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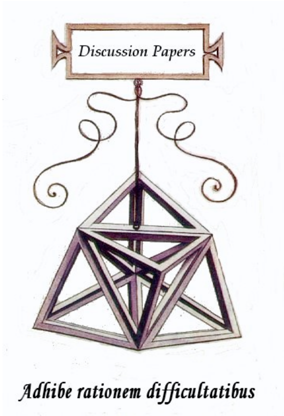


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# Debt concentration and performance of European firms

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n. 00

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# Debt concentration and performance of European firms

**Abstract**

This paper investigates the level of debt specialization across European firms relying on a cross-country comparable sample of manufacturing firms. We find a non-linear relationship between firm debt specialization (i.e. composition of the various types of debt) and firm size and age. In line with previous evidence for US firms, we observe that small and young firms have a more concentrated debt structure (i.e. they rely on few types of debt). Relying on quasi-experimental setting, we also find that firms having a diversified debt structure are less likely to experience a severe reduction in turnover.

**Classificazione JEL**: C24; G31
**Keywords**: Debt concentration, European firm financing, Generalized propensity score

# 1 Introduction

Traditionally bank loans constitute the main source of debt financing for the majority of European firms. As the recent financial crisis has shown, European firms are thus more vulnerable when bank lending tightens. A well developed bond market may therefore represent an alternative source of funding for the real economy when credit squeezes. If a firm can easily access external capital markets and/or switch to alternative sources of funding, the risk of being affected by a negative shocks experienced by its bank-loan providers is notably reduced (see Aoki and Nikolov (2012); De Fiore and Uhlig (2011)).

Indeed, in the recent years, debt capital markets seem to be growing in Europe: issuance of non-financial corporations has boomed in Europe (see Figure (1)), and surpassed for the first time in the crisis year 2009 US issuances (see (Kaya et al., 2013)). Thus, establishing the determinants of this trend (e.g. Custódio et al. (2013)), as well as the way each firm combines the different sources of funding may have important policy implications.

Recent theoretical contributions seek to explain the fall in the share of bank finance in corporate debt during the 2008-9 crisis by providing models where firm debt composition is an endogenous choice. For example, De Fiore and Uhlig (2015) present a DSGE model where firms optimally choose among alternative instruments of external finance. A key feature of their model is the existence of two types of financial intermediaries: banks (which are willing to spend resource to acquire information about firm productivity) and capital markets funds (which are not). Firms can thus choose among alternative instruments of external finance. One of their main finding is that when firms have full flexibility in substituting alternative instruments of debt finance, adverse shocks have very mild effects on investment and output. When firms have no access to the bond market, and banks cannot provide the flexibility needed, the negative real effects of a shock to bank costs are amplified. Similarly, in Crouzet (2014) firms can choose between two types of debt: bank loans and market debt. The central assumption is that banks offer more flexibility than market lenders when a firm is in financial distress. When firms move from bank finance to bond finance, they reduce borrowing and investment as they expect the cost of debt restructuring to increase in the future. As a result, the possibility to access bond market amplifies the negative effect of an increase in bank lending costs.

Previous empirical research has mainly focused on the proportion of investments firms finance externally, and on the determinants of individual sources of finance (e.g. equity, bank loans, leasing), without considering any concise indicator of debt structure (see for example Beck et al. (2008)). We can only mention Rauh and Sufi (2010) and Colla et al. (2013), both of which focus on debt specialization of firms located in the USA. Rauh and Sufi (2010) show that there are differences in the choice of borrowing sources between small and large firms, and between firms with high and low credit ratings. In particular, high-credit quality firms tend to use few tiers of capital, whereas low-quality credit firms tend to use several tiers of capital. However, they rely on a small samples of non-financial rated firms. Colla et al. (2013) investigate the determinants of the debt specialization for both rated and non-rated firms. They find that small (unrated) and opaque firms tend to rely on a fewer types of debt, while large rated and profitable firms borrow from a multiple sources of debt.

We contribute to this literature in three ways. First, we document the pattern of correlations between firm characteristics and debt structure across seven European countries (Austria, France, Germany, Hungary, Italy, Spain, and the United Kingdom). The second contribution of this paper is an analysis at a firm level of the determinant of debt specialization (i.e. of the use of various types of debt). The third contribution is to provide evidence on the causal relationship between firm debt specialization and firm turnover reduction. In particular, we rely on the generalized propensity score matching methodology for continuous variables recently developed by Hirano and Imbens (2004) and Imai and Van Dyk (2004). This quasi-experimental setting allows us to estimate the *average* response of firm turnover at each level of debt concentration (i.e. the *dose-response function)* by comparing firms that are similar in terms of observable characteristics. To check the robustness of these results, we also construct an indicator of debt specialization at country-sector level and use it among the explanatory variables of firm turnover reduction (a procedure similar to Guiso et al. (2004)). At the moment such analyses are not possible with other existing dataset (see below the data description).

This paper is also somehow related to the growing literature studying the capital structure variation and the determinant of debt maturity structure, also known as "granularity of corporate debt." It is well known that short-term debt have several disadvantages. For firms without access to other funds to meet debt repayments, short-term debt can for example lead to early firm liquidation (see Diamond (1991)). However, a recent strand of the literature suggests that firms manage multiple bond issues with different times maturities to mitigate rollover risk and debt overhang (Choi et al. (2013); Diamond and He (2014)). For example, Choi et al. (2013) show that it is less costly for a firm to be exposed to small rollover risks at two points in time rather than being exposed to a large rollover risk at one point in time. They also document a substantial variation in debt granularity among firms. That is, a large number of firms have a highly dispersed maturity structures, while others have a low dispersed maturity structure. They finally document that firm debt becomes more granular during economic downturns (when rollover risks are higher). We contribute to this debate by considering various types of debt with different maturities.

We find that a number of firm characteristics – such as firm size and age – help predict the firm composition of debt specialization. Specifically, in line with the evidence provided by Colla et al. (2013), we observe that small and young firms have a more concentrated debt structure (i.e. they rely on few types of debt). These relationships, however, are not linear and seem to be U-shaped. Among these group of European countries, Spanish and German firms have the most diversified debt structure. Consistently with previous research (see Beck et al. (2008)), we also find that only a few (but distinct group) of firm characteristics help explain the level of each single debt share. In line with the theoretical analysis of De Fiore and Uhlig (2015), we finally find that firms with a more diversified debt structure are – on average – less likely to experience a severe reduction in turnover than firms with the same characteristics, but a higher level of debt specialization.

The remainder of the paper is structured as follows: Section 2 introduces the dataset used in the current study and analyzes the debt structure in each European countries. Section 3 relies on multivariate regressions to relate firm characteristics to debt specialization of firm. Section 4 describes the generalized propensity score methodology, while Section 5 applies this methodology to study the relationship between firm debt concentration and turnover reduction. Finally, Section 6 summarizes and concludes our argument.

## 2 Data description

In this paper, we rely on the recently released EFIGE dataset collected within the project "European Firms In a Global Economy: internal policies for external competitiveness".[1] The dataset covers a large representative and cross-country comparable sample of manufacturing firms (more than 14000 firms) across seven European countries: Austria, France, Germany, Hungary, Italy, Spain, the UK. The data are fully comparable across countries, since it is derived from responses to the same questionnaire. The sampling design follows a stratification by industry, region and firm size structure. To allow adequate statistical inference appropriate *sample weights* will then be used in the following analysis. Results can therefore be extended to the entire population of European firms.

The EFIGE survey includes a wide range of questions which allow us to build both qualitative and quantitative variables on firms' characteristics and activities (e.g. proprietary structure of the firm; R&D investment, internationalization). Some of these questions refer to 2008, whereas others ask for information related to 2009 compared to years 2008/2007 (see Table (1) and (2) for a full description of the firm characteristics we will use). In particular, the dataset also allows us to have information on financial constrained firms, as firms are directly asked whether they applied for a bank loan, and if so, if their demand was successful or rejected. We can also clearly distinguish between listed and non-listed firms. All these information are important and offer a large number of covariates to appropriately perform the propensity score analysis. The key assumption of the GPS methodology (see below) is the *weak unconfoundedness assumption*, which is also known as the assumption of selection on observables: it requires that after controlling for observable characteristics, any remaining difference in treatment intensity (i.e. debt concentration level) across firms is independent of the potential outcome of interests. As this assumption is not statistically testable, to plausibly apply this method, a large set of covariates is thus required.

In relation to firm debt structure, the dataset allows us to collect the share of bank-loans and securities – both short-term and long-term – along with the share of other financial instruments (such as trade-credit, leasing). Specifically, the EFIGE survey in question F1 asks a firm the

[1] See www.efige.org and Altomonte and Aquilante (2012).

following question:

*What is the overall distribution of your **firm's debt structure** in percentage terms (please fill in)?*

| Type of debt | Percentage | | | |
|---|---|---|---|---|
| *1. short term bank debt (up to 12 months)* | | | | % |
| *2. medium to long term bank debt (12 months and over)* | | | | % |
| *3. short-term securities* | | | | % |
| *4. medium and long-term securities* | | | | % |
| *5. other financial instruments* | | | | % |
| Total | 1 | 0 | 0 | % |

which allows us to depict the entire firm debt structure at the end of 2008, see Table (3).[2]

Even if this dataset provides only a snapshot of European firms' debt structure, it has important advantages. At the moment, such an analysis is not possible with other datasets. For example, Amadeus database does not allow to distinguish between bank loans and bonds, which are merged into a single variable. The European Survey on Access to Finance of Enterprises (SAFE), though allowing to distinguish between different types of debt, it only provides the binary information (yes/no) for each source of funding and is mainly focused on SMEs. The World Business Environment Survey (WBES) used by Beck et al. (2008) – tough similar in the spirit – is not up-to-date (i.e. the survey year is 1999) and would result in a much smaller sample size for Europe (i.e. less than 40/50 observations per country).

One *caveat* of this database is that this question is only asked to firms that declared having looked for external financing in the year 2008-2009 (i.e. question F0), which amount to 45% of the interviewed firms. We will account for this selection problem in section 3, and in section 4 where we rely on the entire sample of firms to study the relationship between firm debt-concentration and turnover reduction. Nevertheless, here it is important to stress that by using this dataset we are able to replicate (see below) previous results on the determinants of each single firm debt share (e.g. Beck et al. (2008)) as well as on firm propensity to hold debts (e.g. Faulkender and Petersen (2006)). These results further support the validity of using this database.

Indeed, the EFIGE dataset shows well known phenomena concerning the single sources of funding of European firms (see, for example, Allen et al. (2004)). Specifically, if we analyze firm debt structure, we can see that in bank-based countries (Italy, Spain and Austria) the share of bank debt is quite high (about 85%), whereas in market-based countries (United Kingdom and France) the share of debt securities is much larger than in bank-based countries ( 6-9% vs 2%, see the value of these shares in panel 1 and 2 of Figure (2) and Table (3)). We can also observe that the share of short-term bank loans and securities is higher in Spain, Hungary and Italy compared to Germany, whereas the share of long-term bank loans is lower. In Spain, however, firms can rely on a larger share of long-term securities. In addition, in all these countries, the

[2]The entire questionnaire is available in Altomonte and Aquilante (2012).

shares of debt securities remain fairly low. Moreover, if we consider all types of debts together according to their maturities (see panel 3 of Figure (2) and Table (3)), we can see that in Hungary and Italy there is a higher overall share of short-term debt.

However, the EFIGE dataset also highlights other interesting phenomena. In particular, we can observe that German firms have a more diversified debt structure compared to other European firms. However, to see this latter phenomena, we need to summarize the information about the debt structure of each firm at the end of year into a concise indicator (see Colla et al. (2013) for a similar study in the US). That is, we need to combine into a single indicator the information on the relative amount of bank debt vs corporate securities - both short-term and long-term. Similar to Colla et al. (2013), we chose to rely on the Herfindhal-Hirschmann Index (in the following HHI) – the traditional indicator of market concentration – as our measure of debt-specialization.

The HHI index of debt structure can be calculated as the (squared) sum of the each debt share of the firm normalized according to the number of types of debt. That is,

$$HHI = \frac{[(short\ bank\ loans)^2 + (long\ bank\ loans)^2 + (short\ securities)^2 + (long\ securities)^2 + (other\ financial\ instruments)^2] - 1/5}{1 - 1/5}$$

The index assumes the maximum value of one when there is only one source of funding, and thus the maximum degree of debt specialization. The index assumes instead the value of zero when the firm equally divides the debt across all sources of funding. Relying on EFIGE-data we computed this index for each firms in the sample and averaged it across countries (using the appropriate weights to account for the probability of each firm of being sampled). As Figure (3) shows, the value of the HHI is quite high in all European countries, with the median level (the red circle) being equal to the maximum in some of them, suggesting that European firms do not tend to diversify their debt. Firms located in Germany and Spain seem to have the most diversified structure among these group of countries. Interestingly, as Figure (4) highlights, the variability of the HHI between countries is higher than within the same country but across sectors (only in Austria there is a larger within-country variability). This latter characteristic further points to the usefulness of the cross-country EFIGE dataset to analyze the determinant of firm debt specialization.

# 3 Determinants of firm debt concentration

In Table (4) we study at a firm level the determinants of debt concentration (i.e. the HHI index will be our dependent variable) relying on a fractional logit regression (Papke and Wooldridge (1996)). Reported coefficients are marginal effects. This model can handle a variable which is confined in the interval [0,1] and with a significant number of observations at either zero or one. Although it would not be possible to make any casual claim as we rely on a cross-sectional regression, we can still derive important correlations which can also give insights on the different drivers in European countries. To account for any variable that might affect at sector level the structure of firms debt, we always include sectoral dummies.

In column (a) we start with a dummy for each age class of the firms. The base category are firms older than 20 years old. We can observe that firms aged between 6-20 years old have a higher concentrated debt structure (+3.5%), while young firms (less than 6 years old) seem also to have a slightly higher concentrated structure (+1%), though the coefficient is not statistically significant. There is thus a U-inverse relationship between firm age and debt concentration. We then examine the structure of debt concentration across firms of different size. In column (b) we thus add a dummy for each size class (in terms of number of employees). The base category are small firms (with 10-19 employees). As the coefficient on each category is negative, the grower the firms, the lower will be the concentration index. This result is line with the evidence provided by Colla et al. (2013) for US firms. As it has been highlighted several times in the literature (Berger and Udell (1998)), small firms cannot rely on several sources of funding as for them the (fixed) costs to access to capital markets are higher. This relationship, however, is not linear, and there seems to be a U-relationship between firm size and debt concentration: medium size firms (20-49 employees) have a debt concentration 4% less concentrated, large firms (50-249 employees) 8% less concentrated, and very large firms (over 250 employees) 4% less concentrate. This latter result is consistent with a theoretical model in which banks offer more flexibility than market lenders when the firm is in distress but – outside of financial distress – bank lending have higher intermediation costs than markets (see Crouzet (2014), Bolton and Scharfstein (1996)): when the cost of lending of banks relative to those of markets increases substantially, medium-sized firms switch to a more market-financed debt structure (i.e. a higher concentration debt index).

In column (c) we add a dummy for firms belonging to a group (*Group*) and that have been involved in mergers and acquisition deals (*M&As*). Only being part of a group seems to positively and significantly affect firm debt structure (+3%).

In column (d) we add a dummy equal to one for firms that declared to have been financial constrained (*Financial constraint*s) and experienced an increase in the cost of bank lending (*Increase finance cost*) in 2008. As one would expect, these variables have a negative effect, which is statically and economically significant (about 5% less concentrated), on debt concentration. Firms that were not (fully or partially) granted bank loans, either successfully looked for alternative sources of funding or did not reach the desired amount of credit, resulting in a lower value of the HHI index. To investigate whether information asymmetries are responsible for different debt concentration, we then add a dummy equal to one for firms involved in R&D activities (*R&D*) - as a proxies for firm opaqueness, and a dummy for firm operating outside the domestic market (*Export*). Even in this case, these variables have a negative impact on debt concentration. This result is robust if we replace the R&D dummy with its percentage of firm-turnover, and contrasts with Colla et al. (2013). In column (e), we add a dummy for listed firms. Though as expected the coefficient is negative (i.e. listed firms are expected to rely on more source of funding by having easier access to bond markets), it is not statically significant.

Finally, in column (f) we add a dummy for each country in our dataset to account for all the (unobservable) macroeconomic conditions which may affect debt concentration in year 2008 (such as short-term rate, inflation or default spread, see (Erel et al. (2012))). The base category are firms located in Germany. In all countries but Spain, firms have a higher concentration debt index compared to firms located in Germany. For example, Hungarian firms have a debt structure that is about 13% more concentrated than German firms. This analysis of the Efige-data thus suggests that German and Spanish firms have the most diversified debt structure in Europe.

In addition, in Supplementary Material available online[3], we further show that these results are robust to firm selection into debt (e.g. Faulkender and Petersen (2006); JS Ramalho and da Silva (2009)), relationship lending (Elsas (2005)), industry level of external finance and firm ownership types (e.g. Rajan and Zingales (1995)). In line with previous studies, for example, we find a positive (and thus opposite) effect on firm decision to hold debts (Faulkender and Petersen (2006); JS Ramalho and da Silva (2009)). We finally also study the determinants of each debt component. In line with Beck et al. (2008), we do not find any significant difference in the use of single sources across firm of different age and size.

To summarize, these results suggest that firm size and age affect the composition of firm debt structure (but not the level of each debt share). In particular, small and large firms have a more concentrated debt structure. Germans and Spanish firms have the most diversified structure. These results hold controlling for a number of other firm characteristics and unobservable sector characteristics.

# 4 Generalized propensity score methodology

To estimate the causal effect of different level of debt specialization on firm performance (i.e. level of turnover reduction), we resort to generalized propensity score (GPS) estimation (Hirano and Imbens (2004); Imai and Van Dyk (2004)), which is an extension to continuous treatments of the popular propensity score method for binary treatment developed by Rosenbaum and Rubin (1983). This method can, for example, be used to estimate the causal effect of the frequency and duration of smoking instead of the simple effect of smoking (Imai and Van Dyk (2004)). It has also been used to evaluate the effect of European funds on GDP/capita growth (Becker et al. (2012)). The assessment of the heterogeneity of these treatment effects over the continuous dimension essentially amounts to estimating a *dose-response function.* In this paper, this corresponds to estimating the *average* response - i.e. the level of turnover reduction - that is associated to specific values of the continuous dose - i.e. the level of HHI.

The key challenge is to compare firms with sufficiently similar characteristics but different level of debt concentration (i.e. HHI) in order to construct a quasi-experimental setting.

[3] `https://sites.google.com/site/caterinagiannetti/home/current-research/working-papers`

Let us define a set of potential outcome $\{Y_i(t)\}$ for $t \epsilon T$, where $T$ represents the continuous set of potential treatments defined over the interval $[t_0, t_1]$, and $Y_i(t)$ is referred to as the unit-level dose-response function. For each firm $i$, with $i = 1, ..., N$, we observe a $k \times 1$ vector of covariates, $X_i$; the level of treatment delivered, $T_i$ (i.e. the level of HHI); the corresponding outcome $Y_i = Y_i(T_i)$ (i.e. the level of turnover reduction).

Hirano and Imbens (2004) generalized the concept of unconfoundedness for binary treatments to one of *weak unconfoundedness* for continuous treatments

$$Y(t) \perp T \,|X \quad for\, all\, T \tag{1}$$

Firms differ in their characteristics $X$ such that some are more or less likely to have higher HHI level than others. Weak unconfoundedness means that, after controlling for observable characteristics $X$, any remaining difference in the level of HHI (i.e. $T$) across firms is independent of the potential turnover outcome (i.e. $Y(t)$).

The generalized propensity score is defined as

$$R = r(T\,|X) \tag{2}$$

where $r(t, x) = f_{T|X}(t\,|x)$ is the conditional density of the treatment given the covariates. Similarly to the propensity score with binary treatments, the generalized propensity score is assumed to have a balancing property which requires that, within strata $r(t, x)$, the probability that $T = t$ does not depend on the value of $X$. In other words, conditional on observable characteristics $X$, when looking at two firms with the same *ex-ante* probability of being of having a certain HHI, their actual level of HHI is independent of firm observable characteristics. That is, the propensity score summarizes all the information in a multi-dimensional vector $X$ so that

$$X \perp 1\,\{T = t\}\,\,|r(t, X) \tag{3}$$

In combination with weak unconfoundedness, the balancing property implies that assignment to treatment is *weakly unconfounded given the generalized propensity score.* Then, for every $t$

$$f_T(t|r(t, X), Y(t)) = f_T(t|r(t, x)) \tag{4}$$

Given these results, it is possible to use the GPS methodology to remove bias associated with differences in covariates in three steps:

1. Define and estimate the $r(t, x) = f_{T|X}(t\,|x)$ (i.e. the generalized propensity score)

2. Estimate the conditional expectation of the outcome (i.e. the level of turnover reduction) as a function of two scalar variables, the treatment level T (i.e. the HHI) and the generalized propensity score R: $\beta(t, r) = E[y\,|T = t,\, R = r]$;

3. Estimate the dose-response function at a particular level of the treatment intensity by averaging this conditional expectation over the generalized propensity score at that particular level of the treatment intensity: $\mu(t) = E[\beta(t, r(t, X))]$

The first step consists of modelling and estimating the GPS, while the second step estimates the conditional expectation of the outcome (i.e. the turnover reduction) as a function the treatment variable (i.e. the HHI) and the GPS. These two steps do not have a causal interpretation. The last third step estimates the *dose-response* function. For each firm, we have as many as propensity score as there are levels of the treatment. At each particular level of treatment, the *average* response is obtained by averaging the conditional expectation function over the GPS at that particular level of the treatment. The derivative of the dose–response function with respect to the HHI level —which is commonly referred to as the t*reatment-effect* function — has a causal interpretation, and measures the effect on turnover reduction of an increase in debt specialization.

# 5 Debt structure and firm performance

To get a first insight on the relationship between firm performance and firm debt concentration, we run in Table (5) an ordinal logit regression in which the dependent variable is a categorical variable which account for the reduction in firm turnover in 2009 in comparison with 2008. More precisely, the variable is equal to zero if the firm experienced no reduction, to one if experienced a reduction of 10%, to two if experienced a reduction between 10% and 30%, and to three if the reduction was above 30%. Reported coefficients represent the average of marginal effects for each category of turnover reduction. It is interesting to see that the indicator of debt concentration (i.e. the HHI index) is positively and significantly associated with turnover reduction. That is, firms relying on a less diversified debt structure also end up to get a strong reduction in the turnover. For example, firms with higher level of HHI are 3% less likely to experience no reduction in turnover, while they are 3% more likely to experience a severe reduction (above 30%). This more evident if we report on a graph the predicted probabilities for each class of turnover reduction in relationship with different level of the HHI (see Figure (5)): as this figure highlights the higher the level of HHI, the lower are the predicted probabilities of experiencing no reduction in turnover (see the blu-line with circles). From Table (5) we can also observe that financially constrained firms are also more likely to experience important reduction in turnover (+8%).

Given the cross-sectional nature of our data, however, the actual causality direction is hard to disentangle. In the following, we thus aim to conduct a casual analysis relying on the generalized propensity score estimation.

## 5.1 Pratical implementation of the GPS methodology

**Estimation of the propensity score.** Hirano and Imbens (2004) rely on a normal distribution to estimate the treatment intensity given the covariates. However, in this context, $T$ (i.e. the level of HHI) cannot be assumed to be normally distributed as discount rates are a fractional variable bounded between $[0, 1]$. In addition, it is not possible to resort to GLM to estimate discount rates relying on a fractional logit regressions as in Papke and Wooldridge (1996), i.e. as in Table (4), as this would not allow in the subsequent (second and third) steps to fully specify the density function of the treatment estimates. It is also not possible to assume a Beta distribution as in Bia et al. (2014), as we have several observations at two limits (0 and 1). We therefore resort to a two-limit Tobit Model assuming the following distribution for the treatment intensity given the covariates:[4]

$$T_i|X_i \sim \Phi(L_1 - x_i\beta/\sigma)^{d_0} \cdot 1/\sigma\phi(y_i - x_i\beta/\sigma)^{d_1} \cdot \Phi(L_2 - x_i\beta/\sigma)^{d_2}$$

where $\Phi(.)$ is the standard normal cumulative distribution function, $\phi(.)$ is the standard normal probability density function, $\sigma$ is the standard deviation, $x_i$ is a row vector of covariates and $\beta_1$ a column vector. $L_1$ and $L_2$ are the lower and upper limits of the censored distribution (in our case 0 and 1 respectively), and $y$ is a generic notation for observed values within the limits. For each observation, only one of the exponents $d_j$ $(j = 0, 1, 2)$ will take the value of one, depending upon whether the observed value is either equal to or within the two limits. Table (6) reports the results of the Tobit estimation. Results are in line with those of Table (4). Importantly they confirm a non-linear relationship between firm size and firm debt concentration.

**Common support condition and balancing of covariate**. Similarly to standard propensity score matching methods, we test the common support condition as follows. We divide the sample into three groups $j = 1, 2, 3$ , which are defined by the terciles of the distribution of the HHI index (i.e. debt concentration). For each treatment group $j$, we calculate the median treatment intensity $T_{Mj}$ and evaluate the GPS for the whole sample at median treatment intensities using the estimates for $\beta$ and $\sigma$ derived from Table (6). Hence, we calculate $\hat{R}(T_{Mj}, X_i)$ for each group and each observation $i = 1, .., N$. We then divide the GPS obtained into three blocks. We test the common-support condition by plotting the GPS values $\hat{R}(T_{Mj}, X_i)$ for each block against the GPS values the distribution of the GPS (i.e. $\hat{R}(T_{Mj}, X_i)$) for the rest of the sample. For example, in Figure (6) - panel *a* - we plot the distribution of the GPS for group 1 (see the black bars) against the distribution of the GPS for the rest of the sample, i.e. group 2 and 3 (see the white bars). Similarly for group 2 and 3 (see Figure (6), panel *b* and *c*). By inspecting the overlap of these distributions, we find that there are 90 firms whose GPS is not among the common regions of the three groups. We thus impose the common support by dropping those firms (less than 1% of our sample), for a total of 6664 observations.

To test the balancing property, we apply the approach of blocking on the score suggested by Hirano and Imbens (2004). As above, we again divide the sample into three groups according

[4] Thanks to Alessandra Mattei and Jeff Wooldridge for helping on this point.

to the terciles of the distribution of the debt specialization (i.e. the HHI). Within each group, we evaluate the GPS at the median values of the treatment variable (i.e. the HHI). Then, we divide each group into five blocks by the quintiles of the GPS evaluated at the median level.[5] Within each of these blocks, we compare the mean difference of each covariates with respect to individuals who have a GPS such that they belong to that block (i.e. the same *predicted* treatment intensity) with those who are in the same block, but have a different actual treatment intensity (i.e. groups). That is, we assign each individual to the respective block according to its GPS evaluated at the median level and compare the means of covariates with individuals in a different treatment level (i.e. in the control group), but similar GPS. Table (6) illustrates the group and block structure. For instance, we compare the covariates of 99 observations in group 1/block 1 to 1742 observations in control 1/ block 1. Taking the sum over all blocks and adding the respective control groups yields the total number of observations (i.e. 6664) in the common support regions. If adjustment for the GPS properly balances the covariates, we would expect all differences not to be statistically significant. Table (7) reports the mean *t-statistics* for each group across all covariates. There is evidence that the balancing property is satisfied, with only 3 out 75 t-values significant after controlling for the GPS. We thus conclude that the estimated generalized propensity score perform well in reducing potential treatment bias.

**Estimate the conditional expectation of the outcome.** Using the GPS values estimated in the first stage $\hat{R}$ (see Table (6)) and the observed treatment intensities $T_i$ we can estimate the conditional expectation of the outcome $Y_i$ as a flexible function of these two arguments:

$$\varphi E\{(Y_i \mid T_i, R_i)\} = \alpha_0 + \alpha_1 T_i + \alpha_2 T_i^2 + \alpha_4 \hat{R}_i + \alpha_5 \hat{R}_i^2 + \alpha_6 \hat{R}_i^3 + \alpha_7 T_i \hat{R}_i$$

where the GPS terms aim controlling for selection into treatment intensities. The estimated coefficients have not direct causal interpretation. However, if the estimated coefficients of the GPS terms are equal to zero indicate whether the covariates introduces any bias (Hirano and Imbens (2004)). More precisely, if the GPS terms are jointly significant, their introduction is indeed relevant and significantly reduces the bias of the estimated response of the level of turnover reduction to changes in the level of debt concentration. The results are reported in Table (9). We do not include $T^3$ as it never turned out to be either single or jointly significant.

**Obtain the dose-response function.** The last steps consists of averaging the estimated regression function over the score function evaluated at the desired level of the treatment. Given the estimated parameters $\hat{\alpha}$, the observed level of the HHI (i.e. $T_i$) and the estimated GPS (i.e. $\hat{R}$), the *average* potential outcome (i.e. the average probability) is obtained as

$$E\{Y(t)\} = \frac{1}{N}\sum_{i=1}^{N} \hat{\alpha}_0 + \hat{\alpha}_1 T_i + \hat{\alpha}_2 T_i^2 + \hat{\alpha}_4 \hat{r}(t, X_i) + \hat{\alpha_5} \hat{r}(t, X_i)^2 + \hat{\alpha}_6 \hat{r}(t, X_i)^3 + \hat{\alpha}_7 T_i \hat{r}(t, X_i)$$

The entire dose-response function can then be obtained by estimating this average potential outcome for each level of the treatment.

In other words, for each firm we have to evaluate the GPS for each level of the treatment, so that we have as many propensity scores as there are levels of treatment. Then, for each level

[5] Choosing a finer or coarser specification does not change significantly the results.

of the treatment, we obtain the average response by averaging over all the firm responses. We use bootstrap methods to obtain the standard errors that take into account estimation of the GPS and the $\hat{\alpha}$-parameters. In addition to the dose–response function itself we also display its derivative with respect to HHI level —which is commonly referred to as the treatment-effect function, and it has a causal interpretation. Results are those reported in Figure (7)-(10).

Each figure consists of two parts showing:

1. the *dose-response function* (i.e. the average probability for each potential outcome at each HHI level);

2. the *treatment effect-function* (i.e. the derivative of the dose-response function with a gap equal to 0.1).

The latter function allows us to infer the difference between two levels of debt concentration (HHI vs HHI + 0.1), and it has thus a causal interpretation. For both functions, we report their block-bootstrapped 90% confidence bands.

According to the dose-response function in the left of panel of Figure (7), the probability of experiencing no reduction in turnover does not constantly increase with higher level of HHI. In particular, as the treatment effect-function in the right of panel of Figure (7) suggests, a marginal increase in the level of HHI leads to a reduction in the probability of experiencing no reduction in firm turnover. Similar conclusions can be obtained by looking at the dose-response and treatment-effect functions in Figure (8), which reports the results related to a reduction in turnover lower than 10%. These results are consistent with those obtained in Tab (5).

The estimated dose-response and treatment-effect functions in Figure (9) and Figure (10) also confirm the results of the previous analysis. In particular, as the treatment-effect functions in these figures highlight, at higher the level of debt concentration (i.e. HHI), there is an increase in the probability of experiencing a substantial reduction in firm turnover.

Overall, the results from the propensity score analysis are consistent with the result from the ordinal logit regression (see Table (5)), suggesting that firms with a more diversified debt-structure are less likely to incur in severe turnover reduction. This result is thus in line with the theoretical analysis provided by De Fiore and Uhlig (2015), which show that firms' ability to substitute among alternative instruments of debt finance are important to uphold the economy from adverse real effects of a financial crisis.

## 5.2 Sensitivity analysis

As a final check of the robustness of the results from the generalized propensity score analysis, we construct an indicator of debt specialization by exploiting the entire sample of firms. We proceed in three steps. First of all, we utilize the values of the dummies for each country and sector in Table (4) to construct an index of country debt specialization which varies across countries and sector (a procedure similar to the one used by Guiso et al. (2004) to develop an index of financial development). We are therefore relying on estimations that are obtained using only the sample of firms holding a positive amount of debt. According to this index (see Table (10)), we observe the lowest level of debt concentration in Spain and in Germany, where there is also lower variability across sectors.

In the second step, we use this indicator of country debt specialization as an explanatory variable in the regressions for firm turnover but this time exploiting the entire sample of firms (i.e. including also those firms without any positive amount of debt). The exogeneity of this indicator can be assumed here since the group of firms who hold debt do not coincide completely with the group of firms that have been used to construct the country-measure of debt specialization. However, in this setting (and especially in the third step) the use of country dummies is problematic. We therefore remove countries dummies but control for other country-level macro-economic characteristics by including country gdp per capita in 2007 (which is also a predetermined exogenous variable). Results suggest (see column *a, b, c, d* in Table (11)) that firms in country with higher level of debt specialization are less likely to experience no reduction in turnover (-56%), and more likely to experience important reduction in firms turnover (+26% for reduction between 10-30%, and +41% for reduction above 30%).

# 6 Discussion and Conclusions

During the financial crisis of 2007-09, European banks were concerned about their counterpart exposure to the US sub-prime market and began to hoard liquidity. In order to repair their balance sheets and deleverage, they thus started to progressively tightening credit conditions. As a consequence, in such period of reduced bank credit availability, European firms also started shifting the composition of their debt from bank loans towards debt securities. The way in which bank loans has been replaced with other sources of funding has differed across countries and was related to factors that vary across Member States, such as the role of small firms in the economy, their access to market financing, the importance of the linkages between banks and firms. Everywhere, however, the development of a financial system that is less resilient on banks and offers a broader range of financing alternatives is seen as desirable.

To shed some lights on the determinants of firm debt structure and on the level of debt specialization, in this paper we take advantage of a cross-country comparable sample of manufacturing European firms who answered the EFIGE survey. At the moment, such an analysis is not possible with other existing datasets. The reliance on this dataset, along with survey weights, allows to examine this question in great detail and to extend the results to the entire population of European firms. Our results suggest that firm age and size significantly affect the way each firm combines the different types of debt (i.e. debt concentration). In particular, in line with the evidence provided by Colla et al. (2013) for US firms, small and young firms have a more concentrated debt structure. The relationship, however, are not linear and are U-shaped. Consistent with previous research, we also find that size has an opposite effect on firm choice to hold debt (e.g. JS Ramalho and da Silva (2009)), and it does not affect the level of each debt component (e.g. Beck et al. (2008)). These latter results support the reliability and validity of this dataset for studying the determinants of debt concentration of European firms.

Finally, the richness of the EFIGE database allows us to perform a quasi-experimental analysis. Relying on the generalized propensity score methodology recently developed by Hirano and Imbens (2004) and Imai and Van Dyk (2004), we estimate the average response of firm turnover reduction to each level of debt concentration. Even if we are not able to compare the performance of the same firm with a different debt structure over time, we are able to compare the average performance of firms with very similar characteristics but different level of debt specialization. The evidence resulting from this analysis suggests that it is less likely to observe a severe reduction in firm turnover if firms have a diversified debt structure. This result is thus in line with the theoretical analysis provided by De Fiore and Uhlig (2015), which show that firms' ability to substitute among alternative instruments of debt finance are important to uphold the economy from adverse real effects of a financial crisis. This result has also important policy implications. For example, in the light of the above results it would be beneficial in bank-based countries to encourage firms to rely more on markets as a source of funding to achieve a more diversified structure (and viceversa for market-based countries). As such, a policy that has the potential to bridge the gap between the funding needs of firms and the availability of bank loans (e.g. by promoting market for debt securities with a tax exemption for issuers, as in Italy in 2012, or a favorable environment for bond issuance, as in Germany in 2010) may work properly.

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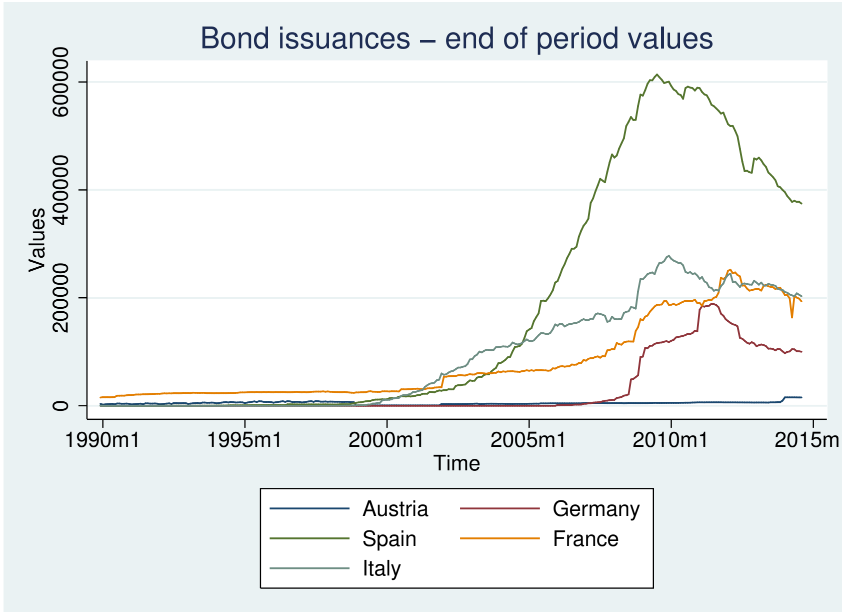
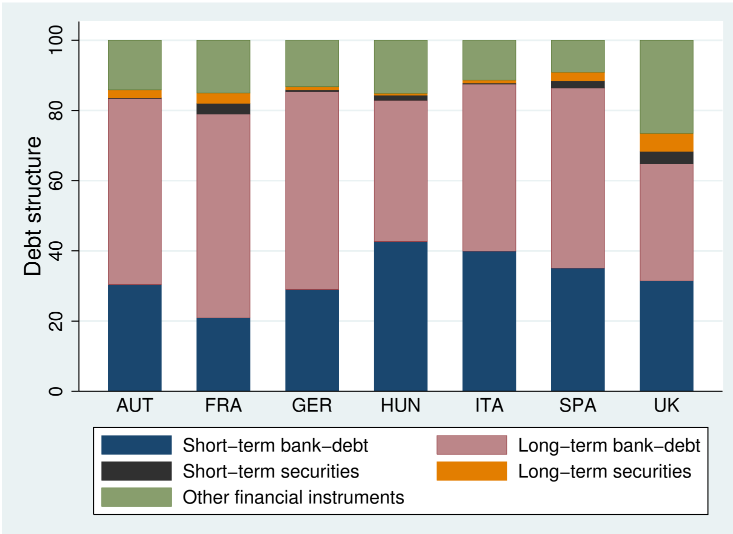
Figure 1: **Bond issuance in Europe**



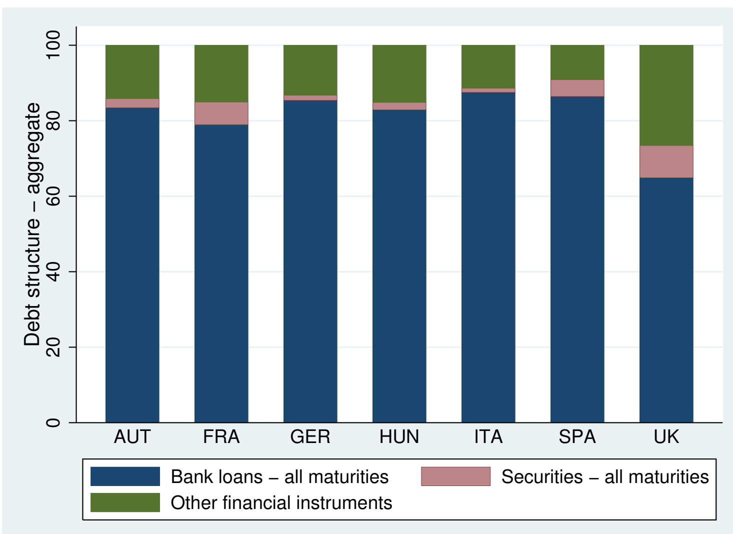

Source: Bank of Italy

Figure 2: **Debt structure of European firms**

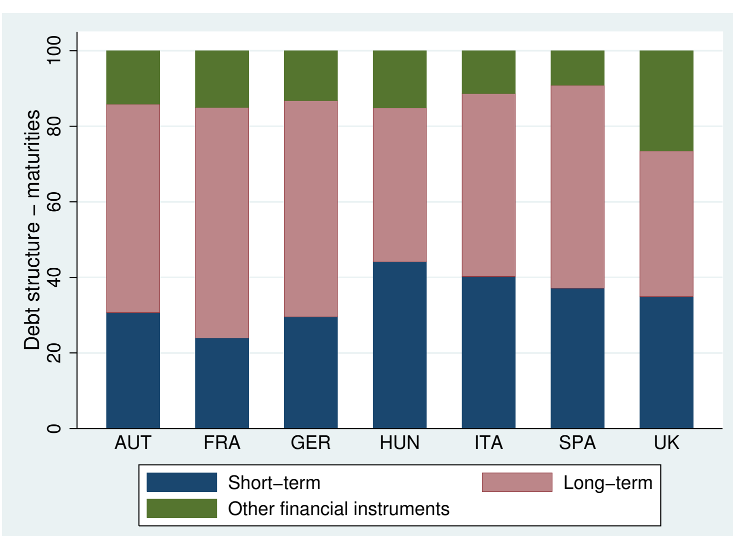
**End of period values -2008**




1.



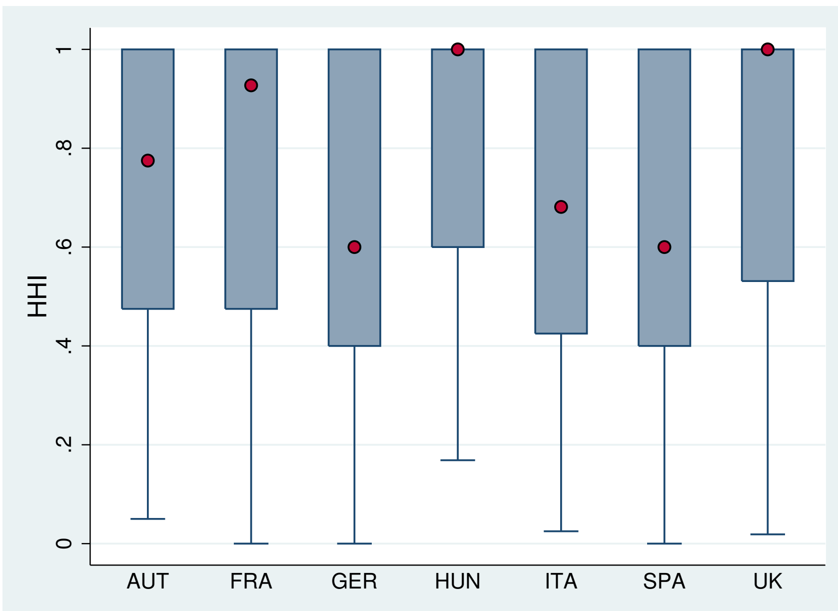

2.




3.

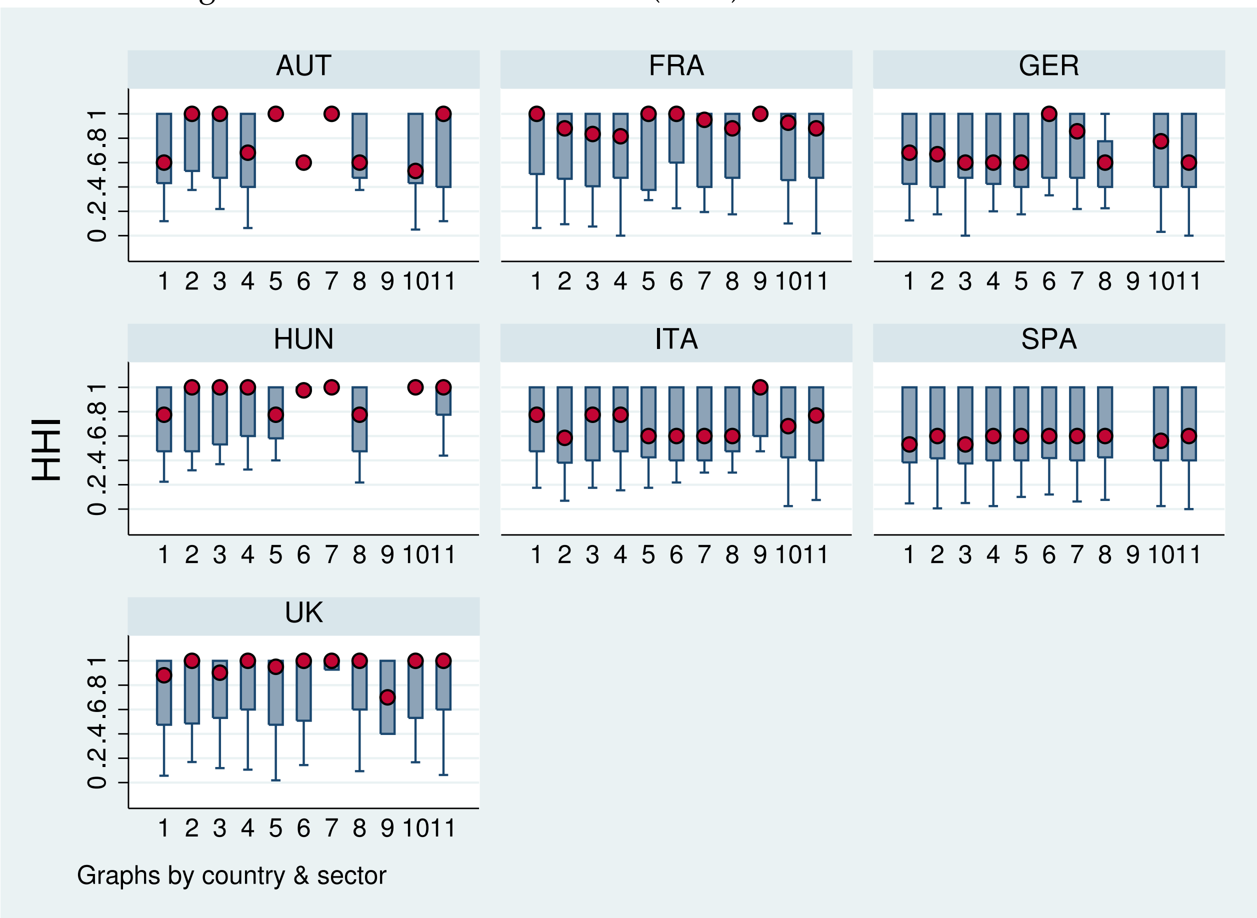
Note: Each graph represents the (weighted) average for each country of each type of firm debt share. For each firm the sum over all types of debt equal 100.

Figure 3: **Concentration of Debt Structure (HHI)**



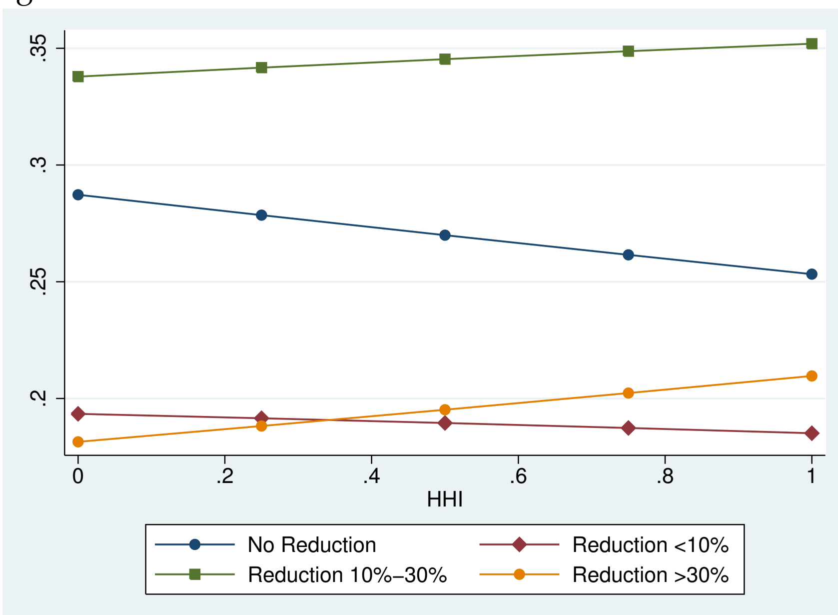

Note: The HHI index is constructed as the (squared) sum of each debt share in 2008. It assumes the maximum value of one when there is only one source of funding, and the minimum value of zero when the debt is equally divided among all sources. The graph represents the (weighted) distribution for each country of the HHI index over the firms in the sample. The red circle represents the median level.

Figure 4: DEBT CONCENTRATION (HHI) ACROSS COUNTRY & SECTOR



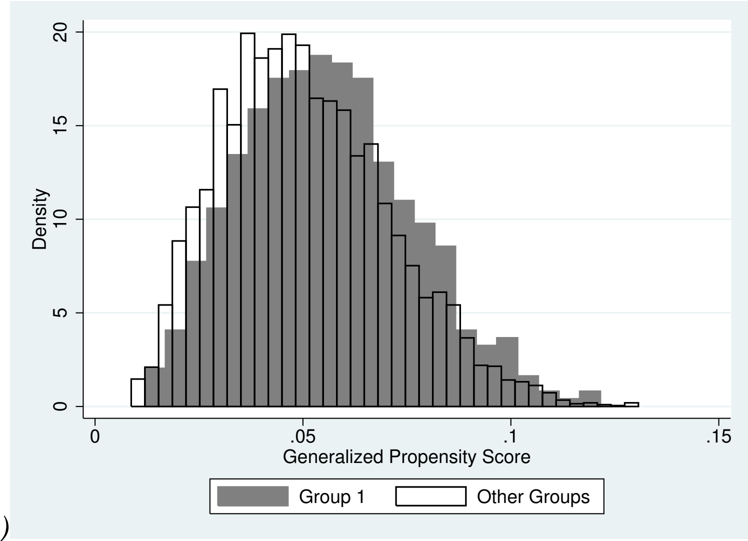

Note: The HHI index is constructed as the (squared) sum of each debt share in 2008. It assumes the maximum value of one when there is only one source of funding, and the minimum value of zero when the debt is equally divided among all sources. The graph represents the (weighted) distribution for each country of the HHI index over the firms in the sample. The red circle represents the median. Sector correspondence with Nace Rev1.1 →Sector 1: *Metal Products* (27-28); Sector 2: *Food & Tobacco* (15-16); Sector 3: *Rubber & Plastics* (25); Sector 4: *Textile & Paper* (17-18, 21-22); Sector 5: *N.E.C* (36-37); Sector 6: *Chemicals* (24); Sector 7: *Transport Equipment* (34-35); Sector 8: *Wood* (20); Sector 9: *Coke & Petroleum Products* (23); Sector 10: *Leather, Eletrical & Optical Equipment* (19, 26,30-33); Sector 11: *Machinery* (29).

Figure 5: **Firm reduction in turnover and debt concentration**

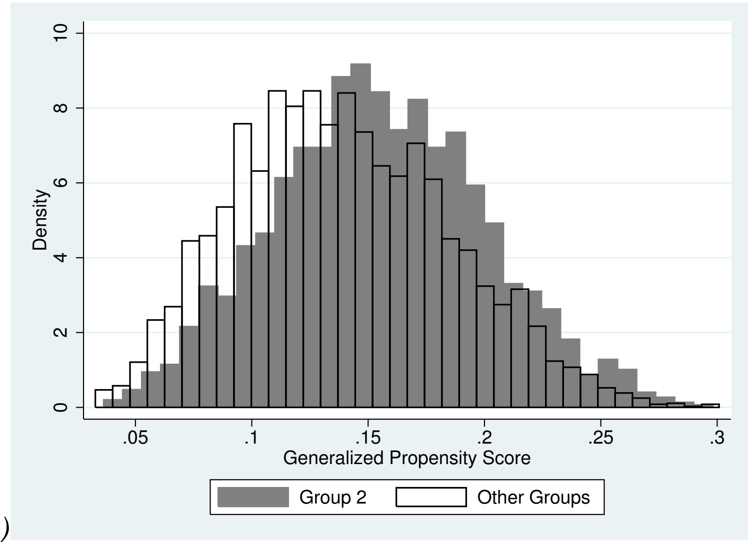



The figure reports the predict probabilities based on Table (5) for each class of firm reduction in turnover according to different values of the debt concentration index HHI.

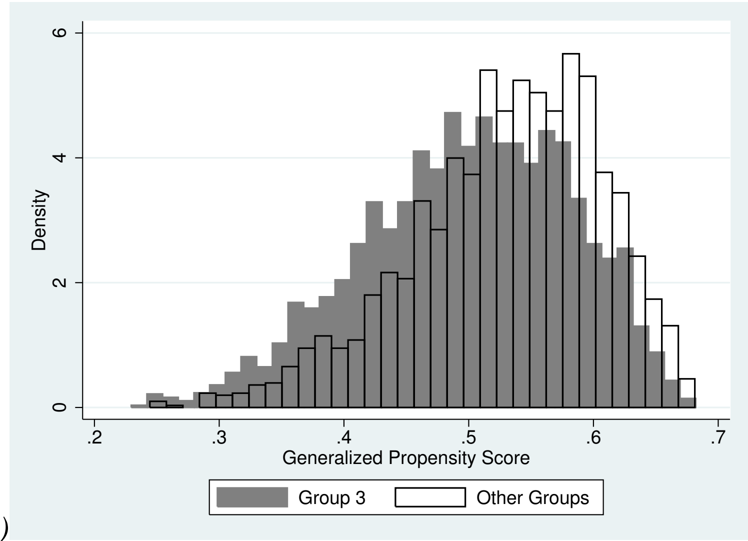
Figure 6: Common Support of the Generalized Propensity Score




*a)*




*b)*




*c)*

Figure 7: DOSE-RESPONSE FUNCTION: NO REDUCTION IN TURNOVER

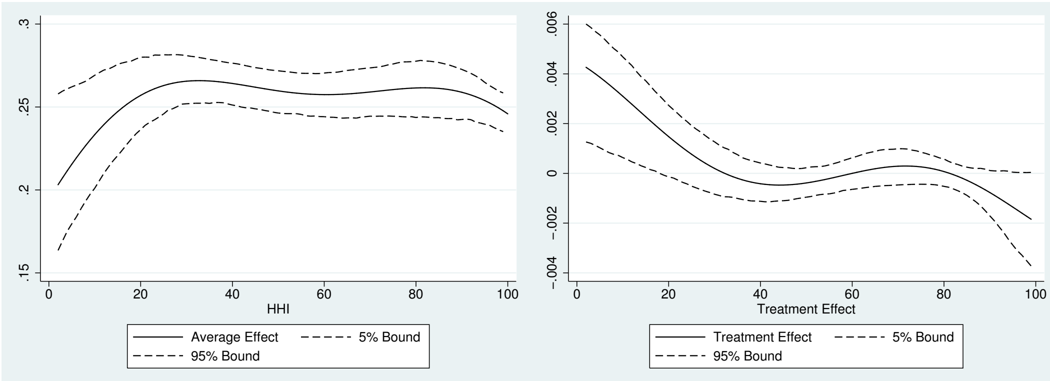



Figure 8: DOSE-RESPONSE FUNCTION: TURNOVER REDUCTION <10%

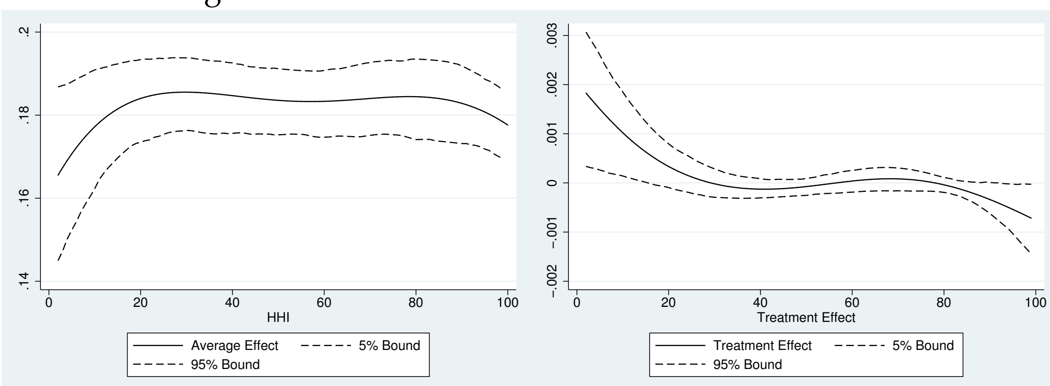



Figure 9: DOSE-RESPONSE FUNCTION: TURNOVER 10%-30%

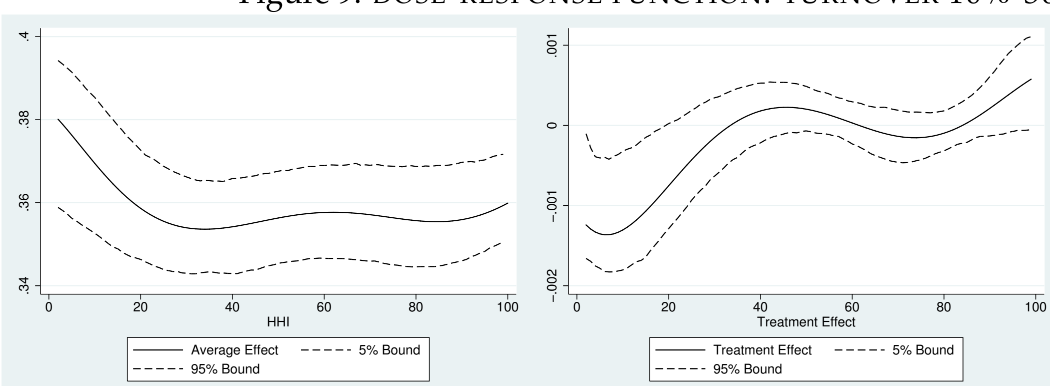



Figure 10: DOSE-RESPONSE FUNCTION: TURNOVER REDUCTION >30%

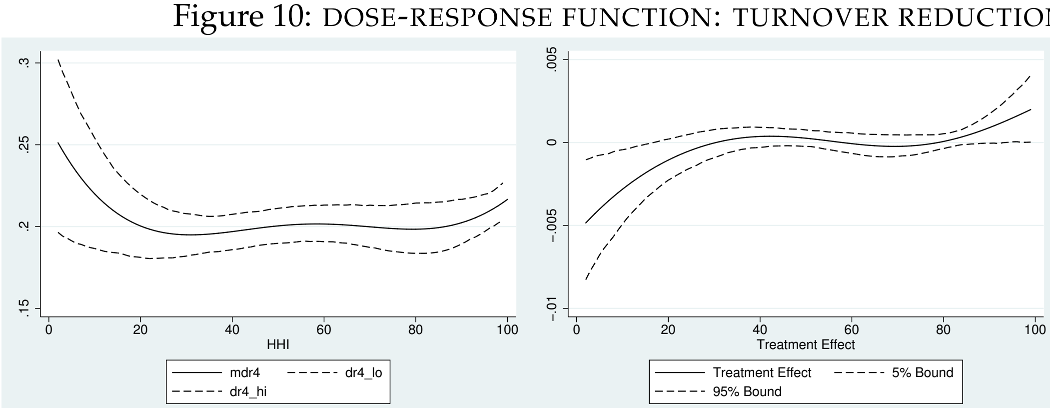


Table 1: VARIABLE DESCRIPTION

| **Variable** | **Description** |
|---|---|
| *HHI* | This variable represents the Herfindhal Hirschmann index of the firm debt in 2009. It is computed as the (squared) sum of the each firm debt share and it is normalized for the number of types of debt. It varies between zero and one. |
| *Turnover reduction* | This is a categorical variable which is equal to 0 if the firm experienced no reduction in turnover, equal to 1 if the firm experienced a reduction below 10%, equal to 2 if experienced a reduction between 10% and 30%, equal to 3 if the firm experienced a reduction in turnover above 30%. |
| *Small firm (10-19 Employees)* | This is a dummy variable equal to one if the number of employees is between 10-19. |
| *Medium firm (20-49 Employees)* | This is a dummy variable equal to one if the number of employees is between 20-49. |
| *Large firm (50-249 Employees)* | This is a dummy variable equal to one if the number of employees is between 50-249. |
| *Very Large firm (over 250 Employees)* | This is a dummy variable equal to one if the number of employees is above 250. |
| *Young firm (< 6 years)* | This is a dummy variable equal to one if the age of the firm is below 6 years old. |
| *Firm 6-20 years* | This is a dummy variable equal to one if the age of the firm is between 6 years old and 20 years old. |
| *Old firms* | This is a dummy variable equal to one if the age of the firm is above 20 years old. |
| *Group* | This is a dummy variable equal to one if the firm belongs to a group. |
| *M&As* | This is a dummy variable equal to one if the firm has acquired or incorporated other firms in the last three years (2007-2009). |
| *Financial constraints* | This is a dummy variable equal to one if the firm has applied for a bank loan in 2009 but the request was not successful. |
| *Increase finance cost* | This is a dummy variable equal to one if the firm has experienced in 2009 an increase in the cost of bank lending. |
| *Listed* | This is a dummy variable equal to one if the firm is listed on a stock exchange. |
| *Export Dummy* | This is a dummy variable equal to one if the firm export the products in foreign markets. |
| *R&D Dummy* | This is a dummy variable equal to one if the firm has undertaken any R&D activities during the last three years (2007-2009). |

Table 2: Firm characteristics across European countries

| | Austria | | France | | Germany | | Hungary | | Italy | | Spain | | United Kingdom | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Variable** | **Mean** | **Std. Dev.** | **Mean** | **Std. Dev.** | **Mean** | **Std. Dev.** | **Mean** | **Std. Dev.** | **Mean** | **Std. Dev.** | **Mean** | **Std. Dev.** | **Mean** | **Std. Dev.** |
| *Small firm (10-19 Employees)* | 0.217 | 0.414 | 0.388 | 0.487 | 0.239 | 0.427 | 0.326 | 0.47 | 0.347 | 0.476 | 0.355 | 0.479 | 0.265 | 0.442 |
| *Medium firm (20-49 Employees)* | 0.49 | 0.502 | 0.38 | 0.486 | 0.466 | 0.499 | 0.408 | 0.492 | 0.512 | 0.5 | 0.467 | 0.499 | 0.424 | 0.495 |
| *Large firm (50-249 Employees)* | 0.236 | 0.426 | 0.187 | 0.39 | 0.251 | 0.434 | 0.218 | 0.414 | 0.125 | 0.33 | 0.158 | 0.365 | 0.266 | 0.442 |
| *Very Large firm (over 250 Employees)* | 0.058 | 0.234 | 0.046 | 0.209 | 0.045 | 0.206 | 0.048 | 0.214 | 0.016 | 0.126 | 0.02 | 0.139 | 0.044 | 0.206 |
| *Young firm (< 6 years)* | 0.242 | 0.43 | 0.274 | 0.446 | 0.349 | 0.477 | 0.788 | 0.409 | 0.342 | 0.475 | 0.436 | 0.496 | 0.343 | 0.475 |
| *Firm 6-20 years* | 0.12 | 0.326 | 0.075 | 0.264 | 0.07 | 0.256 | 0.129 | 0.335 | 0.068 | 0.252 | 0.066 | 0.248 | 0.098 | 0.298 |
| *Old firms (> 20 years)* | 0.638 | 0.482 | 0.65 | 0.477 | 0.58 | 0.494 | 0.083 | 0.277 | 0.589 | 0.492 | 0.498 | 0.5 | 0.558 | 0.497 |
| *Group* | 0.2 | 0.401 | 0.261 | 0.439 | 0.109 | 0.312 | 0.169 | 0.375 | 0.133 | 0.34 | 0.133 | 0.34 | 0.24 | 0.427 |
| *M&As* | 0.166 | 0.373 | 0.091 | 0.287 | 0.141 | 0.348 | 0.052 | 0.222 | 0.084 | 0.277 | 0.084 | 0.277 | 0.152 | 0.359 |
| *Financial constraints* | 0.042 | 0.201 | 0.047 | 0.212 | 0.061 | 0.24 | 0.051 | 0.221 | 0.122 | 0.328 | 0.128 | 0.334 | 0.011 | 0.106 |
| *Increase finance cost* | 0.402 | 0.492 | 0.31 | 0.463 | 0.381 | 0.486 | 0.672 | 0.471 | 0.455 | 0.498 | 0.52 | 0.5 | 0.44 | 0.497 |
| *Listed* | 0.033 | 0.18 | 0.013 | 0.115 | 0.012 | 0.11 | 0.003 | 0.053 | 0.004 | 0.063 | 0.007 | 0.084 | 0.03 | 0.172 |
| *Export Dummy* | 0.617 | 0.488 | 0.509 | 0.5 | 0.522 | 0.5 | 0.573 | 0.496 | 0.683 | 0.465 | 0.539 | 0.499 | 0.596 | 0.491 |
| *R&D Dummy* | 0.58 | 0.495 | 0.527 | 0.5 | 0.542 | 0.499 | 0.288 | 0.454 | 0.565 | 0.496 | 0.467 | 0.499 | 0.537 | 0.499 |
| *Turnover Reduction* | 1.164 | 1.038 | 1.434 | 1.083 | 1.166 | 1.071 | 1.567 | 1.067 | 1.509 | 1.069 | 1.733 | 1.044 | 1.246 | 1.061 |
| Observations | 134 | | 1112 | | 681 | | 237 | | 1859 | | 1908 | | 833 | |

All variables are dummies. The (weighted) mean represents thus the share of firms within each category in the population.

Table 3: DEBT STRUCTURE ACROSS EUROPEAN COUNTRIES

| | Austria | | France | | Germany | | Hungary | | Italy | | Spain | | United Kingdom | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Variable** | **Mean** | **Std. Dev.** | **Mean** | **Std. Dev.** | **Mean** | **Std. Dev.** | **Mean** | **Std. Dev.** | **Mean** | **Std. Dev.** | **Mean** | **Std. Dev.** | **Mean** | **Std. Dev.** |
| Short-term bank loans | 0.305 | 0.345 | 0.209 | 0.32 | 0.29 | 0.332 | 0.426 | 0.425 | 0.399 | 0.377 | 0.351 | 0.334 | 0.314 | 0.395 |
| Long-term bank loans | 0.53 | 0.397 | 0.581 | 0.4 | 0.564 | 0.364 | 0.402 | 0.414 | 0.476 | 0.383 | 0.513 | 0.356 | 0.334 | 0.4 |
| Short-term securities | 0.003 | 0.022 | 0.03 | 0.127 | 0.005 | 0.036 | 0.015 | 0.12 | 0.003 | 0.042 | 0.021 | 0.097 | 0.035 | 0.15 |
| Long-term securities | 0.022 | 0.115 | 0.03 | 0.13 | 0.009 | 0.06 | 0.005 | 0.053 | 0.008 | 0.07 | 0.024 | 0.122 | 0.051 | 0.184 |
| Other financial instruments | 0.141 | 0.32 | 0.15 | 0.311 | 0.132 | 0.28 | 0.151 | 0.338 | 0.114 | 0.269 | 0.091 | 0.236 | 0.265 | 0.407 |
| Bank loans (all maturities) | 0.834 | 0.335 | 0.79 | 0.344 | 0.854 | 0.288 | 0.829 | 0.354 | 0.875 | 0.28 | 0.864 | 0.279 | 0.649 | 0.433 |
| Securities (all maturities) | 0.025 | 0.121 | 0.06 | 0.187 | 0.014 | 0.08 | 0.02 | 0.131 | 0.011 | 0.085 | 0.045 | 0.164 | 0.086 | 0.238 |
| Short-term (all debt types) | 0.307 | 0.345 | 0.239 | 0.333 | 0.295 | 0.331 | 0.441 | 0.427 | 0.402 | 0.377 | 0.371 | 0.338 | 0.349 | 0.403 |
| Long-term (all debt types) | 0.552 | 0.391 | 0.61 | 0.397 | 0.572 | 0.362 | 0.408 | 0.414 | 0.484 | 0.383 | 0.538 | 0.352 | 0.386 | 0.414 |
| HHI index | 0.729 | 0.291 | 0.746 | 0.288 | 0.681 | 0.289 | 0.811 | 0.254 | 0.708 | 0.282 | 0.643 | 0.282 | 0.777 | 0.28 |
| Observations | 134 | | 1112 | | 681 | | 237 | | 1859 | | 1908 | | 833 | |

All variables measure the share of each debt component in firm balance sheet at the end of year 2009. The (weighted) mean represents thus the share of each debt component in the population of firms.

## Table 4: Debt concentration of European Firms

The dependent variable is the HHI index. Since the HHI index is a fraction and varies between 0 and 1, the estimated model is a fractional regression. The base category comprises firms located in Germany, which have a small size (between 10-19 employees), and have more than 20 years old

| | *a* | *b* | *c* | *d* | *e* | *f* |
|---|---|---|---|---|---|---|
| Young (< 6 years) | 0.0124 | 0.0113 | 0.0137* | 0.0134* | 0.0125 | 0.0113 |
| | (0.008) | (0.008) | (0.008) | (0.008) | (0.008) | (0.008) |
| 6-20 years | 0.0347** | 0.0317** | 0.0365** | 0.0367** | 0.0350** | 0.0276* |
| | (0.015) | (0.015) | (0.015) | (0.015) | (0.015) | (0.015) |
| Medium firm (20-49 Employees) | -0.0428*** | -0.0439*** | -0.0432*** | -0.0428*** | -0.0384*** | -0.0379*** |
| | (0.009) | (0.009) | (0.009) | (0.009) | (0.009) | (0.009) |
| Large firm (50-249 Employees) | -0.0782*** | -0.0836*** | -0.0847*** | -0.0850*** | -0.0752*** | -0.0786*** |
| | (0.011) | (0.011) | (0.011) | (0.011) | (0.011) | (0.012) |
| Very Large firm (over 250 Employees) | -0.0394** | -0.0513*** | -0.0532*** | -0.0512** | -0.0392* | -0.0463** |
| | (0.018) | (0.020) | (0.020) | (0.020) | (0.020) | (0.020) |
| Group | | 0.0306*** | 0.0290*** | 0.0289*** | 0.0318*** | 0.0229** |
| | | (0.010) | (0.010) | (0.010) | (0.010) | (0.011) |
| M&As | | -0.0186 | -0.0161 | -0.0166 | -0.0138 | -0.0134 |
| | | (0.012) | (0.012) | (0.012) | (0.012) | (0.012) |
| Financial constraints | | | -0.0546*** | -0.0545*** | -0.0531*** | -0.0372*** |
| | | | (0.013) | (0.013) | (0.013) | (0.013) |
| Increase finance cost | | | -0.0385*** | -0.0382*** | -0.0375*** | -0.0364*** |
| | | | (0.008) | (0.008) | (0.008) | (0.008) |
| *Listed* | | | | -0.0151 | -0.0127 | -0.0223 |
| | | | | (0.038) | (0.038) | (0.038) |
| Export Dummy | | | | | -0.0146* | -0.0169** |
| | | | | | (0.008) | (0.008) |
| R&D Dummy | | | | | -0.0314*** | -0.0307*** |
| | | | | | (0.008) | (0.008) |
| *Austria* | | | | | | 0.0589* |
| | | | | | | (0.031) |
| *France* | | | | | | 0.0576*** |
| | | | | | | (0.016) |
| *Hungary* | | | | | | 0.1269*** |
| | | | | | | (0.022) |
| *Italy* | | | | | | 0.0281** |
| | | | | | | (0.014) |
| *Spain* | | | | | | -0.0377*** |
| | | | | | | (0.014) |
| *United Kingdom* | | | | | | 0.0963*** |
| | | | | | | (0.016) |
| Sector dummies | *Yes* | *Yes* | *Yes* | *Yes* | *Yes* | *Yes* |
| ll | -3260 | -3257 | -3229 | -3224 | -3218 | -3188 |
| N | 6764 | 6762 | 6724 | 6712 | 6712 | 6712 |

*p<0.10,** p<0.05, ***p<0.01

Table 5: DETERMINANTS OF TURNOVER REDUCTION

The estimated model is an ordinal logit using firms with a positive amount of debt. The dependent variable is equal to 0 if the firm experienced no reduction in the turnover, equal to 1 if the firm experienced a reduction below 10%, equal to 2 if experienced a reduction between 10% and 30%, equal to 3 if the firm experienced a reduction in turnover above 30%.

| | *No reduction* | *Reduction* $< 10\%$ | *Reduction* $10\% - 30\%$ | *Reduction* $> 30\%$ |
|---|---|---|---|---|
| HHI | -0.0354*** | -0.0092** | 0.0142** | 0.0304*** |
| | (0.014) | (0.004) | (0.006) | (0.012) |
| Young (< 6 years) | 0.0141* | 0.0037* | -0.0055* | -0.0123* |
| | (0.008) | (0.002) | (0.003) | (0.007) |
| 6-20 years | 0.0671*** | 0.0141*** | -0.0298*** | -0.0514*** |
| | (0.017) | (0.003) | (0.008) | (0.012) |
| Medium firm (20-49 Employees) | -0.0210** | -0.0051** | 0.0088** | 0.0173** |
| | (0.009) | (0.002) | (0.004) | (0.007) |
| Large firm (50-249 Employees) | -0.0429*** | -0.0114*** | 0.0168*** | 0.0375*** |
| | (0.012) | (0.003) | (0.005) | (0.011) |
| Very Large firm (over 250 Employees) | -0.0379 | -0.0099 | 0.0151* | 0.0327 |
| | (0.024) | (0.007) | (0.009) | (0.023) |
| Group | -0.0167 | -0.0045 | 0.0064 | 0.0148 |
| | (0.011) | (0.003) | (0.004) | (0.010) |
| M&As | 0.0415*** | 0.0093*** | -0.0181*** | -0.0328*** |
| | (0.014) | (0.003) | (0.007) | (0.010) |
| Financial constraints | -0.0840*** | -0.0292*** | 0.0251*** | 0.0881*** |
| | (0.011) | (0.005) | (0.002) | (0.014) |
| Increase finance cost | 0.0617 | 0.0121* | -0.0281 | -0.0457 |
| | (0.045) | (0.006) | (0.022) | (0.029) |
| *Listed* | -0.0736*** | -0.0202*** | 0.0296*** | 0.0643*** |
| | (0.008) | (0.002) | (0.003) | (0.007) |
| Export Dummy | -0.0064 | -0.0017 | 0.0026 | 0.0055 |
| | (0.008) | (0.002) | (0.003) | (0.007) |
| R&D Dummy | 0.0332*** | 0.0087*** | -0.0132*** | -0.0287*** |
| | (0.008) | (0.002) | (0.003) | (0.007) |
| *Austria* | 0.0640 | 0.0115** | -0.0315 | -0.0440* |
| | (0.043) | (0.006) | (0.022) | (0.026) |
| *France* | 0.0439** | 0.0087** | -0.0210** | -0.0316** |
| | (0.017) | (0.003) | (0.008) | (0.012) |
| *Hungary* | -0.0279 | -0.0077 | 0.0114 | 0.0242 |
| | (0.025) | (0.007) | (0.010) | (0.022) |
| *Italy* | -0.0094 | -0.0024 | 0.0041 | 0.0078 |
| | (0.013) | (0.003) | (0.006) | (0.011) |
| *Spain* | -0.0808*** | -0.0277*** | 0.0263*** | 0.0821*** |
| | (0.013) | (0.004) | (0.005) | (0.013) |
| *United Kingdom* | 0.0784*** | 0.0129*** | -0.0392*** | -0.0522*** |
| | (0.018) | (0.003) | (0.009) | (0.012) |
| Sector dummies | Yes | Yes | Yes | Yes |
| ll | -8462 | -8462 | -8462 | -8462 |
| N | 6703 | 6703 | 6703 | 6703 |

*p<0.10,** p<0.05, ***p<0.01

Table 6: ESTIMATION OF THE GENERALIZED PROPENSITY SCORE

This table reports the results of a two-limit Tobit model. The dependent variable is the discount rates in 2012. Descriptions of the regressors are available in Table(2).

| **Variable** | **Coeff** | **Std** |
|---|---|---|
| Young (< 6 years) | 0.014 | (0.013) |
| 6-20 years | 0.032 | (0.023) |
| Medium firm (20-49 Employees) | -0.068*** | (0.014) |
| Large firm (50-249 Employees) | -0.145*** | (0.018) |
| Very Large firm (over 250 Employees) | -0.092*** | (0.029) |
| Group | 0.053*** | (0.016) |
| M&As | -0.021 | (0.019) |
| Financial constraints | -0.051** | (0.021) |
| *Listed* | 0.017 | (0.052) |
| Increase finance cost | -0.071*** | (0.012) |
| Export Dummy | -0.027** | (0.013) |
| R&D Dummy | -0.046*** | (0.012) |
| *Austria* | 0.054 | (0.047) |
| *France* | 0.100*** | (0.024) |
| *Hungary* | 0.241*** | (0.038) |
| *Italy* | 0.047** | (0.022) |
| *Spain* | -0.048** | (0.021) |
| *United Kingdom* | 0.168*** | (0.025) |
| Constant | 0.909*** | (0.026) |
| Sigma | 0.439*** | (0.006) |
| Log-likelihood | -4617 | |
| Observations | 6703 | |

## Table 7: Test of the balancing property

This table illustrates the results for test of the balancing properties. Observations are first divided into three "treatment" groups according to the actual level of the HHI: [0-0.300], [0.300-0.500] and [0.500, 1]. In addition, within each group, observations are divided into three blocks according to the estimated GPS. For each variable, we then compare the equality of covariates between units who belong to the the treatment interval of the HHI, and units that are in the same GPS interval but belong to another treatment interval. The balancing property has been tested using a standard two-sided t-test analysis. There is strong evidence against the balancing property when $1.96 < t < 2.576$. Sector correspondence with Nace Rev1.1 are described in the box of Figure (4).

| | *Group 1:* | *HHI [0 - 0.300]* | | *Group 2:* | *HHI [0.300 - 0.500]* | | *Group 3:* | *HHI [0.500 - 1]* | |
|---|---|---|---|---|---|---|---|---|---|
| **Variable** | **Mean** | **Std** | **t-stat** | **Mean** | **Std** | **t-stat** | **Mean** | **Std** | **t-stat** |
| Young (< 6 years) | 0.030 | 0.023 | 1.312 | -0.009 | 0.014 | -0.678 | 0.004 | 0.013 | 0.324 |
| *Firm 6-20 years* | -0.013 | 0.013 | -0.984 | 0.009 | 0.008 | 1.169 | -0.003 | 0.007 | -0.454 |
| *Old firms* | -0.018 | 0.024 | -0.748 | 0.000 | 0.014 | 0.030 | -0.001 | 0.013 | -0.072 |
| *Group* | -0.021 | 0.019 | -1.113 | -0.001 | 0.011 | -0.123 | 0.007 | 0.010 | 0.664 |
| *M&As* | -0.012 | 0.015 | -0.835 | 0.003 | 0.009 | 0.368 | -0.002 | 0.008 | -0.283 |
| *Small firms* | 0.029 | 0.021 | 1.364 | 0.001 | 0.012 | 0.085 | -0.005 | 0.012 | -0.394 |
| *Medium firms* | -0.013 | 0.024 | -0.534 | 0.012 | 0.014 | 0.886 | -0.007 | 0.013 | -0.536 |
| *Large firms* | 0.002 | 0.018 | 0.102 | -0.014 | 0.011 | -1.308 | 0.007 | 0.010 | 0.716 |
| *Very Large firms* | -0.018 | 0.011 | -1.660 | 0.000 | 0.007 | 0.074 | 0.004 | 0.006 | 0.722 |
| *Sector 1* | -0.044 | 0.021 | -2.112 | 0.011 | 0.012 | 0.938 | 0.003 | 0.011 | 0.222 |
| *Sector 2* | 0.002 | 0.015 | 0.161 | -0.001 | 0.009 | -0.165 | -0.000 | 0.008 | -0.050 |
| *Sector 3* | -0.005 | 0.011 | -0.473 | -0.001 | 0.007 | -0.218 | 0.004 | 0.006 | 0.589 |
| *Sector 4* | 0.011 | 0.016 | 0.683 | 0.001 | 0.010 | 0.097 | -0.003 | 0.009 | -0.285 |
| *Sector 5* | 0.019 | 0.012 | 1.540 | -0.003 | 0.007 | -0.420 | -0.003 | 0.007 | -0.501 |
| *Sector 6* | 0.012 | 0.009 | 1.318 | 0.003 | 0.005 | 0.552 | -0.006 | 0.005 | -1.196 |
| *Sector 7* | 0.003 | 0.008 | 0.361 | -0.001 | 0.005 | -0.232 | 0.000 | 0.004 | 0.051 |
| *Sector 8* | 0.007 | 0.011 | 0.694 | -0.004 | 0.006 | -0.622 | 0.000 | 0.006 | 0.074 |
| *Sector 9* | 0.001 | 0.002 | 0.632 | -0.001 | 0.001 | -0.694 | 0.000 | 0.001 | 0.469 |
| *Sector 10* | 0.010 | 0.017 | 0.578 | -0.002 | 0.010 | -0.200 | -0.000 | 0.009 | -0.028 |
| *Sector 11* | -0.017 | 0.015 | -1.114 | -0.002 | 0.009 | -0.194 | 0.005 | 0.008 | 0.646 |
| *Financial constrained* | -0.007 | 0.012 | -0.611 | -0.001 | 0.007 | -0.114 | 0.002 | 0.007 | 0.243 |
| *Increase cost* | -0.001 | 0.022 | -0.028 | -0.004 | 0.013 | -0.278 | 0.001 | 0.012 | 0.078 |
| *R&D* | -0.054 | 0.023 | -2.336 | 0.006 | 0.014 | 0.412 | 0.004 | 0.013 | 0.289 |
| *Listed* | -0.011 | 0.006 | -2.052 | 0.004 | 0.003 | 1.124 | 0.000 | 0.003 | 0.100 |
| *Export* | -0.000 | 0.023 | -0.014 | -0.001 | 0.014 | -0.070 | -0.003 | 0.013 | -0.220 |

Table 8: Cell size for mean comparison of treat and control units

Groups are generated according to the terciles of discount ratio in 2012, whereas blocks are generated according to the quintiles of the GPS evaluated at the median treatment intensity for each group. The sum of observations over blocks in a group yields the total number of observations in that group. The sum of observations in a group with observations from the respective control group yield the total number of observations in the common support region.

| | *Group 1* | *Control 1* | *Group 2* | *Control 2* | *Group 3* | *Control 3* |
|---|---|---|---|---|---|---|
| 1 | 99 | 1,742 | 362 | 1,604 | 880 | 234 |
| 2 | 98 | 1,384 | 361 | 1,075 | 867 | 327 |
| 3 | 98 | 1,141 | 362 | 796 | 875 | 442 |
| 4 | 98 | 1,020 | 361 | 738 | 871 | 569 |
| 5 | 98 | 886 | 361 | 643 | 873 | 724 |
| Total | 491 | 6,173 | 1,807 | 4,856 | 4,366 | 2,296 |

Table 9: ESTIMATIONS OF THE CONDITIONAL EXPECTATION OF OUTCOME

This table reports the coefficients of the dose-response function derived from an ordinal logit regression. The dependent variable is the level of turnover reduction. Standard errors are derived relying on block-bootstrapping (500 replications).

| **Variable** | **Coeff** | **Std** |
|---|---|---|
| $HHI$ | -4.742*** | (1.205) |
| $HHI^2$ | 4.366** | (2.119) |
| $GPS$ | 11.165*** | (2.175) |
| $GPS^2$ | -8.803 | (8.135) |
| $GPS^3$ | 13.074*** | (4.924) |
| $GPS \cdot HHI$ | -10.653* | (5.916) |
| cut 1 | -1.423*** | (0.182) |
| cut 2 | -0.594*** | (0.182) |
| cut 3 | 1.037*** | (0.182) |
| Log-likelihood | -8940 | |
| Observations | 6664 | |

Table 10: INDICATOR OF COUNTRY DEBT CONCENTRATION

The indicator is defined as the level of debt concentration measured at the country-sector level. The coefficients on the country and sector dummies are obtained from Table (4), which relies *only* on those firms who hold a positive amount of debt.

| **Country** | **Mean** | **Std** | **Min** | **Max** |
|---|---|---|---|---|
| *Austria* | 0.738 | 0.020 | 0.710 | 0.771 |
| *France* | 0.760 | 0.036 | 0.724 | 0.855 |
| *Germany* | 0.679 | 0.022 | 0.648 | 0.717 |
| *Hungary* | 0.814 | 0.015 | 0.793 | 0.840 |
| *Italy* | 0.720 | 0.041 | 0.681 | 0.827 |
| *Spain* | 0.647 | 0.023 | 0.615 | 0.687 |
| *United Kingdom* | 0.786 | 0.033 | 0.753 | 0.872 |

Table 11: DETERMINANTS OF TURNOVER REDUCTION

The estimated model is an ordinal logit on the entire sample of firms. The dependent variable is equal to 0 if the firm experienced no reduction in the turnover, equal to 1 if the firm experienced a reduction below 10%, equal to 2 if experienced a reduction between 10% and 30%, equal to 3 if the firm experienced a reduction in turnover above 30%. The country indicator of debt specialization is computed as specified in Table . The IV regressions instrument the country indicator of debt specialization with the financial integration indicator as explained in Section 5.

| | *No reduction (a)* | *No reduction -IV* | *Reduction (b)* | *Reduction -IV* | *Reduction (c)* | *Reduction-IV* | *Reduction* | *Reduction -IV* |
|---|---|---|---|---|---|---|---|---|
| | | | $< 10\%$ | $< 10\%$ | $10\% - 30\%$ | $10\% - 30\%$ | $> 30\%$ | $> 30\%$ |
| *Country debt specialization* | -0.5628*** | -0.4730** | -0.1070*** | 0.1949 | 0.2611*** | 0.4423* | 0.4086*** | -0.1642 |
| | (0.109) | (0.223) | (0.021) | (0.202) | (0.051) | (0.234) | (0.079) | (0.184) |
| *Gdp per capita 2007* | 0.0207*** | 0.0209*** | 0.0039*** | -0.0000 | -0.0096*** | -0.0120*** | -0.0150*** | -0.0089*** |
| | (0.001) | (0.002) | (0.000) | (0.002) | (0.001) | (0.003) | (0.001) | (0.002) |
| Young (< 6 years) | 0.0178*** | 0.0253*** | 0.0034*** | 0.0096 | -0.0083*** | -0.0394*** | -0.0130*** | 0.0046 |
| | (0.006) | (0.008) | (0.001) | (0.007) | (0.003) | (0.008) | (0.005) | (0.007) |
| 6-20 years | 0.0573*** | 0.0937*** | 0.0088*** | -0.0327** | -0.0280*** | -0.0640*** | -0.0382*** | 0.0031 |
| | (0.013) | (0.015) | (0.001) | (0.013) | (0.007) | (0.016) | (0.008) | (0.012) |
| Medium firm (20-49 Employees) | -0.0032 | 0.0045 | -0.0006 | -0.0095 | 0.0015 | 0.0005 | 0.0023 | 0.0045 |
| | (0.007) | (0.008) | (0.001) | (0.008) | (0.003) | (0.009) | (0.005) | (0.007) |
| Large firm (50-249 Employees) | -0.0245*** | -0.0299** | -0.0050*** | 0.0061 | 0.0111*** | 0.0143 | 0.0184*** | 0.0095 |
| | (0.009) | (0.012) | (0.002) | (0.011) | (0.004) | (0.013) | (0.007) | (0.010) |
| Very Large firm (over 250 Employees) | 0.0141 | 0.0135 | 0.0023 | 0.0157 | -0.0068 | -0.0126 | -0.0096 | -0.0166 |
| | (0.018) | (0.023) | (0.003) | (0.020) | (0.009) | (0.024) | (0.012) | (0.019) |
| Group | -0.0253*** | -0.0392*** | -0.0052*** | 0.0037 | 0.0114*** | 0.0236** | 0.0191*** | 0.0119 |
| | (0.008) | (0.011) | (0.002) | (0.010) | (0.004) | (0.011) | (0.006) | (0.009) |
| M&As | 0.0267** | 0.0242* | 0.0045*** | 0.0002 | -0.0128** | 0.0023 | -0.0184*** | -0.0266** |
| | (0.011) | (0.013) | (0.002) | (0.012) | (0.005) | (0.014) | (0.007) | (0.011) |
| Financial constraints | -0.0815*** | -0.0713*** | -0.0225*** | -0.0031 | 0.0317*** | -0.0325 | 0.0723*** | 0.1069*** |
| | (0.013) | (0.019) | (0.005) | (0.017) | (0.004) | (0.020) | (0.014) | (0.016) |
| Increase finance cost | -0.0133 | -0.0093 | -0.0027 | -0.0277 | 0.0060 | 0.0319 | 0.0100 | 0.0052 |
| | (0.023) | (0.030) | (0.005) | (0.027) | (0.010) | (0.031) | (0.018) | (0.025) |
| *Listed* | -0.0700*** | -0.0673*** | -0.0169*** | -0.0226** | 0.0304*** | 0.0254** | 0.0564*** | 0.0644*** |
| | (0.007) | (0.010) | (0.002) | (0.009) | (0.003) | (0.010) | (0.006) | (0.008) |
| Export Dummy | -0.0287*** | -0.0352*** | -0.0053*** | -0.0104 | 0.0135*** | 0.0360*** | 0.0206*** | 0.0096 |
| | (0.006) | (0.008) | (0.001) | (0.007) | (0.003) | (0.009) | (0.005) | (0.007) |
| R&D Dummy | 0.0238*** | 0.0283*** | 0.0046*** | -0.0057 | -0.0110*** | -0.0036 | -0.0173*** | -0.0190*** |
| | (0.006) | (0.008) | (0.001) | (0.007) | (0.003) | (0.008) | (0.005) | (0.007) |
| *Sector dummies* | *Yes* | *Yes* | *Yes* | *Yes* | *Yes* | *Yes* | *Yes* | *Yes* |
| ll | -17941 | | -17941 | | -17941 | | -17941 | |
| N | 14141 | 14141 | 14141 | 14141 | 14141 | 14141 | 14141 | 14141 |

*p<0.10,** p<0.05, ***p<0.01

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