.27 | 0.36 |

Panel B: Firm-level. Dep. var.: total debt maturity

| | (1) | (2) |
|---|---|---|
| EBITDA / Assets | -2.575$^{***}$ | -2.551$^{***}$ |
| | [0.583] | [0.580] |
| Size | 1.993$^{***}$ | 2.022$^{***}$ |
| | [0.413] | [0.424] |
| PPE / Assets | 9.277$^{***}$ | 9.196$^{***}$ |
| | [1.874] | [1.861] |
| Bank FE | No | No |
| Industry FE | Yes | No |
| Time FE | Yes | No |
| Industry × Year FE | No | Yes |
| Nb clusters | 146 | 146 |
| Observations | 58,957 | 58,830 |
| Adj. $R^2$ | 0.286 | 0.289 |

Table 6: Comparison of treated and control banks

This table compares the loan volume and other characteristics of treated and control banks, as defined in Section 4.2. The loan volumes are computed before the treatment by the Dexia shock, as averages over the period from 2006Q3 to 2008Q2. We further break down total loan volumes between loans to municipalities and loans to corporations. Loan volumes are expressed in million euros.

| | N | Mean | Std.Dev. | p25 | Median | p75 |
|---|---|---|---|---|---|---|
| Control banks | | | | | | |
| Municipal loans (EUR mns) | 99 | 317.12 | 1056.51 | 1.11 | 9.56 | 328.97 |
| Corporate loans (EUR mns) | 99 | 1575.90 | 4711.99 | 126.88 | 419.41 | 1293.42 |
| Commercial bank | 97 | 0.34 | 0.48 | 0.00 | 0.00 | 1.00 |
| Cooperative bank | 97 | 0.40 | 0.49 | 0.00 | 0.00 | 1.00 |
| Financial company | 97 | 0.06 | 0.24 | 0.00 | 0.00 | 0.00 |
| Specialized credit institution | 97 | 0.18 | 0.38 | 0.00 | 0.00 | 0.00 |
| Foreign institution | 97 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| Treated banks | | | | | | |
| Municipal loans (EUR mns) | 98 | 565.28 | 1459.32 | 5.93 | 284.42 | 716.08 |
| Corporate loans (EUR mns) | 97 | 1669.83 | 4225.90 | 239.33 | 656.52 | 1374.38 |
| Commercial bank | 98 | 0.19 | 0.40 | 0.00 | 0.00 | 0.00 |
| Cooperative bank | 98 | 0.67 | 0.47 | 0.00 | 1.00 | 1.00 |
| Financial company | 98 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| Specialized credit institution | 98 | 0.12 | 0.33 | 0.00 | 0.00 | 0.00 |
| Foreign institution | 98 | 0.01 | 0.10 | 0.00 | 0.00 | 0.00 |
| Total | | | | | | |
| Municipal loans (EUR mns) | 197 | 440.57 | 1275.74 | 2.54 | 39.44 | 565.18 |
| Corporate loans (EUR mns) | 196 | 1622.39 | 4466.80 | 176.47 | 542.36 | 1333.52 |
| Commercial bank | 195 | 0.27 | 0.44 | 0.00 | 0.00 | 1.00 |
| Cooperative bank | 195 | 0.54 | 0.50 | 0.00 | 1.00 | 1.00 |
| Financial company | 195 | 0.03 | 0.17 | 0.00 | 0.00 | 0.00 |
| Specialized credit institution | 195 | 0.15 | 0.36 | 0.00 | 0.00 | 0.00 |
| Foreign institution | 195 | 0.01 | 0.07 | 0.00 | 0.00 | 0.00 |

## Table 7: Bank lending to municipalities after the Dexia shock

This table regresses the log-difference in average credit amounts between the periods 2006Q3-2008Q2 and 2008Q3-2010Q2 at the bank-borrower-level. Dexia and three state-owned banks are excluded from the sample of banks. In all columns, borrowers are different types of municipalities. Treated municipalities are municipalities that were Dexia-dependent before the shock. The definition of the variables is provided in Appendix A. Robust standard errors are reported in brackets. *, ** and *** denote respectively statistical significance at the 10%, 5% and 1% levels.

| | Credit to municipalities | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| | All | Cities | City groupings | Municip. vehicles |
| Treated municipality | 0.043*** | 0.041*** | 0.057*** | 0.059*** |
| | [0.006] | [0.006] | [0.020] | [0.018] |
| Bank FE | Yes | Yes | Yes | Yes |
| Observations | 34,684 | 25,805 | 3,462 | 4,188 |
| Adj. $R^2$ | 0.04 | 0.05 | 0.04 | 0.02 |

## Table 8: Maturity of new loans to young firms after the Dexia shock

This table estimates a difference-in-differences model with the initial maturity of new loans to young non-financial firms (aged strictly less than 24 months) as dependent variable, using the loan-level sample. The treatment is defined at the bank level, as described in Section 4.2. In sum, a bank is treated by the Dexia shock if it is highly exposed to municipalities borrowing heavily from Dexia before 2008. 3-digit industries with low and high set-up costs are respectively industries in the bottom and the top tercile of the set-up cost distribution. Loan-level controls are dummy variables for subsidized, fixed rate and regulated loans respectively. Counties with high bank competition are counties with an Herfindhal-Hirschmann index (computed based on banks' local corporate loan shares as of 2007) below the median. The estimation period is from 2006 to 2012. Period fixed effects are dummy variables for the two time periods before and after the Dexia shock of 2008 Q3. Standard errors are clustered at the bank level and are reported in brackets. *, ** and *** denote respectively statistical significance at the 10%, 5% and 1% levels.

| | All $< 2y$ | | Low Cost | High Cost | | |
|---|---|---|---|---|---|---|
| | | | | | Low comp. | High comp. |
| Treated bank × Post | -2.760** | -2.939** | -0.474 | -3.839** | -7.743*** | -2.090 |
| | [1.352] | [1.395] | [3.097] | [1.800] | [2.804] | [1.865] |
| Treated bank | -2.436 | -2.211 | -1.493 | -1.863 | 2.047 | -3.403 |
| | [1.641] | [1.703] | [2.430] | [2.073] | [2.118] | [2.371] |
| Industry FE | Yes | No | Yes | Yes | Yes | Yes |
| Quarter FE | Yes | Yes | Yes | Yes | Yes | Yes |
| County FE | Yes | No | Yes | Yes | Yes | Yes |
| Indus. × Period FE | No | Yes | No | No | No | No |
| County × Period FE | No | Yes | No | No | No | No |
| Loan controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Nb clusters | 163 | 163 | 138 | 147 | 108 | 143 |
| Observations | 20,288 | 20,282 | 2,996 | 12,367 | 3,243 | 9,122 |
| Adj. $R^2$ | 0.16 | 0.17 | 0.08 | 0.09 | 0.11 | 0.09 |

Table 9: Comparison of treated and control counties

This table compares treated and control counties. A county is treated by the Dexia shock if banks that lend heavily to Dexia-exposed municipalities before 2008 have a large market share (i.e., above the median across counties). All variables, except for population, are measured as of 2007, either at year-end (median income, employment shares by industries) or at the end of 2007 Q2 (unemployment rate). Population data are coming from the 2008 census.

| | Treated | Control | Diff. | p-value | Observations |
|---|---|---|---|---|---|
| Unemployment rate | 7.340 | 7.779 | -0.438 | 0.163 | 94 |
| Population | 696,152 | 649,284 | 46,868 | 0.650 | 94 |
| Median income | 18,020 | 17,593 | 427 | 0.135 | 94 |
| Share - Manufacturing | 0.261 | 0.264 | -0.003 | 0.880 | 94 |
| Share - Services | 0.637 | 0.629 | 0.008 | 0.642 | 94 |
| Share - Construction | 0.102 | 0.107 | -0.005 | 0.178 | 94 |

Table 10: Firm creation after the Dexia shock

This tables estimates a difference-in-differences model with the yearly number of firm creations at the county-industry-year level as the dependent variable, using a Poisson Pseudo-Maximum likelihood (PPML) estimation method. The sample period is 2007-2010. The post period includes years 2009 and 2010. The treatment is defined at the county level. A county is treated by the Dexia shock if banks that lend heavily to Dexia-exposed municipalities before 2008 have a large market share (i.e., above the median across counties). We compare firm creations in low and high set-up cost industries. Industries with intermediate set-up costs are therefore dropped. 3-digit industries with low and high set-up costs are respectively industries in the bottom and the top tercile of the set-up cost distribution. *Manuf.* refers to manufacturing industries (2-digit codes 10 to 33). *Serv.* refers to scientific, specialized and administrative services to firms (2-digit codes 69 to 82). Standard errors are reported in brackets. *, ** and *** denote respectively statistical significance at the 10%, 5% and 1% levels.

| | All counties | | | Low comp. | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| | All | Manuf. | Serv. | All | Manuf. | Serv. |
| Treated × Post × HighCost | -0.004 | -0.365*** | -0.099 | -0.005 | -1.098*** | -0.051 |
| | [0.017] | [0.109] | [0.064] | [0.030] | [0.349] | [0.160] |
| County × Sector FE | Yes | Yes | Yes | Yes | Yes | Yes |
| County × Post FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Sector × Post FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Log likelihood | -64,326 | -7,543 | -15,240 | -25,891 | -2,822 | -5,811 |
| Observations | 32,800 | 5,840 | 7,728 | 15,524 | 2,592 | 3,676 |

## Figure 1: Stylized facts – Pooled sample: balance sheet structure

This figure plots stylized facts about the capital structure of firms between their creation and age 10. Each line is obtained by computing the mean of the relevant variable in the pooled sample of Diane firms. Total debt is defined to include both financial debt (from banks or other lenders, including family and friends) and payables. In the first five panels, the data are from Diane and the maturity of debt is the residual maturity of total debt. In the last panel, the exact maturity of bank loans at issuance is measured from *M-Contran*.

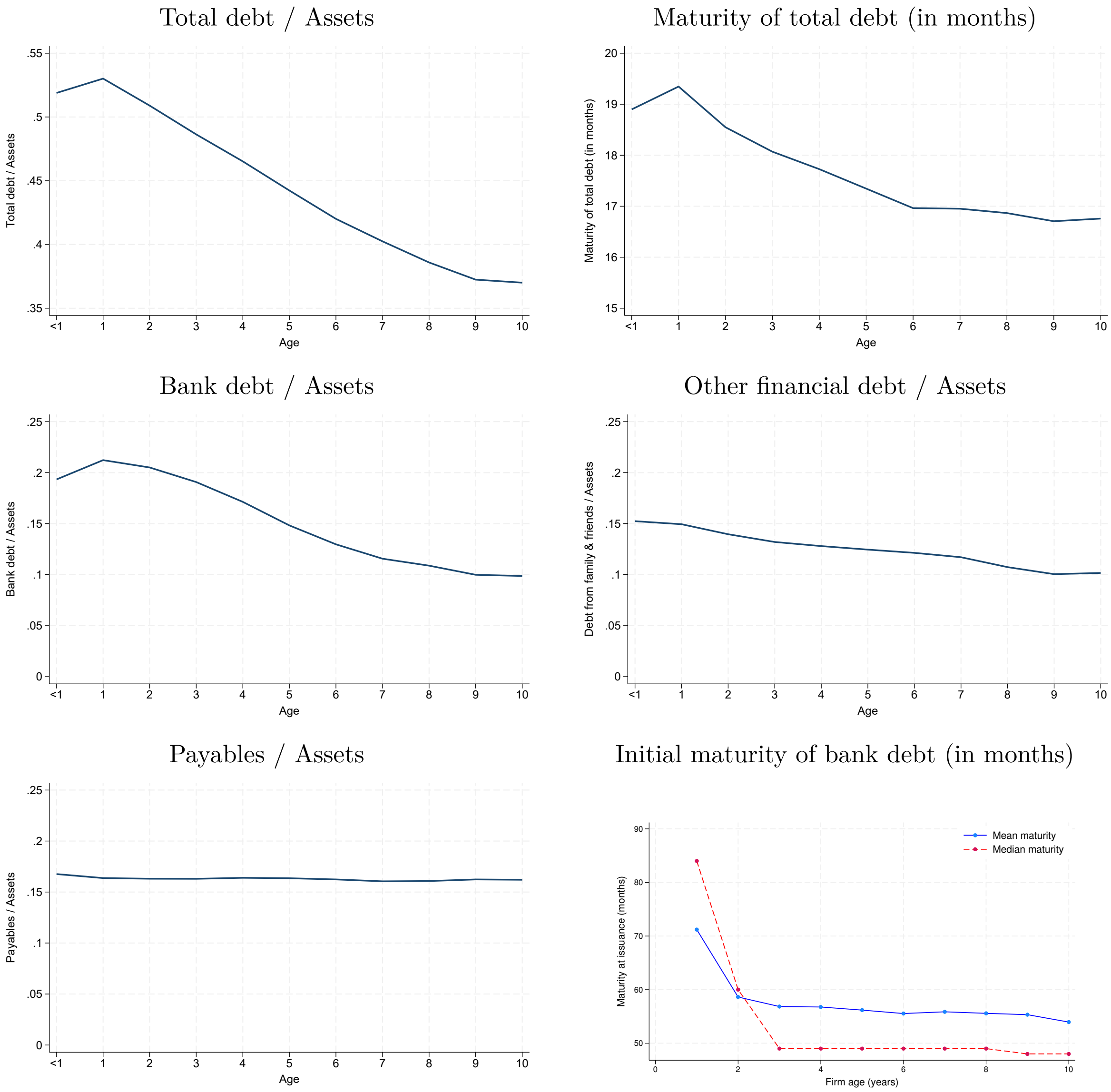

Figure 2: Stylized facts – By set-up cost terciles: balance sheet structure

This figure plots stylized facts about the capital structure of firms between their creation and age 10. Each line is obtained by computing the mean of the relevant variable for all firms in each tercile of the set-up cost distribution. Set-up costs are computed at the 3-digit industry level using the procedure described in Section 2.2. Total debt is defined to include both financial debt (from banks or other lenders, including family and friends) and payables. In the first five panels, the data are from Diane and the maturity of debt is the residual maturity of total debt. In the last panel, the exact maturity of bank loans at issuance is measured from *M-Contran*.

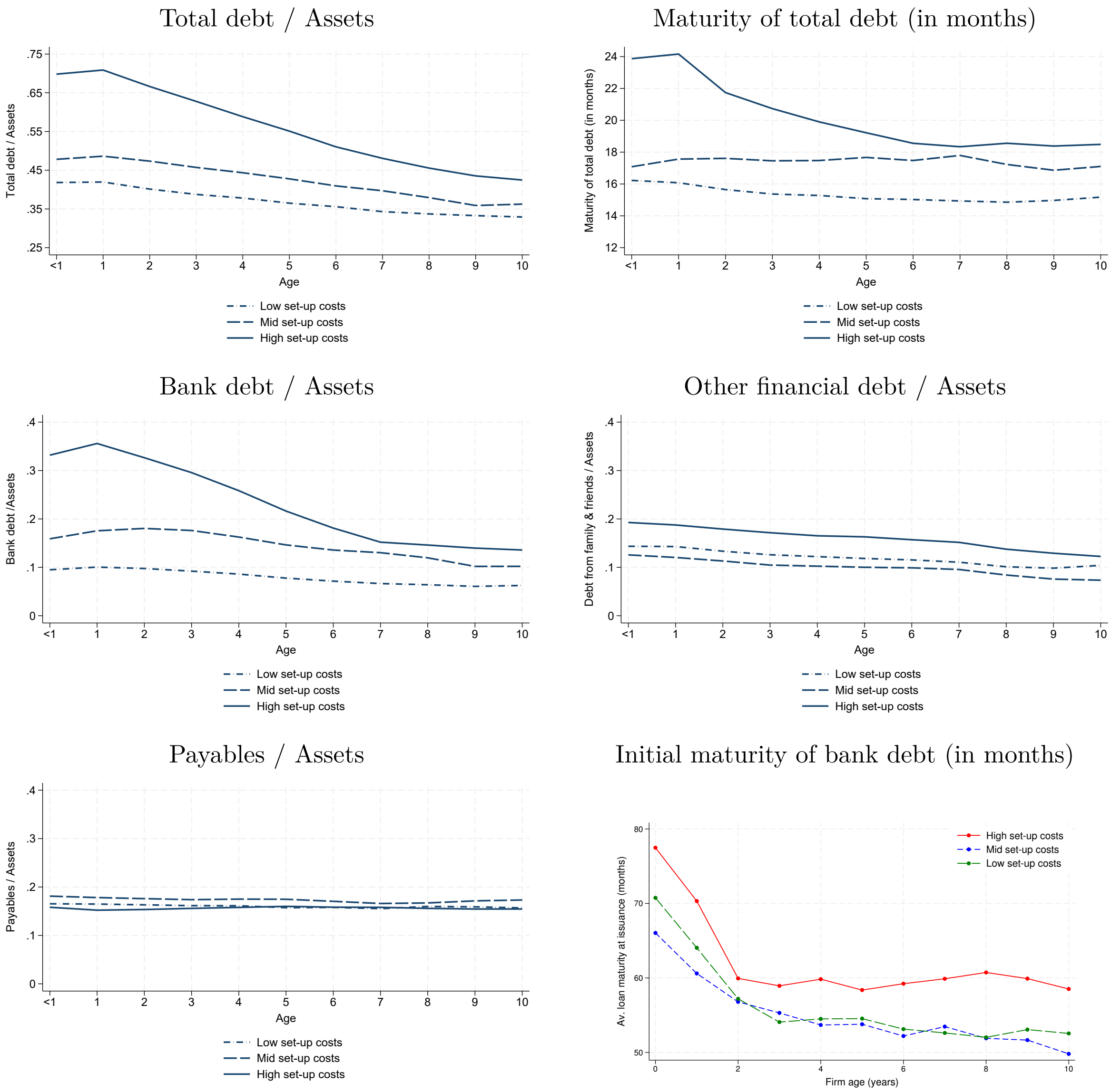

Figure 3: Lending to municipalities across treated and control banks

This figure shows total lending to municipalities across treated and control banks, as defined in Section 4.2. A bank is treated by the Dexia shock if it is highly exposed to municipalities borrowing heavily from Dexia before 2008. The loan volumes are normalized to 100 in 2008Q3.

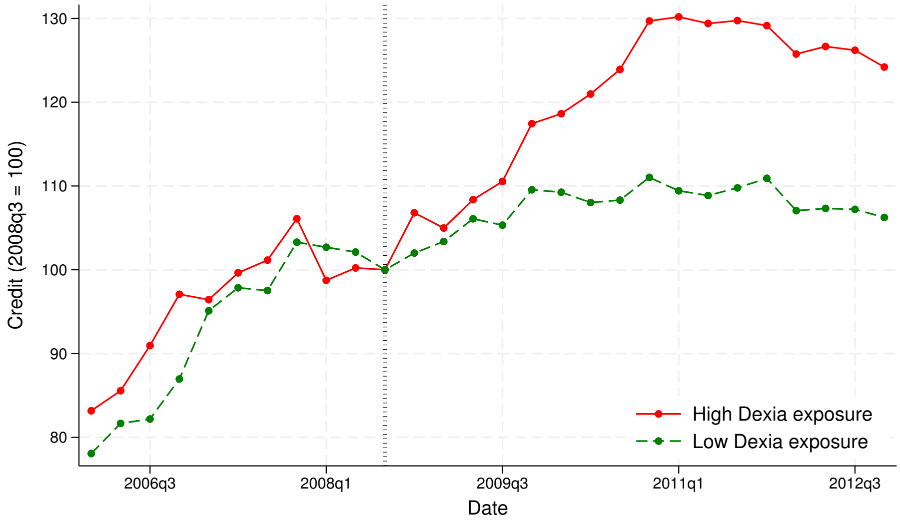

Figure 4: Corporate loan maturity across treated and control banks

This figure shows the initial maturity of loans to young firms (aged strictly less than 24 months) across treated and control banks, as defined in Section 4.2. A bank is treated by the Dexia shock if it is highly exposed to municipalities borrowing heavily from Dexia before 2008.

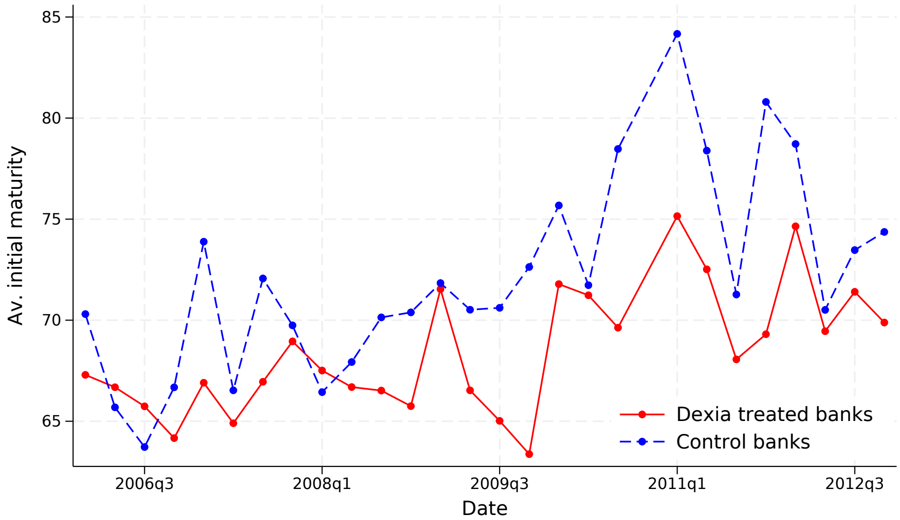

Figure 5: Corporate loan maturity and loan amount across treated and control banks: By set-up costs

This figure shows the initial maturity of loans and loan amounts to young firms (aged strictly less than 24 months) across treated and control banks, as defined in Section 4.2. A bank is treated by the Dexia shock if it is highly exposed to municipalities borrowing heavily from Dexia before 2008. In each panel, we break down the sample between firms in low and high set-up cost industries. 3-digit industries for low and high set-up costs are respectively industries in the bottom and the top tercile of the set-up cost distribution.

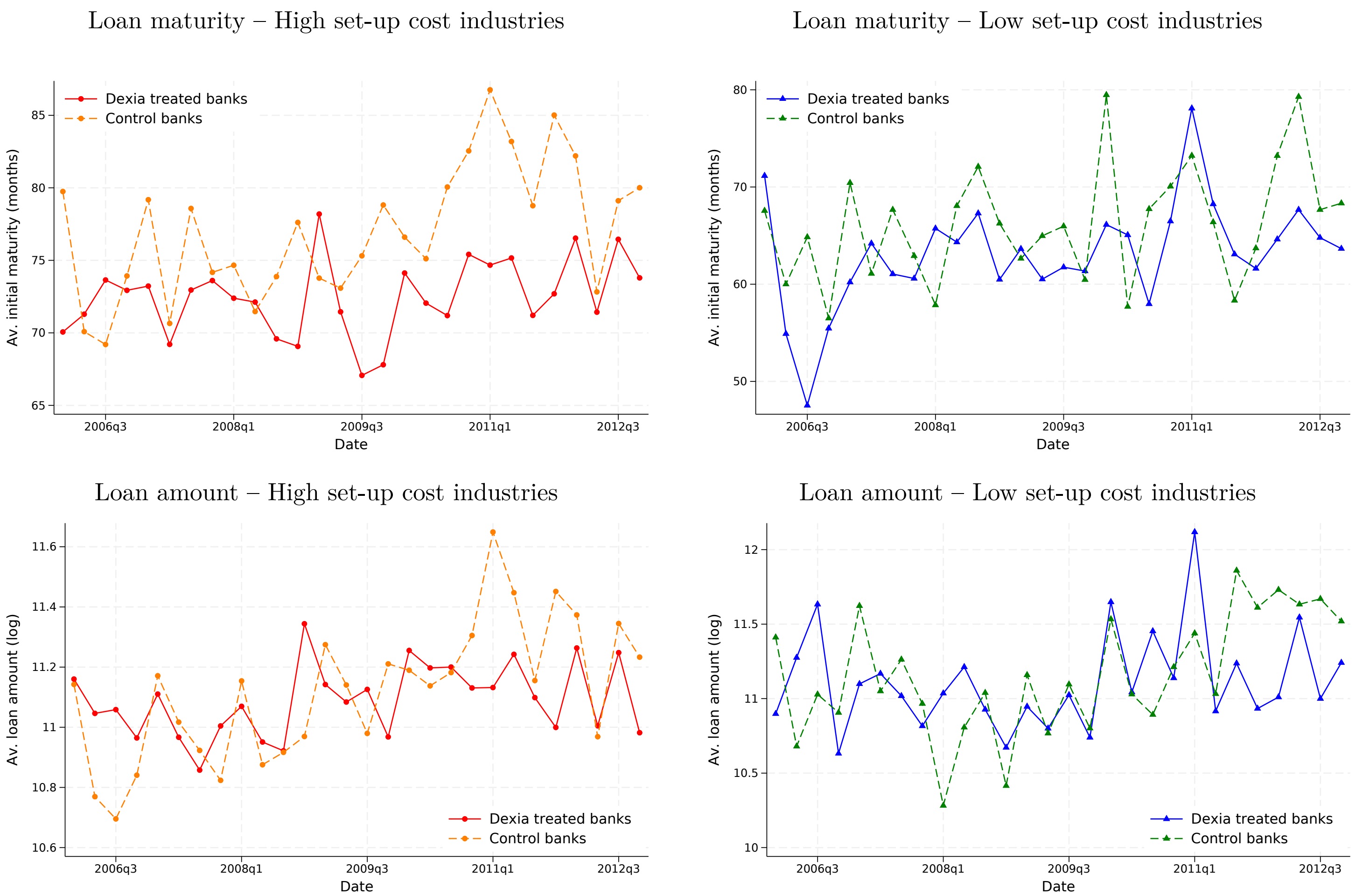

Figure 6: Firm creation and Dexia-treated counties: dynamic specification

This figure shows the coefficient of a dynamic specification of the PPML regression presented in Table 10, column 2. The dependent variable is the number of firm creations in a county-year in manufacturing industries. A county is treated by the Dexia shock if banks that lend heavily to Dexia-exposed municipalities before 2008 have a large market share (i.e., above the median across counties). The bars correspond to 95% confidence intervals.