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This paper investigates the short- and long-term impacts of the Federal Reserve's large-scale asset purchases (LSAPs) on the capital structure of U.S. non-financial firms. To isolate the effects of LSAPs from the impact of concurrent macroeconomic conditions, we exploit cross-industry variations in the ability of firms therein to raise external funds without exhausting their debt capacity. We show that firms' responses to LSAPs strongly depend on the financing decisions of other peers in the same industry. The higher the proportion of firms without high debt burdens in an industry, the stronger the response of firms within the industry to the Fed's asset purchases. Overall, our results show that LSAPs facilitated firms' access to debt financing and that the impacts of LSAPs on firms' capital structure are likely to be long-lasting.

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**Abstract**

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# 1 Introduction

The financial crisis that began in August 2007 had severe effects on the U.S. corporate sector. Financial institutions dealing with subprime mortgages or credit derivatives faced a liquidity crisis which soon spread to the rest of the credit markets. This in turn brought about a reduction in the supply of external finance for non-financial firms. As a result, many firms found it difficult to roll over their debt obligations, with consequent cuts in spending, investment, and employment, as documented in Almeida et al. (2012), Campello et al. (2010), and Duchin et al. (2010), among others, leading to significant falls in the overall level of activity. To revitalize the economy, with the policy rate close to zero, the Federal Reserve resorted to large-scale asset purchases (LSAPs) and other unconventional measures, often referred to as quantitative easing (QE). The empirical evidence so far suggests that the Fed's unconventional policies have been successful at easing financial conditions, overcoming the constraint imposed by the so called lower bound on rates (Bernanke (2020)).[1] Yet the debate on the effectiveness of such policies and the channels through which they function is still far from being settled.

To illustrate, the vast majority of event studies show that LSAPs significantly lowered long-term Treasury and corporate bond yields by reducing both expected future short rates and the term premium (e.g. Bauer and Rudebusch (2014), D'Amico and King (2013), Gagnon et al. (2011), and Krishnamurthy and Vissing-Jorgensen (2011)). At the same time, using a larger population of events to reduce the sensitivity of previous studies to the choice of individual observations, Greenlaw et al. (2018) find that the Fed's interventions only had modest and uncertain impact on yields. They also note that these effects tended to die out quickly. Other studies cast some doubt on the persistence of such effects. Notably, Wright (2012) shows that the Fed's unconventional monetary policies reduced both Treasury and corporate bond yields but these effects were fairly short-lived. In contrast, Swanson (2021) finds that the effects of LSAPs were quite persistent (with the exception of the first QE program announcement).

The literature so far has provided contrasting evaluation of the efficacy of LSAPs in stimulating corporate lending by financial institutions. Rodnyansky and Darmouni (2017) show that banks more exposed to mortgage-backed securities (MBS) significantly increased both their real estate and commercial loans, whilst Chakraborty et al. (2020) document a crowding out effect, whereby banks benefiting from MBS purchases increased mortgage origination, largely at the expense of reducing their commercial and industrial lending.

In this paper we focus on non-financial companies' responses, and ask whether LSAPs facilitated non-financial firms' access to external financing. We also investigate which firms responded the most to the Fed's asset purchases and evaluate whether LSAPs systematically

[1] The empirical literature on the effects of QE has grown very rapidly in the last decade. A non-exhaustive list includes Chakraborty et al. (2020), D'Amico and King (2013), Foley-Fisher et al. (2016), Gagnon et al. (2011), Krishnamurthy and Vissing-Jorgensen (2013), Rodnyansky and Darmouni (2017), and Swanson (2021). Bhattarai and Neely (2020), and Kuttner (2018) provide recent reviews.

affected the way firms finance their operations beyond the transitory responses around policy announcements. To this end, we estimate dynamic panel data models with threshold effects using firm-level data covering the period of the Great Recession, to investigate the impact of LSAPs on non-financial firms' capital structure, distinguishing between short-term and long-term effects.

One key challenge is to isolate the effects of LSAPs on firms' financing decisions from that of concurrent general macroeconomic conditions typically represented in panel data models by unobserved time effects. As it is well recognized in the literature, the effects of macro policy interventions cannot be identified when using standard panel regressions with time effects, since any attempt at eliminating the unobserved time effects will also end up eliminating the observed macro variables. Isolating the impact of LSAPs from the general business cycle conditions is all the more important in our context in light of the recent findings on the strong link between macroeconomic conditions and firms' ability to raise capital, as documented in Begenau and Salomao (2019), Bhamra et al. (2010), Erel et al. (2011), and Halling et al. (2016), among others.

We overcome the identification problem by exploiting the heterogeneity that exists in firms' debt capacity constraints across industries both before and after LSAPs. Specifically, we interact measures of LSAPs, denoted by $q_t$, with two industry-specific measures of spare debt capacity. In line with Myers (1984), a firm is said to have exhausted its debt capacity if its debt to asset ratio is sufficiently high so that further debt issuance could lead to either substantial additional costs or to increased default risk. Lemmon and Zender (2010) consider a firm's ability to issue public rated debt as an indication of large debt capacity. Leary and Roberts (2010) define debt capacities in terms of the leverage ratios of investment-grade rated firms in the same industry-year combination. Accordingly, we use debt to asset ratios (DA) and credit rating (CR) of firms within different industries. In each quarter $t$, we compute the proportion of firms, $\pi_{st}(\gamma)$, within industry $s$, whose DA lies below a given threshold quantile, $\gamma$, and the proportion of firms within industry $s$ with credit rating above a known threshold value (rating) indicating an investment-grade issuer. To avoid simultaneity bias we interact $q_t$ with one-quarter lagged values of these proportions in our analysis. We investigate the relevance of these two measures of debt capacity empirically. The quantile threshold parameter $\gamma$ is estimated by grid search together with other unknown parameters.

An important feature of the above identification strategy is that it recognizes that firms' financing decisions are not made in isolation but are dependent on the financing choices of other firms in the same industry (e.g. Grieser et al. (2021), Leary and Roberts (2014), and MacKay and Phillips (2005)). This allows us to use cross-industry variations in $q_t \times \pi_{s,t-1}(\gamma)$ to separate the effects of $q_t$ from other factors that are common across all industries.

Thresholding has been widely used in the time series literature and more recently in panel data regressions to capture differential impact of macroeconomic shocks or policy interventions across groups or categories. See, for example, Tong (1990), Hansen (1999), Dang et al. (2012) Seo and Shin (2016), and Chudik et al. (2017), among others. Hansen (2011) provides a review of econometric applications of threshold models. Similar ideas are used in corporate finance, but often with some a priori specified threshold value. For example, firms are classified based on lowest/highest quartile or tercile of the empirical distribution of some particular characteristic of interest.[2] In our empirical strategy, the unknown quantile threshold values are estimated within the model rather than being imposed *a priori*. Also in our application, due to the inclusion of interactive effects in the panel regressions and the time-varying nature of the industry-specific proportions, the responses of firms to LSAPs are both non-linear and time-varying.

An important rationale behind our identification strategy is that the effects of LSAPs are heterogeneous and depend on the ability of firms in an industry to issue "safe" debt (as indicated by our leverage threshold variable and the presence of firms with investment grade ratings). This assumption is motivated by the most frequently discussed channels through which LSAPs may reduce interest rates and ease financial conditions.[3] Here we highlight three main channels. The first channel operates *via* some key institutional investors, such as insurance companies and pension funds, with preference for holding near zero-default-risk assets. By reducing the free float of U.S. Treasuries, LSAPs may induce these investors to pay a higher premium for those assets with a very low default risk as the supply is lower. This channel, which is typically referred to as the "safety channel" or "portfolio substitution channel", suggests that LSAPs should lower the yields of safe assets (e.g. Treasuries and high-grade corporate bonds) relative to riskier assets such as lower-grade corporate bonds. As a result, firms with stronger business fundamentals (e.g. lower leverage and higher credit ratings) ought to benefit more from LSAPs. A second important transmission mechanism is the so called "bank lending channel". The Fed's LSAPs increase the value of existing assets on banks' balance sheets (e.g. mortgage-backed securities and/or Treasuries). This raises banks' capital ratios making them more willing to lend. A third mechanism through which LSAPs influence interest rates is the "signalling channel". This channel may affect bond market interest rates *via* the expectations hypothesis because purchases of assets by the Fed reinforce its commitment to maintain interest rates low for long. Also in the case of the bank lending and signalling channels, LSAPs may be more beneficial to firms with adequate debt capacity, whilst over-leveraged firms may find it difficult to take full advantage of the reduction in the cost of credit or the additional credit supply generated by LSAPs without the risk of becoming financially distressed.[4]

[2] See, for example, Flannery and Rangan (2006), and Greenwood et al. (2010).

[3] See Krishnamurthy and Vissing-Jorgensen (2011), and Kuttner (2018) for a detailed discussion on the transmission mechanisms of quantitative easing.

[4] See Flannery and Rangan (2006), and Leary and Roberts (2010), among others, for a discussion on the inability of raising further debt for highly leveraged firms. Ottonello and Winberry (2020) find that firms with

Out of the two industry-specific threshold variables considered, we find that existing firms' debt burdens play a more important role in the transmission of LSAPs, compared to the proportion of firms with investment grade credit ratings. In the case of our benchmark specification, the threshold parameter, $\gamma$, is estimated to be 0.77, just above the upper quartile of the cross-section distribution of firms' DA at a given point in time, indicating that firms with high debt burdens tended to benefit the least from LSAPs. Our estimation results clearly show that industries with higher proportion of firms with DA ratio below the $77^{th}$ quantile on average experienced a larger increase in external debt financing in response to LSAPs.

Finally, by considering a dynamic panel data model we are able to identify the time profile of the effects of LSAPs on firms' capital structure, providing a clear and strong evidence that such effects are long-lasting. At the same time, albeit highly statistically significant, the relatively small magnitude of the estimated long-run effects suggests that LSAPs have contributed only marginally to the rise in U.S. corporate debt ratios of the last decade (as documented for instance by IMF (2019)).

Our empirical results are shown to be robust to a number alternative choices. In the main paper we report estimates obtained using a quantitative policy measure comprising gross purchases of U.S. Treasuries and agency mortgage-backed securities. But, as documented in the online supplement, our results continue to hold when using a policy on/off indicators typically used in the literature. To show the robustness of our results to the choice of dynamic specification we report short-term and long-term estimates for the standard partial adjustment model, as well as for the more general autoregressive distributed lag models. Regarding the control variables, in addition to firm-specific fixed effects we also control for several time-varying industry-specific covariates to further reduce possible omitted variables bias due to the fact that firms in a given industry face common factors that may drive their financing choices. Time effects at the industry levels are controlled by industry-specific linear time trends. It is also shown that our estimation results are robust to the inclusion of several macroeconomic indicators interacted with industry-specific dummies in place of industry-specific linear time trends. Finally, our results continue to hold after correcting for potential small-sample bias arising from the fact that we employ a dynamic panel model with fixed effects where the number of time series observations is small relative to the number of firms/industries in our panel.

In summary, we find statistically highly significant effects of LSAPs on corporate debt financing, but the magnitude of such effects in the long run (averaged over business cycles) are rather small.

low default risk, low debt burdens and high credit ratings were the most responsive to changes in (conventional) monetary policy during the period preceding the global financial crisis.

**Related literature.** Our paper relates to a number of different strands in the literature. One recent strand investigates the relationship between corporate debt issuance and government debt supply. Greenwood et al. (2010) argue that firms behave as liquidity providers, absorbing the supply shocks created by changes in the maturity structure of government debt. They show that firms tend to issue more long-term (short-term) debt when the maturity of government debt decreases (increases) to fill the resulting gap. Badoer and James (2016) argue that this gap filling behaviour only explains the issuance of long-term (but not short-term) corporate bonds and that these issuances are more common for highly rated firms. Similarly, Graham et al. (2014) find that government debt is negatively correlated with corporate debt, especially for larger and less risky firms whose debts are closer substitutes for Treasuries. Although these studies mostly cover the period before the introduction of LSAPs, they provide some insight on how LSAPs may impact firms' financing choices by affecting the overall supply of Treasuries. The current paper provides direct evidence on the effects of LSAPs on firms' capital structure.

There is also a growing literature that looks at the impact of LSAPs using micro-level evidence. Foley-Fisher et al. (2016), FRY henceforth, show that firms more dependent on longer-term debt issued more long-term debt as a result of the Fed's maturity extension program (MEP). Our analysis differs from the FRY study in a number of important respects. First, FRY focus on long-term debt growth. Instead, in line with the literature on capital structure, our main dependent variable is debt to asset ratio. Our choice is consistent with the fact that the asset and liability side of a firm's balance sheet are jointly determined. Second, while FRY's research question only requires a static specification, our empirical model is dynamic and thus accounts for the highly persistence nature of firms' leverage, as documented in Flannery and Rangan (2006) and Lemmon et al. (2008). This in turn allows us to study the long-term effects of LSAPs on firms' financing decisions besides its short-run impact. Third, FRY only focus on the impact of the Fed's purchases around the MEP's announcement. Instead, we jointly evaluate all the first four asset purchases implemented by the Feds' since the first injection in November 2008. Thus, we assess and quantify the overall effects of LSAPs, which is particularly important in light of the fact that QE is becoming part of the standard central bank toolkit. At the same time, we use quarterly observations which are better suited to distinguish the effects of LSAPs from other macroeconomic conditions represented in our model by unobserved time effects. Finally, we exploit a different identification strategy. FRY use a difference-in-difference approach whereby firms which relied more on longer-term debt before the MEP would issue even more of it by filling the gap created by the Fed's Treasury purchases. Instead, motivated by the literature which document that industry factors are important determinants of capital structure, we utilize cross-industry variation in the proportion of firms with spare debt capacity to demonstrate that LSAPs increased firms' leverage in both the short- and the long-run.[5]

Our study is also related to the literature which studies the link between QE and bank lending. Rodnyansky and Darmouni (2017) use a difference-in-difference approach which exploits the fact that banks differ in their prevalence of MBS. They demonstrate that banks with a relatively large fraction of MBS on their balance sheets expanded both real estate lending, and commercial and industrial loans as a results of QE. Similarly to Rodnyansky and Darmouni (2017), Chakraborty et al. (2020) exploit the fact that banks differ in their exposure to MBS purchase to find that banks benefiting from MBS purchases increased mortgage origination, compared to other banks. They also document a crowding out effect: QE encouraged exposed banks to lend more to the housing markets while reducing their commercial and industrial lending. Compared to these two studies, we employ a different empirical and identification strategy, and focus on non-financial firms' capital structure. Contrary to Chakraborty et al. (2020), we find that firms' debt to asset ratios increased as a results of LSAPs.

Our paper also partly relates to the literature that tries to understand the role of financial frictions in the transmission of monetary policy. For example, focusing on the period preceding the global financial crisis, Ottonello and Winberry (2020) find that firms with low default risk were the most responsive to changes in monetary policy. In line with their findings, our paper highlights the important role of existing firms' debt capacity within an industry in the transmission of LSAPs. In addition, our analysis takes into account that a firm's financing decision strongly depends on the financial choice of other firms' within the same industry.

More generally, our paper relates to the vast literature which studies the relative importance of various determinants in non-financial firms' capital structure decisions. Excellent reviews are provided by Frank and Goyal (2008) and Graham and Leary (2011). In line with the findings of MacKay and Phillips (2005), Frank and Goyal (2009), Lemmon et al. (2008), and Leary and Roberts (2014), we find that industry factors are powerful predictors of firms' leverage. Our study is also connected with the research that advocates that capital market segmentation and supply conditions play an important role in observed financial structures (see Baker (2009) for a comprehensive review).

The remainder of the paper is organized as follows: Section 2 describes the data used in the empirical analysis. Section 3 sets out and discusses the identification strategy. Section 4 describes the dynamic panel data regression models used for estimation and inference. Section 5 considers the estimation of the quantile threshold parameters and discusses the main empirical findings. Section 6 provides some concluding remarks. Details of data sources, their summary statistics, together with an extensive set of additional supporting panel regression results are provided in an online supplement.

[5] Giambona et al. (2020) also use firm-level data at annual frequency and identify the effects of QE by exploiting differences in firms' access to the bond market.

## 2 Data

We use an unbalanced panel of U.S. publicly traded non-financial firms observed at quarterly frequencies over the period 2007-Q1 to 2018-Q3. We employ Compustat database to obtain selected measures of firm size, tangibility, cash holdings, leverage, and other firm characteristics which are commonly used in the corporate finance literature.

As a proxy for capital structure we use firm leverage, defined as the ratio of debt to assets, both measured at book values. We prefer book leverage to market leverage to reduce concerns over the possibility that the effects of LSAPs on firms' debt ratios are anticipated. This is because, as noted in Frank and Goyal (2009), contrary to market measures which are typically forward looking, book leverage is a backward looking variable.

In addition to firm-specific data, we also consider several time series variables at the industry level. It has been widely documented that industry conditions, and industry median leverage in particular, are important determinants of firms' capital structure, besides firm-specific characteristics. To construct such industry-specific variables, we group firms in our sample into various industries, based on the three-digit Standard Industrial Classification (SIC). Specifically, firms are grouped into 67 three-digit SIC industries, such that each industry group contains at least 20 firms.[6]

To align our analysis with previous studies on firms' capital structure, we focus on non-financial firms and exclude firms in the regulated utilities (SIC 4900-4999) and those that belong to the non-classifiable sector (SIC codes above or equal to 9900).[7] In total, our data consists of $95,489$ firm-quarter observations, comprised of $3,647$ distinct firms on average observed over 26.2 quarters. Firms in our sample have at least 5 time observations (T) while the maximum T is 47. For the sake of brevity, a detailed description of both the variables under consideration and the sample selection screens, as well as the classification of firms by industry are provided in Section A of the online supplement, where we also provide a number of descriptive and summary statistics at both firm- and industry-level.

**Large-scale asset purchases.** To estimate the effects of the Fed's asset purchases on firms' debt to asset ratios, we employ a quantitative measure of LSAPs obtained from the New York Fed's website. Our primary policy variable of interest is the total gross amount of U.S. Treasuries and agency mortgage-backed securities purchased by the Fed.[8] The use of gross instead of net amount is in line with Chakraborty et al. (2020) who focus on gross purchases

[6] We prefer the three-digit to the two-digit SIC industry classification as the latter would result in fewer industry groups, namely 41. More importantly, the conclusions highlighted in the paper continue to hold also when classifying firms into two-digit SIC industries. Results for the two-digit SIC classification are available from the authors on request.

[7] The SIC codes of excluded financial firms are 6000-6999.

[8] U.S. Treasuries purchases include notes, bonds, and Treasury Inflation-Protected Securities (TIPS).

to capture the Maturity Extension Program through which the Fed used the proceeds of its sales of shorter-term Treasuries to purchase longer-term Treasury securities.

We scale our policy variable so that its average value is unity over the policy sample. This scaling facilitates the interpretations of the estimation results, and makes our estimates based on the quantitative measure directly comparable to the estimates obtained using a qualitative (0,1) policy variable. Our quantitative measure is highly correlated with the qualitative variable (the correlation between the two variables is 0.7298). The quantitative measure is also better suited to capture the magnitude of the Fed's purchases.[9]

# 3 Identification of macro policy effects with heterogeneous outcomes

## 3.1 Identification strategy

As with all macro policy changes, identification of the effects of LSAPs on firms' debt to asset ratios is complicated by the concurrent effects of other macroeconomic developments. A number of recent papers try to exploit differences in banks' holdings of MBS to identify the effects of QE on banks' mortgage lending as well as commercial and industrial loans (e.g. Chakraborty et al. (2020), and Rodnyansky and Darmouni (2017)).[10] To this end, banks' MBS exposure is interacted with a measure of Fed's purchases, and identification of the policy effect is achieved from the differential effects of the policy on bank lending. Interactions are also employed by Foley-Fisher et al. (2016) who utilize differences in firms' long-term debt dependence to study the effects of MEP on firms' long-term debt growth and other characteristics. In this paper, in line with this literature, we employ interactive terms to exploit differences in firms' debt burdens and credit ratings across industries.

The rationale for our identification strategy is based on two considerations. The first is that firms tend to closely align their own financing decisions with the financial choices made by firms from the same industry.[11] The second consideration is the *a priori* belief that firms with higher debt capacity and financial flexibility should be more responsive to the Fed's LSAPs.[12]

The basic idea behind our identification strategy is best described in the context of a static model without dynamics or control variables. Consider the panel regression model

$$y_{is,t} = \mu_{is} + \phi_{st} + \beta_0 \pi_{s,t-1}(\gamma) + \beta_1 q_t \times \pi_{s,t-1}(\gamma) + u_{is,t}, \tag{1}$$

[9] Further information on both the quantitative and qualitative measure of LSAPs are provided in Section A of the online supplement.

[10] Rodnyansky and Darmouni (2017) do not include time effects in their regression model because they also include $q_t$, a measure of quantitative easing, on its own without interactions.

[11] See, for example, Frank and Goyal (2009), Grieser et al. (2021), and Leary and Roberts (2014).

[12] See, for example, Graham et al. (2014), Greenwood et al. (2010), Leary and Roberts (2010), and Lemmon and Zender (2010).

where $y_{is,t}$, is the ratio of debt to assets (DA) of firm $i$ in industry $s = 1, 2, ..., S$, for quarter $t$, while $\pi_{st}(\gamma)$ denotes the proportion of firms in industry $s$ with DA below the $\gamma^{th}$ quantile of the cross-sectional distribution of $y_{is,t}$ across all firms at time $t$. Specifically,

$$\pi_{st}(\gamma) = \frac{1}{N_{st}} \sum_{i=1}^{N_{st}} \mathcal{I}\left[y_{is,t} < g_t(\gamma)\right], \tag{2}$$

where $N_{st}$ denotes the number of firms in industry $s$ during quarter $t$, and $\mathcal{I}(A)$ is an indicator variable that takes the value of one if $A$ is true and zero otherwise. The quantile threshold parameter $\gamma$ $(0 < \gamma < 1)$ is estimated using a grid search procedure to be explained in a separate section. Note that equation (1) only includes a one-quarter lag of $\pi_{st}(\gamma)$ to avoid simultaneous determination of this proportion and the dependent variable. $q_t$ is the quantitative policy variable measuring the size of the Fed's U.S. Treasuries and agency MBS purchases.

We use firm-specific effects, $\mu_{is}$, to remove systematic differences across firms in different industries, and consider industry-time fixed effects, $\phi_{st}$, to remove differences in time effects across industries. Allowing for time effects is critical if we are to avoid confounding the policy effects with other unrelated factors that are likely to have pervasive effects on the outcome variable, $y_{is,t}$. Within the above framework, $\phi_{st}$ is included to capture such time-industry effects that fully take account of non-policy macro factors with differential industry effects. But it is clear that at this level of generality it is not possible to identify $\beta_1$, which is the policy effectiveness coefficient of interest. Some restrictions on $\phi_{st}$ must be entertained. One possible option is to consider an interactive time effect by specifying

$$\phi_{st} = \delta_t + \phi_s f_t, \tag{3}$$

where $\delta_t$ is the common component of $\phi_{st}$, the so-called fixed time effects, and $\phi_s f_t$ is the industry-specific component which is intended to capture non-policy macro variables that have differential outcomes across industries. To identify $\phi_s$ we first note that

$$S^{-1} \sum_{s=1}^{S} \phi_{st} = \delta_t + \left( S^{-1} \sum_{s=1}^{S} \phi_s \right) f_t,$$

and to identify the homogenous effects of non-policy variables from the industry-specific ones we need to set

$$\bar{\phi}_{\circ} = S^{-1} \sum_{s=1}^{S} \phi_s = 0. \tag{4}$$

Under this restriction $\delta_t$ is identified as the common component of non-policy macro variables. But to identify $\phi_s$, and hence $\beta_1$, further restrictions are required. One possibility is to assume $\phi_s$ are distributed independently across $s$ with mean zero and a constant variance, and then estimate $f_t$ for $t = 1, 2, .., T$ along with other parameters. See, for example, Ahn et al. (2001), Bai (2013), and Hayakawa et al. (2021). In this paper we consider an alternative estimation strategy which allows $\phi_s$ to be treated as free parameters to be estimated subject to (4) and for alternative specifications of $f_t$. Using (3) in (1) we have

$$y_{is,t} = \mu_{is} + \delta_t + \phi_s f_t + \beta_0 \pi_{s,t-1}(\gamma) + \beta_1 q_t \times \pi_{s,t-1}(\gamma) + u_{is,t}. \tag{5}$$

The fixed and time effects, $\mu_{is}$ and $\delta_t$, can now be eliminated using standard de-meaning techniques.[13] In standard panel regressions with fixed and time effects identification is achieved by setting $\phi_s = 0$ for all $s$. Here we place the restrictions on $f_t$ and consider identification of $\beta_1$ for arbitrary choices of $\phi_s$ but conditional on alternative specification of $f_t$. In the empirical applications we consider linear trends and set $f_t = t/T$. The panel estimates of $\beta_1$ do not depend on the scales of $f_t$, and it is therefore convenient to set $f_t = f(t/T)$ where $f(x)$ is a general function of $x = t/T$. Changing the scale of $f_t$ only affects the estimates of $\phi_s$, with no consequence for the policy effectiveness coefficient, $\beta_1$. In view of the uncertainty surrounding the choice of $f_t$, the robustness of the estimates of $\beta_0$ and $\beta_1$ are further investigated by experimenting with a number of observed macro-variables as proxies for $f_t$.

Identification of $\beta_1$ also requires a sufficient degree of variations in $q_t$ over time and $\pi_{s,t-1}(\gamma)$ over $s$, such that there is a unique solution for $\beta_0$ and $\beta_1$ to our estimation problem. This is indeed the case in our application, as shown in Section B of the online supplement, where we also provide further details on the optimization problem.

## 3.2 Average policy effect at industry and national levels

For clarity of exposition, suppose the policy is introduced at time $t = T_0$, and the full sample period $t = 1, 2, ..., T$, is split into policy on $(t > T_0)$ and policy off $(t \leq T_0)$ sub-periods. It is clear that post $t = T_0$ we only observe the policy on outcomes, which we denote by $y^1_{is,t} = y_{is,t}$, for $t = T_0 + 1, T_0 + 2, ..., T$. The policy off outcomes over the policy on sample, denoted by $y^0_{i,st}$ are not observed but can be estimated using (5). Specifically, assuming that the proportions, $\pi_{s,t-1}(\gamma)$, are not materially affected by the policy change, we have

$$y^0_{is,t} = E\left(y_{is,t} \left| q_t = 0, \pi_{s,t-1}(\gamma)\right.\right) = \mu_{is} + \delta_t + \phi_s f_t + \beta_0 \pi_{s,t-1}(\gamma)$$

for $t = T_0 + 1, T_0 + 2, ..., T$. The predicted policy effects are given by

$$y^1_{is,t} - y^0_{is,t} = \beta_1 q_t \times \pi_{s,t-1}(\gamma) + u_{is,t}.$$

[13] In our empirical applications, where the panel is unbalanced, we use Wansbeek and Kapteyn (1989) transformations to eliminate $\mu_{is}$ and $\delta_t$. Wansbeek and Kapteyn procedure is equivalent to including both time and fixed effect dummies in the panel regressions, but it is less computationally cumbersome when $sup_t \sum_{s=1}^{S} N_{st}$ is large.

Using this result, we can now compute the average policy effect over the policy on sample at the industry or national level. At the industry level the average policy effect (per quarter) is

$$\begin{aligned} \overline{PE}_s &= \tfrac{1}{T-T_0}\sum_{t=T_0+1}^{T}\left[\tfrac{1}{N_{st}}\sum_{i=1}^{N_{st}}\left(y^1_{is,t}-y^0_{is,t}\right)\right] \\ &= \beta_1\left[\tfrac{1}{T-T_0}\sum_{t=T_0+1}^{T} q_t\times\pi_{s,t-1}(\gamma)\right]+\tfrac{1}{T-T_0}\sum_{t=T_0+1}^{T}\left(\tfrac{1}{N_{st}}\sum_{i=1}^{N_{st}}u_{is,t}\right). \end{aligned}$$

The random component of the last term is likely to be small and will tend to zero with $N_{st}$ and $T-T_0+1$ sufficiently large, and the industry level policy effect is well approximated by

$$\overline{PE}_s=\beta_1\left[\frac{1}{T-T_0}\sum_{t=T_0+1}^{T} q_t\times\pi_{s,t-1}(\gamma)\right]+o_p(1). \tag{6}$$

At the national level the average per quarter policy effect is given by

$$\overline{PE}=\beta_1\left[\frac{1}{T-T_0}\sum_{t=T_0+1}^{T} q_t\times\sum_{s=1}^{S} w_s\pi_{s,t-1}(\gamma)\right], \tag{7}$$

where $w_s$ is the share of industry $s$ in the economy, which can be measured for example by employment shares.

Although the above expressions apply irrespective of whether the strength of the policy varies over the policy period or not, our preferred measure of $q_t$ is the size of the Fed MBS and U.S. Treasuries' purchases because of its greater degree of variability over time as compared to when $q_t$ is a qualitative measure equal to 1 over the policy on period and 0 otherwise. At the same time, we scale our quantitative measure so that its average value over the policy sample is unity. Specifically, let $Q_t>0$ for some $t$, denote the size of Fed's purchases, then $q_t$ ought to be scaled as

$$\begin{aligned} q_t &= 0, && \text{policy off period } (t=1,2,...,T_0), \\ q_t &= \frac{Q_t}{\frac{1}{T-T_0}\sum_{\tau=T_0+1}^{T}Q_\tau}, && \text{policy on period } (t=T_0+1,T_0+2,...,T). \end{aligned}$$

This normalization, besides removing the unit of measurement of the variable, also makes the policy outcomes directly comparable under both qualitative and quantitative policy measures.

## 3.3 Possible confounding effects of policy changes on threshold parameters

The above analysis assumes the threshold parameter, $\gamma$, used to compute the industry proportion, $\pi_{st}(\gamma)$ described in equation (2), is the same under the policy on and policy off periods. Denoting the threshold values during the policy off and policy on periods by $g_t(\gamma_0)$ and $g_t(\gamma_1)$, respectively, and using a similar line of reasoning as above we have

$$y^1_{is,t}-y^0_{is,t}=\beta_0\left[\pi_{s,t-1}(\gamma_1)-\pi_{s,t-1}(\gamma_0)\right]+\beta_1 q_t\times\pi_{s,t-1}(\gamma_1)+u_{is,t},$$

for $t = T_0 + 1, T_0 + 2, ..., T$. The first term can be viewed as an indirect effect of the policy change, which needs to be taken into account. To allow for such a possibility, in our empirical application we consider a more general formulation of (5) and distinguish between the threshold parameter for the construction of the industry-specific proportions before and after the policy change, namely we consider the two-threshold panel regression

$$y_{is,t} = \mu_{is} + \delta_t + \phi_s f_t + \beta_0 \pi_{s,t-1}(\gamma_{pre}) + \beta_1 q_t \times \pi_{s,t-1}(\gamma_{post}) + u_{is,t}, \tag{8}$$

which then ensures that

$$y^1_{is,t} - y^0_{is,t} = \beta_1 q_t \times \pi_{s,t-1}(\gamma_{post}) + u_{is,t}.$$

The separate threshold parameters $\gamma_{pre}$ and $\gamma_{post}$ can be estimated using grid search techniques.

## 3.4 On the choice of the threshold variables

As previously mentioned, our preferred proxy for a firm's ability to increase its stance on leverage following the Fed's LSAPs is the proportion of firms in an industry with DA ratios below the $\gamma$-th quantile, as described in equation (2). An advantage of this measure is that firms in an industry are classified as relatively less constrained by concerns over debt capacity based on the relative position of their DA ratios in the empirical distribution of firms' leverage, rather than on some absolute threshold parameter value.

Our hypothesis is that in order to take advantage of the reduction in the cost of debt and/or increase in the supply of external finance resulting from the Fed's LSAPs, firms should have enough spare debt capacity. The basis for this argument is twofold. On the one hand, firms with lower levels of leverage are better able to borrow and deviate from the long-run target to meet their funding needs (e.g. Flannery and Rangan (2006), Leary and Roberts (2005), Lemmon and Zender (2010)). On the other hand, overleveraged firms are less able to fill the gap of safe assets' supply created by the Fed's asset purchases because issuing further public debt or resorting to additional bank borrowing could lead to financial distress. It is in fact well recognized that higher debt burdens are powerful predictors of future default probabilities and, as such, can be used as a classification benchmark in credit risk analysis (e.g. Bhamra et al. (2010), and Ottonello and Winberry (2020)). Debt ratios have also been found to be a significant predictor of firms' financial constraints (e.g. Kaplan and Zingales (1997) and Hadlock and Pierce (2010)).

Besides leverage, we also consider an alternative threshold variable which exploits differences in firms' investment grade credit ratings (CR) across industries. To this end, we compute the proportion of firms in an industry with CR exceeding the $BBB^-$ grade.[14] Specifically, we

[14] Data on credit ratings (item *splticrm* in Compustat) are only available until 2016-Q4. For the remaining quarters we assume that the proportions take the last available value, i.e. $\pi_{st,CR} = \pi_{s\bar{T},CR}$, for $t > \bar{T}$, where $\bar{T}$ denotes the fourth quarter of 2016. We have checked that our results are not materially affected by this

consider

$$\pi_{st,CR} = \frac{1}{N_{st}} \sum_{i=1}^{N_{st}} \mathcal{I}\left(Rating_{is,t} \geq BBB^{-}\right), \tag{9}$$

as an alternative to $\pi_{st,DA}$ defined by (2). The use of $\pi_{st,CR}$ is motivated by Lemmon and Zender (2010) who utilize the likelihood that a firm can access public debt markets as a proxy for debt capacity. Moreover, recent evidence suggests that higher credit quality firms may be more responsive to LSAPs (e.g. Badoer and James (2016)).

# 4 Panel threshold-ARDL models

We extend the simple static models described in equation (5) and (8) by adding dynamics as well as firm-specific and industry-specific control variables. Our benchmark panel autoregressive distributed lag (ARDL) model is given by

$$\begin{aligned} y_{is,t} &= \mu_{is} + \delta_t + \phi_s f_t + \textstyle\sum_{\ell=0}^{p} \left[\beta_{0,\ell}\pi_{s,t-\ell-1}(\gamma) + \beta_{1,\ell} q_{t-\ell} \times \pi_{s,t-\ell-1}(\gamma)\right] \\ &\quad + \textstyle\sum_{\ell=1}^{p} \lambda_\ell y_{is,t-\ell} + \textstyle\sum_{\ell=0}^{p} \left(\boldsymbol{\alpha}_\ell' \mathbf{x}_{is,t-\ell} + \boldsymbol{\rho}_\ell' \mathbf{w}_{s,t-\ell}\right) + u_{is,t}, \end{aligned} \tag{10}$$

where as mentioned before the dependent variable, $y_{is,t}$, is the ratio of debt to assets (DA) of firm $i$ in industry $s$ for quarter $t$. $\mu_{is}$ and $\delta_t$ denote firm-specific effects and time effects, respectively, while $\phi_s$ is the industry-specific trend coefficient, with $f_t$ proxied by either a scaled linear time trend or observed macro variables. $q_t$ measures the (scaled) size of the Fed's asset purchases, and $\pi_{s,t}(\gamma)$ denotes the proportion of firms in an industry with DA below the $\gamma$-th quantile. The basic models, (5) and (8), are also augmented with up to $p^{th}$ order lags of $y_{is,t}$, as well as the lags of control variables, $\mathbf{x}_{is,t}$ and $\mathbf{w}_{s,t}$.

While identification of the effects of LSAPs comes from cross-industry variation, we control for firm-specific covariates to improve the precision with which the effects of the control variables are estimated. The vector $\mathbf{x}_{is,t}$ includes the following firm-specific characteristics: the ratio of cash to total assets (TA), property, plant, and equipment (PPE) scaled by TA (as a proxy for tangibility), and a measure of firm size (the natural logarithm of TA). In addition, we control for time-varying industry-specific covariates to further reduce possible omitted variables bias due to the fact that firms in an industry face common forces that may drive their financing decisions. The vector of industry-specific variables, $\mathbf{w}_{s,t}$, includes the median (three-digit SIC) industry leverage, and the median industry growth (computed as the median of the changes in the logarithm of firm total assets). The choice of control variables is motivated by the findings of Frank and Goyal (2009) who document that among the variables used from the prior literature, the most relevant ones for explaining firm leverage are firm

assumption by re-running our regression models for the period 2007-Q1 to 2016-Q4. We find that the results highlighted in this paper continue to hold also in this case. There results are available from the authors on request.

size, market to book ratio, measures of tangibility and profitability, the median industry leverage, and expected inflation.[15] The set of variables considered is also commonly used in the corporate finance literature.

We report results for both the partial adjustment model, a commonly used specification in the empirical capital structure research (Graham and Leary (2011)), and the more general ARDL model described in equation (10). The ARDL approach is particularly attractive for our empirical analysis since, among its advantages, it can be used for the analysis of long-run relations, and it is robust to bi-directional feedback effects between firm leverage and its determinants (Pesaran and Shin (1998)). In other words, unlike the partial adjustment specification, the ARDL model takes into account the effects of lagged explanatory variables onto the dependent variable, and it allows for feedback effects from the dependent variable onto the regressors.

The estimation of policy parameters, $\beta_{1,\ell}$, for $\ell = 0, 1, .., p$, encounter two technical challenges: the choice of lag order, $p$, and the estimation of the threshold parameter, $\gamma$. A simultaneous estimation of $p$ and $\gamma$ is computationally demanding and involves a considerable degree of data mining. Here we follow the literature and estimate $\gamma$ for $p = 1$ and 2 and present both sets of results together with results for the partial adjustment model. Also, allowing for different lag orders for policy and control variables involves many permutations with a large number of dynamic specifications to choose from, and using the same lag order across the variables seems a reasonable empirical strategy.

As to the estimation of $\gamma$, we follow the threshold literature and estimate $\gamma$ by grid search, and assume the estimate as given when it comes to estimate the policy parameters of interest. This two-step strategy is justified since the estimates of the threshold parameters are super consistent in the sense that they converge to their true values much faster than the estimate of the policy parameters. This result is shown formally in the context of static threshold panel data models by Hansen (1999), and investigated further for panel threshold-ARDL models by Chudik et al. (2017). In view of these theoretical results in what follows we do not provide standard errors for threshold estimates and compute the standard errors of the policy effects taking the estimated value of the threshold parameter as given.

[15] Differently from Frank and Goyal (2009), we do not include expected inflation (or other observed macroeconomic variables) as our model is more general as it allows for time effects. We exclude the market to book ratio from our benchmark model because the associated coefficients were often insignificant, both in statistic and economic terms. Nevertheless, we will later show that our estimation results are robust to the inclusion of additional explanatory variables, such as the market to book ratio, R&D expense to TA, and the median industry Q, among others.

# 5 Estimation and empirical findings

## 5.1 Quantile threshold parameter estimates

For a given choice of $p$, the quantile threshold parameter $\gamma$ in (2), is estimated by minimizing the sum of squared residuals (SSR) for different values of $\gamma$ in the range $0.25 \leq \gamma \leq 0.9$ in increments of 0.01.[16] Specifically, for a given $p$ and for each value of $\gamma$ within the grid we run the panel regressions described in equation (10) by both fixed and time effects (FE–TE) over the sample period 2007-Q1 to 2018-Q3. We do so for both the partial adjustment and the ARDL($p$) models, for $p = 1, 2$.

The estimated threshold parameters for the single-threshold model (where $\gamma_{pre} = \gamma_{post} = \gamma$) are shown in the upper panel of Table 1. The estimated quantile threshold parameter, $\hat{\gamma}$, is equal to 0.56 for the partial adjustment model, and it is higher at 0.76 when we use the more general ARDL($p$) specifications, irrespective of the choice of $p = 1$ or 2.

Table 1: **Estimated quantile threshold parameters**

Estimates of the quantile threshold parameters from a grid search procedure across both the partial adjustment model and the ARDL specifications described in equation (10). The upper panel shows the estimated threshold parameters for the single-threshold panel regression model, where $\gamma_{pre} = \gamma_{post}$. The lower panel displays results for the two-threshold model, where $\gamma_{pre} \neq \gamma_{post}$. The estimation sample consists of an unbalanced panel of $3,647$ U.S. publicly traded non-financial firms observed at a quarterly frequency over the period 2007:Q1 - 2018:Q3.

| | Par. Adj. | ARDL(1) | ARDL(2) |
|---|---|---|---|
| | | $\gamma_{pre} = \gamma_{post} = \gamma$ | |
| $\hat{\gamma}$ | 0.56 | 0.76 | 0.76 |
| | | $\gamma_{pre} \neq \gamma_{post}$ | |
| $\hat{\gamma}_{pre}$ | 0.56 | 0.56 | 0.56 |
| $\hat{\gamma}_{post}$ | 0.77 | 0.77 | 0.77 |

As we shall see, the different estimates obtained for $\gamma$, depending on whether a partial adjustment or ARDL specifications are used, only applies to the single-threshold case, where we assume $\gamma_{pre} = \gamma_{post}$. Following the more general model discussed in Subsection 3.3, we also estimate the threshold parameters allowing these parameters to differ over the periods pre- and post introduction of LSAPs. The grid search procedure is now carried out over values of $\gamma_{pre}$ and $\gamma_{post}$ in the grid formed by $0.25 \leq \gamma_{pre} \leq 0.9$ and $0.25 \leq \gamma_{post} \leq 0.9$, in 0.01 increments for both $\gamma_{pre}$ and $\gamma_{post}$. The estimation results for this case are reported in the lower panel of Table 1. It can be seen that we obtain the same estimates $\hat{\gamma}_{pre} = 0.56$ and $\hat{\gamma}_{post} = 0.77$, across all the three model specifications, and irrespective of the lag order $p = 1, 2$. Both threshold

[16] We start our grid search for $\gamma_{DA}$ from 0.25 instead of 0.1 because the $q$-th quantile of DA is equal to zero for all values of $q$ below 0.21. Further details are provided in Section B of the online supplement.

estimates lie well within the grid, with the estimate for the post LSAPs period being notably higher.

These estimates suggest that the higher the proportions of firms in an industry with relatively low levels of leverage, the more likely it is that firms in that industry can take advantage of their lower debt burdens to increase their DA ratios, as compared to firms in industries with higher proportions of more leveraged firms. This type of firm behaviour has been documented for instance by Flannery and Rangan (2006), among others. In addition, our estimates suggest that the Fed's purchases may have also benefited firms with moderate debt levels conditional on not being over-leveraged, with the effects of LSAPs being stronger when the proportions of firms in an industry without high debt burdens are higher. This may be due to the fact that these firms being less constrained by concerns over debt capacity can act most aggressively in response to LSAPs to increase their leverage ratios.

We shall see in the next subsection that the estimated regression coefficients associated with the interaction of our measure of LSAPs and the industry-specific threshold leverage variable, $\pi_{st,DA}$, corroborate these hypotheses.

## 5.2 Short and long-run effects of LSAPs and estimates of other firm and industry-specific features

Given the threshold values we now present the estimates of some of the key parameters of the panel regressions in equation (10) using both fixed and time effects (FE–TE) over the period 2007-Q1 to 2018-Q3. The results are summarized in Table 2 where we report the estimates of the net short-run effects defined as the sum of estimated coefficients of current and the $p$ lagged values of the regressor under consideration. In this way we allows for possible over-shooting of the estimates whereby a large positive initial impact is reversed subsequently with some negative lagged effects. For example, the net short-run policy effect is defined by $\varphi_{1,DA} = \sum_{\ell=0}^{p} \beta_{1,\ell,DA}$, where $\beta_{1,\ell,DA}$ is the coefficient of $q_{t-\ell} \times \pi_{s,t-\ell-1,DA}(\hat{\gamma})$ in the threshold-panel regression defined by (10), with $p$ equal to zero for the partial adjustment model, and $p = 1, 2$ for the panel ARDL(1) and ARDL(2) regressions, respectively. The first three columns show results for the single-threshold panel regression model, while the last three columns report the estimates for the two-threshold model, which is our preferred specification. Full panel regression estimation results are provided in Section C of the online supplement.

As can be seen, the estimate of $\varphi_{1,DA}$ (the coefficient of $LSAPs \times \pi_{DA}$ in the summary result tables) is positive and highly significant under all specifications while its magnitude differs across specifications. We find that the higher the *ex ante* proportion of firms which are not over-leveraged in an industry, the more effective the LSAPs in facilitating firms' access to external financing. This corroborates our hypothesis that firms with adequate debt capacity are the most responsive to the introduction of LSAPs, and that how a firm responds to the

Fed's purchases strongly depends on the responses of other firms in the same industry.

Table 2: **FE–TE estimates of the net short-run effects of LSAPs on debt to asset ratios of non-financial firms**

Estimates of net short-run effects of LSAPs on firms' debt to asset ratios (DA) as well as the effects of both firm- and industry-specific variables on DA, for both the partial adjustment model and the ARDL specifications described in equation (10). Net short-run effects are defined as the sum of the estimated coefficients of current and the $p$ lagged values of the regressor under consideration. The first three columns report results for the single-threshold panel regression model, where $\gamma_{pre} = \gamma_{post}$. The last three columns report results for the two-threshold panel regression, where $\gamma_{pre} \neq \gamma_{post}$. The estimated quantile threshold parameters are shown in Table 1. All regressions include both firm-specific effects and time effects as well as industry-specific linear time trends. $LSAPs$ is the (scaled) amount of U.S. Treasuries and agency MBS purchased by the Fed; $\pi_{DA}(\gamma)$ denotes the proportion of firms in an industry with DA below the $\gamma$-th quantile; $\pi_{CR}$ is the proportion of firms in an industry with investment grade credit ratings. The sample consists of an unbalanced panel of $3,647$ U.S. publicly traded non-financial firms observed at a quarterly frequency over the period 2007:Q1 - 2018:Q3. Robust standard errors (in parentheses) are computed using the delta method (*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$).

| | Dependent variable: debt to assets (DA) | | | | | |
|---|---|---|---|---|---|---|
| | $\gamma_{pre} = \gamma_{post} = \gamma$ | | | $\gamma_{pre} \neq \gamma_{post}$ | | |
| | Par. Adj. | ARDL(1) | ARDL(2) | Par. Adj. | ARDL(1) | ARDL(2) |
| $\pi_{DA}$ | 0.0445*** | 0.0136*** | 0.0156*** | 0.0464*** | 0.0150*** | 0.0188*** |
| | (0.0042) | (0.0045) | (0.0049) | (0.0040) | (0.0046) | (0.0051) |
| $LSAPs \times \pi_{DA}$ | 0.0041*** | 0.0060*** | 0.0069*** | 0.0083*** | 0.0077*** | 0.0090*** |
| | (0.0013) | (0.0017) | (0.0019) | (0.0015) | (0.0016) | (0.0018) |
| $\pi_{CR}$ | 0.0077 | 0.0023 | 0.0026 | 0.0077 | 0.0042 | 0.0056 |
| | (0.0113) | (0.0115) | (0.0117) | (0.0112) | (0.0117) | (0.0118) |
| $LSAPs \times \pi_{CR}$ | 0.0033 | 0.0008 | 0.0003 | 0.0034 | 0.0019 | 0.0015 |
| | (0.0028) | (0.0028) | (0.0031) | (0.0026) | (0.0027) | (0.0031) |
| Lagged DA | 0.8264*** | 0.8337*** | 0.8386*** | 0.8266*** | 0.8337*** | 0.8386*** |
| | (0.0053) | (0.0052) | (0.0050) | (0.0053) | (0.0052) | (0.0050) |
| Cash to assets | -0.0496*** | -0.0380*** | -0.0365*** | -0.0496*** | -0.0380*** | -0.0364*** |
| | (0.0034) | (0.0030) | (0.0030) | (0.0034) | (0.0030) | (0.0030) |
| PPE to assets | 0.0248*** | 0.0236*** | 0.0218*** | 0.0249*** | 0.0236*** | 0.0219*** |
| | (0.0053) | (0.0047) | (0.0047) | (0.0053) | (0.0047) | (0.0047) |
| Size | 0.0051*** | 0.0030*** | 0.0034*** | 0.0051*** | 0.0030*** | 0.0034*** |
| | (0.0008) | (0.0008) | (0.0008) | (0.0008) | (0.0008) | (0.0008) |
| Industry Leverage | 0.1390*** | 0.0630*** | 0.0624*** | 0.1417*** | 0.0717*** | 0.0711*** |
| | (0.0075) | (0.0069) | (0.0075) | (0.0075) | (0.0082) | (0.0090) |
| Industry Growth | -0.0488*** | -0.1020*** | -0.1006*** | -0.0502*** | -0.1052*** | -0.1063*** |
| | (0.0132) | (0.0175) | (0.0209) | (0.0131) | (0.0176) | (0.0210) |
| Fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Time effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry linear trends | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 84,548 | 84,548 | 84,548 | 84,548 | 84,548 | 84,548 |
| $N$ | 3,647 | 3,647 | 3,647 | 3,647 | 3,647 | 3,647 |
| $max(T_i)$ | 44 | 44 | 44 | 44 | 44 | 44 |
| $avg(T_i)$ | 23.2 | 23.2 | 23.2 | 23.2 | 23.2 | 23.2 |
| $med(T_i)$ | 19 | 19 | 19 | 19 | 19 | 19 |
| $min(T_i)$ | 2 | 2 | 2 | 2 | 2 | 2 |

These results hold across both the partial adjustment model and the ARDL specifications. However, even the largest estimate of $\varphi_{1,DA}$ obtained for the two-threshold panel ARDL(2) model at 0.009 (0.0018) is rather small in economic importance.

The effects of $\pi_{DA}$ (without the interaction with the LSAPs variable) on firms' leverage are also positive and statistically significant. This indicates that the proportion of firms within the same industry without high debt burdens helps predict firms' financing decisions. This is in line with the findings of Flannery and Rangan (2006) and Lemmon and Zender (2010) who show that concerns over debt capacity influence firm financing behaviour.

However, we find that the proportion of firms with investment grade credit ratings in an industry ($\pi_{CR}$) does not significantly capture the uneven effects of LSAPs on firms' debt to asset ratios. Similarly, $\pi_{CR}$ without the interaction with LSAPs, is not a significant predictor of firms' leverage. These findings corroborate the view that firms' financial decisions are made in accordance with the leverage choices of other firms in the same industry but are less dependent on the characteristics of peer firms, such as credit rating, in line with the findings of Leary and Roberts (2014).

With respect to the other control variables, our findings are in line with the existing literature on firms' capital structure. First, leverage appears to be highly persistent, an aspect which has been widely documented (e.g. Lemmon et al. (2008)). Second, firms with more tangible assets and larger size tend to have higher leverage. Third, firms with higher cash holdings tend to operate with lower leverage. This finding is in line with the results of Hadlock and Pierce (2010), who document that more financially constrained firms hold cash for precautionary reasons. Finally, as in previous empirical studies, we find that industry median leverage is one of the key drivers of capital structure. The associated coefficient is the most important in magnitude besides the autoregressive coefficient. We note that the partial adjustment model tends to overestimate the economic effects of industry leverage as compared to the ARDL specifications. We also find that higher industry median growth results in lower leverage in line with the trade-off theory's prediction (Frank and Goyal (2009)).

Another important question is whether the Fed's purchases had long-lasting effects on firms' capital structure. While there is some evidence on the persistence of the effects of LSAPs on corporate and Treasury yields, albeit with some contrasting results (e.g. Greenlaw et al. (2018), Swanson (2021)), and Wright (2012)), less attention has been paid, to the best of our knowledge, on how this translated into firms' preference about their leverage ratios. Our dynamic panel model provides a suitable setting to answer this question. To this end, Table 3 reports the estimated long-run effects of LSAPs and other determinants on firms' leverage ratios. As before, the first three columns report results for the single-threshold panel regression model, while the last three columns show results for the two-threshold panel regression.

Table 3: **FE–TE estimates of the long-run effects of LSAPs on debt to asset ratios of non-financial firms**

Estimates of the long-run effects of LSAPs on firms' debt to asset ratios (DA) as well as the effects of both firm- and industry-specific variables on DA. We report results for both the partial adjustment model and the ARDL specifications described in equation (10). The first three columns report results for the single-threshold panel regression model, where $\gamma_{pre} = \gamma_{post}$. The last three columns report results for the two-threshold panel regression, where $\gamma_{pre} \neq \gamma_{post}$. The estimated quantile threshold parameters are shown in Table 1. All regressions include both firm-specific effects and time effects as well as industry-specific linear time trends. $LSAPs$ is the (scaled) amount of U.S. Treasuries and agency MBS purchased by the Fed; $\pi_{DA}(\gamma)$ denotes the proportion of firms in an industry with DA below the $\gamma$-th quantile; $\pi_{CR}$ is the proportion of firms in an industry with investment grade credit ratings. The sample consists of an unbalanced panel of $3,647$ U.S. publicly traded non-financial firms observed at a quarterly frequency over the period 2007:Q1 - 2018:Q3. Robust standard errors (in parentheses) are computed using the delta method (*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$).

| | Dependent variable: debt to assets (DA) | | | | | |
|---|---|---|---|---|---|---|
| | $\gamma_{pre} = \gamma_{post} = \gamma$ | | | $\gamma_{pre} \neq \gamma_{post}$ | | |
| | Par. Adj. | ARDL(1) | ARDL(2) | Par. Adj. | ARDL(1) | ARDL(2) |
| $\pi_{DA}$ | 0.2561*** | 0.0817*** | 0.0965*** | 0.2674*** | 0.0903*** | 0.1165*** |
| | (0.0254) | (0.0274) | (0.0308) | (0.0243) | (0.0279) | (0.0320) |
| $LSAPs \times \pi_{DA}$ | 0.0236*** | 0.0360*** | 0.0425*** | 0.0479*** | 0.0465*** | 0.0559*** |
| | (0.0077) | (0.0105) | (0.0121) | (0.0088) | (0.0097) | (0.0111) |
| $\pi_{CR}$ | 0.0444 | 0.0141 | 0.0161 | 0.0443 | 0.0250 | 0.0344 |
| | (0.0652) | (0.0692) | (0.0723) | (0.0647) | (0.0701) | (0.0733) |
| $LSAPs \times \pi_{CR}$ | 0.0187 | 0.0046 | 0.0016 | 0.0197 | 0.0112 | 0.0092 |
| | (0.0164) | (0.0167) | (0.0194) | (0.0149) | (0.0164) | (0.0192) |
| Cash to assets | -0.2860*** | -0.2286*** | -0.2260*** | -0.2860*** | -0.2285*** | -0.2257*** |
| | (0.0189) | (0.0175) | (0.0179) | (0.0189) | (0.0175) | (0.0179) |
| PPE to assets | 0.1429*** | 0.1418*** | 0.1352*** | 0.1435*** | 0.1420*** | 0.1357*** |
| | (0.0306) | (0.0283) | (0.0290) | (0.0306) | (0.0283) | (0.0290) |
| Size | 0.0295*** | 0.0183*** | 0.0213*** | 0.0295*** | 0.0183*** | 0.0212*** |
| | (0.0046) | (0.0045) | (0.0046) | (0.0046) | (0.0045) | (0.0046) |
| Industry Leverage | 0.8009*** | 0.3789*** | 0.3869*** | 0.8170*** | 0.4309*** | 0.4403*** |
| | (0.0452) | (0.0414) | (0.0460) | (0.0455) | (0.0498) | (0.0565) |
| Industry Growth | -0.2809*** | -0.6135*** | -0.6232*** | -0.2896*** | -0.6323*** | -0.6588*** |
| | (0.0762) | (0.1072) | (0.1309) | (0.0763) | (0.1079) | (0.1317) |
| Fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Time effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry linear trends | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 84,548 | 84,548 | 84,548 | 84,548 | 84,548 | 84,548 |
| $N$ | 3,647 | 3,647 | 3,647 | 3,647 | 3,647 | 3,647 |
| $max(T_i)$ | 44 | 44 | 44 | 44 | 44 | 44 |
| $avg(T_i)$ | 23.2 | 23.2 | 23.2 | 23.2 | 23.2 | 23.2 |
| $med(T_i)$ | 19 | 19 | 19 | 19 | 19 | 19 |
| $min(T_i)$ | 2 | 2 | 2 | 2 | 2 | 2 |

Once again, focusing on the policy effectiveness coefficient in the case of the leverage threshold variable, the long-run effects are computed as $\theta_{1,DA} = \varphi_{1,DA} \left(1 - \sum_{\ell=1}^{p} \lambda_\ell\right)^{-1}$, where as shown before $\varphi_{1,DA} = \sum_{\ell=0}^{p} \beta_{1,\ell,DA}$, for $p = 0, 1, 2$, while $\lambda_\ell$ denote the autoregressive coefficients. Because leverage is highly persistent, we find more economically meaningful effects of LSAPs on firms' capital structure in the long-run. Our results confirm that LSAPs significantly contributed to higher debt to asset ratios in the long-run, although the magnitude of the effects suggests that concerns over firms' excessive risk-taking (in the forms of higher debt ratios) due to LSAPs were at least in part overstated.

Overall, our results suggest that LSAPs facilitated firms' access to credit, and that their effectiveness depends on the ability of firms to issue new debt safely. The higher the proportion of firms without high leverage ratios in an industry, the stronger the response of firms to LSAPs in the same industry. We also document that the effects of LSAPs are long lasting.

## 5.3 The effects of LSAPs at industry and national levels

We now discuss the estimates of the average policy effects (APE) at the industry and national levels as set out in equations (6) and (7), respectively. For brevity, we only report the results for our preferred specification, namely the two-threshold ARDL(2) model. The estimates are displayed in Figure 1.[17] The blue bars report the estimated APE by industry based on the interaction of our quantitative measure of LSAPs and the leverage threshold variable, $\pi_{DA}$. Three-digit SIC industries are sorted from largest to smallest industry median leverage (averaged over time).

The estimates show a relatively high degree of heterogeneity in the effects of LSAPs on firms' debt to asset ratios across industries, largely driven by the cross-industry variation in the proportions of firms without high debt burdens ($\pi_{DA}(\hat{\gamma}_{post})$). The APE vary from 0.0021 for the automotive dealers' industry, which is one of the industries in our sample with largest median leverage, to 0.0089 for educational services' industry, one of the least leveraged industry in our sample. As another example, we note that airlines which typically rely on debt financing more than software companies (see Baker (2009)) also tended to benefit less than the latter industry from LSAPs.

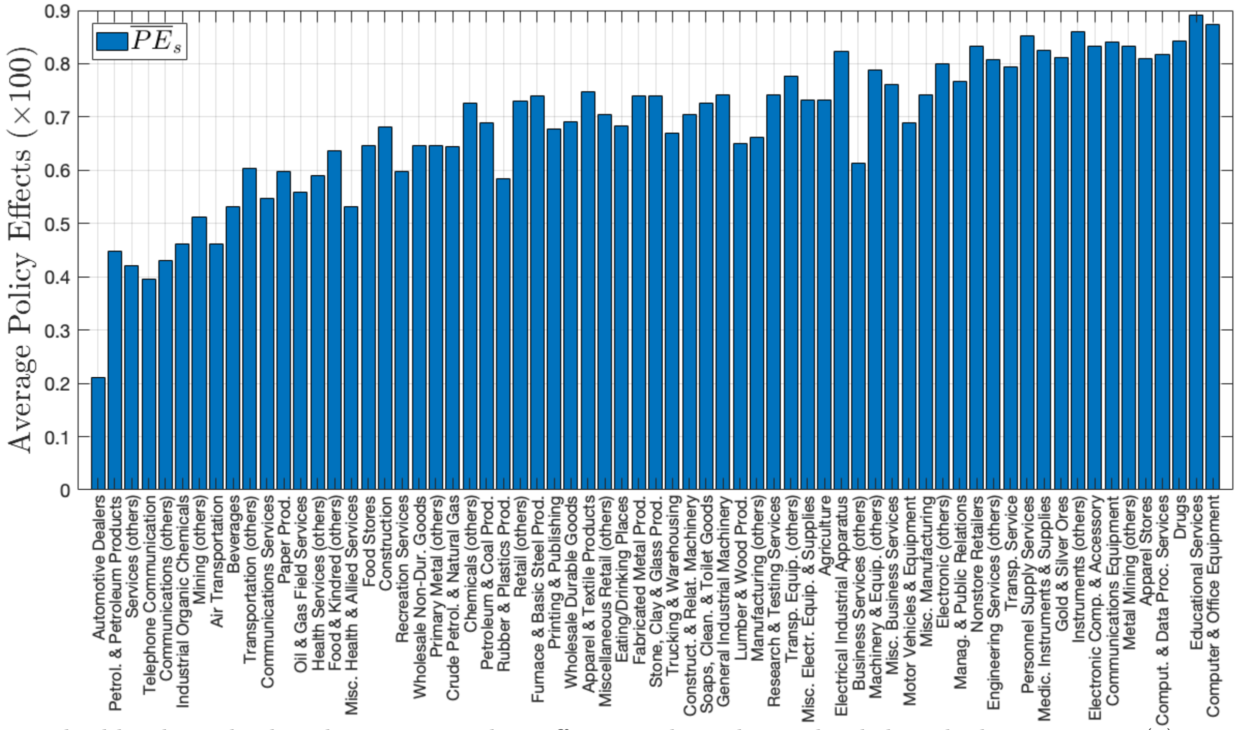
The policy effects at the national level are computed as averages using industry-specific weights. As weights we consider both employment and firm size shares over the full sample.[18] The estimated APE at the national level is equal to 0.0066 and 0.0062 when using average employment and firm size as share of an industry in the economy, respectively. Due to the relatively large number of industries in our sample, the weights do not seem to have a big impact on the estimated national effects, and in fact using equal constant weights across industries leads to a similar estimate, namely 0.0068. We have also experimented with using average sectoral employment or firm size over a three-year period (instead of over the entire sample) to compute the weights, obtaining very similar results. These estimates once again

[17] Similar results are obtained for the partial adjustment and ARDL(1) models.

[18] To compute the employment shares we used annual data at the firm-level from the Compustat annual database. See Section C.2 of the online supplement for more details on the weights used.

highlight the rather small magnitude of the LSAPs effects despite the statistical significance of the underlying estimates.

Figure 1: **Average policy effects ($\overline{PE}_s \times 100$) at the industry level ordered by industry median leverage**




The blue bars display the average policy effects at the industry level described in equation (6), based on the interaction of our quantitative measure of LSAPs and one-quarter lagged values of $\pi_{DA}(\hat{\gamma}_{post})$. The x-axis reports the three-digit SIC industries sorted from largest to smallest industry median leverage, averaged over time.

## 5.4 Robustness analysis

We now consider the robustness of our main empirical results to (a) the inclusion of observed macro-variables as proxies for $f_t$ in (10), (b) using several additional control variables, (c) using $(0, 1)$ measures of LSAPs instead of our quantitative measure, and (d) correcting for small-$T$ bias of the FE-TE estimates we have used so far. The estimation results for these robustness exercises are provided in the online supplement.

### 5.4.1 Observed macroeconomic indicators as proxies for $f_t$

As discussed in subsection 3.1, in order to identify the policy effectiveness coefficient of interest, we need to place some restriction on the industry-time fixed effects, $\phi_{st}$, described in equation (3). Our solution is to allow $\phi_s$ to be freely estimated conditional on alternative specifications of $f_t$. As our benchmark we use scaled industry-specific linear time trends. Here we consider a model with multiple observed factors by using three macroeconomic indicators typically employed in the literature, as proxies for $f_t$, namely (i) growth in real GDP, (ii) the term spread (computed as the difference between 10-year and 3-month Treasury bond yields), and (iii) the one-year-ahead expected inflation. Real GDP growth is used as an indicator of common cyclicality in firm financing decisions (e.g. Frank and Goyal (2009), and Erel et al. (2011)). The term spread is included as it reflects expectations of future short-term rates and of future economic performances (e.g. Gürkaynak and Wright (2012)). Finally, we consider expected inflation as it is likely to affect firms' debt issuance (Frank and Goyal (2009)).

We first note that the estimated threshold parameters are in line with the benchmark case.[19] Focusing on the two-threshold model, the estimate of $\gamma_{pre}$ is equal to 0.52 for the partial adjustment and ARDL(1) models, and equal to 0.56 for the ARDL(2) specification. The estimates of $\gamma_{post}$ for the partial adjustment and ARDL specifications (at 0.77 and 0.78 respectively) are almost the same as the estimates we obtain when using linear time trends for $f_t$. Similarly, the effects of LSAPs remain highly statistically significant, with the net short-run effects, $\varphi_{1,DA} = \sum_{\ell=0}^{p} \beta_{1,\ell,DA}$, estimated to be 0.0072 for the partial adjustment model, and 0.0062 for the ARDL(2) model. These estimates are smaller than 0.0083 and 0.0090 which we obtain for the partial adjustment and ARDL(2) models when using linear time trends for $f_t$. Slightly weaker results are also obtained in the single-threshold model when using the macro variables as proxies for $f_t$. The effects of LSAPs through the interaction with the credit rating threshold variable remain statistically insignificant when using the macro indicators.

#### 5.4.2 Additional control variables

In addition to the control variables already included in our benchmark model, we also estimated the threshold panel regressions with the following additional regressors: market to book ratio, research and development (R&D) expense scaled by total assets, and the industry median of several firm-level variables. The results (reported in Section E of the online supplement) show that estimates of the policy effectiveness coefficients and their statistical significance are not substantially affected by the inclusion of these new control variables to the benchmark specifications.

#### 5.4.3 Qualitative versus quantitative measures of LSAPs

As noted earlier, in our benchmark model we use a quantitative measure of LSAPs because of its greater degree of variability over time and given that it is more likely to accurately capture the intensity of the Fed's purchases over time. But given the use of $(0, 1)$ indicators of policy in the literature, and as a robustness check, we also re-estimated the panel regressions in (10) with our quantitative measure of LSAPs replaced with a dummy variable which takes the value of unity during policy on periods and zero otherwise. We obtain information on the quarters

[19] Estimation results are provided in Section D of the online supplement.

during which the Fed's asset purchases were implemented from the New York Fed's website (see also Kuttner (2018)). In particular, we set $q_t$ equal to one during the two sub-periods: 2008Q4 - 2010Q1 (corresponding to the first program, typically labelled as QE1), 2010Q4 - 2014Q4, where the last interval includes QE2 (2010Q4 - 2011Q2), the maturity extension program (MEP, 2011Q3 - 2012Q4), and QE3 (2012Q3 - 2012Q4).

As shown in Section F of the online supplement, the estimated threshold parameters are unaffected regardless of whether we use the $(0,1)$ or quantitative measure of LSAPs in the case of the single-threshold panel regressions. For the two-threshold panel regressions, the estimates of threshold values almost coincide for the partial adjustment and our preferred ARDL(2) model, with the exception of the ARDL(1) model which yields a lower estimate of $\gamma_{post}$, namely 0.36. The estimates of net short-run policy effects, $\varphi_{1,DA}$, are in line with those obtained using the quantitative measure in terms of statistical significance albeit they are slightly larger in magnitude. When using the $(0,1)$ policy measures, the estimated values of the net short-run policy effects are 0.0120 and 0.0118 for the partial adjustment and ARDL(2) models, respectively, whilst we obtain the estimates of 0.0083 and 0.0090 when using the quantitative measure for $q_t$. These difference are partly due to different mean scales of $q_t$ under the two measurement scenarios. The sample mean of the $(0,1)$ policy indicator is 0.49, as compared to 0.83 for the quantitative version of $q_t$.

The main notable difference in the estimates relate to the net short-term effect of the policy variable based on credit rating, namely when we use $q_t \times \pi_{s,t-1,CR}$, where $\pi_{st,CR}$ is defined by (9), which was not statistically significant and now becomes significant when we use the $(0,1)$ measure for $q_t$, albeit not across all specifications. At the same time, the estimates of the policy effects based on $q_t \times \pi_{s,t-1,DA}$ continue to be statistically highly significantly and relatively more important as a predictor of firms' debt to asset ratios.

#### 5.4.4 Small–T bias and half-panel jackknife FE–TE estimation

It is well known that standard within-group estimators for linear dynamic panel data models with fixed effects suffer from small–$T$ bias. In our application, after using the first 3 observations to generate the lagged values as regressors (recall that $p_{max} = 2$), we end up with a highly unbalanced panel with the number of time series observations in panel regressions ($T_i$ for firm $i$) ranging from 2 to 44, that correspond to 5 and 47 available quarterly observations. The main reason for including firms with $T_i = 2$ observations in the panel regressions was to avoid sample selection bias that could result from dropping newly founded firms with a short history. However, the inclusion of such firms could lead to small $T$ bias which we address here.

We approach the problem from two perspectives. First we consider the implications of dropping firms with very few time series observations and see if this makes that much of a difference to the estimates of the policy effects. Accordingly, we re-estimate equation (10) including firms with at least 8 or 10 time series observations. As documented in Section G of the online supplement, the streamlining of the data set to reduce the small–$T$ bias does not seem to have meaningful effects on the estimates or their statistical significance. The estimates of the net short-term policy effects are hardly affected by dropping firms with very few time series observations. This is partly due to the rather low proportion of firms in our sample with fewer than 8 or 10 observations.[20]

Whilst this is reassuring, the FE-TE estimates could still be subject to the small $T$ bias, since there is a large number of firms in our sample with $T < 20$, as documented in Chudik et al. (2018) (CPY henceforth) using Monte Carlo experiments. Therefore, as a second robustness check, we examined the extent to which our estimation results hold after correcting for the small–$T$ bias by applying the half-panel jackknife method also proposed by CPY.[21] This estimation procedure is well suited for our empirical analysis as it allows for fixed and time effects, and it is appropriate for both balanced and unbalanced panels with large cross-section dimension and moderate T. In addition, it yields more accurate inference in the presence of weakly exogenous regressors.[22]

The implementation of the half-panel jackknife bias correction requires splitting the time series observations on each firm into equal sub-samples, with each sub-sample having at least 2 observations. With this in mind, we include firms with at least 8 time series observations, and in the case of firms with odd numbers of observations, we follow CPY and drop the first observation before dividing the sample into two sub-samples. We then apply Wansbeek and Kapteyn (1989) transformation to remove the fixed and time effects from each of the two sub-samples separately, before computing the half-panel jackknife estimators.[23]

The first notable implication of this new estimation strategy is the larger estimates obtained for the coefficients of the lagged dependent variables, $y_{is,t-\ell}$ for $\ell = 1$ and 2, which is in line with the known downward bias of the corresponding FE estimates (Nickell (1981)). We also find that amongst the control variables, cash to assets, industry leverage and industry growth continue to be highly statistically significant, while the estimates for the PPE to asset ratio and

[20] The number of firms available after selecting only firms with at least 8 time observations is $3,236$ ($88.7\%$ of the initial sample). In this case, after removing the pre-sample, the minimum, average, and maximum $T$ are equal to 5, 25.7, and 44, respectively. Instead, when selecting firms with at least 10 observations, the number of firms included in the sample is equal to $3,011$ ($82.6\%$ of the initial sample), and the minimum, average, and maximum $T$ after excluding the pre-sample are equal to 7, 27.2, and 44, respectively.

[21] In the context of linear dynamic panel data models with possibly weakly exogenous regressors, with $N$ (the number of cross-sections) large relative to $T$ (the number of time observations), CPY show that the bias of the half-panel jackknife FE–TE estimator is of order $T^{-2}$ and it only requires that $N/T^3 \to 0$, as $N, T \to \infty$ for valid inference. Instead the FE–E estimator requires $N/T \to 0$, as $N, T \to \infty$ jointly, and thus a larger $T$ to avoid potentially biased estimation and size distortions.

[22] In particular, the half-panel jackknife method is applicable even when the error terms are correlated with future values of the regressors without requiring to specify the particular nature of weak exogeneity of the regressors. We refer the interested reader to CPY for further details.

[23] Because of the super consistency property of the threshold estimators, to compute the jackknife estimator we use the threshold parameters estimated in the benchmark specification as reported in Table 1.

firm size become statistically insignificant. This is due to the fact that jackknife standard errors are generally larger than the standard FE–TE estimates which tend to be under-estimated. These differences apply to both the partial adjustment model and the ARDL panel regressions.

More importantly, the estimates of net short-run policy effects continue to be highly statistically significant even after applying the jackknife bias correction. The jackknife estimates of $\varphi_{1,DA}$ are equal to 0.0079 and 0.0082 for the two-threshold partial adjustment and ARDL(2) model, respectively. Recall that the corresponding standard FE-TE estimates are 0.0083 and 0.0090. However, due to the larger estimates obtained for the coefficients of lagged dependent variables, the estimated long-run effects of LSAPs are much larger after the jackknife bias correction. Based on the standard FE–TE estimates, the long-run policy effects are estimated to vary between 0.0236 and 0.0559 across the various specifications considered (as shown in Table 3). By comparison, the jackknife estimates vary between 0.0817 and 0.1633, depending on the particular dynamic specifications.

# 6 Concluding remarks

In this paper, we estimate dynamic panel data models with threshold effects to quantify both the short- and long-term effects of the Fed's LSAPs on firms' capital structure. To disentangle the impact of LSAPs from that of concurrent macroeconomic conditions, we exploit cross-industry variations in the ability of firms therein to raise additional external funds without exhausting their debt capacity. An important aspect of this identification strategy is that it recognizes that firms' financing decisions, and hence firms' responses to LSAPs, depend on the financing choices made by other firms in the same industry. To this end, we construct two industry-specific measures of spare debt capacity which we then interact with our measures of LSAPs: (i) a leverage threshold variable, measured by the proportion of firms in an industry with debt to asset ratios below an estimated threshold, and (ii) a credit rating variable, given by the proportion of firms in an industry with investment grade credit ratings.

We treat the quantile threshold of the leverage variable as an unknown parameter, and find that the quantile value that gives the best fit in our preferred specification is equal to 0.77. We then test whether a higher proportion of firms in an industry with leverage below the 77-th quantile predicts a stronger impact of LSAPs on firms' capital structure. We find robust evidence in support of this hypothesis. Our results demonstrate that existing debt burdens within an industry are a good predictor of a firm's ability to increase its debt financing in response to the Fed's asset purchases. Instead, we find that the proportion of investment grade firms in an industry does not significantly capture the uneven effects of LSAPs on firms' debt to asset ratios. Among, the two industry-specific measures of debt capacity considered (without their interaction with LSAPs), only the leverage threshold variable helps predict firms' leverage, corroborating the view that firms set their capital structure in accordance with the financial choices rather than characteristics of other peers in the same industry.

Finally, our dynamic panel data models enable us to identify the time profile of the effects of LSAPs on firms' capital structure. Our analysis provides a clear and strong evidence that such effects are long-lasting. To the best of our knowledge, this aspect has not received enough attention so far.

To conclude, our results suggest that LSAPs facilitated firms' access to external debt financing, and that their effectiveness depends on the ability of firms (within an industry) to issue new debt. At the same time, albeit highly statistically significant, the relatively small magnitude of the estimated long-run effects indicates that LSAPs have contributed only marginally to the rise in U.S. corporate debt ratios of the last decade or so.

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Online Supplement for

# Causal effects of the Fed's large-scale asset purchases on firms' capital structure

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## Introduction

This online supplement is organized in seven sections. Section A provides detailed information on the data used in the empirical analysis, and the various filters used in the sample selection process. It also discusses the classification of firms by industries while providing several summary statistics at both firm and industry levels. Section B provides additional information on both the identification and estimation strategy. Section C reports the estimation results for the benchmark specifications, when the macro policy intervention variable, $q_t$, denotes the scaled gross amount of U.S. Treasuries and mortgage-backed securities purchased by the Fed. Section D shows estimation results when selected macro-variables interacted with industry-specific dummies are used in place of industry-specific linear trends. Section E presents the estimates of the policy effectiveness coefficients when including several additional control variables to the benchmark specifications. In Section F, we report estimation results for the case where the macro policy intervention variable is a qualitative dummy variable equal to one during policy on periods. Section G shows estimation results after correcting for potential small-sample bias.

# A Data sources, data filters and summary statistics

This section provides detailed information on the data used in our empirical analysis. In subsection A.1, we describe the main variables of our dataset. In subsection A.2, we discuss the sample selection screens. Summary statistics are reported in subsection A.3. In subsection A.4, we describe our classification of firms by industries. Finally, subsection A.5 provides some summary statistics at the industry level.

## A.1 Construction of the dependent and explanatory variables

Table A.1 describes the main firm- and industry-specific variables used in our empirical analysis, which are obtained from Compustat (quarterly) database.

Table A.1: **List of variables and definitions**

This table describes several variables considered in our empirical analysis. The market to book ratio is based on Badoer and James (2016). To calculate the Tobin's Q we use the definition of Duchin et al. (2010) which is the ratio of the market value of assets (MVA) to a weighted average of MVA and total assets (TA). When data on deferred taxes (*txdbq*), used in the construction of MVA, are missing we set them equal to zero. This is consistent with the numerator used in the definition of Tobin's Q in Foley-Fisher et al. (2016). By construction, our measure of Tobin's Q is bounded above at 10. Following Badoer and James (2016), when computing research and development expense (*xrdq*) scaled by total assets, we set *xrdq* to zero if missing.

| **Variable** | **Definition** | **Compustat** |
|---|---|---|
| Total debt to total assets | Sum of short- and long-term debt scaled by total assets | (dlttq+dlcq)/atq |
| Long-term debt to TA | Long-term debt scaled by total assets | dlttq/atq |
| Short-term debt to TA | Debt in current liabilities scaled by total assets | dlcq/atq |
| Debt to equity | Ratio of total debt to book value of equity | (dlttq+dlcq) / ceqq |
| Market to book | Market capitalization divided by total book value | (ltq-txditcq+prccq*cshoq+pstkq)/atq. |
| Market value of assets (MVA) | The sum of total assets and market value of common equity minus common equity and deferred taxes | (atq + (cshoq*prccq) - ceqq - txdbq) |
| Tobin's Q | Market value of assets divided by a weighted sum of book value of assets (0.9) and market value of assets (0.1). | (MVA)/(0.9*atq + 0.1*MVA) |
| Cash to TA | Cash and short-term investments scaled by total assets | cheq/atq |
| Cash flow to TA | Sum of income before extraordinary items and depreciation and amortization scaled by total assets | (ibq + dpq)/atq |
| PPE to TA | Property, plant, and equipment scaled by total assets | ppentq/atq |
| R&D to TA | Research and development expense scaled by total assets | xrdq/atq |
| Rating | S&P domestic long-term issuer credit rating | splticrm |
| Size | Natural logarithm of total assets | log(atq) |
| Median industry growth | Median change in the log of total assets within each industry by quarter | |
| Median industry leverage | Median debt to asset ratios within each industry by quarter | |

**Large-scale asset purchases (LSAPs).** In our empirical analysis, our preferred measure of LSAPs is the the total gross amount of U.S. Treasuries and agency mortgage-backed securities (MBS) purchased by the Fed. To construct this quantitative measure, we obtain data from the the New York Fed's website. U.S. Treasuries' purchases include notes, bonds, and Treasury Inflation-Protected Securities (TIPS). As a robustness check, we also report results using a qualitative measure of LSAPs. In this case, our policy variable is a dummy variable equal to one during policy on periods and zero otherwise. To construct this variable we obtain information on the operation dates from the New York Fed's website. Further details are given in Table A.2 which provides a short summary of the Fed's asset purchase programs until 2018, including the dates of implementation.

Table A.2: **Description of the major large-scale asset purchase programs**
The dates and description of the various Fed's interventions are obtained from the New York Fed's website (https://www.newyorkfed.org/markets/programs-archive/large-scale-asset-purchases). See also Kuttner (2018) and Swanson (2021). MEP stands for Maturity Extension Program, also known as Operation Twist. MBSs stands for mortgage-backed securities.

| Program | Start Date | End Date | Description |
|---|---|---|---|
| QE1 | Nov 2008 | Mar 2010 | The Fed purchased \$175 billion (bn) in agency debt, \$1,250bn in agency MBS, and \$300bn in longer-term Treasury securities. |
| QE2 | Nov 2010 | Jun 2011 | The Fed purchased \$600bn of longer-dated Treasuries. |
| MEP | Sep 2011 | Dec 2012 | The Fed purchased \$667bn of 6- to 30-year Treasuries offset by sales of \$634bn in Treasuries with remaining maturities less or equal to 3 years and \$33 billion of Treasuries' redemptions. |
| QE3 | Sep 2012 | Oct 2014 | The Fed purchased \$40bn in agency MBSs per month from Sep 2012 until Dec 2013, and \$45bn of long-term Treasuries per month throughout 2013. In Jan 2014 the purchases of MBS and long-term Treasuries dropped to \$35bn and \$40bn per month, respectively. Both purchases decreased by \$5bn after each FOMC meeting until October 2014. |

To make our quantitative measure of LSAPs directly comparable to the qualitative (dummy) policy variable, we scale the former so that its average value is unity over the policy sample. This scaling also facilitates the interpretations of the estimation results by removing the unit of measurement of the variable. The dynamics of both the quantitative and qualitative policy variables are depicted in Figure 2.

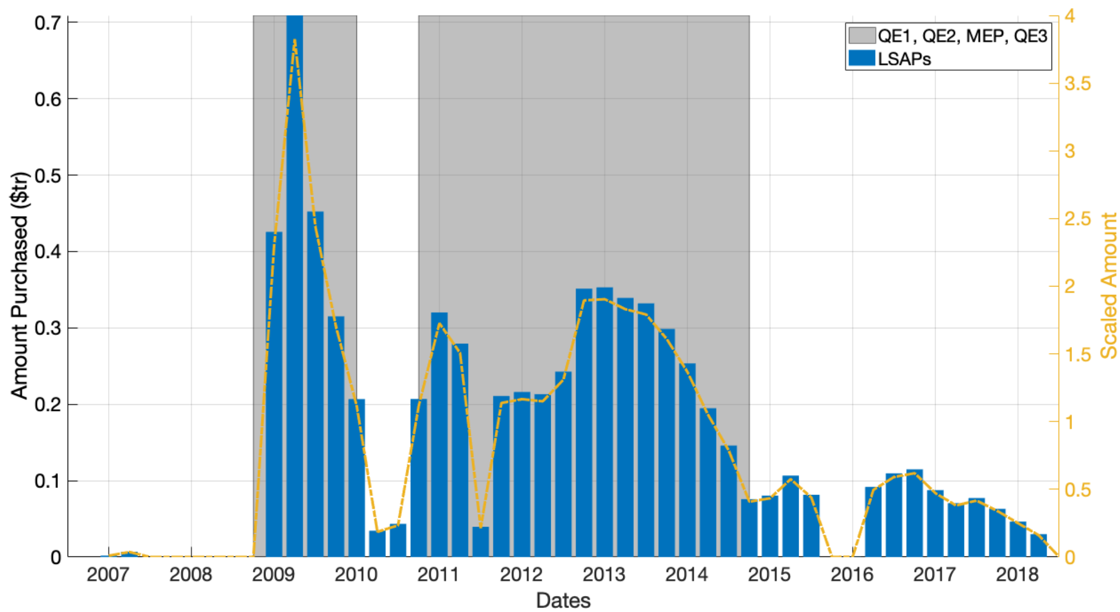
**Macroeconomic indicators.** In one of our robustness analyses, we employ the following macroeconomic indicators:

- *Real GDP growth* is the percent changes from preceding quarter in real gross domestic product obtained from the U.S. Bureau of Economic Analysis. The extracted data are already seasonally adjusted, and the percent changes are expressed at annual rates.

- *Term spread* is the difference between the 10-year and the 3-month Treasury bond yields. The 10-year yield is the market yield on U.S. Treasury securities at 10-year constant maturity, quoted on investment basis, obtained from the Federal Reserve System's website. The data are available on a daily frequency and are converted into a quarterly frequency by averaging over a quarter.

- *Expected inflation* denotes expectations (i.e. median forecasts) for one-year-ahead annual average CPI inflation. The series is contained in the Survey of Professional Forecasters conducted by the Federal Reserve Bank of Philadelphia.

Figure 2: **Fed's large-scale asset purchases**




The blue bars display quarterly purchases (in trillion dollars) of U.S. Treasuries and agency mortgage-backed securities by the Federal Reserve. The yellow line shows our scaled amount of LSAPs measured on the right-hand side y-axis. The scale used is such that its average value is unity over the period where purchases took place. The shaded grey areas denote the main Fed's interventions over the sample period considered, as described in Table A.2. Source: New York Fed.

## A.2 Data filters and sample selection

To align our analysis with previous studies (e.g. Leary and Roberts (2014)), we disregard observations from financial firms (SIC 6000-6999) and regulated utilities (SIC 4900-4999) whose financing choices may dictated by regulatory considerations, as well as from firms belonging to the non-classifiable sector (SIC codes above or equal to 9900), which in our sample mainly consists of non-operating firms (i.e. firms that operate no assets on their own).

The sample period includes years from 2007-Q1 to 2018-Q3. We drop firms with gaps in between periods for the following variables: (i) total debt to total assets (TA), (ii) cash to TA, (iii) market to book, (iv) property plant and equipment (PPE) to TA, and (v) size.

We select only firms with at least 5 consecutive time observations based on the above firm characteristics. This choice is dictated by our econometric strategy which uses autoregressive distributed lag (ARDL) models.

We exclude firms with total debt to TA greater than one. At the same time, we make sure that a firm's total debt is not negative. In total there is only one firm with negative debt which we remove. Finally, we note that the following variables - debt to equity (DE), market to book (MB), cash flow to TA (CF2A), and R&D to TA - take implausible values for a relatively small number of firms. This is shown in Table A.3. In the upper panel, it reports various percentiles for the above mentioned firm characteristics. The lower panel shows the number of firms associated with those percentiles. To remove the effects of these outliers we proceed as follows. First, we drop firms with DE and CF2A below the 0.05% or above the 99.95% percentiles, as well as firms with MB and R&D to TA above the 99.95% percentiles. We also drop firms with negative R&D. We then winsorize DE and CF2A at the 1st and 99th percentiles, and both MB and R&D to TA at the 99th percentile.

Table A.4 reports the number of firms dropped after removing the outliers.

Table A.3: **Percentiles (%) and number of firms by percentiles after applying all filters but before removing outliers**

The upper panel reports various percentiles for those firm characteristics which show implausible values. The lower panel displays the number of firms with values below (above) the lower (upper) percentiles. For example, after applying all filters but before removing the outliers for market to book, there are 22 firms with market to book above 2746.21, the 99.95% percentile.

| Variable \ Percentile (%) | **min** | **0.05** | **0.1** | **0.2** | **99.8** | **99.9** | **99.95** | **max** |
|---|---|---|---|---|---|---|---|---|
| **Debt to equity** | -2995.95 | -198.22 | -101.93 | -51.54 | 67.43 | 148.02 | 268.38 | 38732.00 |
| **Market to book** | 0.03 | 0.10 | 0.16 | 0.23 | 294.83 | 873.28 | 2746.21 | 146344.76 |
| **Cash flow to TA** | -855.55 | -9.39 | -5.00 | -2.55 | 0.37 | 0.55 | 0.82 | 105.00 |
| **R&D to TA** | -1.09 | 0.00 | 0.00 | 0.00 | 0.49 | 0.70 | 0.95 | 41.00 |

| | **N. Firms with values** $< p_\tau$ | | | **N. Firms with values** $> p_\tau$ | | | |
|---|---|---|---|---|---|---|---|
| | **0.05** | **0.1** | **0.2** | **99.8** | **99.9** | **99.95** | |
| **Debt to equity** | 46 | 76 | 127 | 134 | 83 | 48 | |
| **Market to book** | 9 | 21 | 42 | 52 | 36 | 22 | |
| **Cash flow to TA** | 29 | 50 | 90 | 157 | 83 | 46 | |
| **R&D to TA** | 42 | 58 | 58 | 91 | 54 | 29 | |

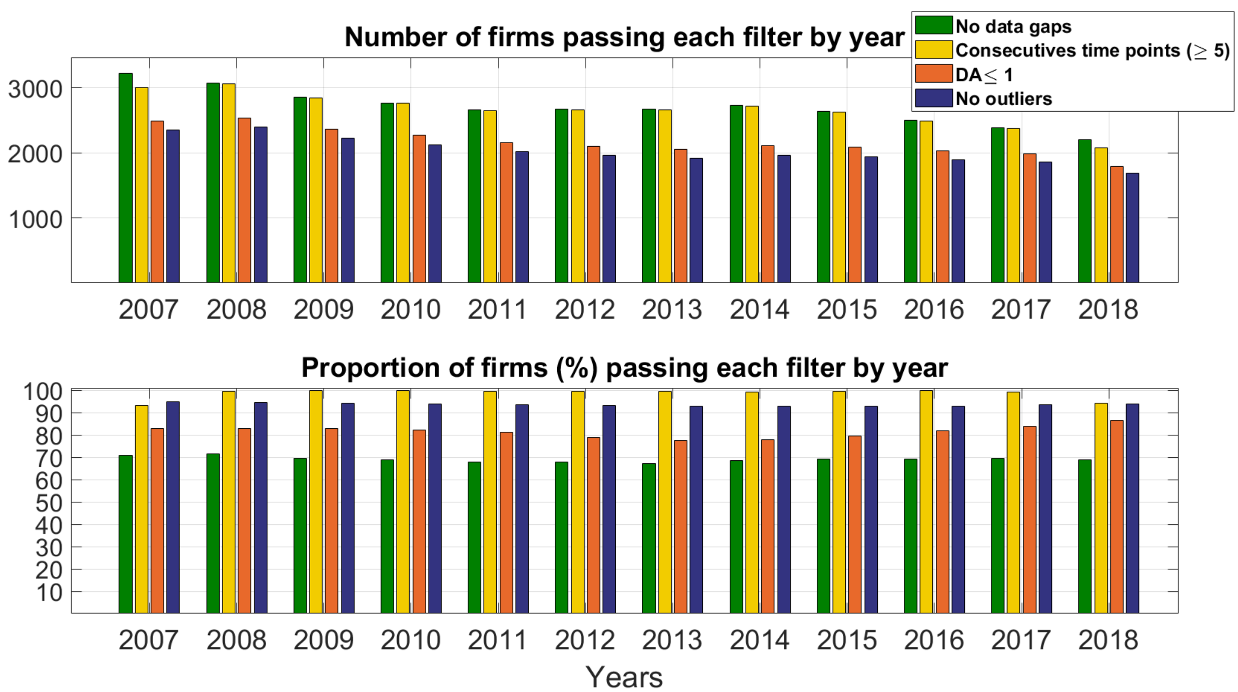
Table A.4: **Number of firms dropped while removing outliers**

We (sequentially) drop firms whose debt to equity ratio is lower (greater) than the 0.05% (99.95%) percentile, firms whose market to book ratio is greater than the 99.95% percentile, and firms with cash flow to TA lower (greater) than the 0.05% (99.95%) percentile. We also exclude firms with negative R&D to TA as well as firms with R&D to TA greater than the 99.95% percentile. TA stands for total assets.

| | Lower Tail | | Upper Tail | |
|---|---|---|---|---|
| | Drop if | N. Drops | Drop if | N. Drops |
| **Debt to equity** | $< 0.05\%$ | 46 | $> 99.95\%$ | 36 |
| **Market to book** | | | $> 99.95\%$ | 20 |
| **Cash flow to TA** | $< 0.05\%$ | 21 | $> 99.95\%$ | 45 |
| **R&D to TA** | $< 0$ | 54 | $> 99.95\%$ | 14 |
| Tot. | | 121 | | 115 |

To summarise our sample selection screens, Figure 3 displays the number of firms and percentage of firms selected each year in our sample after applying each filter. Annual statistics are obtained by averaging quarterly statistics within each year.

Figure 3: **Sample selection**




Annual statistics are obtained by averaging quarterly statistics within each year. The upper panel shows the number of firms available by year after applying each filter. The lower panel displays the percentage of firms that pass each filter by year. We consider four filters. First, we drop firms with data gaps in between period in total debt to total assets (TA), cash to TA, market to book, PPE to TA, and size (green bars). Second, we drop firms with less than 5 consecutive time observations (yellow bars). Third, we exclude firms with a ratio of debt to assets greater than 1 (orange bars). Finally, we remove firms with outliers (blues bars).

More details are provided in Table A.5, where we report the empirical frequency distribution of firms by year as well as the percentage of firms that pass each filter by year.

Table A.5: **Empirical frequency distribution of firms by year**

Columns 2 to 5 display the number of firms per year after applying each filter. Annual statistics are obtained by averaging quarterly statistics within each year. The columns *% Pass F1*, *% Pass F2*, and *% Pass F3* report the percentage of firms that pass the first filter (no data gaps), the percentage of firms remaining after applying the second of filter ($\geq 5$ time points), and the percentage of firms that pass the third filter (debt to asset ratios less or equal to 1), respectively. Column *% Pass F4* shows the percentage of selected firms with no outliers. Finally, the column *% All Filters* denotes the percentage of firms meeting all four filters, computed as the ratio of the total number of selected firms to the total number of firms available before applying any filter, in percentage terms.

| **Year** | **No data gaps** | **Consecutive time points ($\geq 5$)** | **DA $\leq 1$** | **No outliers** | **% Pass F1** | **% Pass F2** | **% Pass F3** | **% Pass F4** | **% All filters** |
|---|---|---|---|---|---|---|---|---|---|
| 2007 | 3213.5 | 2995.8 | 2485.0 | 2352.5 | 70.8 | 93.3 | 83.0 | 94.7 | 51.9 |
| 2008 | 3069.8 | 3058.0 | 2530.3 | 2389.8 | 71.4 | 99.6 | 82.7 | 94.4 | 55.6 |
| 2009 | 2850.0 | 2845.5 | 2359.8 | 2218.8 | 69.6 | 99.8 | 82.9 | 94.0 | 54.2 |
| 2010 | 2764.5 | 2758.0 | 2268.3 | 2125.3 | 68.8 | 99.8 | 82.2 | 93.7 | 52.9 |
| 2011 | 2660.3 | 2650.0 | 2154.3 | 2014.8 | 67.7 | 99.6 | 81.3 | 93.5 | 51.3 |
| 2012 | 2674.5 | 2658.8 | 2100.5 | 1956.3 | 67.7 | 99.4 | 79.0 | 93.1 | 49.5 |
| 2013 | 2668.5 | 2653.5 | 2057.3 | 1910.8 | 67.2 | 99.4 | 77.5 | 92.9 | 48.1 |
| 2014 | 2727.8 | 2709.3 | 2106.3 | 1956.8 | 68.6 | 99.3 | 77.7 | 92.9 | 49.2 |
| 2015 | 2635.0 | 2626.0 | 2086.3 | 1936.8 | 69.0 | 99.7 | 79.5 | 92.8 | 50.8 |
| 2016 | 2496.0 | 2490.8 | 2034.0 | 1891.5 | 69.3 | 99.8 | 81.7 | 93.0 | 52.5 |
| 2017 | 2388.8 | 2367.5 | 1981.8 | 1855.5 | 69.5 | 99.1 | 83.7 | 93.6 | 54.0 |
| 2018 | 2201.7 | 2075.7 | 1793.3 | 1685.0 | 69.0 | 94.2 | 86.5 | 94.0 | 52.8 |
| **Tot. num. firms** | 5,666 | 4,946 | 3,883 | 3,647 | | | | | |
| **Min num. quarters** | 1 | 5 | 5 | 5 | | | | | |
| **Mean num. quarters** | 22.4 | 25.4 | 26.3 | 26.2 | | | | | |
| **Median num. quarters** | 18 | 22 | 22 | 22 | | | | | |
| **Max num. quarters** | 47 | 47 | 47 | 47 | | | | | |
| **Tot. firm-quarter obs.** | 127,199 | 125,479 | 102,034 | 95,489 | | | | | |

After applying all filters, we end up with a sample of 3,647 distinct firms. The total number of firm-quarter observations is 95,489.[24] The panel data is unbalanced with the number of time series data points available by firm varying between 5 and 47, on average 26.2 quarters.

## A.3 Summary statistics

This subsection provides some summary statistics. Table A.6 shows how data on firm characteristics considered change after applying each data filter. Summary statistics for selected firm characteristics computed on the final filtered sample are reported in Table A.7. Finally, Table A.8 reports the frequency of firms by number of consecutive data points (based on the filtered sample).

[24] The actual number of firm-quarter observations used in our empirical analysis is slightly lower due to the presence of lagged dependent and explanatory variables.

Table A.6: **Summary statistics after applying each filter**

Summary statistics for selected firm characteristics after applying each filter. TA stands for total assets.

| | **Filter** | **Obs.** | **mean** | **std** | **min** | **max** | **1%** | **25%** | **50%** | **75%** | **99%** |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | None | 178897 | 2.03 | 61.60 | -0.05 | 18116.00 | 0.00 | 0.01 | 0.19 | 0.41 | 16.21 |
| | No Gaps | 127199 | 1.69 | 31.47 | -0.05 | 5319.00 | 0.00 | 0.01 | 0.19 | 0.41 | 16.82 |
| **Total debt to TA** | 5 Cont. Obs. | 125479 | 1.60 | 26.83 | -0.05 | 3172.48 | 0.00 | 0.01 | 0.19 | 0.41 | 16.53 |
| | TD2A≤ 1 | 102034 | 0.20 | 0.20 | 0.00 | 1.00 | 0.00 | 0.00 | 0.15 | 0.33 | 0.79 |
| | No Outliers | 95489 | 0.20 | 0.20 | 0.00 | 1.00 | 0.00 | 0.00 | 0.15 | 0.32 | 0.76 |
| | Winsoriz. | 95489 | 0.20 | 0.20 | 0.00 | 1.00 | 0.00 | 0.00 | 0.15 | 0.32 | 0.76 |
| | None | 182475 | 0.36 | 7.72 | -0.12 | 2071.00 | 0.00 | 0.00 | 0.10 | 0.31 | 2.00 |
| | No Gaps | 127199 | 0.35 | 5.89 | -0.12 | 836.50 | 0.00 | 0.00 | 0.08 | 0.29 | 2.24 |
| **Long-term debt to TA** | 5 Cont. Obs. | 125479 | 0.35 | 5.93 | -0.12 | 836.50 | 0.00 | 0.00 | 0.08 | 0.29 | 2.19 |
| | TD2A≤ 1 | 102034 | 0.16 | 0.19 | 0.00 | 1.00 | 0.00 | 0.00 | 0.09 | 0.27 | 0.74 |
| | No Outliers | 95489 | 0.16 | 0.18 | 0.00 | 1.00 | 0.00 | 0.00 | 0.09 | 0.27 | 0.71 |
| | Winsoriz. | 95489 | 0.16 | 0.18 | 0.00 | 1.00 | 0.00 | 0.00 | 0.09 | 0.27 | 0.71 |
| | None | 179284 | 1.67 | 60.74 | -0.07 | 18116.00 | 0.00 | 0.00 | 0.01 | 0.05 | 12.74 |
| | No Gaps | 127199 | 1.34 | 30.24 | -0.07 | 5319.00 | 0.00 | 0.00 | 0.01 | 0.06 | 12.96 |
| **Short-term debt to TA** | 5 Cont. Obs. | 125479 | 1.26 | 25.35 | -0.07 | 3172.31 | 0.00 | 0.00 | 0.01 | 0.06 | 12.80 |
| | TD2A≤ 1 | 102034 | 0.04 | 0.09 | 0.00 | 1.00 | 0.00 | 0.00 | 0.01 | 0.04 | 0.48 |
| | No Outliers | 95489 | 0.04 | 0.09 | 0.00 | 1.00 | 0.00 | 0.00 | 0.01 | 0.04 | 0.46 |
| | Winsoriz. | 95489 | 0.04 | 0.09 | 0.00 | 1.00 | 0.00 | 0.00 | 0.01 | 0.04 | 0.46 |
| | None | 179505 | 1.28 | 290.80 | -16305.61 | 110579.73 | -12.98 | 0.00 | 0.14 | 0.71 | 16.78 |
| | No Gaps | 127191 | 0.99 | 131.46 | -12846.64 | 38732.00 | -11.96 | 0.00 | 0.13 | 0.68 | 15.12 |
| **Debt to equity** | 5 Cont. Obs. | 125473 | 1.00 | 132.35 | -12846.64 | 38732.00 | -11.96 | 0.00 | 0.13 | 0.69 | 15.10 |
| | TD2A≤ 1 | 102030 | 1.40 | 139.43 | -2995.95 | 38732.00 | -8.65 | 0.00 | 0.22 | 0.76 | 12.86 |
| | No Outliers | 95488 | 0.65 | 6.31 | -195.93 | 264.72 | -5.82 | 0.00 | 0.24 | 0.75 | 9.96 |
| | Winsoriz. | 95488 | 0.61 | 1.63 | -5.82 | 9.96 | -5.82 | 0.00 | 0.24 | 0.75 | 9.96 |
| | None | 161328 | 84.45 | 2867.63 | 0.01 | 597663.23 | 0.49 | 1.15 | 1.70 | 3.23 | 532.49 |
| | No Gaps | 127199 | 69.41 | 2608.83 | 0.03 | 597663.23 | 0.47 | 1.15 | 1.71 | 3.36 | 383.43 |
| **Market to book** | 5 Cont. Obs. | 125479 | 53.01 | 1547.64 | 0.03 | 172747.00 | 0.47 | 1.15 | 1.71 | 3.34 | 350.99 |
| | TD2A≤ 1 | 102034 | 12.83 | 824.11 | 0.03 | 146344.76 | 0.45 | 1.08 | 1.52 | 2.46 | 28.53 |
| | No Outliers | 95489 | 2.89 | 20.45 | 0.03 | 2686.65 | 0.44 | 1.08 | 1.50 | 2.38 | 15.69 |
| | Winsoriz. | 95489 | 2.20 | 2.23 | 0.03 | 15.69 | 0.44 | 1.08 | 1.50 | 2.38 | 15.69 |
| | None | 176011 | 2.34 | 2.01 | 0.01 | 10.14 | 0.54 | 1.15 | 1.60 | 2.61 | 9.91 |
| | No Gaps | 127199 | 2.39 | 2.05 | 0.04 | 10.14 | 0.51 | 1.14 | 1.61 | 2.72 | 9.77 |
| **Tobin's Q** | 5 Cont. Obs. | 125479 | 2.38 | 2.04 | 0.04 | 10.14 | 0.51 | 1.14 | 1.60 | 2.71 | 9.75 |
| | TD2A≤ 1 | 102034 | 1.85 | 1.29 | 0.04 | 10.00 | 0.49 | 1.08 | 1.45 | 2.15 | 7.60 |
| | No Outliers | 95489 | 1.78 | 1.15 | 0.04 | 9.97 | 0.48 | 1.08 | 1.43 | 2.10 | 6.36 |
| | Winsoriz. | 95489 | 1.78 | 1.15 | 0.04 | 9.97 | 0.48 | 1.08 | 1.43 | 2.10 | 6.36 |
| | None | 184051 | 0.24 | 0.27 | -1.18 | 1.00 | 0.00 | 0.04 | 0.13 | 0.35 | 0.98 |
| | No Gaps | 127199 | 0.24 | 0.28 | -1.18 | 1.00 | 0.00 | 0.03 | 0.12 | 0.36 | 0.98 |
| **Cash to TA** | 5 Cont. Obs. | 125479 | 0.24 | 0.27 | -1.18 | 1.00 | 0.00 | 0.03 | 0.12 | 0.36 | 0.98 |
| | TD2A≤ 1 | 102034 | 0.23 | 0.26 | -0.08 | 1.00 | 0.00 | 0.04 | 0.12 | 0.33 | 0.97 |
| | No Outliers | 95489 | 0.22 | 0.26 | -0.08 | 1.00 | 0.00 | 0.04 | 0.12 | 0.32 | 0.97 |
| | Winsoriz. | 95489 | 0.22 | 0.26 | -0.08 | 1.00 | 0.00 | 0.04 | 0.12 | 0.32 | 0.97 |
| | None | 179224 | -2.18 | 328.77 | -127324.00 | 2203.00 | -8.02 | -0.04 | 0.01 | 0.03 | 0.19 |
| | No Gaps | 123824 | -0.69 | 34.25 | -9045.50 | 2203.00 | -7.55 | -0.07 | 0.01 | 0.03 | 0.22 |
| **Cash flow to TA** | 5 Cont. Obs. | 122191 | -0.67 | 34.01 | -9045.50 | 2203.00 | -7.33 | -0.07 | 0.01 | 0.03 | 0.22 |
| | TD2A≤ 1 | 99780 | -0.05 | 3.21 | -855.55 | 105.00 | -0.74 | -0.02 | 0.02 | 0.03 | 0.13 |
| | No Outliers | 93397 | -0.02 | 0.17 | -7.47 | 0.81 | -0.51 | -0.01 | 0.02 | 0.03 | 0.12 |
| | Winsoriz. | 93397 | -0.01 | 0.09 | -0.51 | 0.12 | -0.51 | -0.01 | 0.02 | 0.03 | 0.12 |
| | None | 183854 | 0.23 | 0.25 | 0.00 | 2.45 | 0.00 | 0.05 | 0.13 | 0.34 | 0.93 |
| | No Gaps | 127199 | 0.24 | 0.26 | 0.00 | 2.45 | 0.00 | 0.04 | 0.14 | 0.36 | 0.94 |
| **PPE to TA** | 5 Cont. Obs. | 125479 | 0.24 | 0.26 | 0.00 | 2.45 | 0.00 | 0.04 | 0.14 | 0.37 | 0.94 |
| | TD2A≤ 1 | 102034 | 0.25 | 0.25 | 0.00 | 1.00 | 0.00 | 0.05 | 0.15 | 0.37 | 0.93 |
| | No Outliers | 95489 | 0.25 | 0.25 | 0.00 | 1.00 | 0.00 | 0.06 | 0.16 | 0.37 | 0.93 |
| | Winsoriz. | 95489 | 0.25 | 0.25 | 0.00 | 1.00 | 0.00 | 0.06 | 0.16 | 0.37 | 0.93 |
| | None | 184102 | 0.13 | 20.85 | -6.92 | 8825.00 | 0.00 | 0.00 | 0.00 | 0.02 | 0.47 |
| | No Gaps | 127199 | 0.12 | 24.79 | -3.41 | 8825.00 | 0.00 | 0.00 | 0.00 | 0.02 | 0.54 |
| **R&D to TA** | 5 Cont. Obs. | 125479 | 0.12 | 24.96 | -3.41 | 8825.00 | 0.00 | 0.00 | 0.00 | 0.02 | 0.54 |
| | TD2A≤ 1 | 102034 | 0.02 | 0.16 | -1.09 | 41.00 | 0.00 | 0.00 | 0.00 | 0.02 | 0.24 |
| | No Outliers | 95489 | 0.02 | 0.04 | 0.00 | 0.94 | 0.00 | 0.00 | 0.00 | 0.02 | 0.20 |
| | Winsoriz. | 95489 | 0.02 | 0.04 | 0.00 | 0.20 | 0.00 | 0.00 | 0.00 | 0.02 | 0.20 |
| | None | 184102 | 5.12 | 3.03 | -6.91 | 13.19 | -3.91 | 3.38 | 5.49 | 7.25 | 10.88 |
| | No Gaps | 127199 | 4.73 | 2.96 | -6.91 | 13.19 | -3.24 | 2.92 | 4.94 | 6.86 | 10.76 |
| **Size** (log of TA) | 5 Cont. Obs. | 125479 | 4.75 | 2.96 | -6.91 | 13.19 | -3.17 | 2.92 | 4.95 | 6.87 | 10.78 |
| | TD2A≤ 1 | 102034 | 5.46 | 2.42 | -6.91 | 13.19 | -0.23 | 3.75 | 5.48 | 7.19 | 10.91 |
| | No Outliers | 95489 | 5.58 | 2.33 | -5.30 | 13.19 | 0.34 | 3.89 | 5.58 | 7.25 | 10.95 |
| | Winsoriz. | 95489 | 5.58 | 2.33 | -5.30 | 13.19 | 0.34 | 3.89 | 5.58 | 7.25 | 10.95 |

Table A.7: **Summary statistics based on the filtered sample**

This table presents the number of observations, mean, standard deviation and different percentiles for selected firm characteristics computed after applying all filters. LT and ST stand for long-term and short-term, respectively. TA stands for total assets.

| | **N. obs.** | **mean** | **std** | **min** | **max** | **5%** | **25%** | **50%** | **75%** | **95%** |
|---|---|---|---|---|---|---|---|---|---|---|
| **Tot. debt to TA** | 95,489 | 0.20 | 0.20 | 0.00 | 1.00 | 0.00 | 0.00 | 0.15 | 0.32 | 0.58 |
| **LT debt to TA** | 95,489 | 0.16 | 0.18 | 0.00 | 1.00 | 0.00 | 0.00 | 0.09 | 0.27 | 0.52 |
| **ST debt to TA** | 95,489 | 0.04 | 0.09 | 0.00 | 1.00 | 0.00 | 0.00 | 0.01 | 0.04 | 0.21 |
| **Market to book** | 95,489 | 2.20 | 2.23 | 0.03 | 15.69 | 0.70 | 1.08 | 1.50 | 2.38 | 5.97 |
| **Tobin's Q** | 95,489 | 1.78 | 1.15 | 0.04 | 9.97 | 0.74 | 1.08 | 1.43 | 2.10 | 3.99 |
| **Cash to TA** | 95,489 | 0.22 | 0.26 | -0.08 | 1.00 | 0.00 | 0.04 | 0.12 | 0.32 | 0.84 |
| **Cash flow to TA** | 93,397 | -0.01 | 0.09 | -0.51 | 0.12 | -0.19 | -0.01 | 0.02 | 0.03 | 0.06 |
| **PPE to TA** | 95,489 | 0.25 | 0.25 | 0.00 | 1.00 | 0.01 | 0.06 | 0.16 | 0.37 | 0.80 |
| **R&D to TA** | 95,489 | 0.02 | 0.04 | 0.00 | 0.20 | 0.00 | 0.00 | 0.00 | 0.02 | 0.09 |
| **Size** (log of TA) | 95,489 | 5.58 | 2.33 | -5.30 | 13.19 | 1.86 | 3.89 | 5.58 | 7.25 | 9.35 |

Table A.8: **Empirical frequency distribution of firms by number of consecutive time observations (based on the filtered sample)**

The first column, *N. Obs.*, indicates the number of time period observations. The columns *N. firms* and *% of firms* report the frequency and percentage of firms by number of consecutive observations available, respectively. The column (firms) *with* $\geq x$ *obs.* shows the frequency of firms that have at least $5, 6, 7, ...$ number of consecutive data points.

| **N. Obs.** | **N. firms** | **% of firms** | $\geq x$ **obs.** | **N. obs.** | **N. firms** | **% of firms** | $\geq x$ **obs.** |
|---|---|---|---|---|---|---|---|
| 5 | 128 | 3.5 | 3647 | 27 | 60 | 1.6 | 1594 |
| 6 | 130 | 3.6 | 3519 | 28 | 34 | 0.9 | 1534 |
| 7 | 153 | 4.2 | 3389 | 29 | 34 | 0.9 | 1500 |
| 8 | 98 | 2.7 | 3236 | 30 | 40 | 1.1 | 1466 |
| 9 | 127 | 3.5 | 3138 | 31 | 53 | 1.5 | 1426 |
| 10 | 108 | 3.0 | 3011 | 32 | 34 | 0.9 | 1373 |
| 11 | 109 | 3.0 | 2903 | 33 | 29 | 0.8 | 1339 |
| 12 | 77 | 2.1 | 2794 | 34 | 36 | 1.0 | 1310 |
| 13 | 105 | 2.9 | 2717 | 35 | 39 | 1.1 | 1274 |
| 14 | 89 | 2.4 | 2612 | 36 | 34 | 0.9 | 1235 |
| 15 | 121 | 3.3 | 2523 | 37 | 29 | 0.8 | 1201 |
| 16 | 88 | 2.4 | 2402 | 38 | 24 | 0.7 | 1172 |
| 17 | 92 | 2.5 | 2314 | 39 | 27 | 0.7 | 1148 |
| 18 | 96 | 2.6 | 2222 | 40 | 30 | 0.8 | 1121 |
| 19 | 98 | 2.7 | 2126 | 41 | 23 | 0.6 | 1091 |
| 20 | 74 | 2.0 | 2028 | 42 | 27 | 0.7 | 1068 |
| 21 | 72 | 2.0 | 1954 | 43 | 24 | 0.7 | 1041 |
| 22 | 82 | 2.2 | 1882 | 44 | 54 | 1.5 | 1017 |
| 23 | 68 | 1.9 | 1800 | 45 | 40 | 1.1 | 963 |
| 24 | 51 | 1.4 | 1732 | 46 | 82 | 2.2 | 923 |
| 25 | 47 | 1.3 | 1681 | 47 | 841 | 23.1 | 841 |
| 26 | 40 | 1.1 | 1634 | Tot. | 3647 | 100 | |

## A.4 Industrial classification

In this subsection, we describe the grouping of firms into various industries based on the three-digit Standard Industrial Classification (SIC). Because some industries in our sample only include a handful of firms, we require each industry to contain at least 20 distinct firms. Three-digit SIC industries with less than 20 firms are grouped together within each two-digit SIC industry.

As shown in Table A.9, some industries in our sample contain less than 20 firms also at the two-digit SIC level. As a result, these industries are grouped together within each division, and no further sub-grouping (at the three-digit) is undertaken. To illustrate, the division *Mining* (two-digit SIC $10 - 14$) contains four two-digit SIC industries. The first group, metal mining (SIC 10), contains 52 distinct firms. The second group, coal mining (SIC 12), includes 19 firms. The third, oil and gas extraction (SIC 13), comprises 221 firms, while the fourth, non-metallic minerals except fuels (SIC 14), only contains 13 firms. Based on the criterion mentioned above, we group firms in SIC 12 and 14 together. We denote this new group of all the remaining two-digit SIC industries within the mining division as "mining (others)". For this group, we do not undertake further three-digit SIC sub-grouping.

Table A.9: **Number of firms and two-digit SIC industries within each division**

The first row (*# of firms*) reports the number of firms within each major division. The second row (*# of 2-dig SIC industries*) shows the number of non-empty 2-digit SIC industries within each division. The third (fourth) row displays the number of 2-digit industries with less (more) than 20 firms. The last row reports the number of 2-digit SIC industries within each division after regrouping industries with less than 20 firms. Note that we do not sub-group firms into 2-dig SIC industries for the division agriculture (SIC $01 - 09$) and construction (SIC $15 - 17$) because the number of firms within these divisions is not large enough.

| | **Industry divisions (by SIC)** | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| **Division** | A | B | C | D | E | F | G | I |
| **Division name** | Agr. | Mining | Construct. | Manuf. | Transp. | Wholesale | Retail | Services |
| **2-dig SIC range** | 01 - 09 | 10 - 14 | 15 - 17 | 20 - 39 | 40 - 49 | 50 - 51 | 52 - 59 | 70 - 88 |
| Number (#) of firms | 23 | 305 | 43 | 1872 | 216 | 142 | 253 | 793 |
| # of 2-dig SIC industries | | 4 | | 20 | 8 | 2 | 8 | 11 |
| # of 2-dig SIC with $0 <$ # firms $< 20$ | | 2 | | 4 | 4 | 0 | 3 | 6 |
| # of 2-dig SIC with # firms $\geq 20$ | | 2 | | 16 | 4 | 2 | 5 | 5 |
| # of 2-dig SIC after regrouping | 1 | 3 | 1 | 17 | 5 | 2 | 6 | 6 |

In total, firms in our sample can be divided into 67 three-digit SIC industries. These are listed in Table A.10, where we report information on the SIC codes, number of firms within each three-digit SIC industry, as well as information on the corresponding two-digit SIC industries. To illustrate, the two-digit SIC industry *Machinery & Equipment* (SIC 35), containing in total 161 firms, can be divided into 4 three-digit SIC industries of which *Machinery & Equipment (others)* consists of several three-digit SIC industries each composed of less than 20 firms.

## Table A.10: **Three-digit SIC industry classification**

The first column enumerates the three-digit SIC industries in our sample. Column *3-dig SIC* and *3-dig SIC description* report the three-digit Standard Industrial Classification (SIC) codes and the corresponding industry group names, respectively, while column # *(3-dig)* displays the number of firms within each group. Columns *2-dig SIC* and *2-dig SIC description* provide the two-digit SIC codes and the major group names to which the three-digit SIC industries belong, respectively. Finally, column # *(2-dig)* reports the total number of firms within each two-digit SIC industry.

| n. | 3-dig SIC | 3-dig SIC description | # (3-dig) | 2-dig SIC | 2-dig SIC description | # (2-dig) |
|---|---|---|---|---|---|---|
| 1 | 010; 020; 070 | Agriculture | 23 | 01; 02; 07 | Agriculture | 23 |
| 2 | 104 | Gold & Silver Ores | 30 | 10 | Metal Mining | 52 |
| 3 | 100; 109 | Metal Mining (others) | 22 | | | |
| 4 | 131 | Crude Petrol. & Natural Gas | 180 | 13 | Oil & Gas Extraction | 221 |
| 5 | 138 | Oil & Gas Field Services | 41 | | | |
| 6 | 122; 140 | Mining (others) | 32 | 12; 14 | Mining (others) | 32 |
| 7 | 152; 153; 154; 160; 162; 170; 173 | Construction | 43 | 15; 16; 17 | Construction | 43 |
| 8 | 208 | Beverages | 27 | 20 | Food and Kindred | 99 |
| 9 | 200; 201; 202; 203; 204; 205; 206; 207; 209 | Food & Kindred (others) | 72 | | | |
| 10 | 230; 232; 233; 234; 239 | Apparel & Textile Products | 33 | 23 | Apparel & Textile Products | 33 |
| 11 | 240; 242; 243; 245 | Lumber & Wood Prod. | 24 | 24 | Lumber & Wood Prod. | 24 |
| 12 | 261; 262; 263; 265; 267 | Paper Prod. | 31 | 26 | Paper Prod. | 31 |
| 13 | 271; 272; 273; 274; 275; 276; 278; 279 | Printing & Publishing | 26 | 27 | Printing & Publishing | 26 |
| 14 | 283 | Drugs | 516 | 28 | Chemicals | 640 |
| 15 | 284 | Soaps, Clean. & Toilet Goods | 24 | | | |
| 16 | 286 | Industrial Organic Chemicals | 25 | | | |
| 17 | 280; 281; 282; 285; 287; 289 | Chemicals (others) | 75 | | | |
| 18 | 291; 299 | Petroleum & Coal Prod. | 28 | 29 | Petroleum & Coal Prod. | 28 |
| 19 | 301; 302; 306; 308 | Rubber & Plastics Prod. | 30 | 30 | Rubber & Plastics Prod. | 30 |
| 20 | 321; 322; 324; 325; 326; 327; 329 | Stone, Clay & Glass Prod. | 20 | 32 | Stone, Clay & Glass Prod. | 20 |
| 21 | 331 | Furnace & Basic Steel Prod. | 20 | 33 | Primary Metal | 43 |
| 22 | 333; 334; 335; 336; 339 | Primary Metal (others) | 23 | | | |
| 23 | 342; 344; 345; 346; 347; 348; 349 | Fabricated Metal Prod. | 44 | 34 | Fabricated Metal Prod. | 44 |
| 24 | 353 | Construct. & Relat. Machinery | 28 | 35 | Machinery & Equipment | 161 |
| 25 | 356 | General Industrial Machinery | 22 | | | |
| 26 | 357 | Computer & Office Equipment | 60 | | | |
| 27 | 351; 352; 354; 355; 358; 359 | Machinery & Equip. (others) | 51 | | | |
| 28 | 362 | Electrical Industrial Apparatus | 24 | 36 | Electronic | 294 |
| 29 | 366 | Communications Equipment | 80 | | | |
| 30 | 367 | Electronic Comp. & Accessory | 132 | | | |
| 31 | 369 | Misc. Electr. Equip. & Supplies | 24 | | | |
| 32 | 360; 361; 363; 364; 365 | Electronic (others) | 34 | | | |
| 33 | 371 | Motor Vehicles & Equipment | 42 | 37 | Transp. Equip. | 81 |
| 34 | 372; 373; 374; 375; 376; 379 | Transp. Equip. (others) | 39 | | | |
| 35 | 382; 381; 385; 386; 387 | Instruments (others) | 85 | 38 | Instruments | 246 |
| 36 | 384 | Medic. Instruments & Supplies | 161 | | | |
| 37 | 391; 393; 394; 395; 399 | Misc. Manufacturing | 29 | 39 | Misc. Manufacturing | 29 |
| 38 | 210; 211; 220; 221; 222; 227; 251; 252; 253; 254; 259; 310; 314 | Manufacturing (others) | 43 | 21; 22; 25; 31 | Manufacturing (others) | 43 |

Table A.10: (cont.)

| n. | 3-dig SIC | 3-dig SIC description | # (3-dig) | 2-dig SIC | 2-dig SIC description | # (2-dig) |
|---|---|---|---|---|---|---|
| 39 | 421 | Trucking & Warehousing | 26 | 42 | Trucking & Warehousing | 26 |
| 40 | 451; 452; 458 | Air Transportation | 32 | 45 | Air Transportation | 32 |
| 41 | 470; 473 | Transp. Service | 20 | 47 | Transp. Service | 20 |
| 42 | 481 | Telephone Communication | 31 | 48 | Communications | 102 |
| 43 | 489 | Communications Services | 41 | | | |
| 44 | 483; 484; 488 | Communications (others) | 30 | | | |
| 45 | 401; 410; 440; 441; 461 | Transportation (others) | 36 | 40; 41; 44; 46 | Transportation (others) | 36 |
| 46 | 500; 501; 503; 504; 505; 506; 507; 508; 509 | Wholesale Durable Goods | 78 | 50 | Wholesale Durable Goods | 78 |
| 47 | 517 | Petrol. & Petroleum Products | 22 | 51 | Wholesale Non-Dur. Goods | 64 |
| 48 | 511; 512; 513; 514; 515; 516; 518; 519 | Wholesale Non-Dur. Goods | 42 | | | |
| 49 | 540; 541 | Food Stores | 25 | 54 | Food Stores | 25 |
| 50 | 550; 553 | Automotive Dealers | 24 | 55 | Automotive Dealers | 24 |
| 51 | 560; 562; 565; 566 | Apparel Stores | 39 | 56 | Apparel Stores | 39 |
| 52 | 581 | Eating/Drinking Places | 56 | 58 | Eating/Drinking Places | 56 |
| 53 | 596 | Nonstore Retailers | 29 | 59 | Miscellaneous Retail | 74 |
| 54 | 590; 591; 594; 599 | Miscellaneous Retail (others) | 45 | | | |
| 55 | 520; 521; 531; 533; 539; 570; 571; 573 | Retail (others) | 35 | 52; 53; 57 | Retail (others) | 35 |
| 56 | 736 | Personnel Supply Services | 20 | 73 | Business Services | 522 |
| 57 | 737 | Comput. & Data Proc. Services | 431 | | | |
| 58 | 738 | Misc. Business Services | 34 | | | |
| 59 | 731; 732; 733; 734; 735 | Business Services (others) | 37 | | | |
| 60 | 790; 794; 799 | Recreation Services | 41 | 79 | Recreation Services | 41 |
| 61 | 809 | Misc. Health & Allied Services | 26 | 80 | Health Services | 88 |
| 62 | 800; 801; 805; 806; 807; 808 | Health Services (others) | 62 | | | |
| 63 | 820 | Educational Services | 23 | 82 | Educational Services | 23 |
| 64 | 873 | Research & Testing Services | 21 | 87 | Engineering Services | |
| 65 | 874 | Manag. & Public Relations | 24 | | | |
| 66 | 870; 871; 872 | Engineering Services (others) | 28 | | | |
| 67 | 701; 720; 750; 751; 781; 782; 783; 811; 830; 835 | Services (others) | 46 | 70; 72; 75; 78 81; 83 | Services (others) | 46 |

Table A.11 reports some statistics on the empirical frequency distribution of firms by year across the three-digit SIC industries.

Table A.11: **Frequency of firms across three-digit SIC industries and over time**
Annual statistics obtained by averaging quarterly statistics within each year. Columns *min* and *max* report the minimum and maximum number of firms in an industry over time, respectively. Columns *med* and *mean* display the median and average number of firms in an industry in a particular year; *std* measures the standard deviation across all industries at each point in time.

| Year | min | max | med | mean | std |
|---|---|---|---|---|---|
| 2007 | 9.3 | 256.8 | 23.8 | 35.1 | 41.9 |
| 2008 | 10.0 | 250.5 | 24.3 | 35.7 | 41.2 |
| 2009 | 10.0 | 221.0 | 22.3 | 33.1 | 36.4 |
| 2010 | 9.8 | 203.8 | 21.0 | 31.7 | 34.1 |
| 2011 | 9.3 | 193.0 | 19.8 | 30.1 | 32.8 |
| 2012 | 8.5 | 187.5 | 19.0 | 29.2 | 31.9 |
| 2013 | 9.5 | 192.5 | 19.8 | 28.5 | 32.6 |
| 2014 | 9.3 | 242.8 | 19.3 | 29.2 | 37.7 |
| 2015 | 9.0 | 267.8 | 18.8 | 28.9 | 39.5 |
| 2016 | 8.5 | 287.5 | 18.0 | 28.2 | 40.6 |
| 2017 | 7.0 | 300.0 | 18.0 | 27.7 | 41.3 |
| 2018 | 6.0 | 272.0 | 16.3 | 25.1 | 37.3 |

## A.5 Three-digit SIC industry characteristics

This subsection provides some summary statistics for selected variables at the industry-level.

In Panel A of Table A.12, we report on differences in industry characteristics (such as industry median leverage, size, profitability, etc.), according to different degree of financial leverage. In particular, industry-quarter observations are sorted into quintiles based on debt to asset ratios. For each of these quantiles, we report the average of the selected industry-specific characteristics. As can be seen firms in higher leverage industries tend to be larger and have more tangible assets, whilst firms in lower leverage industries tend to be characterised by both higher cash holdings and also higher market to book ratios as well as larger Tobin's Q. The relation between leverage and age or industry growth is more nonlinear.

It is interesting to note that some of the above documented patterns at the industry-level also hold at the firm-level, as documented by Graham and Leary (2011). Similar conclusions hold when sorting industry-quarter observations by cash to assets (Panel B) or size quintiles (Panel C). These relations are also illustrated in Figure 4 which shows the average of several industry-quarter observations, sorted into deciles from lowest to highest industry median leverage.

Table A.12: **Industry characteristics sorted into quintiles**

The statistics in this table are obtained as follows. First, at each point in time, we compute the median of selected firm characteristics within each three-digit SIC industry. These industry-quarter observations are then sorted into quintiles based on debt to assets (panel A), cash to assets (panel B), or size (panel C). For each quintile we then report the average of the selected characteristics (listed in the first column). TA denotes total assets. A description of the variables considered can be found in Table A.1.

Panel A: Sorting by debt to assets

| | Debt to assets quintile | | | | |
|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | 5 |
| Tot. debt to TA | 0.05 | 0.14 | 0.20 | 0.25 | 0.36 |
| Size (log of TA) | 4.85 | 5.39 | 5.99 | 6.51 | 6.80 |
| Age (years) | 14.29 | 17.27 | 18.66 | 18.47 | 16.02 |
| Cash flow to TA | 0.00 | 0.02 | 0.02 | 0.02 | 0.02 |
| Cash to TA | 0.23 | 0.11 | 0.07 | 0.06 | 0.06 |
| PPE to TA | 0.18 | 0.20 | 0.28 | 0.33 | 0.37 |
| Market to book | 1.80 | 1.48 | 1.43 | 1.38 | 1.35 |
| Tobin's Q | 1.64 | 1.40 | 1.37 | 1.33 | 1.31 |
| Industry growth (%) | 0.21 | 0.62 | 0.61 | 0.48 | 0.54 |

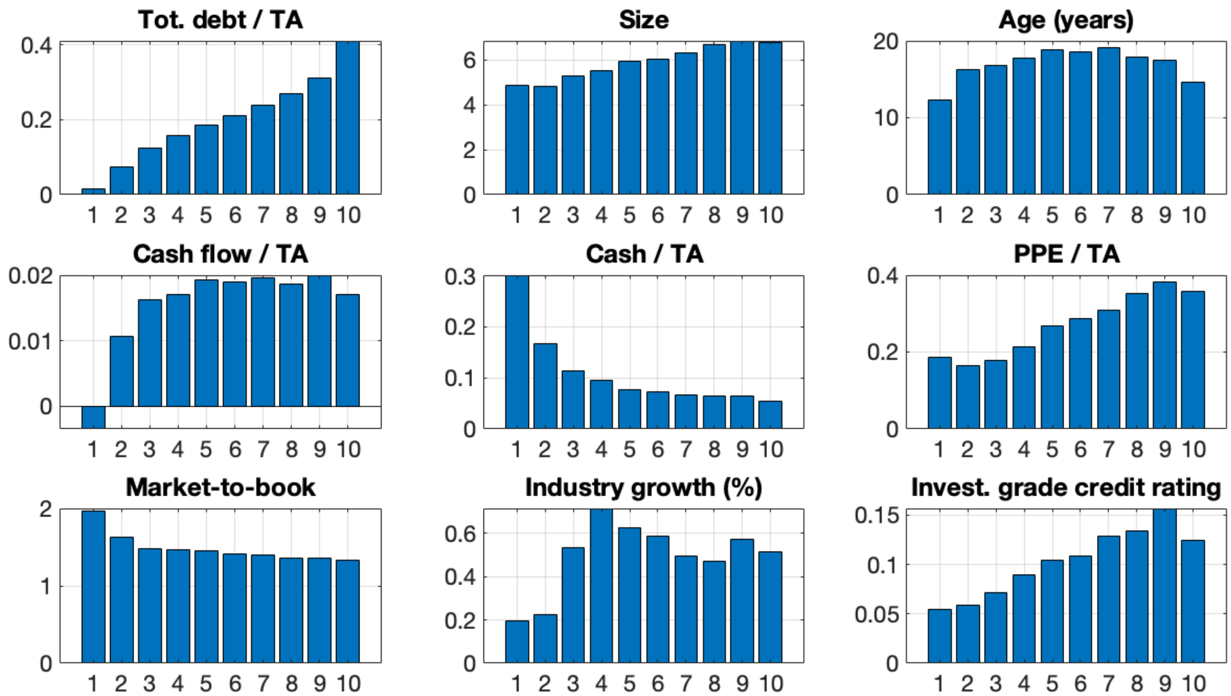
Panel B: Sorting by cash to assets

| | Cash to assets quintile | | | | |
|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | 5 |
| Tot. debt to TA | 0.29 | 0.24 | 0.20 | 0.18 | 0.08 |
| Size (log of TA) | 6.69 | 6.30 | 5.89 | 5.62 | 5.04 |
| Age (years) | 17.30 | 17.93 | 17.95 | 17.14 | 14.43 |
| Cash flow to TA | 0.02 | 0.02 | 0.02 | 0.02 | 0.01 |
| Cash to TA | 0.03 | 0.06 | 0.08 | 0.11 | 0.26 |
| PPE to TA | 0.38 | 0.31 | 0.26 | 0.23 | 0.16 |
| Market to book | 1.32 | 1.41 | 1.45 | 1.47 | 1.77 |
| Tobin's Q | 1.28 | 1.35 | 1.39 | 1.40 | 1.62 |
| Industry growth (%) | 0.69 | 0.58 | 0.36 | 0.53 | 0.32 |

Panel C: Sorting by size

| | Size quintile | | | | |
|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | 5 |
| Tot. debt to TA | 0.11 | 0.14 | 0.20 | 0.24 | 0.30 |
| Size (log of TA) | 4.31 | 5.25 | 5.92 | 6.56 | 7.49 |
| Age (years) | 14.72 | 15.37 | 17.37 | 18.58 | 18.70 |
| Cash flow to TA | 0.00 | 0.02 | 0.02 | 0.02 | 0.02 |
| Cash to TA | 0.18 | 0.14 | 0.09 | 0.07 | 0.06 |
| PPE to TA | 0.20 | 0.20 | 0.27 | 0.28 | 0.41 |
| Market to book | 1.77 | 1.49 | 1.39 | 1.47 | 1.30 |
| Tobin's Q | 1.62 | 1.41 | 1.34 | 1.41 | 1.27 |
| Industry growth (%) | 0.01 | 0.60 | 0.54 | 0.73 | 0.58 |

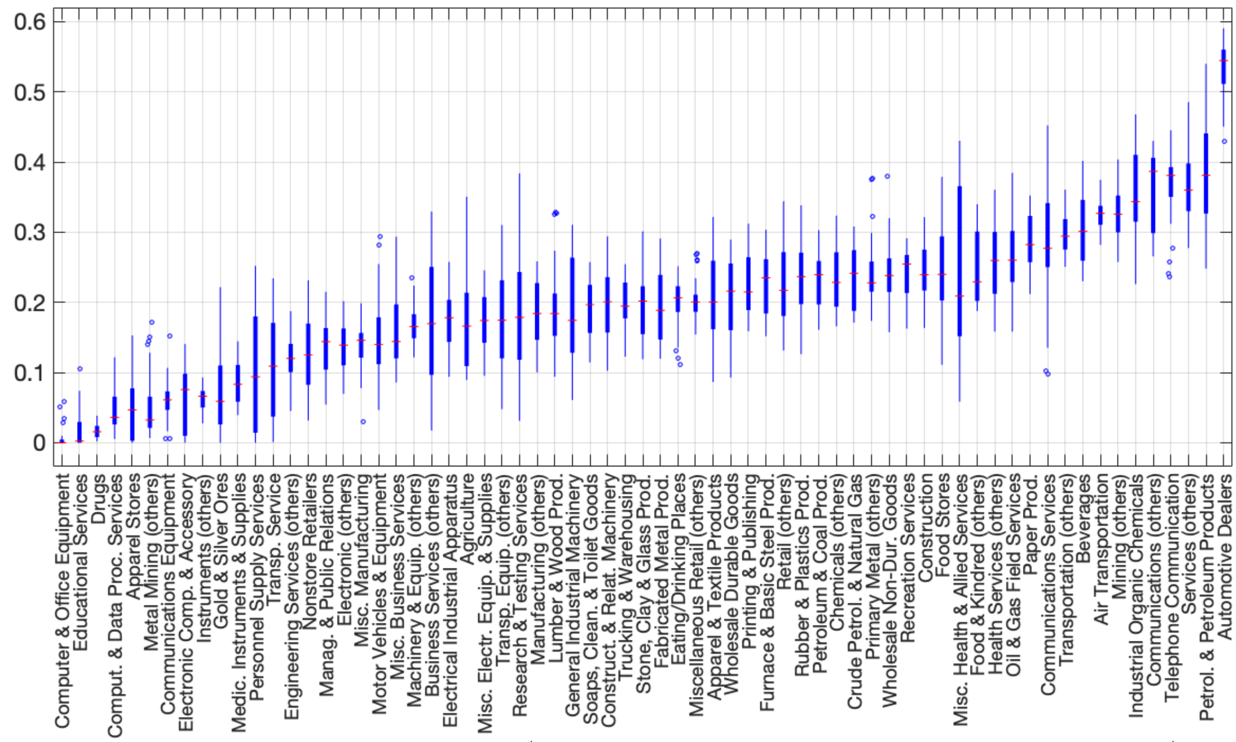
Figure 4: **Industry characteristics across debt to assets deciles**




Industry characteristics across total debt to total assets deciles. TA denotes total assets. A description of the variables can be found in Table A.1. Invest. grade credit rating is the proportion of firms in an industry with investment grade credit rating.

Finally, Figure 5 displays the box plots for industry median leverage for each three-digit SIC industry, sorted from smallest to largest industry median leverage (averaged over time). It shows a significant degree of heterogeneity in the use of leverage across industries. It is also readily apparent that industry median leverages tend to vary over time.

Figure 5: **Leverage across three-digit SIC industries**




Box plots for industry median leverage (where leverage is defined as total debt to total assets). On each box, the central mark indicates the median, and the bottom and top edges of the (dark blue) box display the 25th and 75th percentiles,respectively. The x-axis reports the three-digit SIC industries sorted from smallest to largest industry median leverage (averaged over time).

# B Identification strategy and estimation

We now provide some additional information on our identification and the estimation strategies discussed in Sections 3 and 4 of the paper, respectively.

## B.1 Panel regression model

For ease of reference, we report the basic regression model. Abstracting from dynamics or control variables for clarity of exposition, our panel regression model of interest is

$$y_{is,t} = \mu_{is} + \delta_t + \phi_s f_t + \beta_0 \pi_{s,t-1}(\gamma) + \beta_1 q_t \times \pi_{s,t-1}(\gamma) + u_{is,t}. \tag{B.1}$$

where $y_{is,t}$, is the ratio of debt to assets (DA) of firm $i$ in industry $s = 1, 2, ..., S$ for quarter $t$,. $\mu_{is}$ denotes firm-specific effects, $\delta_t$ is the so-called fixed time effects, and $\phi_s f_t$ is an industry-specific coefficient multiplying the non-policy macro variable. $q_t$ is the quantitative policy variable measuring the size of the Fed's U.S. Treasuries and agency MBS purchases. $\pi_{st}(\gamma)$ denotes the proportion of firms in industry $s$ with DA below the $\gamma^{th}$ quantile of the cross-sectional distribution of $y_{is,t}$ across all firms at time $t$. Specifically,

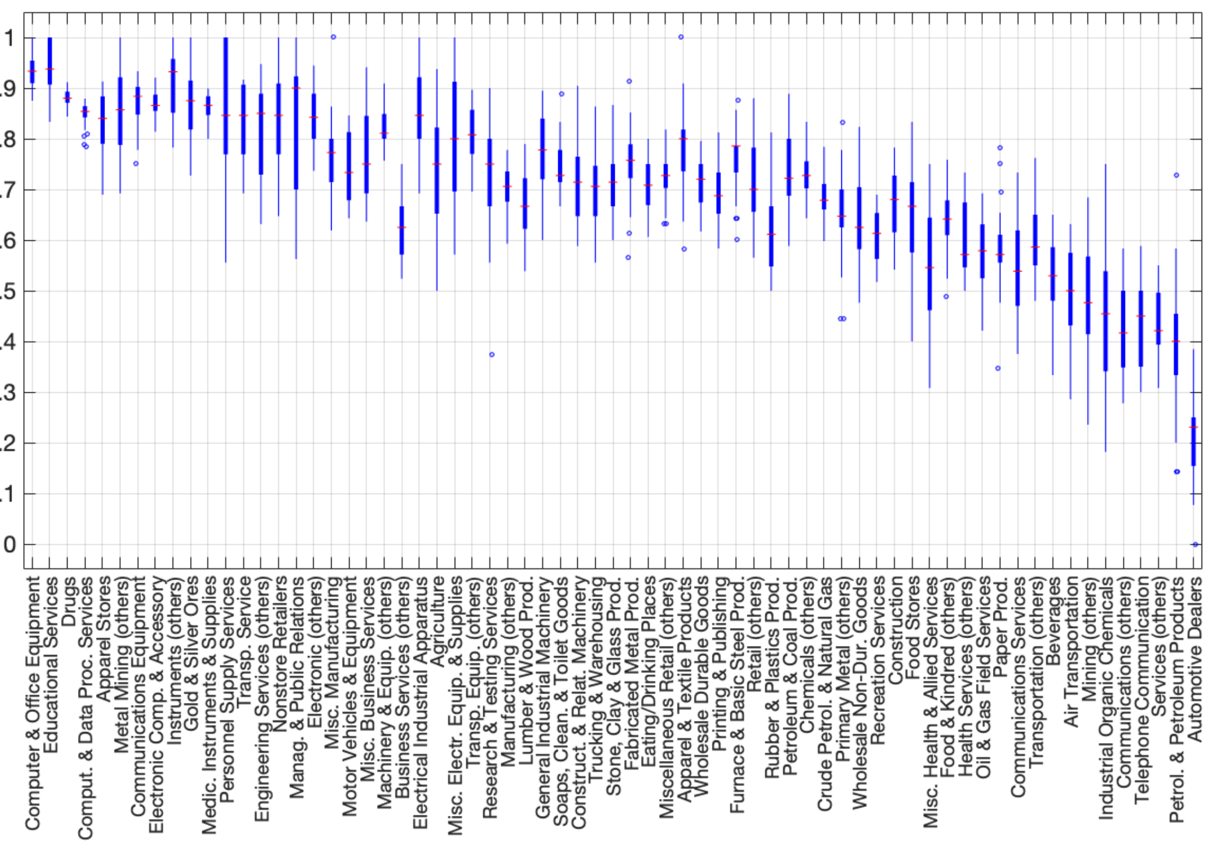
$$\pi_{st}(\gamma) = \frac{1}{N_{st}} \sum_{i=1}^{N_{st}} \mathcal{I}\left[y_{is,t} < g_t(\gamma)\right], \tag{B.2}$$

where $N_{st}$ denotes the number of firms in industry $s$ during quarter $t$, and $\mathcal{I}(A)$ is an indicator variable that takes the value of 1 if $A$ is true and zero otherwise. The quantile threshold value $\gamma$ $(0 < \gamma < 1)$ is unknown and it is estimated using a grid search procedure described in the subsection B.3.

## B.2 Cross-industry variation to identify the policy effects

As discussed in the paper, identification of the policy effectiveness coefficient, $\beta_1$, in equation (B.1), requires a sufficient degree of variations in $q_t$ over time and $\pi_{st}(\gamma)$ across industries. We demonstrate this graphically.

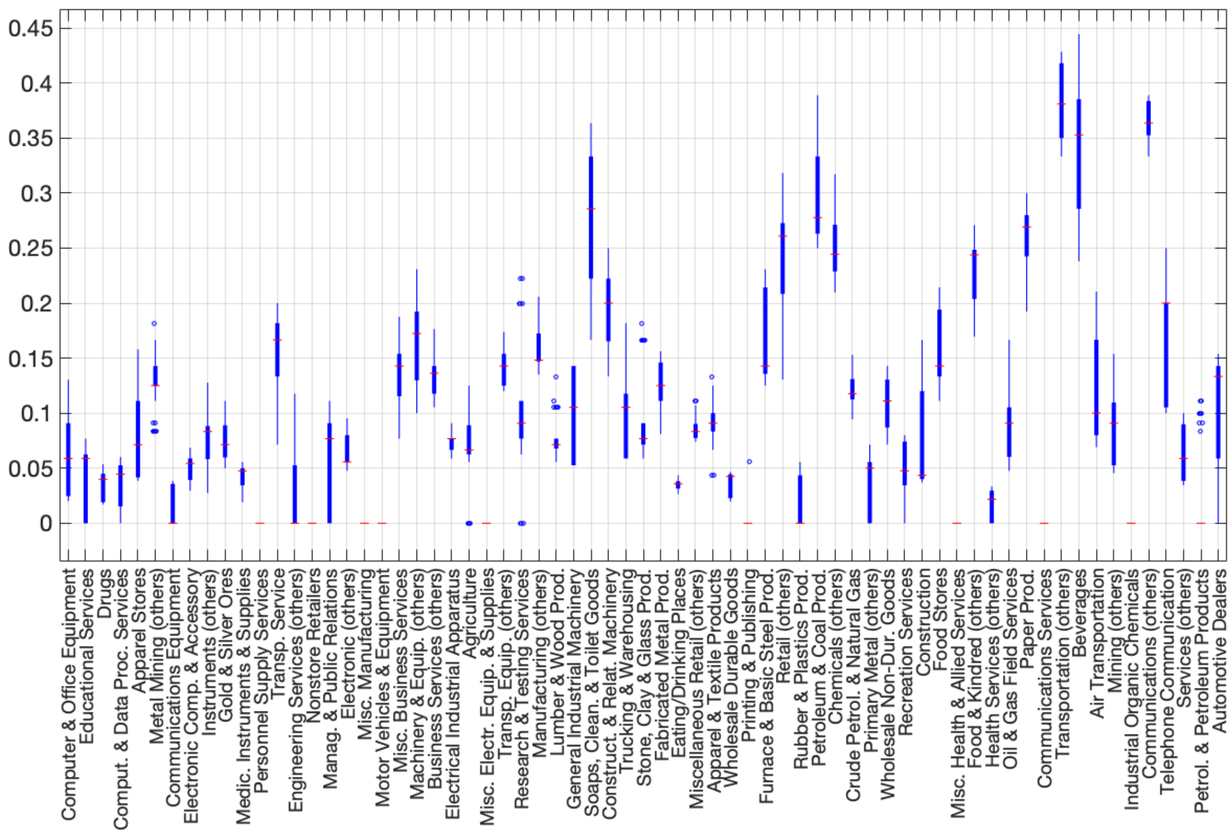
Figure 6: **Proportion of firms with debt to asset ratios below the upper quartile by industry**




Box plots for the proportion of firms in each industry with debt to asset ratios (DA) below the upper quartile ($\pi_{st,DA}(75)$). On each box, the central mark indicates the median, and the bottom and top edges of the (dark blue) box display the 25th and 75th percentiles, respectively. The x-axis reports the three-digit SIC industries sorted from smallest to largest industry median leverage (averaged over time).

In Figure 6, we report the box plots for $\pi_{st}(75)$, the proportions of firms with DA below the upper quartile (sorted from smallest to largest industry median leverage), across the three-digit SIC industries to illustrate that they show significant variation across industries and also over time. Figure 7 display the box plots for the proportions of firms in an industry with investment grade ratings, again sorted by industry median leverage.

Figure 7: **Proportion of firms with investment grade ratings by industry**




Box plots for the proportion of firms in each industry with investment grade credit ratings ($\pi_{st,CR}$). On each box, the central mark indicates the median, and the bottom and top edges of the (dark blue) box display the 25th and 75th percentiles,respectively. The x-axis reports the three-digit SIC industries sorted from smallest to largest industry median leverage (averaged over time).

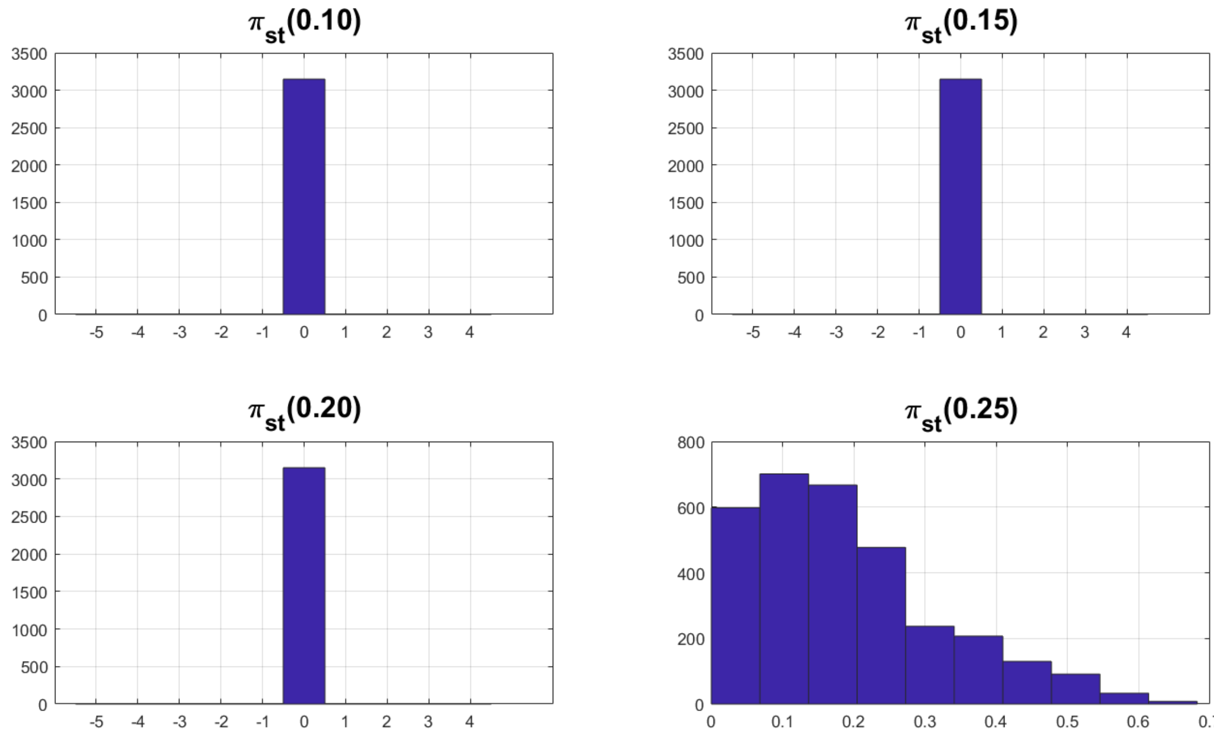
## B.3 Quantile threshold parameter estimates

As discussed in the paper, the grid search procedure used to estimate $\gamma$ consists in selecting many values of $\gamma$ along a grid, compute the sum of squared residuals (SSR) for each of these values, to then choose as estimates the value that provides the smallest SSR. We calculate the SSR for all values of $0.25 \leq \gamma \leq 0.9$ in increments of 0.01.

Here we show why we choose to start the grid search at 0.25 instead of 0.1. To do so, in Figure 8 we display the sample distribution of $\pi_{st}(\gamma)$ for $\gamma = 0.10, 0.15, 0.20, 0.25$. It is clear that we cannot start the grid search from 0.1 because by construction, $\pi_{st}(\gamma) = 0$ whenever

$g_t(\gamma) = 0$, and given that the $q$-th quantile of DA is equal to zero for all values of $q$ below 0.21.

Figure 8: **Histogram plot of $\pi_{st}(\gamma)$ for selected values of $\gamma$**




Each panel displays the sample distribution of $\pi_{st}(\gamma)$ (across sectors and over time) for different values of $\gamma \in \{0.10, 0.15, 0.20, 0.25\}$. In both upper panels as well as in the left-hand side bottom panel, $\pi_{st}(\gamma) = 0$ for all $s$ and $t$.

## B.4 Quantile threshold validation

As a robustness check, we validate the computation of our main industry-specific proportion. From (B.2), we have

$$\sum_{s=1}^{S} N_{st}\pi_{st}(\gamma) = \sum_{s=1}^{S}\sum_{i=1}^{N_{st}} \mathcal{I}\left[y_{is,t} < g_t(\gamma)\right].$$

By dividing both sides by $N_t$, the total number of firms at quarter $t$, we get

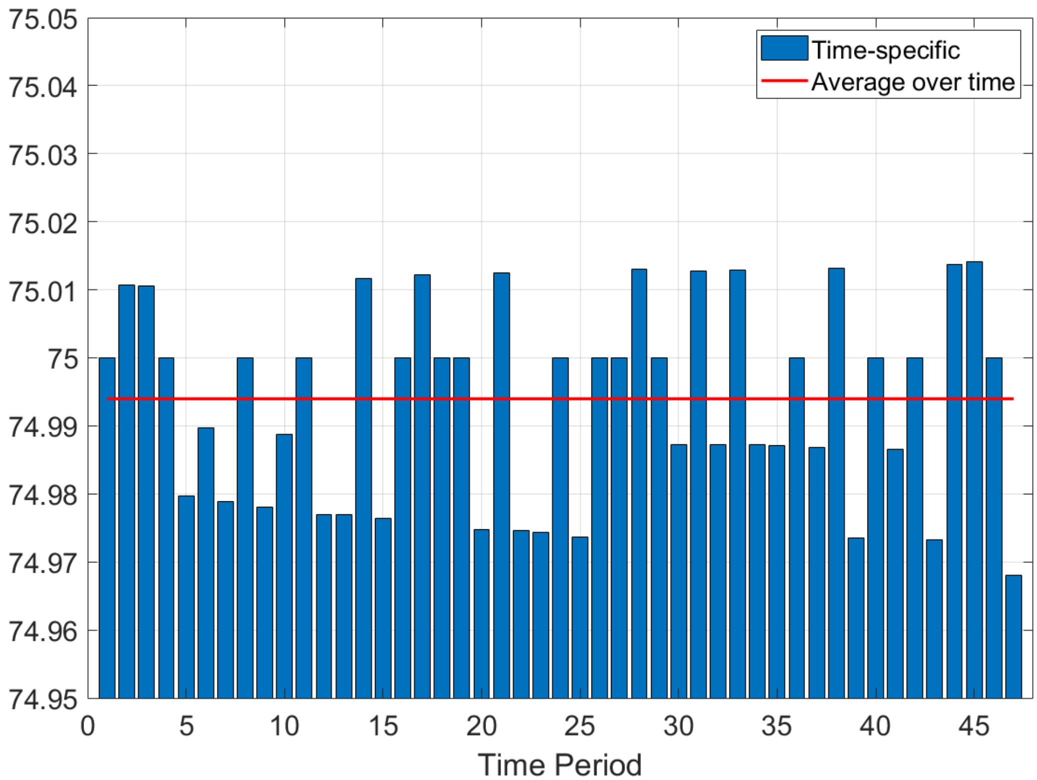
$$\sum_{s=1}^{S} \frac{N_{st}}{N_t}\pi_{st}(\gamma) = \frac{1}{N_t}\sum_{s=1}^{S}\sum_{i=1}^{N_{st}} \mathcal{I}\left[y_{is,t} < g_t(\gamma)\right] = \gamma,$$

which can be written more compactly as

$$\sum_{s=1}^{S} w_{st}\pi_{st}(\gamma) = \gamma, \tag{B.3}$$

where $w_{st} = (N_{st}/N_t)$ is the proportion of all firms in industry $s$ at time $t$. We have verified that our computations of $\pi_{st}(\gamma)$ satisfy the identity described in equation (B.3) for all values of $\gamma$ considered. As an illustration, in Figure 9 we plot (B.3) when $\gamma = 0.75$, over time.

Figure 9: **Quantile threshold validation: illustrative example**




Bar plot of $\sum_{s=1}^{S} w_{st}\pi_{st}(0.75)$ $(\times 100)$ at each point in time, where $\pi_{st}(0.75)$ is the proportion of firms in industry $s$ with debt to asset ratios (DA) below the $75^{th}$ quantile of the cross-sectional distribution of DA across all firms at time $t$, and $w_{st} = (N_{st}/N_t)$ is the proportion of all firms in industry $s$ at time $t$. The red line is obtained by averaging $\sum_{s=1}^{S} w_{st}\pi_{st}(0.75)$ over time.

## B.5 Optimization problem

We now provide further details on the optimization problem. Our estimation strategy allows $\{\phi_s$ for $s = 1, 2, ..., S\}$, reported in equation (B.1), to be treated as free parameters to be estimated for alternative specifications of $f_t$, subject to

$$\bar{\phi}_{\circ} = S^{-1} \sum_{s=1}^{S} \phi_s = 0. \tag{B.4}$$

The fixed and time effects, $\mu_{is}$ and $\delta_t$, can then be eliminated using standard de-meaning techniques to yield[25]

$$Y_{is,t} = \left(\phi_s f_t - \phi_s \bar{f} - \bar{\phi}_\circ f_t + \bar{f}\bar{\phi}_\circ\right) + \beta_0 \Pi_{s,t-1}(\gamma) + \beta_1 Z_{s,t-1}(\gamma) + U_{is,t}, \tag{B.5}$$

where $\bar{f} = T^{-1}\sum_{t=1}^{T} f_t$, $Y_{is,t} = y_{is,t} - \bar{y}_{is\circ} - \bar{y}_{\circ\circ t} + \bar{y}_{\circ\circ\circ}$, $U_{is,t} = u_{is,t} - \bar{u}_{is\circ} - \bar{u}_{\circ\circ t} + \bar{u}_{\circ\circ\circ}$,

$$\Pi_{s,t-1}(\gamma) = \pi_{s,t-1}(\gamma) - \pi_{s\circ}(\gamma) - \pi_{\circ,t-1}(\gamma) + \pi_{\circ\circ}(\gamma),$$

$$\begin{aligned} Z_{st}(\gamma) &= q_t \times \pi_{s,t-1}(\gamma) - T^{-1}\textstyle\sum_{t=1}^{T} q_t \times \pi_{s,t-1}(\gamma) \\ &\quad - q_t \times \pi_{\circ,t-1}(\gamma) + T^{-1}\textstyle\sum_{t=1}^{T} q_t \times \pi_{\circ,t-1}(\gamma), \end{aligned}$$

$$\begin{aligned} \bar{y}_{is\circ} &= T^{-1}\textstyle\sum_{t=1}^{T} y_{is,t}, & \bar{y}_{\circ\circ t} &= S^{-1}\textstyle\sum_{s=1}^{S}\left(\frac{1}{N_{st}}\sum_{i=1}^{N_{st}} y_{is,t}\right) \\ \bar{y}_{\circ\circ\circ} &= T^{-1}\textstyle\sum_{t=1}^{T} \bar{y}_{\circ\circ t}, & \pi_{s\circ}(\gamma) &= T^{-1}\textstyle\sum_{t=1}^{T} \pi_{s,t-1}(\gamma), \\ \pi_{\circ,t-1}(\gamma) &= S^{-1}\textstyle\sum_{s=1}^{S} \pi_{s,t-1}(\gamma)\ , & \pi_{\circ\circ}(\gamma) &= S^{-1}\textstyle\sum_{s=1}^{S} \pi_{s\circ}(\gamma). \end{aligned}$$

But under (B.4) the first term of (B.5) simplifies and we have

$$Y_{is,t} = \phi_s\left(f_t - \bar{f}\right) + \beta_0 \Pi_{s,t-1}(\gamma) + \beta_1 Z_{s,t-1}(\gamma) + U_{is,t}, \tag{B.6}$$

which can be estimated for any given trend function, $f_t$, using least squares by solving the following optimization problem

$$min_{\beta_0,\beta_1,\phi} \sum_{s=1}^{S}\sum_{t=1}^{T}\sum_{i=1}^{N_{st}} \left[Y_{is,t} - \phi_s\left(f_t - \bar{f}\right) - \beta_0 \Pi_{s,t-1}(\gamma) - \beta_1 Z_{s,t-1}(\gamma)\right]^2, \tag{B.7}$$

where $\phi = (\phi_1, \phi_2, ...., \phi_S)'$, subject to the restriction (B.4).

In practice, we consider an unconstrained optimization problem whereby instead of including all the $S$ industry-specific dummies to be interacted with $f_t$, we consider the first industry as benchmark and subtract the latter from the other industry dummies. In other words, we include in the regression model: $(d_s - d_1) \times f_t$, for $s = 2, 3, ..., S$, where $d_s$ is an indicator variables that takes the value 1 if firm $i$ belongs to industry $s$ and zero otherwise.

[25] To simplify the derivations here we considered a balanced panel, but use Wansbeek and Kapteyn (1989) transformations to eliminate $\mu_{is}$ and $\delta_t$ in our empirical applications where the panel is unbalanced. Wansbeek and Kapteyn procedure is equivalent to including both time and fixed effect dummies in the panel regressions, but it is less computationally cumbersome when $sup_t \sum_{s=1}^{S} N_{st}$ is large, where $N_{st}$ denotes the number of firms in industry $s$ during quarter $t$.

# C Estimation results for benchmark specifications

## C.1 Full estimation results

This subsection reports additional estimation results for the benchmark panel regression model given in equation (10) of the paper, also shown below for ease of reference:

$$\begin{aligned} y_{is,t} &= \mu_{is} + \delta_t + \phi_s f_t + \textstyle\sum_{\ell=0}^{p} \left[\beta_{0,\ell}\pi_{s,t-\ell-1}(\gamma) + \beta_{1,\ell} q_{t-\ell} \times \pi_{s,t-\ell-1}(\gamma)\right] \\ &\quad + \textstyle\sum_{\ell=1}^{p} \lambda_\ell y_{is,t-\ell} + \sum_{\ell=0}^{p} \left(\boldsymbol{\alpha}_\ell' \mathbf{x}_{is,t-\ell} + \boldsymbol{\rho}_\ell' \mathbf{w}_{s,t-\ell}\right) + u_{is,t}, \end{aligned} \tag{C.8}$$

where as before the dependent variable, $y_{is,t}$, is the ratio of debt to assets (DA) of firm $i$ in industry $s$ for quarter $t$. $\mu_{is}$ and $\delta_t$ denote firm-specific effects and time effects, respectively, while $\phi_s f_t$ is the industry-specific trend coefficient multiplying the scaled linear time trend. $q_t$ measures the scaled size of the Fed's asset purchases, and $\pi_{s,t}(\gamma)$ denotes the proportion of firms in an industry with DA below the $\gamma$-th quantile. $\mathbf{x}_{is,t}$ and $\mathbf{w}_{s,t}$ are a vector of firm- and industry-specific characteristics, respectively.

As discussed in the paper, we use a two-step strategy whereby we first estimate $\gamma$ by grid search, to then take the estimate as given when it comes to estimate the coefficients of equation (C.8). This two-step estimation strategy is justified due to the known super consistency of the estimators of the threshold parameters.

Estimation of the threshold parameters is discussed in more details in the paper. Below we report Table C.13 summarising the estimates of the threshold parameters in the benchmark specifications, for ease of reference.

Table C.13: **Estimated quantile threshold parameters**

Estimates of the quantile threshold parameters from a grid search procedure across both the partial adjustment model and the ARDL specifications described in equation (10). The upper panel shows the estimated threshold parameters for the single-threshold panel regression model, where $\gamma_{pre} = \gamma_{post}$. The lower panel displays results for the two-threshold model, where $\gamma_{pre} \neq \gamma_{post}$. The estimation sample consists of an unbalanced panel of 3,647 U.S. publicly traded non-financial firms observed at a quarterly frequency over the period 2007:Q1 - 2018:Q3.

| | Par. Adj. | ARDL(1) | ARDL(2) |
|---|---|---|---|
| | | $\gamma_{pre} = \gamma_{post} = \gamma$ | |
| $\hat{\gamma}$ | 0.56 | 0.76 | 0.76 |
| | | $\gamma_{pre} \neq \gamma_{post}$ | |
| $\hat{\gamma}_{pre}$ | 0.56 | 0.56 | 0.56 |
| $\hat{\gamma}_{post}$ | 0.77 | 0.77 | 0.77 |

Table C.14 reports the estimated coefficients for the partial adjustment model, while Table C.15 and C.16 report the estimates for the ARDL(1) and ARDL(2) specification, respectively.

Table C.14: **FE–TE estimates of the effects of LSAPs on firm's debt to asset ratios based on the partial adjustment model**

Estimates of the coefficients of the partial adjustment model based on equation (C.8). The dependent variable is debt to asset ratio (DA). $q_t \times \pi_{s,t-1,DA}(\hat{\gamma}_{post})$ denotes the interaction of $q_t$, the amount of U.S. Treasuries and agency MBS purchased by the Fed scaled by its average over the policy on period, and $\pi_{s,t-1,DA}(\hat{\gamma}_{post})$, the one-quarter lagged proportion of firms in an industry with DA below the $\hat{\gamma}^{th}_{post}$ quantile. $q_t \times \pi_{s,t-1,CR}$ denotes the interaction of $q_t$ and the one-quarter lagged proportion of firms in an industry with investment grade credit ratings. In the first three columns, we report results for the single-threshold panel regression model, where $\gamma_{pre} = \gamma_{post} = \gamma$. In this case, $\hat{\gamma} = 0.56$. The last two columns report results for the two-threshold panel regression, where $\hat{\gamma}_{pre} = 0.56$ and $\hat{\gamma}_{post} = 0.77$. All regressions include both firm-specific effects and time effects as well as industry-specific linear time trends. The sample consists of an unbalanced panel of $3,647$ U.S. publicly traded non-financial firms observed at a quarterly frequency over the period 2007:Q1 - 2018:Q3. Robust standard errors in parentheses (*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$).

| | Dependent variable: debt to assets ($DA_t$) | | | | |
|---|---|---|---|---|---|
| | $\gamma_{pre} = \gamma_{post} = \gamma$ | | | $\gamma_{pre} \neq \gamma_{post}$ | |
| | (1) | (2) | (3) | (4) | (5) |
| $\pi_{s,t-1,DA}(\hat{\gamma}_{pre})$ | 0.0447*** | | 0.0445*** | 0.0460*** | 0.0464*** |
| | (0.0041) | | (0.0042) | (0.0040) | (0.0040) |
| $q_t \times \pi_{s,t-1,DA}(\hat{\gamma}_{post})$ | 0.0033*** | | 0.0041*** | 0.0077*** | 0.0083*** |
| | (0.0012) | | (0.0013) | (0.0014) | (0.0015) |
| $\pi_{s,t-1,CR}$ | | -0.0001 | 0.0077 | | 0.0077 |
| | | (0.0112) | (0.0113) | | (0.0112) |
| $q_t \times \pi_{s,t-1,CR}$ | | -0.0023 | 0.0033 | | 0.0034 |
| | | (0.0025) | (0.0028) | | (0.0026) |
| $DA_{t-1}$ | 0.8264*** | 0.8249*** | 0.8264*** | 0.8266*** | 0.8266*** |
| | (0.0053) | (0.0053) | (0.0053) | (0.0053) | (0.0053) |
| $Cash/TA_t$ | -0.0496*** | -0.0500*** | -0.0496*** | -0.0496*** | -0.0496*** |
| | (0.0034) | (0.0034) | (0.0034) | (0.0034) | (0.0034) |
| $PPE/TA_t$ | 0.0249*** | 0.0243*** | 0.0248*** | 0.0250*** | 0.0249*** |
| | (0.0053) | (0.0053) | (0.0053) | (0.0053) | (0.0053) |
| $Size_t$ | 0.0051*** | 0.0051*** | 0.0051*** | 0.0051*** | 0.0051*** |
| | (0.0008) | (0.0008) | (0.0008) | (0.0008) | (0.0008) |
| $Industry\ leverage_t$ | 0.1391*** | 0.1010*** | 0.1390*** | 0.1414*** | 0.1417*** |
| | (0.0075) | (0.0064) | (0.0075) | (0.0075) | (0.0075) |
| $Industry\ growth_t$ | -0.0483*** | -0.0361*** | -0.0488*** | -0.0499*** | -0.0502*** |
| | (0.0131) | (0.0131) | (0.0132) | (0.0131) | (0.0131) |
| Fixed effects | Yes | Yes | Yes | Yes | Yes |
| Time effects | Yes | Yes | Yes | Yes | Yes |
| Industry linear trends | Yes | Yes | Yes | Yes | Yes |
| Observations | 84,548 | 84,548 | 84,548 | 84,548 | 84,548 |
| $N$ | 3,647 | 3,647 | 3,647 | 3,647 | 3,647 |
| $max(T_i)$ | 44 | 44 | 44 | 44 | 44 |
| $avg(T_i)$ | 23.2 | 23.2 | 23.2 | 23.2 | 23.2 |
| $med(T_i)$ | 19 | 19 | 19 | 19 | 19 |
| $min(T_i)$ | 2 | 2 | 2 | 2 | 2 |

Table C.15: **FE–TE estimates of the effects of LSAPs on non-financial firm's debt to asset ratios based on the ARDL(1) model**

Estimates of the coefficients of the ARDL(1) model described in equation (C.8). The dependent variable is debt to asset ratio (DA). $q_{t-\ell} \times \pi_{s,t-\ell-1,DA}(\hat{\gamma}_{post})$ denotes the interaction of $q_{t-\ell}$, the amount of U.S. Treasuries and agency MBS purchased by the Fed scaled by its average over the policy on period, and $\pi_{s,t-\ell-1,DA}(\hat{\gamma}_{post})$, the one-quarter lagged proportion of firms in an industry with DA below the $\hat{\gamma}_{post}^{th}$ quantile, for $\ell = 0, 1$. $q_{t-\ell} \times \pi_{s,t-\ell-1,CR}$ denotes the interaction of $q_{t-\ell}$ and the one-quarter lagged proportion of firms in an industry with investment grade credit ratings, for $\ell = 0, 1$. In the first three columns, we report results for the single-threshold panel regression model, where $\gamma_{pre} = \gamma_{post} = \gamma$. In this case, $\hat{\gamma} = 0.76$. The last two columns report results for the two-threshold panel regression, where $\hat{\gamma}_{pre} = 0.56$ and $\hat{\gamma}_{post} = 0.77$. All regressions include both firm-specific effects and time effects as well as industry-specific linear time trends. The sample consists of an unbalanced panel of 3,647 U.S. publicly traded non-financial firms observed at a quarterly frequency over the period 2007:Q1 - 2018:Q3. Robust standard errors in parentheses (*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$).

| | Dependent variable: debt to assets ($DA_t$) | | | | |
|---|---|---|---|---|---|
| | $\gamma_{pre} = \gamma_{post} = \gamma$ | | | $\gamma_{pre} \neq \gamma_{post}$ | |
| | (1) | (2) | (3) | (4) | (5) |
| $\pi_{s,t-1,DA}(\hat{\gamma}_{pre})$ | 0.0152*** | | 0.0155*** | 0.0193*** | 0.0197*** |
| | (0.0051) | | (0.0051) | (0.0049) | (0.0050) |
| $q_t \times \pi_{s,t-1,DA}(\hat{\gamma}_{post})$ | 0.0031 | | 0.0029 | 0.0049*** | 0.0051** |
| | (0.0020) | | (0.0021) | (0.0019) | (0.0020) |
| $\pi_{s,t-2,DA}(\hat{\gamma}_{pre})$ | -0.0017 | | -0.0019 | -0.0045 | -0.0047 |
| | (0.0049) | | (0.0049) | (0.0044) | (0.0044) |
| $q_{t-1} \times \pi_{s,t-2,DA}(\hat{\gamma}_{post})$ | 0.0028 | | 0.0031 | 0.0025 | 0.0026 |
| | (0.0018) | | (0.0020) | (0.0018) | (0.0019) |
| $\pi_{s,t-1,CR}$ | | 0.0339* | 0.0318* | | 0.0316* |
| | | (0.0190) | (0.0189) | | (0.0190) |
| $q_t \times \pi_{s,t-1,CR}$ | | -0.0021 | -0.0006 | | 0.0008 |
| | | (0.0032) | (0.0033) | | (0.0033) |
| $\pi_{s,t-2,CR}$ | | -0.0277 | -0.0295 | | -0.0274 |
| | | (0.0189) | (0.0189) | | (0.0189) |
| $q_{t-1} \times \pi_{s,t-2,CR}$ | | -0.0011 | 0.0014 | | 0.0011 |
| | | (0.0028) | (0.0031) | | (0.0030) |
| $DA_{t-1}$ | 0.8337*** | 0.8333*** | 0.8337*** | 0.8337*** | 0.8337*** |
| | (0.0052) | (0.0052) | (0.0052) | (0.0052) | (0.0052) |
| $Cash/TA_t$ | -0.0930*** | -0.0929*** | -0.0930*** | -0.0929*** | -0.0929*** |
| | (0.0078) | (0.0078) | (0.0078) | (0.0078) | (0.0078) |
| $Cash/TA_{t-1}$ | 0.0549*** | 0.0548*** | 0.0549*** | 0.0549*** | 0.0549*** |
| | (0.0075) | (0.0075) | (0.0075) | (0.0075) | (0.0075) |
| $PPE/TA_t$ | 0.0632*** | 0.0633*** | 0.0632*** | 0.0632*** | 0.0632*** |
| | (0.0168) | (0.0168) | (0.0168) | (0.0168) | (0.0168) |
| $PPE/TA_{t-1}$ | -0.0396** | -0.0398** | -0.0396** | -0.0395** | -0.0395** |
| | (0.0168) | (0.0168) | (0.0168) | (0.0168) | (0.0168) |
| $Size_t$ | 0.0289*** | 0.0288*** | 0.0289*** | 0.0289*** | 0.0289*** |
| | (0.0038) | (0.0038) | (0.0038) | (0.0038) | (0.0038) |
| $Size_{t-1}$ | -0.0258*** | -0.0258*** | -0.0258*** | -0.0258*** | -0.0258*** |
| | (0.0038) | (0.0038) | (0.0038) | (0.0038) | (0.0038) |

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Table C.15: (cont.)

| | Dependent variable: debt to assets ($DA_t$) | | | | |
|---|---|---|---|---|---|
| | $\gamma_{pre} = \gamma_{post} = \gamma$ | | | $\gamma_{pre} \neq \gamma_{post}$ | |
| | (1) | (2) | (3) | (4) | (5) |
| $Industry\ leverage_t$ | 0.2158*** | 0.2137*** | 0.2155*** | 0.2153*** | 0.2150*** |
| | (0.0098) | (0.0099) | (0.0099) | (0.0099) | (0.0099) |
| $Industry\ leverage_{t-1}$ | -0.1527*** | -0.1647*** | -0.1525*** | -0.1438*** | -0.1433*** |
| | (0.0098) | (0.0096) | (0.0098) | (0.0104) | (0.0104) |
| $Industry\ growth_t$ | -0.0694*** | -0.0644*** | -0.0692*** | -0.0712*** | -0.0712*** |
| | (0.0137) | (0.0137) | (0.0137) | (0.0137) | (0.0137) |
| $Industry\ growth_{t-1}$ | -0.0329*** | -0.0273** | -0.0328*** | -0.0344*** | -0.0340*** |
| | (0.0119) | (0.0119) | (0.0119) | (0.0119) | (0.0119) |
| Fixed effects | Yes | Yes | Yes | Yes | Yes |
| Time effects | Yes | Yes | Yes | Yes | Yes |
| Industry linear trends | Yes | Yes | Yes | Yes | Yes |
| Observations | 84,548 | 84,548 | 84,548 | 84,548 | 84,548 |
| $N$ | 3,647 | 3,647 | 3,647 | 3,647 | 3,647 |
| $max(T_i)$ | 44 | 44 | 44 | 44 | 44 |
| $avg(T_i)$ | 23.2 | 23.2 | 23.2 | 23.2 | 23.2 |
| $med(T_i)$ | 19 | 19 | 19 | 19 | 19 |
| $min(T_i)$ | 2 | 2 | 2 | 2 | 2 |

Table C.16: **FE–TE estimates of the effects of LSAPs on non-financial firm's debt to asset ratios based on the ARDL(2) model**

Estimates of the coefficients of the ARDL(2) model described in equation (C.8). The dependent variable is debt to asset ratio (DA). $q_{t-\ell} \times \pi_{s,t-\ell-1,DA}(\hat{\gamma}_{post})$ denotes the interaction of $q_{t-\ell}$, the amount of U.S. Treasuries and agency MBS purchased by the Fed scaled by its average over the policy on period, and $\pi_{s,t-\ell-1,DA}(\hat{\gamma}_{post})$, the one-quarter lagged proportion of firms in an industry with DA below the $\hat{\gamma}^{th}_{post}$ quantile, for $\ell = 0, 1, 2$. $q_{t-\ell} \times \pi_{s,t-\ell-1,CR}$ denotes the interaction of $q_{t-\ell}$ and the one-quarter lagged proportion of firms in an industry with investment grade credit ratings, for $\ell = 0, 1, 2$. In the first three columns, we report results for the single-threshold panel regression model, where $\gamma_{pre} = \gamma_{post} = \gamma$. In this case, $\hat{\gamma} = 0.76$. The last two columns report results for the two-threshold panel regression, where $\hat{\gamma}_{pre} = 0.56$ and $\hat{\gamma}_{post} = 0.77$. All regressions include both firm-specific effects and time effects as well as industry-specific linear time trends. The sample consists of an unbalanced panel of $3,647$ U.S. publicly traded non-financial firms observed at a quarterly frequency over the period 2007:Q1 - 2018:Q3. Robust standard errors in parentheses (*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$).

| | Dependent variable: debt to assets ($DA_t$) | | | | |
|---|---|---|---|---|---|
| | $\gamma_{pre} = \gamma_{post} = \gamma$ | | | $\gamma_{pre} \neq \gamma_{post}$ | |
| | (1) | (2) | (3) | (4) | (5) |
| $\pi_{s,t-1,DA}(\hat{\gamma}_{pre})$ | 0.0125** | | 0.0128** | 0.0176*** | 0.0181*** |
| | (0.0052) | | (0.0052) | (0.0050) | (0.0051) |
| $q_t \times \pi_{s,t-1,DA}(\hat{\gamma}_{post})$ | 0.0037* | | 0.0035 | 0.0058*** | 0.0058*** |
| | (0.0021) | | (0.0022) | (0.0020) | (0.0021) |
| $\pi_{s,t-2,DA}(\hat{\gamma}_{pre})$ | -0.0021 | | -0.0022 | -0.0086 | -0.0088 |
| | (0.0061) | | (0.0062) | (0.0055) | (0.0055) |
| $q_{t-1} \times \pi_{s,t-2,DA}(\hat{\gamma}_{post})$ | 0.0012 | | 0.0016 | 0.0001 | 0.0003 |
| | (0.0026) | | (0.0028) | (0.0025) | (0.0027) |
| $\pi_{s,t-3,DA}(\hat{\gamma}_{pre})$ | 0.0052 | | 0.0049 | 0.0096** | 0.0095** |
| | (0.0050) | | (0.0051) | (0.0043) | (0.0043) |
| $q_{t-2} \times \pi_{s,t-3,DA}(\hat{\gamma}_{post})$ | 0.0019 | | 0.0018 | 0.0030 | 0.0029 |
| | (0.0021) | | (0.0022) | (0.0019) | (0.0021) |
| $\pi_{s,t-1,CR}$ | | 0.0353* | 0.0317* | | 0.0322* |
| | | (0.0191) | (0.0190) | | (0.0191) |
| $q_t \times \pi_{s,t-1,CR}$ | | -0.0027 | -0.0010 | | 0.0005 |
| | | (0.0034) | (0.0036) | | (0.0036) |
| $\pi_{s,t-2,CR}$ | | -0.0268 | -0.0266 | | -0.0267 |
| | | (0.0246) | (0.0247) | | (0.0247) |
| $q_{t-1} \times \pi_{s,t-2,CR}$ | | 0.0006 | 0.0019 | | 0.0010 |
| | | (0.0042) | (0.0045) | | (0.0045) |
| $\pi_{s,t-3,CR}$ | | -0.0013 | -0.0025 | | 0.0001 |
| | | (0.0180) | (0.0180) | | (0.0180) |
| $q_{t-2} \times \pi_{s,t-3,CR}$ | | -0.0020 | -0.0006 | | 0.0000 |
| | | (0.0033) | (0.0035) | | (0.0035) |
| $DA_{t-1}$ | 0.8123*** | 0.8120*** | 0.8123*** | 0.8125*** | 0.8125*** |
| | (0.0091) | (0.0091) | (0.0091) | (0.0091) | (0.0091) |
| $DA_{t-2}$ | 0.0263*** | 0.0262*** | 0.0263*** | 0.0261*** | 0.0261*** |
| | (0.0077) | (0.0077) | (0.0077) | (0.0077) | (0.0077) |
| $Cash/TA_t$ | -0.0930*** | -0.0930*** | -0.0930*** | -0.0929*** | -0.0930*** |
| | (0.0078) | (0.0078) | (0.0078) | (0.0078) | (0.0078) |
| $Cash/TA_{t-1}$ | 0.0532*** | 0.0531*** | 0.0532*** | 0.0531*** | 0.0531*** |
| | (0.0080) | (0.0080) | (0.0080) | (0.0080) | (0.0080) |
| $Cash/TA_{t-2}$ | 0.0034 | 0.0032 | 0.0034 | 0.0034 | 0.0034 |
| | (0.0044) | (0.0044) | (0.0044) | (0.0044) | (0.0044) |

Continued on next page.

Table C.16: (cont.)

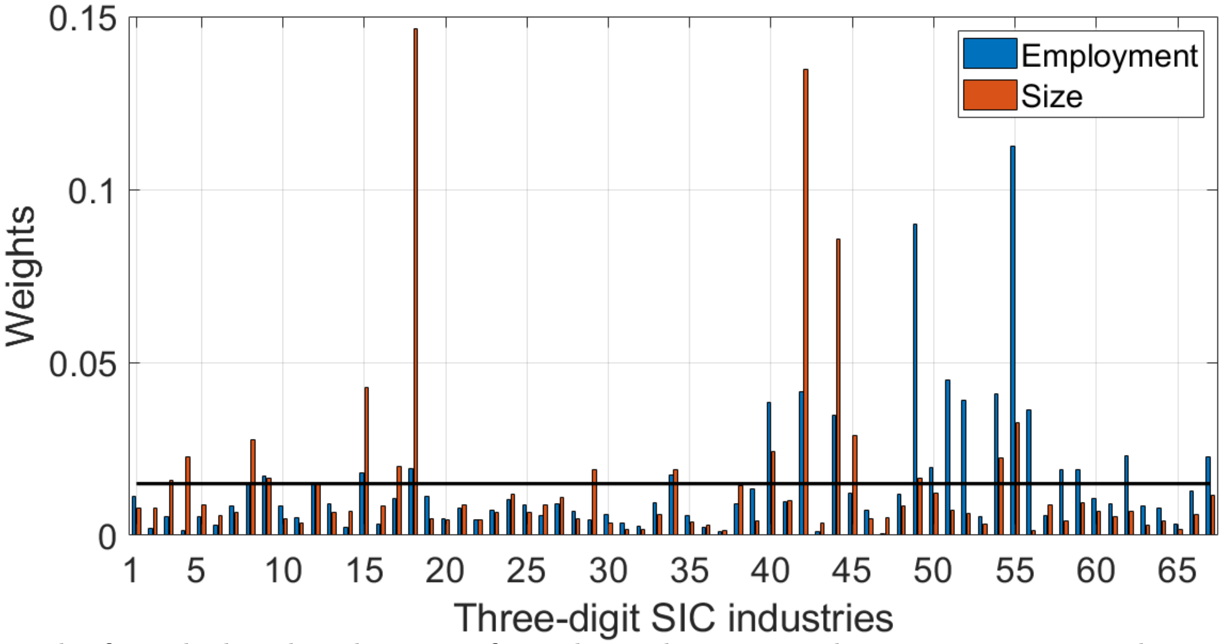
| | Dependent variable: debt to assets ($DA_t$) | | | | |
|---|---|---|---|---|---|
| | $\gamma_{pre} = \gamma_{post} = \gamma$ | | | $\gamma_{pre} \neq \gamma_{post}$ | |
| | (1) | (2) | (3) | (4) | (5) |
| $PPE/TA_t$ | 0.0640*** | 0.0641*** | 0.0640*** | 0.0640*** | 0.0640*** |
| | (0.0168) | (0.0168) | (0.0168) | (0.0168) | (0.0168) |
| $PPE/TA_{t-1}$ | -0.0336* | -0.0337* | -0.0336* | -0.0336* | -0.0337* |
| | (0.0180) | (0.0180) | (0.0180) | (0.0180) | (0.0180) |
| $PPE/TA_{t-2}$ | -0.0085 | -0.0088 | -0.0085 | -0.0084 | -0.0084 |
| | (0.0088) | (0.0088) | (0.0088) | (0.0088) | (0.0088) |
| $Size_t$ | 0.0287*** | 0.0287*** | 0.0287*** | 0.0287*** | 0.0287*** |
| | (0.0038) | (0.0038) | (0.0038) | (0.0038) | (0.0038) |
| $Size_{t-1}$ | -0.0298*** | -0.0298*** | -0.0298*** | -0.0298*** | -0.0298*** |
| | (0.0040) | (0.0040) | (0.0040) | (0.0040) | (0.0040) |
| $Size_{t-2}$ | 0.0045*** | 0.0045*** | 0.0045*** | 0.0045*** | 0.0045*** |
| | (0.0017) | (0.0017) | (0.0017) | (0.0017) | (0.0017) |
| $Industry\ leverage_t$ | 0.2154*** | 0.2138*** | 0.2152*** | 0.2152*** | 0.2149*** |
| | (0.0098) | (0.0099) | (0.0099) | (0.0099) | (0.0099) |
| $Industry\ leverage_{t-1}$ | -0.1488*** | -0.1580*** | -0.1486*** | -0.1377*** | -0.1370*** |
| | (0.0114) | (0.0113) | (0.0114) | (0.0119) | (0.0119) |
| $Industry\ leverage_{t-2}$ | -0.0039 | -0.0088 | -0.0042 | -0.0064 | -0.0068 |
| | (0.0090) | (0.0086) | (0.0090) | (0.0098) | (0.0098) |
| $Industry\ growth_t$ | -0.0689*** | -0.0639*** | -0.0687*** | -0.0707*** | -0.0706*** |
| | (0.0137) | (0.0137) | (0.0138) | (0.0137) | (0.0138) |
| $Industry\ growth_{t-1}$ | -0.0276** | -0.0217* | -0.0275** | -0.0294** | -0.0290** |
| | (0.0121) | (0.0121) | (0.0121) | (0.0121) | (0.0121) |
| $Industry\ growth_{t-2}$ | -0.0039 | 0.0000 | -0.0044 | -0.0063 | -0.0067 |
| | (0.0115) | (0.0116) | (0.0116) | (0.0115) | (0.0116) |
| Fixed effects | Yes | Yes | Yes | Yes | Yes |
| Time effects | Yes | Yes | Yes | Yes | Yes |
| Industry linear trends | Yes | Yes | Yes | Yes | Yes |
| Observations | 84,548 | 84,548 | 84,548 | 84,548 | 84,548 |
| $N$ | 3,647 | 3,647 | 3,647 | 3,647 | 3,647 |
| $max(T_i)$ | 44 | 44 | 44 | 44 | 44 |
| $avg(T_i)$ | 23.2 | 23.2 | 23.2 | 23.2 | 23.2 |
| $med(T_i)$ | 19 | 19 | 19 | 19 | 19 |
| $min(T_i)$ | 2 | 2 | 2 | 2 | 2 |

## C.2 The effects of LSAPs at industry and national levels

We now provide some additional details related to the computation of the average policy effects at the industry and national level described in equation (6) and (7) of the paper, respectively.

To calculate the average per quarter policy effect at the national level, we need to compute the share of industry $s$ in the economy. To this extent, we use two measures: (i) employment (measured as the average number of employees per firm within an industry), and (ii) size (measured as firm's total asset, in millions of dollars, averaged across firms and over time, within an industry). The industry-specific weights obtained from both measures are shown in Figure 10.

Figure 10: **Industry-specific weights based on firm size and employment**




This figure displays the industry-specific weights used to compute the average per quarter policy effect at the national level. The blue bars indicate industry shares based on the average number of employees per firm within an industry. The orange bars report the weights based on average firm size within an industry. The black horizontal line shows the weights based on a simple average (i.e. giving the same weight to each industry).

The estimates of the average policy effects (APE) at the industry and national level described in equation (6) and (7) for the preferred two-threshold ARDL(2) model are reported in the paper. Although not reported there for brevity, similar conclusions hold in the partial adjustment and ARDL(1) model.

To provide additional information on the heterogeneity of the counterfactual estimates by industry characteristics, we regress the APE at the industry level on a constant and several industry features, such as the industry median leverage, industry median size and market to book, as well as cash, cash flow, and PPE scaled by total assets (TA), all averaged over time. The estimated intercept parameter varies between 0.0088 and 0.0099 and it is always highly statistically significant. The other two important determinants are leverage and cash to TA. Higher values of both results in lower APE, which corroborates the view that the prevalence of firms with lower debt capacity and more financially constrained firms, as indicated by higher cash holdings, reduce the effectiveness of LSAPs. The other variables considered do not play an equally important role in explaining the heterogeneity of APE across industries.

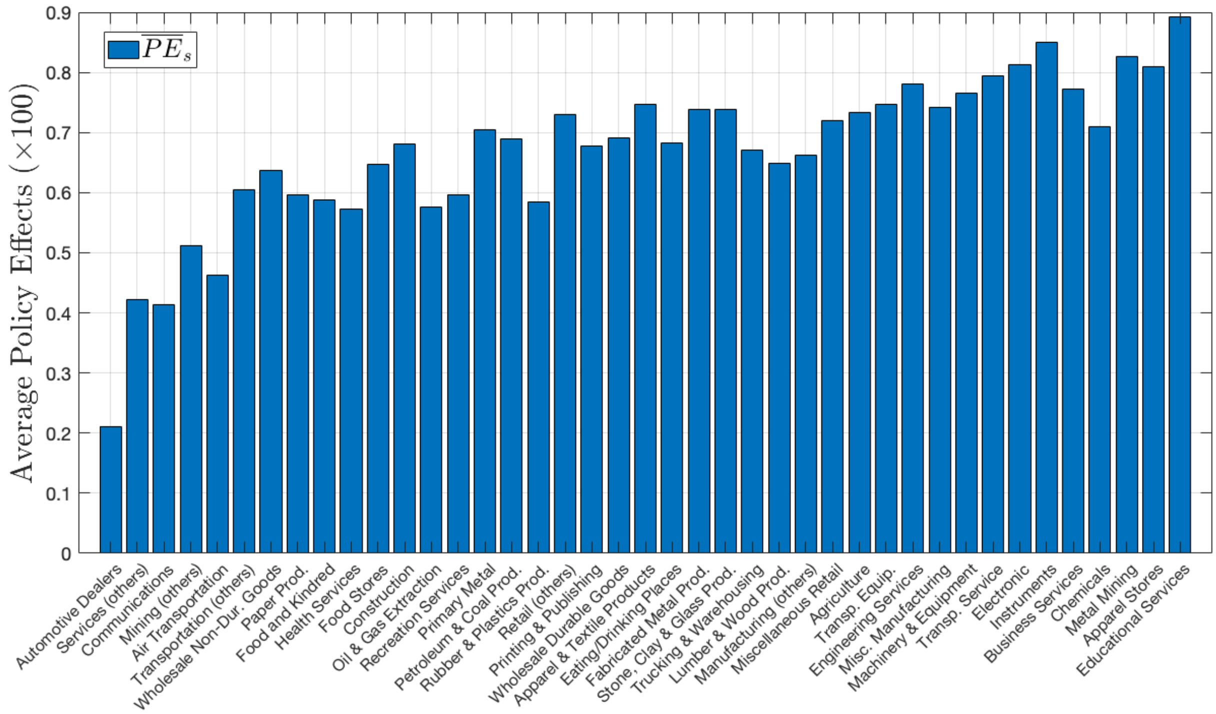
Table C.17: **The heterogeneity of the estimated policy effects by industry features**

This table reports the OLS estimates from a cross-section regression of the average policy effects (APE) at the three-digit SIC industry level on a constant and several industry-specific characteristics. The APE, described in equation (6), are based on the industry leverage, $\pi_{DA}$, and are estimated using the two-threshold ARDL(2) model. The regressors considered are averages over time of industry median debt to asset ratio (DA), industry median size, industry median cash, cash flow, and PPE scaled by total assets, and industry median market to book (MB). Robust standard errors in parentheses (*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$).

| | Dependent variable: Average policy effects at the industry level | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| *constant* | 0.0094*** | 0.0088*** | 0.0099*** | 0.0095*** | 0.0099*** | 0.0094*** |
| | (0.0001) | (0.0004) | (0.0002) | (0.0004) | (0.0004) | (0.0006) |
| $DA$ | -0.0126*** | -0.0135*** | -0.0141*** | -0.0147*** | -0.0130*** | -0.0148*** |
| | (0.0006) | (0.0008) | (0.0006) | (0.0008) | (0.0007) | (0.0008) |
| $Size$ | | 0.0001 | | 0.0001 | | 0.0002* |
| | | (0.0001) | | (0.0001) | | (0.0001) |
| $Cash/TA$ | | | -0.0025*** | -0.0024*** | | -0.0031*** |
| | | | (0.0006) | (0.0006) | | (0.0006) |
| $Cashflow/TA$ | | | | | | -0.0049 |
| | | | | | | (0.0052) |
| $PPE/TA$ | | | | | -0.0003 | 0.0000 |
| | | | | | (0.0002) | (0.0002) |
| $MB$ | | | | | -0.0002 | -0.0006** |
| | | | | | (0.0003) | (0.0003) |
| *Observations* | 67 | 67 | 67 | 67 | 67 | 67 |

Finally, in Figure 11 we show the estimated APE using the broader two-digit SIC industry classification. To obtain the APE at the two-digit SIC we average the policy effects at the three-digit SIC using weights based on employment.

Figure 11: **Average policy effects ($\overline{PE}_s \times 100$) at the (2-dig SIC) industry level ordered by industry median leverage**




The blue bars display the average policy effects (APE) at the industry level as described in equation (6), based on the interaction of our quantitative measure of LSAPs and one-quarter lagged values of the leverage variable, $\pi_{DA}$. The x-axis reports the two-digit SIC industries sorted from largest to smallest industry median leverage, averaged over time. APE at the two-digit SIC industry level are obtained as weighted averages of the APE from the three-digit SIC classification, using employment shares as weights.

# D Observed macroeconomic indicators as proxies for $f_t$

This section reports the estimation results when replacing the scaled industry-specific linear trends with observed macroeconomic indicators as proxies for $f_t$. Following the literature, we consider three main macroeconomic indicators: (i) growth in real GDP, (ii) the term spread (computed as the difference between 10-year and 3-month Treasury bond yields), and (iii) the one-year-ahead expected inflation.

## D.1 Quantile threshold parameter estimates

The estimated threshold parameters for this case are shown in Table D.18.

Table D.18: **Estimated quantile threshold parameters when using observed macro indicators as proxies for $f_t$**

Estimates of the quantile threshold parameters from a grid search procedure across both the partial adjustment model and the ARDL specifications described in equation (C.8). The upper panel shows the estimated threshold parameters for the single-threshold panel regression model, where $\gamma_{pre} = \gamma_{post}$. The lower panel displays results for the two-threshold model, where $\gamma_{pre} \neq \gamma_{post}$. The estimation sample consists of an unbalanced panel of 3,647 U.S. publicly traded non-financial firms observed at a quarterly frequency over the period 2007:Q1 - 2018:Q3.

| | Par. Adj. | ARDL(1) | ARDL(2) |
|---|---|---|---|
| | | $\gamma_{pre} = \gamma_{post} = \gamma$ | |
| $\hat{\gamma}$ | 0.56 | 0.56 | 0.56 |
| | | $\gamma_{pre} \neq \gamma_{post}$ | |
| $\hat{\gamma}_{pre}$ | 0.52 | 0.52 | 0.56 |
| $\hat{\gamma}_{post}$ | 0.77 | 0.78 | 0.78 |

## D.2 Short- and long-run effects of LSAPs when using observed macroeconomic indicators as proxies for $f_t$

Table D.19 reports the estimates of the net short-run effects of LSAPs and other firm- and industry-specific characteristics on firms' leverage. The estimated long-run effects are provided in Table D.20.

Table D.19: **FE–TE estimates of the net short-run effects of LSAPs on debt to asset ratios of non-financial firms. Macroeconomic indicators as proxies for $f_t$**

Estimates of net short-run effects of LSAPs on firms' debt to asset ratios (DA) as well as the effects of both firm- and industry-specific variables on DA, for both the partial adjustment model and the ARDL specifications described in equation (C.8). Net short-run effects are defined as the sum of the estimated coefficients of current and the $p$ lagged values of the regressor under consideration. The first three columns report results for the single-threshold panel regression model, where $\gamma_{pre} = \gamma_{post}$. The last three columns report results for the two-threshold panel regression, where $\gamma_{pre} \neq \gamma_{post}$. The estimated quantile threshold parameters are shown in Table D.18. All regressions include both firm-specific effects and time effects as well as several macro-variables interacted with industry-specific dummies. $LSAPs$ is the (scaled) amount of U.S. Treasuries and agency MBS purchased by the Fed; $\pi_{DA}(\gamma)$ denotes the proportion of firms in an industry with DA below the $\gamma$-th quantile; $\pi_{CR}$ is the proportion of firms in an industry with investment grade credit ratings. The sample consists of an unbalanced panel of $3,647$ U.S. publicly traded non-financial firms observed at a quarterly frequency over the period 2007:Q1 - 2018:Q3. Robust standard errors (in parentheses) are computed using the delta method (*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$).

| | Dependent variable: debt to assets (DA) | | | | | |
|---|---|---|---|---|---|---|
| | $\gamma_{pre} = \gamma_{post} = \gamma$ | | | $\gamma_{pre} \neq \gamma_{post}$ | | |
| | Par. Adj. | ARDL(1) | ARDL(2) | Par. Adj. | ARDL(1) | ARDL(2) |
| $\pi_{DA}$ | 0.0417*** | 0.0088* | 0.0126** | 0.0430*** | 0.0102** | 0.0145*** |
| | (0.0042) | (0.0048) | (0.0054) | (0.0040) | (0.0045) | (0.0050) |
| $LSAPs \times \pi_{DA}$ | 0.0027* | 0.0035** | 0.0031 | 0.0072*** | 0.0059*** | 0.0062*** |
| | (0.0014) | (0.0016) | (0.0020) | (0.0016) | (0.0018) | (0.0021) |
| $\pi_{CR}$ | -0.0019 | -0.0064 | -0.0052 | -0.0023 | -0.0058 | -0.0041 |
| | (0.0093) | (0.0096) | (0.0099) | (0.0093) | (0.0095) | (0.0098) |
| $LSAPs \times \pi_{CR}$ | 0.0013 | 0.0016 | 0.0012 | 0.0021 | 0.0006 | 0.0007 |
| | (0.0032) | (0.0035) | (0.0042) | (0.0029) | (0.0031) | (0.0038) |
| Lagged DA | 0.8279*** | 0.8348*** | 0.8399*** | 0.8279*** | 0.8349*** | 0.8401*** |
| | (0.0053) | (0.0052) | (0.0050) | (0.0053) | (0.0052) | (0.0050) |
| Cash to assets | -0.0504*** | -0.0385*** | -0.0370*** | -0.0504*** | -0.0386*** | -0.0370*** |
| | (0.0034) | (0.0030) | (0.0029) | (0.0034) | (0.0030) | (0.0029) |
| PPE to assets | 0.0239*** | 0.0230*** | 0.0212*** | 0.0239*** | 0.0230*** | 0.0211*** |
| | (0.0052) | (0.0046) | (0.0046) | (0.0052) | (0.0046) | (0.0046) |
| Size | 0.0053*** | 0.0032*** | 0.0036*** | 0.0053*** | 0.0032*** | 0.0036*** |
| | (0.0008) | (0.0008) | (0.0008) | (0.0008) | (0.0008) | (0.0008) |
| Industry Leverage | 0.1245*** | 0.0552*** | 0.0534*** | 0.1261*** | 0.0571*** | 0.0561*** |
| | (0.0073) | (0.0080) | (0.0088) | (0.0072) | (0.0080) | (0.0089) |
| Industry Growth | -0.0500*** | -0.1135*** | -0.1212*** | -0.0504*** | -0.1139*** | -0.1236*** |
| | (0.0138) | (0.0193) | (0.0229) | (0.0137) | (0.0194) | (0.0229) |
| Fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Time effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry linear trends | No | No | No | No | No | No |
| Ind. dummy × macro-var. | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 84,548 | 84,548 | 84,548 | 84,548 | 84,548 | 84,548 |
| $N$ | 3,647 | 3,647 | 3,647 | 3,647 | 3,647 | 3,647 |
| $max(T_i)$ | 44 | 44 | 44 | 44 | 44 | 44 |
| $avg(T_i)$ | 23.2 | 23.2 | 23.2 | 23.2 | 23.2 | 23.2 |
| $med(T_i)$ | 19 | 19 | 19 | 19 | 19 | 19 |
| $min(T_i)$ | 2 | 2 | 2 | 2 | 2 | 2 |

Table D.20: **FE–TE estimates of the long-run effects of LSAPs on debt to asset ratios of non-financial firms. Macroeconomic indicators as proxies for $f_t$**

Estimates of the long-run effects of LSAPs on firms' debt to asset ratios (DA) as well as the effects of both firm- and industry-specific variables on DA. We report results for both the partial adjustment model and the ARDL specifications described in equation (C.8). The first three columns report results for the single-threshold panel regression model, where $\gamma_{pre} = \gamma_{post}$. The last three columns report results for the two-threshold panel regression, where $\gamma_{pre} \neq \gamma_{post}$. The estimated quantile threshold parameters are shown in Table D.18. All regressions include both firm-specific effects and time effects as well as several macro-variables interacted with industry-specific dummies. $LSAPs$ is the (scaled) amount of U.S. Treasuries and agency MBS purchased by the Fed; $\pi_{DA}(\gamma)$ denotes the proportion of firms in an industry with DA below the $\gamma$-th quantile; $\pi_{CR}$ is the proportion of firms in an industry with investment grade credit ratings. The sample consists of an unbalanced panel of 3,647 U.S. publicly traded non-financial firms observed at a quarterly frequency over the period 2007:Q1 - 2018:Q3. Robust standard errors (in parentheses) are computed using the delta method (*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$).

| | Dependent variable: debt to assets (DA) | | | | | |
|---|---|---|---|---|---|---|
| | $\gamma_{pre} = \gamma_{post} = \gamma$ | | | $\gamma_{pre} \neq \gamma_{post}$ | | |
| | Par. Adj. | ARDL(1) | ARDL(2) | Par. Adj. | ARDL(1) | ARDL(2) |
| $\pi_{DA}$ | 0.2424*** | 0.0534* | 0.0786** | 0.2499*** | 0.0619** | 0.0907*** |
| | (0.0254) | (0.0291) | (0.0337) | (0.0240) | (0.0276) | (0.0315) |
| $LSAPs \times \pi_{DA}$ | 0.0154* | 0.0214** | 0.0194 | 0.0421*** | 0.0358*** | 0.0385*** |
| | (0.0084) | (0.0098) | (0.0127) | (0.0095) | (0.0111) | (0.0133) |
| $\pi_{CR}$ | -0.0113 | -0.0386 | -0.0325 | -0.0134 | -0.0350 | -0.0259 |
| | (0.0541) | (0.0583) | (0.0621) | (0.0538) | (0.0577) | (0.0614) |
| $LSAPs \times \pi_{CR}$ | 0.0075 | 0.0097 | 0.0078 | 0.0120 | 0.0035 | 0.0047 |
| | (0.0185) | (0.0209) | (0.0265) | (0.0166) | (0.0186) | (0.0237) |
| Cash to assets | -0.2928*** | -0.2332*** | -0.2309*** | -0.2931*** | -0.2335*** | -0.2310*** |
| | (0.0189) | (0.0175) | (0.0179) | (0.0189) | (0.0175) | (0.0179) |
| PPE to assets | 0.1389*** | 0.1393*** | 0.1322*** | 0.1392*** | 0.1391*** | 0.1320*** |
| | (0.0304) | (0.0283) | (0.0289) | (0.0304) | (0.0283) | (0.0290) |
| Size | 0.0308*** | 0.0193*** | 0.0222*** | 0.0307*** | 0.0193*** | 0.0223*** |
| | (0.0046) | (0.0045) | (0.0046) | (0.0046) | (0.0045) | (0.0046) |
| Industry Leverage | 0.7231*** | 0.3343*** | 0.3339*** | 0.7328*** | 0.3461*** | 0.3507*** |
| | (0.0437) | (0.0484) | (0.0552) | (0.0434) | (0.0483) | (0.0558) |
| Industry Growth | -0.2906*** | -0.6870*** | -0.7569*** | -0.2927*** | -0.6900*** | -0.7726*** |
| | (0.0805) | (0.1196) | (0.1453) | (0.0804) | (0.1198) | (0.1458) |
| Fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Time effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry linear trends | No | No | No | No | No | No |
| Ind. dummy × macro-var. | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 84,548 | 84,548 | 84,548 | 84,548 | 84,548 | 84,548 |
| $N$ | 3,647 | 3,647 | 3,647 | 3,647 | 3,647 | 3,647 |
| $max(T_i)$ | 44 | 44 | 44 | 44 | 44 | 44 |
| $avg(T_i)$ | 23.2 | 23.2 | 23.2 | 23.2 | 23.2 | 23.2 |
| $med(T_i)$ | 19 | 19 | 19 | 19 | 19 | 19 |
| $min(T_i)$ | 2 | 2 | 2 | 2 | 2 | 2 |

# E Additional control variables

In this subsection we demonstrate that our empirical results are also robust to the inclusion of an even larger set of both firm- and industry-level regressors. Table E.21 and E.22 report the estimated net short-run effects of LSAPs across various specifications which differ in the number of explanatory variables included in the model. The former table focuses on the single-threshold panel regression model while the latter is based on the two-threshold model. For the sake of brevity, we focus on the ARDL(2) model but the same conclusions apply to the partial adjustment and ARDL(1) model.

Table E.21: **FE–TE estimates of the net short-run effects of LSAPs on debt to asset ratios of non-financial firms based on the single-threshold ARDL(2) model**

Estimates of net short-run effects of LSAPs on firms' debt to asset ratios (DA) based on the single-threshold ARDL(2) model described in equation (C.8), where $\hat{\gamma} = 0.76$. Net short-run effects are defined as the sum of the estimated coefficients of current and the lagged values of the regressor under consideration. All regressions include both firm-specific effects and time effects as well as industry-specific linear time trends. $LSAPs$ is the (scaled) amount of U.S. Treasuries and agency MBS purchased by the Fed; $\pi_{DA}(\gamma)$ denotes the proportion of firms in an industry with DA below the $\gamma$-th quantile; $\pi_{CR}$ is the proportion of firms in an industry with investment grade credit ratings. The sample consists of an unbalanced panel of 3,647 U.S. publicly traded non-financial firms observed at a quarterly frequency over the period 2007:Q1 - 2018:Q3. Robust standard errors (in parentheses) are computed using the delta method (*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$).

| | Dependent variable: debt to assets (DA) | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $\pi_{DA}(\hat{\gamma}_{pre})$ | 0.0156*** | 0.0159*** | 0.0161*** | 0.0162*** | 0.0164*** | 0.0164*** |
| | (0.0049) | (0.0050) | (0.0050) | (0.0050) | (0.0050) | (0.0050) |
| $LSAPs \times \pi_{DA}(\hat{\gamma}_{post})$ | 0.0069*** | 0.0068*** | 0.0069*** | 0.0066*** | 0.0067*** | 0.0066*** |
| | (0.0019) | (0.0020) | (0.0020) | (0.0020) | (0.0020) | (0.0020) |
| $\pi_{CR}$ | 0.0026 | 0.0004 | 0.0016 | 0.0010 | 0.0008 | 0.0008 |
| | (0.0117) | (0.0117) | (0.0117) | (0.0120) | (0.0121) | (0.0121) |
| $LSAPs \times \pi_{CR}$ | 0.0003 | 0.0003 | 0.0000 | 0.0004 | 0.0002 | 0.0002 |
| | (0.0031) | (0.0031) | (0.0031) | (0.0032) | (0.0031) | (0.0031) |
| | Firm-specific variables | | | | | |
| Lagged DA | Y | Y | Y | Y | Y | Y |
| Cash/TA | Y | Y | Y | Y | Y | Y |
| MB | | Y | Y | | | Y |
| PPE/TA | Y | Y | Y | Y | Y | Y |
| R&D/TA | | | Y | | Y | Y |
| Size | Y | Y | Y | Y | Y | Y |
| | Industry-specific variables | | | | | |
| Industry Leverage | Y | Y | Y | Y | Y | Y |
| Industry Growth | Y | Y | Y | Y | Y | Y |
| Industry Q | | Y | Y | Y | Y | |
| Industry Cash/TA | | | | Y | Y | Y |
| Industry MB | | | | | | Y |
| Industry PPE/TA | | | | Y | Y | Y |
| Industry R&D/TA | | | | | Y | Y |
| Industry Size | | | | Y | Y | Y |
| Fixed effects | Y | Y | Y | Y | Y | Y |
| Time effects | Y | Y | Y | Y | Y | Y |
| Industry linear trends | Y | Y | Y | Y | Y | Y |

Table E.22: **FE–TE estimates of the net short-run effects of LSAPs on debt to asset ratios of non-financial firms based on the two-threshold ARDL(2) model**

Estimates of net short-run effects of LSAPs on firms' debt to asset ratios (DA) based on the two-threshold ARDL(2) model described in equation (C.8), where $\hat{\gamma}_{pre} = 0.56$ and $\hat{\gamma}_{post} = 0.77$. Net short-run effects are defined as the sum of the estimated coefficients of current and the $p$ lagged values of the regressor under consideration. All regressions include both firm-specific effects and time effects as well as industry-specific linear time trends. $LSAPs$ is the (scaled) amount of U.S. Treasuries and agency MBS purchased by the Fed; $\pi_{DA}(\gamma)$ denotes the proportion of firms in an industry with DA below the $\gamma$-th quantile; $\pi_{CR}$ is the proportion of firms in an industry with investment grade credit ratings. The sample consists of an unbalanced panel of $3,647$ U.S. publicly traded non-financial firms observed at a quarterly frequency over the period 2007:Q1 - 2018:Q3. Robust standard errors (in parentheses) are computed using the delta method (*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$).

| | Dependent variable: debt to assets (DA) | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $\pi_{DA}(\hat{\gamma}_{pre})$ | 0.0188*** | 0.0197*** | 0.0201*** | 0.0200*** | 0.0202*** | 0.0201*** |
| | (0.0051) | (0.0051) | (0.0051) | (0.0052) | (0.0052) | (0.0052) |
| $LSAPs \times \pi_{DA}(\hat{\gamma}_{post})$ | 0.0090*** | 0.0090*** | 0.0092*** | 0.0089*** | 0.0090*** | 0.0089*** |
| | (0.0018) | (0.0018) | (0.0018) | (0.0018) | (0.0018) | (0.0018) |
| $\pi_{CR}$ | 0.0056 | 0.0036 | 0.0049 | 0.0035 | 0.0037 | 0.0037 |
| | (0.0118) | (0.0119) | (0.0119) | (0.0122) | (0.0122) | (0.0122) |
| $LSAPs \times \pi_{CR}$ | 0.0015 | 0.0015 | 0.0013 | 0.0016 | 0.0014 | 0.0014 |
| | (0.0031) | (0.0031) | (0.0031) | (0.0031) | (0.0031) | (0.0031) |
| | Firm-specific variables | | | | | |
| Lagged DA | Y | Y | Y | Y | Y | Y |
| Cash/TA | Y | Y | Y | Y | Y | Y |
| MB | | Y | Y | | | Y |
| PPE/TA | Y | Y | Y | Y | Y | Y |
| R&D/TA | | | Y | | Y | Y |
| Size | Y | Y | Y | Y | Y | Y |
| | Industry-specific variables | | | | | |
| Industry Leverage | Y | Y | Y | Y | Y | Y |
| Industry Growth | Y | Y | Y | Y | Y | Y |
| Industry Q | | Y | Y | Y | Y | |
| Industry Cash/TA | | | | Y | Y | Y |
| Industry MB | | | | | | Y |
| Industry PPE/TA | | | | Y | Y | Y |
| Industry R&D/TA | | | | | Y | Y |
| Industry Size | | | | Y | Y | Y |
| Fixed effects | Y | Y | Y | Y | Y | Y |
| Time effects | Y | Y | Y | Y | Y | Y |
| Industry linear trends | Y | Y | Y | Y | Y | Y |

# F Estimation results using a qualitative measure of LSAPs

As discussed in the paper, in our benchmark model we use a quantitative measure of LSAPs because of its greater degree of variability over time and given that it is better suited to capture the magnitude of the Fed's purchases. As a robustness check, we re-estimate the ARDL specifications described in (C.8) replacing our quantitative measure of LSAPs with a qualitative dummy variable equal to one during policy on periods and zero otherwise.[26] Subsection F.1 reports the estimated quantile threshold parameters. The estimated regression coefficients for both the partial adjustment and ARDL specifications are reported in Subsection F.2. Finally, in Subsection F.3 presents the estimated short- and long-run coefficients.

## F.1 Quantile threshold parameter estimates

The estimated threshold parameters after replacing our quantitative measure of LSAPs with a qualitative measure, are shown in the upper panel of Table F.23.

Table F.23: **Estimated quantile threshold parameters when using a qualitative measure of LSAPs**

Estimates of the quantile threshold parameters from a grid search procedure across both the partial adjustment model and the ARDL specifications described in equation (C.8). The upper panel shows the estimated threshold parameters for the single-threshold panel regression model, where $\gamma_{pre} = \gamma_{post}$. The lower panel displays results for the two-threshold model, where $\gamma_{pre} \neq \gamma_{post}$. The estimation sample consists of an unbalanced panel of $3,647$ U.S. publicly traded non-financial firms observed at a quarterly frequency over the period 2007:Q1 - 2018:Q3.

| | Par. Adj. | ARDL(1) | ARDL(2) |
|---|---|---|---|
| | | $\gamma_{pre} = \gamma_{post} = \gamma$ | |
| $\hat{\gamma}$ | 0.56 | 0.76 | 0.76 |
| | | $\gamma_{pre} \neq \gamma_{post}$ | |
| $\hat{\gamma}_{pre}$ | 0.56 | 0.69 | 0.56 |
| $\hat{\gamma}_{post}$ | 0.76 | 0.36 | 0.77 |

[26] See Subsection A.1 of this online supplement for a more detailed description of the qualitative policy variable.

## F.2 Full estimation results using a qualitative measures of LSAPs

Table F.24: **FE–TE estimates of the effects of LSAPs on non-financial firm's debt to asset ratios based on the partial adjustment model**

Estimates of the coefficients of the partial adjustment model based on equation (C.8). The dependent variable is debt to asset ratios (DA). $q_t \times \pi_{s,t-1,DA}(\hat{\gamma}_{post})$ denotes the interaction of $q_t$, a dummy variable equal to one during periods of LSAPs, and $\pi_{s,t-1,DA}(\hat{\gamma}_{post})$, the one-quarter lagged proportion of firms in an industry with DA below the $\hat{\gamma}^{th}_{post}$ quantile. $q_t \times \pi_{s,t-1,CR}$ denotes the interaction of $q_t$ and the one-quarter lagged proportion of firms in an industry with investment grade credit ratings. In the first three columns, we report results for the single-threshold panel regression model, where $\gamma_{pre} = \gamma_{post} = \gamma$. In this case, $\hat{\gamma} = 0.56$. The last two columns report results for the two-threshold panel regression, where $\hat{\gamma}_{pre} = 0.56$ and $\hat{\gamma}_{post} = 0.76$. All regressions include both firm-specific effects and time effects as well as industry-specific linear time trends. The sample consists of an unbalanced panel of 3,647 U.S. publicly traded non-financial firms observed at a quarterly frequency over the period 2007:Q1 - 2018:Q3. Robust standard errors in parentheses (*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$).

| | Dependent variable: debt to assets ($DA_t$) | | | | |
|---|---|---|---|---|---|
| | $\gamma_{pre} = \gamma_{post} = \gamma$ | | | $\gamma_{pre} \neq \gamma_{post}$ | |
| | (1) | (2) | (3) | (4) | (5) |
| $\pi_{s,t-1,DA}(\hat{\gamma}_{pre})$ | 0.0468*** | | 0.0458*** | 0.0460*** | 0.0465*** |
| | (0.0042) | | (0.0043) | (0.0040) | (0.0040) |
| $q_t \times \pi_{s,t-1,DA}(\hat{\gamma}_{post})$ | 0.0017 | | 0.0045* | 0.0096*** | 0.0120*** |
| | (0.0020) | | (0.0024) | (0.0024) | (0.0025) |
| $\pi_{s,t-1,CR}$ | | -0.0049 | 0.0036 | | 0.0023 |
| | | (0.0112) | (0.0113) | | (0.0112) |
| $q_t \times \pi_{s,t-1,CR}$ | | 0.0042 | 0.0119** | | 0.0137*** |
| | | (0.0042) | (0.0050) | | (0.0045) |
| $DA_{t-1}$ | 0.8264*** | 0.8249*** | 0.8264*** | 0.8265*** | 0.8266*** |
| | (0.0053) | (0.0053) | (0.0053) | (0.0053) | (0.0053) |
| $Cash/TA_t$ | -0.0496*** | -0.0500*** | -0.0497*** | -0.0496*** | -0.0497*** |
| | (0.0034) | (0.0034) | (0.0034) | (0.0034) | (0.0034) |
| $PPE/TA_t$ | 0.0248*** | 0.0243*** | 0.0247*** | 0.0249*** | 0.0247*** |
| | (0.0053) | (0.0053) | (0.0053) | (0.0053) | (0.0053) |
| $Size_t$ | 0.0051*** | 0.0051*** | 0.0051*** | 0.0051*** | 0.0051*** |
| | (0.0008) | (0.0008) | (0.0008) | (0.0008) | (0.0008) |
| $Industry\ leverage_t$ | 0.1393*** | 0.1014*** | 0.1399*** | 0.1401*** | 0.1416*** |
| | (0.0075) | (0.0064) | (0.0075) | (0.0075) | (0.0075) |
| $Industry\ growth_t$ | -0.0469*** | -0.0356*** | -0.0459*** | -0.0483*** | -0.0467*** |
| | (0.0131) | (0.0131) | (0.0131) | (0.0131) | (0.0131) |
| Fixed effects | Yes | Yes | Yes | Yes | Yes |
| Time effects | Yes | Yes | Yes | Yes | Yes |
| Industry linear trends | Yes | Yes | Yes | Yes | Yes |
| Observations | 84,548 | 84,548 | 84,548 | 84,548 | 84,548 |
| $N$ | 3,647 | 3,647 | 3,647 | 3,647 | 3,647 |
| $max(T_i)$ | 44 | 44 | 44 | 44 | 44 |
| $avg(T_i)$ | 23.2 | 23.2 | 23.2 | 23.2 | 23.2 |
| $med(T_i)$ | 19 | 19 | 19 | 19 | 19 |
| $min(T_i)$ | 2 | 2 | 2 | 2 | 2 |

Table F.25: **FE–TE estimates of the effects of LSAPs on non-financial firm's debt to asset ratios based on the ARDL(1) model**

Estimates of the coefficients of the ARDL(1) model described in equation (C.8). The dependent variable is debt to asset ratio (DA). $q_{t-\ell} \times \pi_{s,t-\ell-1,DA}(\hat{\gamma}_{post})$ denotes the interaction of $q_{t-\ell}$, a dummy variable equal to one during periods of LSAPs, and $\pi_{s,t-\ell-1,DA}(\hat{\gamma}_{post})$, the one-quarter lagged proportion of firms in an industry with DA below the $\hat{\gamma}_{post}^{th}$ quantile, for $\ell = 0, 1$. $q_{t-\ell} \times \pi_{s,t-\ell-1,CR}$ denotes the interaction of $q_{t-\ell}$ and the one-quarter lagged proportion of firms in an industry with investment grade credit ratings, for $\ell = 0, 1$. In the first three columns, we report results for the single-threshold panel regression model, where $\gamma_{pre} = \gamma_{post} = \gamma$. In this case, $\hat{\gamma} = 0.76$. The last two columns report results for the two-threshold panel regression, where $\hat{\gamma}_{pre} = 0.69$ and $\hat{\gamma}_{post} = 0.36$. All regressions include both firm-specific effects and time effects as well as industry-specific linear time trends. The sample consists of an unbalanced panel of $3,647$ U.S. publicly traded non-financial firms observed at a quarterly frequency over the period 2007:Q1 - 2018:Q3. Robust standard errors in parentheses (*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$).

| | Dependent variable: debt to assets ($DA_t$) | | | | |
|---|---|---|---|---|---|
| | $\gamma_{pre} = \gamma_{post} = \gamma$ | | | $\gamma_{pre} \neq \gamma_{post}$ | |
| | (1) | (2) | (3) | (4) | (5) |
| $\pi_{s,t-1,DA}(\hat{\gamma}_{pre})$ | 0.0149*** | | 0.0148*** | 0.0145*** | 0.0148*** |
| | (0.0053) | | (0.0053) | (0.0045) | (0.0045) |
| $q_t \times \pi_{s,t-1,DA}(\hat{\gamma}_{post})$ | 0.0053 | | 0.0058 | 0.0099*** | 0.0123*** |
| | (0.0038) | | (0.0040) | (0.0032) | (0.0035) |
| $\pi_{s,t-2,DA}(\hat{\gamma}_{pre})$ | -0.0006 | | -0.001 | 0.0055 | 0.0052 |
| | (0.0051) | | (0.0052) | (0.0043) | (0.0043) |
| $q_{t-1} \times \pi_{s,t-2,DA}(\hat{\gamma}_{post})$ | 0.0019 | | 0.0025 | -0.0048 | -0.005 |
| | (0.0037) | | (0.0038) | (0.0031) | (0.0033) |
| $\pi_{s,t-1,CR}$ | | 0.0327* | 0.0299 | | 0.026 |
| | | (0.0193) | (0.0193) | | (0.0194) |
| $q_t \times \pi_{s,t-1,CR}$ | | -0.0011 | 0.0023 | | 0.0111 |
| | | (0.0073) | (0.0077) | | (0.0080) |
| $\pi_{s,t-2,CR}$ | | -0.0296 | -0.0306 | | -0.0276 |
| | | (0.0194) | (0.0194) | | (0.0195) |
| $q_{t-1} \times \pi_{s,t-2,CR}$ | | 0.0013 | 0.0035 | | -0.0017 |
| | | (0.0073) | (0.0076) | | (0.0080) |
| $DA_{t-1}$ | 0.8337*** | 0.8333*** | 0.8337*** | 0.8337*** | 0.8337*** |
| | (0.0052) | (0.0052) | (0.0052) | (0.0052) | (0.0052) |
| $Cash/TA_t$ | -0.0929*** | -0.0929*** | -0.0929*** | -0.0929*** | -0.0929*** |
| | (0.0078) | (0.0078) | (0.0078) | (0.0078) | (0.0078) |
| $Cash/TA_{t-1}$ | 0.0548*** | 0.0547*** | 0.0548*** | 0.0548*** | 0.0547*** |
| | (0.0075) | (0.0075) | (0.0075) | (0.0075) | (0.0075) |
| $PPE/TA_t$ | 0.0633*** | 0.0633*** | 0.0633*** | 0.0633*** | 0.0632*** |
| | (0.0168) | (0.0168) | (0.0168) | (0.0168) | (0.0168) |
| $PPE/TA_{t-1}$ | -0.0397** | -0.0399** | -0.0398** | -0.0397** | -0.0397** |
| | (0.0168) | (0.0168) | (0.0168) | (0.0168) | (0.0168) |
| $Size_t$ | 0.0289*** | 0.0289*** | 0.0289*** | 0.0289*** | 0.0289*** |
| | (0.0038) | (0.0038) | (0.0038) | (0.0038) | (0.0038) |
| $Size_{t-1}$ | -0.0258*** | -0.0259*** | -0.0258*** | -0.0258*** | -0.0258*** |
| | (0.0038) | (0.0038) | (0.0038) | (0.0038) | (0.0038) |

Continued on next page.

Table F.25: (cont.)

| | Dependent variable: debt to assets ($DA_t$) | | | | |
|---|---|---|---|---|---|
| | $\gamma_{pre} = \gamma_{post} = \gamma$ | | | $\gamma_{pre} \neq \gamma_{post}$ | |
| | (1) | (2) | (3) | (4) | (5) |
| $Industry\ leverage_t$ | 0.2161*** | 0.2137*** | 0.2158*** | 0.2171*** | 0.2171*** |
| | (0.0099) | (0.0099) | (0.0099) | (0.0099) | (0.0099) |
| $Industry\ leverage_{t-1}$ | -0.1538*** | -0.1646*** | -0.1532*** | -0.1485*** | -0.1468*** |
| | (0.0099) | (0.0096) | (0.0099) | (0.0100) | (0.0100) |
| $Industry\ growth_t$ | -0.0674*** | -0.0646*** | -0.0670*** | -0.0684*** | -0.0678*** |
| | (0.0137) | (0.0136) | (0.0136) | (0.0137) | (0.0137) |
| $Industry\ growth_{t-1}$ | -0.0324*** | -0.0268** | -0.0315*** | -0.0305** | -0.0303** |
| | (0.0119) | (0.0119) | (0.0119) | (0.0119) | (0.0119) |
| Fixed effects | Yes | Yes | Yes | Yes | Yes |
| Time effects | Yes | Yes | Yes | Yes | Yes |
| Industry linear trends | Yes | Yes | Yes | Yes | Yes |
| Observations | 84,548 | 84,548 | 84,548 | 84,548 | 84,548 |
| $N$ | 3,647 | 3,647 | 3,647 | 3,647 | 3,647 |
| $max(T_i)$ | 44 | 44 | 44 | 44 | 44 |
| $avg(T_i)$ | 23.2 | 23.2 | 23.2 | 23.2 | 23.2 |
| $med(T_i)$ | 19 | 19 | 19 | 19 | 19 |
| $min(T_i)$ | 2 | 2 | 2 | 2 | 2 |

Table F.26: **FE–TE estimates of the effects of LSAPs on non-financial firm's debt to asset ratios based on the ARDL(2) model**

Estimates of the coefficients of the ARDL(2) model described in equation (C.8). The dependent variable is debt to asset ratio (DA). $q_{t-\ell} \times \pi_{s,t-\ell-1,DA}(\hat{\gamma}_{post})$ denotes the interaction of $q_{t-\ell}$, a dummy variable equal to one during periods of LSAPs, and $\pi_{s,t-\ell-1,DA}(\hat{\gamma}_{post})$, the one-quarter lagged proportion of firms in an industry with DA below the $\hat{\gamma}_{post}^{th}$ quantile, for $\ell = 0, 1, 2$. $q_{t-\ell} \times \pi_{s,t-\ell-1,CR}$ denotes the interaction of $q_{t-\ell}$ and the one-quarter lagged proportion of firms in an industry with investment grade credit ratings, for $\ell = 0, 1, 2$. In the first three columns, we report results for the single-threshold panel regression model, where $\gamma_{pre} = \gamma_{post} = \gamma$. In this case, $\hat{\gamma} = 0.76$. The last two columns report results for the two-threshold panel regression, where $\hat{\gamma}_{pre} = 0.56$ and $\hat{\gamma}_{post} = 0.77$. All regressions include both firm-specific effects and time effects as well as industry-specific linear time trends. The sample consists of an unbalanced panel of $3,647$ U.S. publicly traded non-financial firms observed at a quarterly frequency over the period 2007:Q1 - 2018:Q3. Robust standard errors in parentheses (*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$).

| | Dependent variable: debt to assets ($DA_t$) | | | | |
|---|---|---|---|---|---|
| | $\gamma_{pre} = \gamma_{post} = \gamma$ | | | $\gamma_{pre} \neq \gamma_{post}$ | |
| | (1) | (2) | (3) | (4) | (5) |
| $\pi_{s,t-1,DA}(\hat{\gamma}_{pre})$ | 0.0127** | | 0.0125** | 0.0174*** | 0.0181*** |
| | (0.0053) | | (0.0054) | (0.0050) | (0.0051) |
| $q_t \times \pi_{s,t-1,DA}(\hat{\gamma}_{post})$ | 0.0056 | | 0.0061 | 0.0086** | 0.0093** |
| | (0.0038) | | (0.0040) | (0.0035) | (0.0036) |
| $\pi_{s,t-2,DA}(\hat{\gamma}_{pre})$ | -0.0016 | | -0.0021 | -0.0091* | -0.0094* |
| | (0.0062) | | (0.0063) | (0.0055) | (0.0055) |
| $q_{t-1} \times \pi_{s,t-2,DA}(\hat{\gamma}_{post})$ | 0.0004 | | 0.002 | -0.0007 | 0.0007 |
| | (0.0046) | | (0.0048) | (0.0043) | (0.0044) |
| $\pi_{s,t-3,DA}(\hat{\gamma}_{pre})$ | 0.0057 | | 0.0059 | 0.0095** | 0.0097** |
| | (0.0051) | | (0.0052) | (0.0043) | (0.0043) |
| $q_{t-2} \times \pi_{s,t-3,DA}(\hat{\gamma}_{post})$ | 0.0016 | | 0.0003 | 0.0029 | 0.0017 |
| | (0.0036) | | (0.0037) | (0.0033) | (0.0034) |
| $\pi_{s,t-1,CR}$ | | 0.0349* | 0.031 | | 0.0318 |
| | | (0.0194) | (0.0194) | | (0.0194) |
| $q_t \times \pi_{s,t-1,CR}$ | | -0.0022 | 0.0015 | | 0.0034 |
| | | (0.0074) | (0.0077) | | (0.0077) |
| $\pi_{s,t-2,CR}$ | | -0.0334 | -0.0319 | | -0.0325 |
| | | (0.0257) | (0.0258) | | (0.0258) |
| $q_{t-1} \times \pi_{s,t-2,CR}$ | | 0.0102 | 0.0111 | | 0.011 |
| | | (0.0092) | (0.0095) | | (0.0095) |
| $\pi_{s,t-3,CR}$ | | 0.0034 | 0.0017 | | 0.0039 |
| | | (0.0186) | (0.0186) | | (0.0186) |
| $q_{t-2} \times \pi_{s,t-3,CR}$ | | -0.0101* | -0.0088 | | -0.0081 |
| | | (0.0061) | (0.0064) | | (0.0063) |
| $DA_{t-1}$ | 0.8124*** | 0.8120*** | 0.8123*** | 0.8126*** | 0.8125*** |
| | (0.0091) | (0.0091) | (0.0091) | (0.0091) | (0.0091) |
| $DA_{t-2}$ | 0.0262*** | 0.0262*** | 0.0263*** | 0.0260*** | 0.0261*** |
| | (0.0077) | (0.0077) | (0.0077) | (0.0077) | (0.0077) |
| $Cash/TA_t$ | -0.0929*** | -0.0930*** | -0.0930*** | -0.0929*** | -0.0929*** |
| | (0.0078) | (0.0078) | (0.0078) | (0.0078) | (0.0078) |
| $Cash/TA_{t-1}$ | 0.0531*** | 0.0531*** | 0.0531*** | 0.0531*** | 0.0531*** |
| | (0.0080) | (0.0080) | (0.0080) | (0.0080) | (0.0080) |
| $Cash/TA_{t-2}$ | 0.0033 | 0.0032 | 0.0033 | 0.0033 | 0.0033 |
| | (0.0044) | (0.0044) | (0.0044) | (0.0044) | (0.0044) |

Continued on next page.

Table F.26: (cont.)

| | Dependent variable: debt to assets ($DA_t$) | | | | |
|---|---|---|---|---|---|
| | $\gamma_{pre} = \gamma_{post} = \gamma$ | | | $\gamma_{pre} \neq \gamma_{post}$ | |
| | (1) | (2) | (3) | (4) | (5) |
| $PPE/TA_t$ | 0.0642*** | 0.0641*** | 0.0641*** | 0.0641*** | 0.0641*** |
| | (0.0168) | (0.0168) | (0.0168) | (0.0168) | (0.0168) |
| $PPE/TA_{t-1}$ | -0.0337* | -0.0338* | -0.0338* | -0.0337* | -0.0338* |
| | (0.0180) | (0.0180) | (0.0180) | (0.0180) | (0.0180) |
| $PPE/TA_{t-2}$ | -0.0087 | -0.0088 | -0.0086 | -0.0086 | -0.0086 |
| | (0.0088) | (0.0088) | (0.0088) | (0.0088) | (0.0088) |
| $Size_t$ | 0.0287*** | 0.0287*** | 0.0287*** | 0.0287*** | 0.0287*** |
| | (0.0038) | (0.0038) | (0.0038) | (0.0038) | (0.0038) |
| $Size_{t-1}$ | -0.0298*** | -0.0298*** | -0.0298*** | -0.0298*** | -0.0298*** |
| | (0.0040) | (0.0040) | (0.0040) | (0.0040) | (0.0040) |
| $Size_{t-2}$ | 0.0045*** | 0.0045*** | 0.0045*** | 0.0045*** | 0.0045*** |
| | (0.0017) | (0.0017) | (0.0017) | (0.0017) | (0.0017) |
| $Industry\ leverage_t$ | 0.2156*** | 0.2136*** | 0.2153*** | 0.2151*** | 0.2148*** |
| | (0.0098) | (0.0099) | (0.0099) | (0.0099) | (0.0099) |
| $Industry\ leverage_{t-1}$ | -0.1493*** | -0.1580*** | -0.1489*** | -0.1388*** | -0.1375*** |
| | (0.0114) | (0.0113) | (0.0114) | (0.0119) | (0.0120) |
| $Industry\ leverage_{t-2}$ | -0.0047 | -0.0086 | -0.0046 | -0.0083 | -0.0081 |
| | (0.0090) | (0.0086) | (0.0091) | (0.0098) | (0.0098) |
| $Industry\ growth_t$ | -0.0669*** | -0.0646*** | -0.0668*** | -0.0687*** | -0.0685*** |
| | (0.0137) | (0.0136) | (0.0136) | (0.0137) | (0.0137) |
| $Industry\ growth_{t-1}$ | -0.0264** | -0.0198 | -0.0244** | -0.0275** | -0.0256** |
| | (0.0121) | (0.0121) | (0.0121) | (0.0121) | (0.0121) |
| $Industry\ growth_{t-2}$ | -0.0024 | -0.0003 | -0.0038 | -0.0041 | -0.0056 |
| | (0.0115) | (0.0116) | (0.0116) | (0.0116) | (0.0116) |
| Fixed effects | Yes | Yes | Yes | Yes | Yes |
| Time effects | Yes | Yes | Yes | Yes | Yes |
| Industry linear trends | Yes | Yes | Yes | Yes | Yes |
| Observations | 84,548 | 84,548 | 84,548 | 84,548 | 84,548 |
| $N$ | 3,647 | 3,647 | 3,647 | 3,647 | 3,647 |
| $max(T_i)$ | 44 | 44 | 44 | 44 | 44 |
| $avg(T_i)$ | 23.2 | 23.2 | 23.2 | 23.2 | 23.2 |
| $med(T_i)$ | 19 | 19 | 19 | 19 | 19 |
| $min(T_i)$ | 2 | 2 | 2 | 2 | 2 |

## F.3 Short- and long-run effects using a qualitative measure of LSAPs

Table F.27: **FE–TE estimates of the net short-run effects of LSAPs on debt to asset ratios of non-financial firms**

Estimates of net short-run effects of LSAPs on firms' debt to asset ratios (DA) as well as the effects of both firm- and industry-specific variables on DA, for both the partial adjustment model and the ARDL specifications described in equation (C.8). Net short-run effects are defined as the sum of the estimated coefficients of current and the $p$ lagged values of the regressor under consideration. The first three columns report results for the single-threshold panel regression model, where $\gamma_{pre} = \gamma_{post}$. The last three columns report results for the two-threshold panel regression, where $\gamma_{pre} \neq \gamma_{post}$. The estimated quantile threshold parameters are shown in Table F.23. All regressions include both firm-specific effects and time effects as well as industry-specific linear time trends. $LSAPs$ is a dummy variable equal to one during periods of LSAPs; $\pi_{DA}(\gamma)$ denotes the proportion of firms in an industry with DA below the $\gamma$-th quantile; $\pi_{CR}$ is the proportion of firms in an industry with investment grade credit ratings. The sample consists of an unbalanced panel of 3,647 U.S. publicly traded non-financial firms observed at a quarterly frequency over the period 2007:Q1 - 2018:Q3. Robust standard errors (in parentheses) are computed using the delta method (*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$).

| | Dependent variable: debt to assets (DA) | | | | | |
|---|---|---|---|---|---|---|
| | $\gamma_{pre} = \gamma_{post} = \gamma$ | | | $\gamma_{pre} \neq \gamma_{post}$ | | |
| | Par. Adj. | ARDL(1) | ARDL(2) | Par. Adj. | ARDL(1) | ARDL(2) |
| $\pi_{DA}$ | 0.0458*** | 0.0138*** | 0.0162*** | 0.0465*** | 0.0200*** | 0.0183*** |
| | (0.0043) | (0.0048) | (0.0052) | (0.0040) | (0.0041) | (0.0051) |
| $LSAPs \times \pi_{DA}$ | 0.0045* | 0.0083*** | 0.0085*** | 0.0120*** | 0.0073*** | 0.0118*** |
| | (0.0024) | (0.0030) | (0.0032) | (0.0025) | (0.0025) | (0.0028) |
| $\pi_{CR}$ | 0.0036 | -0.0006 | 0.0008 | 0.0023 | -0.0016 | 0.0031 |
| | (0.0113) | (0.0115) | (0.0117) | (0.0112) | (0.0116) | (0.0118) |
| $LSAPs \times \pi_{CR}$ | 0.0119** | 0.0059 | 0.0038 | 0.0137*** | 0.0094* | 0.0062 |
| | (0.0050) | (0.0047) | (0.0049) | (0.0045) | (0.0049) | (0.0048) |
| Lagged DA | 0.8264*** | 0.8337*** | 0.8386*** | 0.8266*** | 0.8337*** | 0.8386*** |
| | (0.0053) | (0.0052) | (0.0050) | (0.0053) | (0.0052) | (0.0050) |
| Cash to assets | -0.0497*** | -0.0381*** | -0.0366*** | -0.0497*** | -0.0382*** | -0.0366*** |
| | (0.0034) | (0.0030) | (0.0030) | (0.0034) | (0.0030) | (0.0030) |
| PPE to assets | 0.0247*** | 0.0235*** | 0.0217*** | 0.0247*** | 0.0234*** | 0.0217*** |
| | (0.0053) | (0.0047) | (0.0047) | (0.0053) | (0.0047) | (0.0047) |
| Size | 0.0051*** | 0.0030*** | 0.0034*** | 0.0051*** | 0.0030*** | 0.0034*** |
| | (0.0008) | (0.0008) | (0.0008) | (0.0008) | (0.0008) | (0.0008) |
| Industry Leverage | 0.1399*** | 0.0626*** | 0.0618*** | 0.1416*** | 0.0702*** | 0.0692*** |
| | (0.0075) | (0.0070) | (0.0075) | (0.0075) | (0.0074) | (0.0091) |
| Industry Growth | -0.0459*** | -0.0985*** | -0.0950*** | -0.0467*** | -0.0981*** | -0.0997*** |
| | (0.0131) | (0.0175) | (0.0208) | (0.0131) | (0.0176) | (0.0209) |
| Fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Time effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry linear trends | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 84,548 | 84,548 | 84,548 | 84,548 | 84,548 | 84,548 |
| $N$ | 3,647 | 3,647 | 3,647 | 3,647 | 3,647 | 3,647 |
| $max(T_i)$ | 44 | 44 | 44 | 44 | 44 | 44 |
| $avg(T_i)$ | 23.2 | 23.2 | 23.2 | 23.2 | 23.2 | 23.2 |
| $med(T_i)$ | 19 | 19 | 19 | 19 | 19 | 19 |
| $min(T_i)$ | 2 | 2 | 2 | 2 | 2 | 2 |

Table F.28: **FE–TE estimates of the long-run effects of LSAPs on debt to asset ratios of non-financial firms**

Estimates of the long-run effects of LSAPs on firms' debt to asset ratios (DA) as well as the effects of both firm- and industry-specific variables on DA. We report results for both the partial adjustment model and the ARDL specifications described in equation (C.8). The first three columns report results for the single-threshold panel regression model, where $\gamma_{pre} = \gamma_{post}$. The last three columns report results for the two-threshold panel regression, where $\gamma_{pre} \neq \gamma_{post}$. The estimated quantile threshold parameters are shown in Table F.23. All regressions include both firm-specific effects and time effects as well as industry-specific linear time trends. $LSAPs$ is a dummy variable equal to one during periods of LSAPs; $\pi_{DA}(\gamma)$ denotes the proportion of firms in an industry with DA below the $\gamma$-th quantile; $\pi_{CR}$ is the proportion of firms in an industry with investment grade credit ratings. The sample consists of an unbalanced panel of 3,647 U.S. publicly traded non-financial firms observed at a quarterly frequency over the period 2007:Q1 - 2018:Q3. Robust standard errors (in parentheses) are computed using the delta method (*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$).

| | Dependent variable: debt to assets (DA) | | | | | |
|---|---|---|---|---|---|---|
| | $\gamma_{pre} = \gamma_{post} = \gamma$ | | | $\gamma_{pre} \neq \gamma_{post}$ | | |
| | Par. Adj. | ARDL(1) | ARDL(2) | Par. Adj. | ARDL(1) | ARDL(2) |
| $\pi_{DA}$ | 0.2637*** | 0.0831*** | 0.1006*** | 0.2679*** | 0.1204*** | 0.1133*** |
| | (0.0259) | (0.0288) | (0.0324) | (0.0244) | (0.0252) | (0.0322) |
| $LSAPs \times \pi_{DA}$ | 0.0262* | 0.0499*** | 0.0525*** | 0.0692*** | 0.0440*** | 0.0729*** |
| | (0.0139) | (0.0180) | (0.0198) | (0.0145) | (0.0149) | (0.0174) |
| $\pi_{CR}$ | 0.0208 | -0.0037 | 0.0048 | 0.0135 | -0.0098 | 0.0192 |
| | (0.0654) | (0.0694) | (0.0725) | (0.0648) | (0.0700) | (0.0733) |
| $LSAPs \times \pi_{CR}$ | 0.0687** | 0.0354 | 0.0234 | 0.0791*** | 0.0563* | 0.0386 |
| | (0.0288) | (0.0280) | (0.0303) | (0.0258) | (0.0297) | (0.0301) |
| Cash to assets | -0.2863*** | -0.2291*** | -0.2266*** | -0.2865*** | -0.2295*** | -0.2264*** |
| | (0.0189) | (0.0175) | (0.0179) | (0.0189) | (0.0175) | (0.0179) |
| PPE to assets | 0.1424*** | 0.1412*** | 0.1344*** | 0.1427*** | 0.1410*** | 0.1347*** |
| | (0.0306) | (0.0283) | (0.0290) | (0.0306) | (0.0283) | (0.0290) |
| Size | 0.0293*** | 0.0182*** | 0.0212*** | 0.0294*** | 0.0183*** | 0.0211*** |
| | (0.0046) | (0.0045) | (0.0046) | (0.0046) | (0.0045) | (0.0046) |
| Industry Leverage | 0.8057*** | 0.3766*** | 0.3829*** | 0.8164*** | 0.4223*** | 0.4290*** |
| | (0.0453) | (0.0415) | (0.0462) | (0.0456) | (0.0446) | (0.0569) |
| Industry Growth | -0.2646*** | -0.5921*** | -0.5886*** | -0.2692*** | -0.5896*** | -0.6174*** |
| | (0.0758) | (0.1069) | (0.1301) | (0.0758) | (0.1073) | (0.1308) |
| Fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Time effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry linear trends | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 84,548 | 84,548 | 84,548 | 84,548 | 84,548 | 84,548 |
| $N$ | 3,647 | 3,647 | 3,647 | 3,647 | 3,647 | 3,647 |
| $max(T_i)$ | 44 | 44 | 44 | 44 | 44 | 44 |
| $avg(T_i)$ | 23.2 | 23.2 | 23.2 | 23.2 | 23.2 | 23.2 |
| $med(T_i)$ | 19 | 19 | 19 | 19 | 19 | 19 |
| $min(T_i)$ | 2 | 2 | 2 | 2 | 2 | 2 |

# G Small-T bias and half-panel jackknife FE-TE estimation

In this section we report estimation results after correcting for potential small-sample bias arising from the fact that we employ a dynamic panel model with fixed effects where the number of time series observations for some of the firms in our sample is small. Subsection G.1 and G.2 report the estimated short- and long-run effects after dropping firms with few time series observations, namely firms with less than 8 and 10 time observations, respectively.

Subsection G.3 reports estimation results after correcting for the small-$T$ bias by applying the half-panel jackknife method.

## G.1 Short- and long-run effects of LSAPs for firms with at least 8 time observations

Table G.29: **FE–TE estimates of the net short-run effects of LSAPs on debt to asset ratios of non-financial firms (with at least 8 observations)**

Estimates of net short-run effects of LSAPs on firms' debt to asset ratios (DA) as well as the effects of both firm- and industry-specific variables on DA, for both the partial adjustment model and the ARDL specifications described in equation (C.8). Net short-run effects are defined as the sum of the estimated coefficients of current and the $p$ lagged values of the regressor under consideration. The first three columns report results for the single-threshold panel regression model, where $\gamma_{pre} = \gamma_{post}$. The last three columns report results for the two-threshold panel regression, where $\gamma_{pre} \neq \gamma_{post}$. The estimated quantile threshold parameters are shown in Table 1. All regressions include both firm-specific effects and time effects as well as industry-specific linear time trends. $LSAPs$ is the (scaled) amount of U.S. Treasuries and agency MBS purchased by the Fed; $\pi_{DA}(\gamma)$ denotes the proportion of firms in an industry with DA below the $\gamma$-th quantile; $\pi_{CR}$ is the proportion of firms in an industry with investment grade credit ratings. The sample only includes firms with at least 8 time observations, resulting in an unbalanced panel of 3,236 U.S. publicly traded non-financial firms observed at a quarterly frequency over the period 2007:Q1 - 2018:Q3. Robust standard errors (in parentheses) are computed using the delta method (*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$).

| | Dependent variable: debt to assets (DA) | | | | | |
|---|---|---|---|---|---|---|
| | $\gamma_{pre} = \gamma_{post} = \gamma$ | | | $\gamma_{pre} \neq \gamma_{post}$ | | |
| | Par. Adj. | ARDL(1) | ARDL(2) | Par. Adj. | ARDL(1) | ARDL(2) |
| $\pi_{DA}$ | 0.0436*** | 0.0136*** | 0.0156*** | 0.0455*** | 0.0151*** | 0.0184*** |
| | (0.0042) | (0.0045) | (0.0050) | (0.0040) | (0.0046) | (0.0051) |
| $LSAPs \times \pi_{DA}$ | 0.0041*** | 0.0060*** | 0.0069*** | 0.0083*** | 0.0077*** | 0.0091*** |
| | (0.0013) | (0.0017) | (0.0019) | (0.0015) | (0.0016) | (0.0018) |
| $\pi_{CR}$ | 0.0094 | 0.0053 | 0.004 | 0.0093 | 0.0072 | 0.0068 |
| | (0.0113) | (0.0115) | (0.0117) | (0.0112) | (0.0116) | (0.0118) |
| $LSAPs \times \pi_{CR}$ | 0.0031 | 0.0005 | 0.0001 | 0.0033 | 0.0016 | 0.0014 |
| | (0.0029) | (0.0028) | (0.0031) | (0.0026) | (0.0027) | (0.0031) |
| Lagged DA | 0.8301*** | 0.8374*** | 0.8415*** | 0.8303*** | 0.8374*** | 0.8415*** |
| | (0.0053) | (0.0052) | (0.0050) | (0.0053) | (0.0052) | (0.0050) |
| Cash to assets | -0.0489*** | -0.0375*** | -0.0360*** | -0.0489*** | -0.0375*** | -0.0360*** |
| | (0.0034) | (0.0030) | (0.0030) | (0.0034) | (0.0030) | (0.0030) |
| PPE to assets | 0.0240*** | 0.0229*** | 0.0208*** | 0.0241*** | 0.0229*** | 0.0209*** |
| | (0.0053) | (0.0047) | (0.0047) | (0.0053) | (0.0047) | (0.0047) |
| Size | 0.0050*** | 0.0030*** | 0.0034*** | 0.0050*** | 0.0030*** | 0.0034*** |
| | (0.0008) | (0.0008) | (0.0008) | (0.0008) | (0.0008) | (0.0008) |
| Industry Leverage | 0.1372*** | 0.0625*** | 0.0620*** | 0.1398*** | 0.0710*** | 0.0704*** |
| | (0.0074) | (0.0069) | (0.0075) | (0.0075) | (0.0082) | (0.0090) |
| Industry Growth | -0.0476*** | -0.1022*** | -0.0971*** | -0.0491*** | -0.1053*** | -0.1028*** |
| | (0.0132) | (0.0176) | (0.0209) | (0.0132) | (0.0177) | (0.0210) |
| Fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Time effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry linear trends | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 83,290 | 83,290 | 83,290 | 83,290 | 83,290 | 83,290 |
| $N$ | 3,236 | 3,236 | 3,236 | 3,236 | 3,236 | 3,236 |
| $max(T_i)$ | 44 | 44 | 44 | 44 | 44 | 44 |
| $avg(T_i)$ | 25.7 | 25.7 | 25.7 | 25.7 | 25.7 | 25.7 |
| $med(T_i)$ | 23 | 23 | 23 | 23 | 23 | 23 |
| $min(T_i)$ | 5 | 5 | 5 | 5 | 5 | 5 |

Table G.30: **FE–TE estimates of the long-run effects of LSAPs on debt to asset ratios of non-financial firms (with at least 8 observations)**

Estimates of the long-run effects of LSAPs on firms' debt to asset ratios (DA) as well as the effects of both firm- and industry-specific variables on DA. We report results for both the partial adjustment model and the ARDL specifications described in equation (C.8). The first three columns report results for the single-threshold panel regression model, where $\gamma_{pre} = \gamma_{post}$. The last three columns report results for the two-threshold panel regression, where $\gamma_{pre} \neq \gamma_{post}$. The estimated quantile threshold parameters are shown in Table 1. All regressions include both firm-specific effects and time effects as well as industry-specific linear time trends. $LSAPs$ is the (scaled) amount of U.S. Treasuries and agency MBS purchased by the Fed; $\pi_{DA}(\gamma)$ denotes the proportion of firms in an industry with DA below the $\gamma$-th quantile; $\pi_{CR}$ is the proportion of firms in an industry with investment grade credit ratings. The sample only includes firms with at least 8 time observations, resulting in an unbalanced panel of 3,236 U.S. publicly traded non-financial firms observed at a quarterly frequency over the period 2007:Q1 - 2018:Q3. Robust standard errors (in parentheses) are computed using the delta method (*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$).

| | Dependent variable: debt to assets (DA) | | | | | |
|---|---|---|---|---|---|---|
| | $\gamma_{pre} = \gamma_{post} = \gamma$ | | | $\gamma_{pre} \neq \gamma_{post}$ | | |
| | Par. Adj. | ARDL(1) | ARDL(2) | Par. Adj. | ARDL(1) | ARDL(2) |
| $\pi_{DA}$ | 0.2565*** | 0.0835*** | 0.0984*** | 0.2679*** | 0.0928*** | 0.1159*** |
| | (0.0258) | (0.0280) | (0.0314) | (0.0247) | (0.0285) | (0.0325) |
| $LSAPs \times \pi_{DA}$ | 0.0240*** | 0.0370*** | 0.0433*** | 0.0490*** | 0.0476*** | 0.0572*** |
| | (0.0078) | (0.0107) | (0.0124) | (0.0090) | (0.0099) | (0.0113) |
| $\pi_{CR}$ | 0.0553 | 0.0326 | 0.0251 | 0.0550 | 0.0440 | 0.0428 |
| | (0.0664) | (0.0704) | (0.0735) | (0.0660) | (0.0714) | (0.0746) |
| $LSAPs \times \pi_{CR}$ | 0.0182 | 0.0034 | 0.0008 | 0.0194 | 0.0100 | 0.0087 |
| | (0.0168) | (0.0170) | (0.0198) | (0.0152) | (0.0168) | (0.0196) |
| Cash to assets | -0.2879*** | -0.2308*** | -0.2272*** | -0.2879*** | -0.2306*** | -0.2269*** |
| | (0.0191) | (0.0178) | (0.0181) | (0.0192) | (0.0178) | (0.0181) |
| PPE to assets | 0.1412*** | 0.1407*** | 0.1312*** | 0.1418*** | 0.1409*** | 0.1317*** |
| | (0.0314) | (0.0290) | (0.0296) | (0.0314) | (0.0291) | (0.0296) |
| Size | 0.0296*** | 0.0182*** | 0.0214*** | 0.0297*** | 0.0182*** | 0.0214*** |
| | (0.0047) | (0.0046) | (0.0047) | (0.0048) | (0.0046) | (0.0047) |
| Industry Leverage | 0.8076*** | 0.3840*** | 0.3912*** | 0.8242*** | 0.4366*** | 0.4445*** |
| | (0.0459) | (0.0422) | (0.0468) | (0.0463) | (0.0508) | (0.0574) |
| Industry Growth | -0.2802*** | -0.6283*** | -0.6127*** | -0.2894*** | -0.6472*** | -0.6484*** |
| | (0.0780) | (0.1097) | (0.1335) | (0.0781) | (0.1105) | (0.1343) |
| Fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Time effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry linear trends | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 83,290 | 83,290 | 83,290 | 83,290 | 83,290 | 83,290 |
| $N$ | 3,236 | 3,236 | 3,236 | 3,236 | 3,236 | 3,236 |
| $max(T_i)$ | 44 | 44 | 44 | 44 | 44 | 44 |
| $avg(T_i)$ | 25.7 | 25.7 | 25.7 | 25.7 | 25.7 | 25.7 |
| $med(T_i)$ | 23 | 23 | 23 | 23 | 23 | 23 |
| $min(T_i)$ | 5 | 5 | 5 | 5 | 5 | 5 |

## G.2 Short- and long-run effects of LSAPs for firms with at least 10 time observations

Table G.31: **FE–TE estimates of the net short-run effects of LSAPs on debt to asset ratios of non-financial firms (with at least 10 observations)**

Estimates of net short-run effects of LSAPs on firms' debt to asset ratios (DA) as well as the effects of both firm- and industry-specific variables on DA, for both the partial adjustment model and the ARDL specifications described in equation (C.8). Net short-run effects are defined as the sum of the estimated coefficients of current and the $p$ lagged values of the regressor under consideration. The first three columns report results for the single-threshold panel regression model, where $\gamma_{pre} = \gamma_{post}$. The last three columns report results for the two-threshold panel regression, where $\gamma_{pre} \neq \gamma_{post}$. The estimated quantile threshold parameters are shown in Table 1. All regressions include both firm-specific effects and time effects as well as industry-specific linear time trends. $LSAPs$ is the (scaled) amount of U.S. Treasuries and agency MBS purchased by the Fed; $\pi_{DA}(\gamma)$ denotes the proportion of firms in an industry with DA below the $\gamma$-th quantile; $\pi_{CR}$ is the proportion of firms in an industry with investment grade credit ratings. The sample only includes firms with at least 10 time observations, resulting in an unbalanced panel of $3,011$ U.S. publicly traded non-financial firms observed at a quarterly frequency over the period 2007:Q1 - 2018:Q3. Robust standard errors (in parentheses) are computed using the delta method (*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$).

| | Dependent variable: debt to assets (DA) | | | | | |
|---|---|---|---|---|---|---|
| | $\gamma_{pre} = \gamma_{post} = \gamma$ | | | $\gamma_{pre} \neq \gamma_{post}$ | | |
| | Par. Adj. | ARDL(1) | ARDL(2) | Par. Adj. | ARDL(1) | ARDL(2) |
| $\pi_{DA}$ | 0.0431*** | 0.0137*** | 0.0153*** | 0.0451*** | 0.0153*** | 0.0182*** |
| | (0.0042) | (0.0045) | (0.0049) | (0.0039) | (0.0046) | (0.0051) |
| $LSAPs \times \pi_{DA}$ | 0.0042*** | 0.0065*** | 0.0070*** | 0.0085*** | 0.0083*** | 0.0092*** |
| | (0.0013) | (0.0017) | (0.0019) | (0.0015) | (0.0016) | (0.0018) |
| $\pi_{CR}$ | 0.0083 | 0.0048 | 0.0043 | 0.0083 | 0.0067 | 0.0071 |
| | (0.0113) | (0.0114) | (0.0116) | (0.0112) | (0.0116) | (0.0118) |
| $LSAPs \times \pi_{CR}$ | 0.0037 | 0.0011 | 0.0004 | 0.0038 | 0.0021 | 0.0017 |
| | (0.0028) | (0.0027) | (0.0031) | (0.0026) | (0.0027) | (0.0031) |
| Lagged DA | 0.8342*** | 0.8411*** | 0.8447*** | 0.8345*** | 0.8411*** | 0.8447*** |
| | (0.0053) | (0.0052) | (0.0050) | (0.0053) | (0.0052) | (0.0050) |
| Cash to assets | -0.0483*** | -0.0369*** | -0.0355*** | -0.0483*** | -0.0368*** | -0.0355*** |
| | (0.0034) | (0.0030) | (0.0030) | (0.0034) | (0.0030) | (0.0030) |
| PPE to assets | 0.0200*** | 0.0218*** | 0.0196*** | 0.0201*** | 0.0219*** | 0.0197*** |
| | (0.0052) | (0.0046) | (0.0046) | (0.0052) | (0.0046) | (0.0046) |
| Size | 0.0051*** | 0.0031*** | 0.0035*** | 0.0051*** | 0.0031*** | 0.0035*** |
| | (0.0008) | (0.0008) | (0.0008) | (0.0008) | (0.0008) | (0.0008) |
| Industry Leverage | 0.1362*** | 0.0616*** | 0.0602*** | 0.1389*** | 0.0699*** | 0.0686*** |
| | (0.0074) | (0.0069) | (0.0075) | (0.0075) | (0.0082) | (0.0090) |
| Industry Growth | -0.0466*** | -0.1054*** | -0.0956*** | -0.0482*** | -0.1085*** | -0.1012*** |
| | (0.0133) | (0.0177) | (0.0211) | (0.0132) | (0.0178) | (0.0211) |
| Fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Time effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry linear trends | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 82,038 | 82,038 | 82,038 | 82,038 | 82,038 | 82,038 |
| $N$ | 3,011 | 3,011 | 3,011 | 3,011 | 3,011 | 3,011 |
| $max(T_i)$ | 44 | 44 | 44 | 44 | 44 | 44 |
| $avg(T_i)$ | 27.2 | 27.2 | 27.2 | 27.2 | 27.2 | 27.2 |
| $med(T_i)$ | 25 | 25 | 25 | 25 | 25 | 25 |
| $min(T_i)$ | 7 | 7 | 7 | 7 | 7 | 7 |

Table G.32: **FE–TE estimates of the long-run effects of LSAPs on debt to asset ratios of non-financial firms (with at least 10 observations)**

Estimates of the long-run effects of LSAPs on firms' debt to asset ratios (DA) as well as the effects of both firm- and industry-specific variables on DA. We report results for both the partial adjustment model and the ARDL specifications described in equation (C.8). The first three columns report results for the single-threshold panel regression model, where $\gamma_{pre} = \gamma_{post}$. The last three columns report results for the two-threshold panel regression, where $\gamma_{pre} \neq \gamma_{post}$. The estimated quantile threshold parameters are shown in Table 1. All regressions include both firm-specific effects and time effects as well as industry-specific linear time trends. $LSAPs$ is the (scaled) amount of U.S. Treasuries and agency MBS purchased by the Fed; $\pi_{DA}(\gamma)$ denotes the proportion of firms in an industry with DA below the $\gamma$-th quantile; $\pi_{CR}$ is the proportion of firms in an industry with investment grade credit ratings. The sample only includes firms with at least 10 time observations, resulting in an unbalanced panel of $3,011$ U.S. publicly traded non-financial firms observed at a quarterly frequency over the period 2007:Q1 - 2018:Q3. Robust standard errors (in parentheses) are computed using the delta method (*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$).

| | Dependent variable: debt to assets (DA) | | | | | |
|---|---|---|---|---|---|---|
| | $\gamma_{pre} = \gamma_{post} = \gamma$ | | | $\gamma_{pre} \neq \gamma_{post}$ | | |
| | Par. Adj. | ARDL(1) | ARDL(2) | Par. Adj. | ARDL(1) | ARDL(2) |
| $\pi_{DA}$ | 0.2600*** | 0.0865*** | 0.0986*** | 0.2723*** | 0.0962*** | 0.1169*** |
| | (0.0264) | (0.0285) | (0.0320) | (0.0253) | (0.0292) | (0.0332) |
| $LSAPs \times \pi_{DA}$ | 0.0256*** | 0.0411*** | 0.0453*** | 0.0516*** | 0.0520*** | 0.0595*** |
| | (0.0080) | (0.0106) | (0.0125) | (0.0091) | (0.0099) | (0.0115) |
| $\pi_{CR}$ | 0.0498 | 0.0300 | 0.0278 | 0.0500 | 0.0421 | 0.0456 |
| | (0.0681) | (0.0720) | (0.0750) | (0.0677) | (0.0730) | (0.0761) |
| $LSAPs \times \pi_{CR}$ | 0.0221 | 0.0070 | 0.0028 | 0.0229 | 0.0135 | 0.0107 |
| | (0.0171) | (0.0173) | (0.0202) | (0.0156) | (0.0171) | (0.0200) |
| Cash to assets | -0.2915*** | -0.2320*** | -0.2287*** | -0.2916*** | -0.2319*** | -0.2285*** |
| | (0.0197) | (0.0183) | (0.0185) | (0.0197) | (0.0183) | (0.0185) |
| PPE to assets | 0.1206*** | 0.1374*** | 0.1263*** | 0.1212*** | 0.1376*** | 0.1268*** |
| | (0.0312) | (0.0294) | (0.0298) | (0.0312) | (0.0294) | (0.0298) |
| Size | 0.0306*** | 0.0194*** | 0.0226*** | 0.0307*** | 0.0194*** | 0.0225*** |
| | (0.0048) | (0.0047) | (0.0048) | (0.0049) | (0.0047) | (0.0048) |
| Industry Leverage | 0.8214*** | 0.3876*** | 0.3878*** | 0.8388*** | 0.4398*** | 0.4416*** |
| | (0.0471) | (0.0430) | (0.0477) | (0.0475) | (0.0518) | (0.0584) |
| Industry Growth | -0.2813*** | -0.6635*** | -0.6157*** | -0.2910*** | -0.6828*** | -0.6514*** |
| | (0.0803) | (0.1132) | (0.1370) | (0.0804) | (0.1140) | (0.1378) |
| Fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Time effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry linear trends | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 82,038 | 82,038 | 82,038 | 82,038 | 82,038 | 82,038 |
| $N$ | 3,011 | 3,011 | 3,011 | 3,011 | 3,011 | 3,011 |
| $max(T_i)$ | 44 | 44 | 44 | 44 | 44 | 44 |
| $avg(T_i)$ | 27.2 | 27.2 | 27.2 | 27.2 | 27.2 | 27.2 |
| $med(T_i)$ | 25 | 25 | 25 | 25 | 25 | 25 |
| $min(T_i)$ | 7 | 7 | 7 | 7 | 7 | 7 |

## G.3 Half-panel jackknife FE-TE estimates

### G.3.1 Half-panel jackknife estimation results

Table G.33: **Half-panel jackknife FE–TE estimates of the of LSAPs on non-financial firm's debt to asset ratios based on the partial adjustment model**

Estimates of the coefficients of the partial adjustment model based on equation (C.8). The dependent variable is debt to asset ratio (DA). $q_t \times \pi_{s,t-1,DA}(\hat{\gamma}_{post})$ denotes the interaction of $q_t$, the amount of U.S. Treasuries and agency MBS purchased by the Fed scaled by its average over the policy on period, and $\pi_{s,t-1,DA}(\hat{\gamma}_{post})$, the one-quarter lagged proportion of firms in an industry with DA below the $\hat{\gamma}^{th}_{post}$ quantile. $q_t \times \pi_{s,t-1,CR}$ denotes the interaction of $q_t$ and the one-quarter lagged proportion of firms in an industry with investment grade credit ratings. In the first three columns, we report results for the single-threshold panel regression model, where $\gamma_{pre} = \gamma_{post} = \gamma$. In this case, $\hat{\gamma} = 0.56$. The last two columns report results for the two-threshold panel regression, where $\hat{\gamma}_{pre} = 0.56$ and $\hat{\gamma}_{post} = 0.77$. All regressions include both firm-specific effects and time effects as well as industry-specific linear time trends. The sample only includes firms with at least 8 time observations, resulting in an unbalanced panel of 3,236 U.S. publicly traded non-financial firms observed at a quarterly frequency over the period 2007:Q1 - 2018:Q3. Robust standard errors in parentheses (*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$).

| | Dependent variable: debt to assets ($DA_t$) | | | | |
|---|---|---|---|---|---|
| | $\gamma_{pre} = \gamma_{post} = \gamma$ | | | $\gamma_{pre} \neq \gamma_{post}$ | |
| | (1) | (2) | (3) | (4) | (5) |
| $\pi_{s,t-1,DA}(\hat{\gamma}_{pre})$ | 0.0399*** | | 0.0392*** | 0.0414*** | 0.0417*** |
| | (0.0049) | | (0.0050) | (0.0047) | (0.0047) |
| $q_t \times \pi_{s,t-1,DA}(\hat{\gamma}_{post})$ | 0.0036** | | 0.0051*** | 0.0070*** | 0.0079*** |
| | (0.0014) | | (0.0016) | (0.0017) | (0.0018) |
| $\pi_{s,t-1,CR}$ | | -0.0005 | 0.002 | | 0.0013 |
| | | (0.0149) | (0.0151) | | (0.0150) |
| $q_t \times \pi_{s,t-1,CR}$ | | -0.0005 | 0.0071** | | 0.0061** |
| | | (0.0030) | (0.0034) | | (0.0031) |
| $DA_{t-1}$ | 0.9373*** | 0.9364*** | 0.9373*** | 0.9374*** | 0.9375*** |
| | (0.0068) | (0.0068) | (0.0068) | (0.0068) | (0.0068) |
| $Cash/TA_t$ | -0.0377*** | -0.0380*** | -0.0377*** | -0.0376*** | -0.0377*** |
| | (0.0045) | (0.0045) | (0.0045) | (0.0045) | (0.0045) |
| $PPE/TA_t$ | 0.0036 | 0.0025 | 0.0035 | 0.0037 | 0.0036 |
| | (0.0075) | (0.0075) | (0.0075) | (0.0075) | (0.0075) |
| $Size_t$ | 0.0001 | 0.0001 | 0.0001 | 0.0002 | 0.0001 |
| | (0.0012) | (0.0012) | (0.0012) | (0.0012) | (0.0012) |
| $Industry\ leverage_t$ | 0.1178*** | 0.0758*** | 0.1184*** | 0.1201*** | 0.1211*** |
| | (0.0091) | (0.0080) | (0.0091) | (0.0091) | (0.0091) |
| $Industry\ growth_t$ | -0.0519*** | -0.0372** | -0.0520*** | -0.0540*** | -0.0540*** |
| | (0.0151) | (0.0151) | (0.0151) | (0.0151) | (0.0151) |
| Fixed effects | Yes | Yes | Yes | Yes | Yes |
| Time effects | Yes | Yes | Yes | Yes | Yes |
| Industry linear trends | Yes | Yes | Yes | Yes | Yes |
| Observations | 82,092 | 82,092 | 82,092 | 82,092 | 82,092 |
| $N$ | 3,236 | 3,236 | 3,236 | 3,236 | 3,236 |
| $max(T_i)$ | 44 | 44 | 44 | 44 | 44 |
| $avg(T_i)$ | 25.4 | 25.4 | 25.4 | 25.4 | 25.4 |
| $med(T_i)$ | 22 | 22 | 22 | 22 | 22 |
| $min(T_i)$ | 4 | 4 | 4 | 4 | 4 |

Table G.34: **Half-panel jackknife FE–TE estimates of the effects of LSAPs on non-financial firm's debt to asset ratios based on the ARDL(1) model**

Estimates of the coefficients of the ARDL(1) model described in equation (C.8). The dependent variable is debt to asset ratio (DA). $q_{t-\ell} \times \pi_{s,t-\ell-1,DA}(\hat{\gamma}_{post})$ denotes the interaction of $q_{t-\ell}$, the amount of U.S. Treasuries and agency MBS purchased by the Fed scaled by its average over the policy on period, and $\pi_{s,t-\ell-1,DA}(\hat{\gamma}_{post})$, the one-quarter lagged proportion of firms in an industry with DA below the $\hat{\gamma}^{th}_{post}$ quantile, for $\ell = 0, 1$. $q_{t-\ell} \times \pi_{s,t-\ell-1,CR}$ denotes the interaction of $q_{t-\ell}$ and the one-quarter lagged proportion of firms in an industry with investment grade credit ratings, for $\ell = 0, 1$. In the first three columns, we report results for the single-threshold panel regression model, where $\gamma_{pre} = \gamma_{post} = \gamma$. In this case, $\hat{\gamma} = 0.76$. The last two columns report results for the two-threshold panel regression, where $\hat{\gamma}_{pre} = 0.56$ and $\hat{\gamma}_{post} = 0.77$. All regressions include both firm-specific effects and time effects as well as industry-specific linear time trends. The sample only includes firms with at least 8 time observations, resulting in an unbalanced panel of 3,236 U.S. publicly traded non-financial firms observed at a quarterly frequency over the period 2007:Q1 - 2018:Q3. Robust standard errors in parentheses (*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$).

| | Dependent variable: debt to assets ($DA_t$) | | | | |
|---|---|---|---|---|---|
| | $\gamma_{pre} = \gamma_{post} = \gamma$ | | | $\gamma_{pre} \neq \gamma_{post}$ | |
| | (1) | (2) | (3) | (4) | (5) |
| $\pi_{s,t-1,DA}(\hat{\gamma}_{pre})$ | 0.0146*** | | 0.0144*** | 0.0147*** | 0.0152*** |
| | (0.0055) | | (0.0056) | (0.0055) | (0.0056) |
| $q_t \times \pi_{s,t-1,DA}(\hat{\gamma}_{post})$ | 0.0015 | | 0.0014 | 0.0034 | 0.0036 |
| | (0.0022) | | (0.0023) | (0.0021) | (0.0022) |
| $\pi_{s,t-2,DA}(\hat{\gamma}_{pre})$ | -0.0064 | | -0.0067 | -0.0077 | -0.0078 |
| | (0.0053) | | (0.0054) | (0.0047) | (0.0047) |
| $q_{t-1} \times \pi_{s,t-2,DA}(\hat{\gamma}_{post})$ | 0.0050** | | 0.0057*** | 0.0039** | 0.0043** |
| | (0.0020) | | (0.0021) | (0.0019) | (0.0020) |
| $\pi_{s,t-1,CR}$ | | 0.0315 | 0.0271 | | 0.0252 |
| | | (0.0208) | (0.0207) | | (0.0208) |
| $q_t \times \pi_{s,t-1,CR}$ | | -0.0003 | 0.0006 | | 0.0022 |
| | | (0.0036) | (0.0038) | | (0.0038) |
| $\pi_{s,t-2,CR}$ | | -0.0220 | -0.0242 | | -0.0229 |
| | | (0.0202) | (0.0202) | | (0.0203) |
| $q_{t-1} \times \pi_{s,t-2,CR}$ | | -0.0007 | 0.0039 | | 0.0024 |
| | | (0.0032) | (0.0035) | | (0.0034) |
| $DA_{t-1}$ | 0.9429*** | 0.9428*** | 0.9429*** | 0.9429*** | 0.9430*** |
| | (0.0066) | (0.0066) | (0.0066) | (0.0067) | (0.0067) |
| $Cash/TA_t$ | -0.0942*** | -0.0942*** | -0.0942*** | -0.0942*** | -0.0942*** |
| | (0.0090) | (0.0090) | (0.0090) | (0.0090) | (0.0090) |
| $Cash/TA_{t-1}$ | 0.0671*** | 0.0670*** | 0.0671*** | 0.0671*** | 0.0671*** |
| | (0.0085) | (0.0085) | (0.0085) | (0.0085) | (0.0085) |
| $PPE/TA_t$ | 0.0601*** | 0.0602*** | 0.0600*** | 0.0600*** | 0.0600*** |
| | (0.0197) | (0.0198) | (0.0197) | (0.0198) | (0.0198) |
| $PPE/TA_{t-1}$ | -0.0584*** | -0.0586*** | -0.0583*** | -0.0582*** | -0.0582*** |
| | (0.0199) | (0.0199) | (0.0199) | (0.0199) | (0.0199) |
| $Size_t$ | 0.0278*** | 0.0277*** | 0.0278*** | 0.0278*** | 0.0278*** |
| | (0.0045) | (0.0045) | (0.0045) | (0.0045) | (0.0045) |
| $Size_{t-1}$ | -0.0276*** | -0.0277*** | -0.0276*** | -0.0276*** | -0.0277*** |
| | (0.0045) | (0.0045) | (0.0045) | (0.0045) | (0.0045) |

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Table G.34: (cont.)

| | Dependent variable: debt to assets ($DA_t$) | | | | |
|---|---|---|---|---|---|
| | $\gamma_{pre} = \gamma_{post} = \gamma$ | | | $\gamma_{pre} \neq \gamma_{post}$ | |
| | (1) | (2) | (3) | (4) | (5) |
| *Industry leverage*$_t$ | 0.2167*** | 0.2149*** | 0.2169*** | 0.2164*** | 0.2166*** |
| | (0.0109) | (0.0110) | (0.0109) | (0.0110) | (0.0110) |
| *Industry leverage*$_{t-1}$ | -0.1706*** | -0.1802*** | -0.1703*** | -0.1660*** | -0.1650*** |
| | (0.0108) | (0.0104) | (0.0108) | (0.0117) | (0.0117) |
| *Industry growth*$_t$ | -0.0708*** | -0.0640*** | -0.0700*** | -0.0721*** | -0.0715*** |
| | (0.0156) | (0.0155) | (0.0156) | (0.0156) | (0.0156) |
| *Industry growth*$_{t-1}$ | -0.0413*** | -0.0354*** | -0.0418*** | -0.0421*** | -0.0424*** |
| | (0.0136) | (0.0136) | (0.0136) | (0.0136) | (0.0136) |
| Fixed effects | Yes | Yes | Yes | Yes | Yes |
| Time effects | Yes | Yes | Yes | Yes | Yes |
| Industry linear trends | Yes | Yes | Yes | Yes | Yes |
| Observations | 82,092 | 82,092 | 82,092 | 82,092 | 82,092 |
| $N$ | 3,236 | 3,236 | 3,236 | 3,236 | 3,236 |
| $max(T_i)$ | 44 | 44 | 44 | 44 | 44 |
| $avg(T_i)$ | 25.4 | 25.4 | 25.4 | 25.4 | 25.4 |
| $med(T_i)$ | 22 | 22 | 22 | 22 | 22 |
| $min(T_i)$ | 4 | 4 | 4 | 4 | 4 |

Table G.35: **Half-panel jackknife FE–TE estimates of the effects of LSAPs on non-financial firm's debt to asset ratios based on the ARDL(2) model**

Estimates of the coefficients of the ARDL(2) model described in equation (C.8). The dependent variable is debt to asset ratio (DA). $q_{t-\ell} \times \pi_{s,t-\ell-1,DA}(\hat{\gamma}_{post})$ denotes the interaction of $q_{t-\ell}$, the amount of U.S. Treasuries and agency MBS purchased by the Fed scaled by its average over the policy on period, and $\pi_{s,t-\ell-1,DA}(\hat{\gamma}_{post})$, the one-quarter lagged proportion of firms in an industry with DA below the $\hat{\gamma}^{th}_{post}$ quantile, for $\ell = 0, 1, 2$. $q_{t-\ell} \times \pi_{s,t-\ell-1,CR}$ denotes the interaction of $q_{t-\ell}$ and the one-quarter lagged proportion of firms in an industry with investment grade credit ratings, for $\ell = 0, 1, 2$. In the first three columns, we report results for the single-threshold panel regression model, where $\gamma_{pre} = \gamma_{post} = \gamma$. In this case, $\hat{\gamma} = 0.76$. The last two columns report results for the two-threshold panel regression, where $\hat{\gamma}_{pre} = 0.56$ and $\hat{\gamma}_{post} = 0.77$. All regressions include both firm-specific effects and time effects as well as industry-specific linear time trends. The sample only includes firms with at least 8 time observations, resulting in an unbalanced panel of 3,236 U.S. publicly traded non-financial firms observed at a quarterly frequency over the period 2007:Q1 - 2018:Q3. Robust standard errors in parentheses (*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$).

| | Dependent variable: debt to assets ($DA_t$) | | | | |
|---|---|---|---|---|---|
| | $\gamma_{pre} = \gamma_{post} = \gamma$ | | | $\gamma_{pre} \neq \gamma_{post}$ | |
| | (1) | (2) | (3) | (4) | (5) |
| $\pi_{s,t-1,DA}(\hat{\gamma}_{pre})$ | 0.0118** | | 0.0119** | 0.0125** | 0.0131** |
| | (0.0056) | | (0.0056) | (0.0055) | (0.0055) |
| $q_t \times \pi_{s,t-1,DA}(\hat{\gamma}_{post})$ | 0.0018 | | 0.0014 | 0.0039* | 0.0038* |
| | (0.0023) | | (0.0024) | (0.0022) | (0.0023) |
| $\pi_{s,t-2,DA}(\hat{\gamma}_{pre})$ | -0.0070 | | -0.0079 | -0.0131** | -0.0132** |
| | (0.0063) | | (0.0064) | (0.0058) | (0.0058) |
| $q_{t-1} \times \pi_{s,t-2,DA}(\hat{\gamma}_{post})$ | 0.0038 | | 0.0052* | 0.0019 | 0.0028 |
| | (0.0026) | | (0.0028) | (0.0025) | (0.0026) |
| $\pi_{s,t-3,DA}(\hat{\gamma}_{pre})$ | 0.0038 | | 0.0042 | 0.0068 | 0.0067 |
| | (0.0054) | | (0.0054) | (0.0046) | (0.0046) |
| $q_{t-2} \times \pi_{s,t-3,DA}(\hat{\gamma}_{post})$ | 0.0013 | | 0.0005 | 0.0022 | 0.0016 |
| | (0.0022) | | (0.0024) | (0.0021) | (0.0022) |
| $\pi_{s,t-1,CR}$ | | 0.0350* | 0.0295 | | 0.0263 |
| | | (0.0209) | (0.0208) | | (0.0208) |
| $q_t \times \pi_{s,t-1,CR}$ | | -0.0020 | -0.0010 | | 0.0008 |
| | | (0.0039) | (0.0041) | | (0.0040) |
| $\pi_{s,t-2,CR}$ | | -0.0149 | -0.0161 | | -0.0152 |
| | | (0.0247) | (0.0247) | | (0.0248) |
| $q_{t-1} \times \pi_{s,t-2,CR}$ | | 0.0039 | 0.0074 | | 0.0054 |
| | | (0.0044) | (0.0047) | | (0.0046) |
| $\pi_{s,t-3,CR}$ | | -0.0072 | -0.0076 | | -0.0071 |
| | | (0.0191) | (0.0191) | | (0.0191) |
| $q_{t-2} \times \pi_{s,t-3,CR}$ | | -0.0049 | -0.0038 | | -0.0031 |
| | | (0.0037) | (0.0039) | | (0.0039) |
| $DA_{t-1}$ | 0.9120*** | 0.9118*** | 0.9120*** | 0.9121*** | 0.9121*** |
| | (0.0102) | (0.0102) | (0.0102) | (0.0102) | (0.0102) |
| $DA_{t-2}$ | 0.0376*** | 0.0378*** | 0.0376*** | 0.0375*** | 0.0375*** |
| | (0.0089) | (0.0089) | (0.0089) | (0.0089) | (0.0089) |
| $Cash/TA_t$ | -0.0945*** | -0.0944*** | -0.0945*** | -0.0945*** | -0.0945*** |
| | (0.0090) | (0.0090) | (0.0090) | (0.0090) | (0.0090) |
| $Cash/TA_{t-1}$ | 0.0615*** | 0.0614*** | 0.0615*** | 0.0615*** | 0.0615*** |
| | (0.0089) | (0.0089) | (0.0089) | (0.0089) | (0.0089) |
| $Cash/TA_{t-2}$ | 0.0091* | 0.0090* | 0.0090* | 0.0091* | 0.0090* |
| | (0.0052) | (0.0052) | (0.0052) | (0.0052) | (0.0052) |

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Table G.35: (cont.)

| | Dependent variable: debt to assets ($DA_t$) | | | | |
|---|---|---|---|---|---|
| | $\gamma_{pre} = \gamma_{post} = \gamma$ | | | $\gamma_{pre} \neq \gamma_{post}$ | |
| | (1) | (2) | (3) | (4) | (5) |
| $PPE/TA_t$ | 0.0614*** | 0.0615*** | 0.0613*** | 0.0613*** | 0.0613*** |
| | (0.0197) | (0.0198) | (0.0197) | (0.0197) | (0.0197) |
| $PPE/TA_{t-1}$ | -0.0438** | -0.0439** | -0.0438** | -0.0438** | -0.0437** |
| | (0.0202) | (0.0202) | (0.0202) | (0.0202) | (0.0202) |
| $PPE/TA_{t-2}$ | -0.0193* | -0.0194* | -0.0192* | -0.0190* | -0.0190* |
| | (0.0106) | (0.0106) | (0.0106) | (0.0106) | (0.0106) |
| $Size_t$ | 0.0276*** | 0.0276*** | 0.0276*** | 0.0276*** | 0.0276*** |
| | (0.0045) | (0.0045) | (0.0045) | (0.0045) | (0.0045) |
| $Size_{t-1}$ | -0.0332*** | -0.0333*** | -0.0332*** | -0.0333*** | -0.0333*** |
| | (0.0046) | (0.0046) | (0.0046) | (0.0046) | (0.0046) |
| $Size_{t-2}$ | 0.0061*** | 0.0061*** | 0.0061*** | 0.0061*** | 0.0061*** |
| | (0.0020) | (0.0020) | (0.0020) | (0.0020) | (0.0020) |
| $Industry\ leverage_t$ | 0.2166*** | 0.2157*** | 0.2169*** | 0.2167*** | 0.2170*** |
| | (0.0109) | (0.0110) | (0.0109) | (0.0110) | (0.0110) |
| $Industry\ leverage_{t-1}$ | -0.1613*** | -0.1694*** | -0.1613*** | -0.1546*** | -0.1540*** |
| | (0.0119) | (0.0118) | (0.0119) | (0.0126) | (0.0126) |
| $Industry\ leverage_{t-2}$ | -0.0119 | -0.0142 | -0.0121 | -0.0167 | -0.0169 |
| | (0.0098) | (0.0093) | (0.0098) | (0.0107) | (0.0107) |
| $Industry\ growth_t$ | -0.0706*** | -0.0639*** | -0.0694*** | -0.0719*** | -0.0710*** |
| | (0.0156) | (0.0156) | (0.0156) | (0.0156) | (0.0156) |
| $Industry\ growth_{t-1}$ | -0.0315** | -0.0266* | -0.0320** | -0.0317** | -0.0319** |
| | (0.0137) | (0.0136) | (0.0137) | (0.0137) | (0.0137) |
| $Industry\ growth_{t-2}$ | -0.0064 | -0.0028 | -0.0070 | -0.0064 | -0.0069 |
| | (0.0131) | (0.0132) | (0.0132) | (0.0131) | (0.0132) |
| Fixed effects | Yes | Yes | Yes | Yes | Yes |
| Time effects | Yes | Yes | Yes | Yes | Yes |
| Industry linear trends | Yes | Yes | Yes | Yes | Yes |
| Observations | 82,092 | 82,092 | 82,092 | 82,092 | 82,092 |
| $N$ | 3,236 | 3,236 | 3,236 | 3,236 | 3,236 |
| $max(T_i)$ | 44 | 44 | 44 | 44 | 44 |
| $avg(T_i)$ | 25.4 | 25.4 | 25.4 | 25.4 | 25.4 |
| $med(T_i)$ | 22 | 22 | 22 | 22 | 22 |
| $min(T_i)$ | 4 | 4 | 4 | 4 | 4 |

### G.3.2 Half-panel jackknife FE–TE estimates of the short- and long-run effects of LSAPs

Table G.36: **Half-panel jackknife FE–TE estimates of the net short-run effects of LSAPs on debt to asset ratios of non-financial firms**

Estimates of net short-run effects of LSAPs on firms' debt to asset ratios (DA) as well as the effects of both firm- and industry-specific variables on DA, for both the partial adjustment model and the ARDL specifications described in equation (C.8). Net short-run effects are defined as the sum of the estimated coefficients of current and the $p$ lagged values of the regressor under consideration. The first three columns report results for the single-threshold panel regression model, where $\gamma_{pre} = \gamma_{post}$. The last three columns report results for the two-threshold panel regression, where $\gamma_{pre} \neq \gamma_{post}$. The estimated quantile threshold parameters are shown in Table 1. All regressions include both firm-specific effects and time effects as well as industry-specific linear time trends. $LSAPs$ is the (scaled) amount of U.S. Treasuries and agency MBS purchased by the Fed; $\pi_{DA}(\gamma)$ denotes the proportion of firms in an industry with DA below the $\gamma$-th quantile; $\pi_{CR}$ is the proportion of firms in an industry with investment grade credit ratings. The sample only includes firms with at least 8 time observations, resulting in an unbalanced panel of 3,236 U.S. publicly traded non-financial firms observed at a quarterly frequency over the period 2007:Q1 - 2018:Q3. Robust standard errors (in parentheses) are computed using the delta method (*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$).

| | Dependent variable: debt to assets (DA) | | | | | |
|---|---|---|---|---|---|---|
| | $\gamma_{pre} = \gamma_{post} = \gamma$ | | | $\gamma_{pre} \neq \gamma_{post}$ | | |
| | Par. Adj. | ARDL(1) | ARDL(2) | Par. Adj. | ARDL(1) | ARDL(2) |
| $\pi_{DA}$ | 0.0392*** | 0.0077 | 0.0082 | 0.0417*** | 0.0074 | 0.0066 |
| | (0.0050) | (0.0056) | (0.0062) | (0.0047) | (0.0058) | (0.0065) |
| $LSAPs \times \pi_{DA}$ | 0.0051*** | 0.0072*** | 0.0072*** | 0.0079*** | 0.0079*** | 0.0082*** |
| | (0.0016) | (0.0020) | (0.0024) | (0.0018) | (0.0019) | (0.0021) |
| $\pi_{CR}$ | 0.0020 | 0.0029 | 0.0058 | 0.0013 | 0.0023 | 0.0040 |
| | (0.0151) | (0.0155) | (0.0160) | (0.0150) | (0.0158) | (0.0162) |
| $LSAPs \times \pi_{CR}$ | 0.0071** | 0.0044 | 0.0026 | 0.0061** | 0.0047 | 0.0030 |
| | (0.0034) | (0.0033) | (0.0040) | (0.0031) | (0.0033) | (0.0039) |
| Lagged DA | 0.9373*** | 0.9429*** | 0.9496*** | 0.9375*** | 0.9430*** | 0.9497*** |
| | (0.0068) | (0.0066) | (0.0067) | (0.0068) | (0.0067) | (0.0067) |
| Cash to assets | -0.0377*** | -0.0271*** | -0.0240*** | -0.0377*** | -0.0272*** | -0.0240*** |
| | (0.0045) | (0.0042) | (0.0043) | (0.0045) | (0.0042) | (0.0043) |
| PPE to assets | 0.0035 | 0.0017 | -0.0017 | 0.0036 | 0.0018 | -0.0015 |
| | (0.0075) | (0.0070) | (0.0072) | (0.0075) | (0.0070) | (0.0072) |
| Size | 0.0001 | 0.0001 | 0.0005 | 0.0001 | 0.0001 | 0.0005 |
| | (0.0012) | (0.0012) | (0.0012) | (0.0012) | (0.0012) | (0.0012) |
| Industry Leverage | 0.1184*** | 0.0465*** | 0.0435*** | 0.1211*** | 0.0517*** | 0.0462*** |
| | (0.0091) | (0.0088) | (0.0097) | (0.0091) | (0.0104) | (0.0118) |
| Industry Growth | -0.0520*** | -0.1117*** | -0.1084*** | -0.0540*** | -0.1140*** | -0.1099*** |
| | (0.0151) | (0.0215) | (0.0267) | (0.0151) | (0.0215) | (0.0267) |
| Fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Time effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry linear trends | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 82,092 | 82,092 | 82,092 | 82,092 | 82,092 | 82,092 |
| $N$ | 3,236 | 3,236 | 3,236 | 3,236 | 3,236 | 3,236 |
| $max(T_i)$ | 44 | 44 | 44 | 44 | 44 | 44 |
| $avg(T_i)$ | 25.4 | 25.4 | 25.4 | 25.4 | 25.4 | 25.4 |
| $med(T_i)$ | 22 | 22 | 22 | 22 | 22 | 22 |
| $min(T_i)$ | 4 | 4 | 4 | 4 | 4 | 4 |

Table G.37: **Half-panel jackknife FE–TE estimates of the long-run effects of LSAPs on debt to asset ratios of non-financial firms**

Estimates of the long-run effects of LSAPs on firms' debt to asset ratios (DA) as well as the effects of both firm- and industry-specific variables on DA. We report results for both the partial adjustment model and the ARDL specifications described in equation (C.8). The first three columns report results for the single-threshold panel regression model, where $\gamma_{pre} = \gamma_{post}$. The last three columns report results for the two-threshold panel regression, where $\gamma_{pre} \neq \gamma_{post}$. The estimated quantile threshold parameters are shown in Table 1. All regressions include both firm-specific effects and time effects as well as industry-specific linear time trends. $LSAPs$ is the (scaled) amount of U.S. Treasuries and agency MBS purchased by the Fed; $\pi_{DA}(\gamma)$ denotes the proportion of firms in an industry with DA below the $\gamma$-th quantile; $\pi_{CR}$ is the proportion of firms in an industry with investment grade credit ratings. The sample only includes firms with at least 8 time observations, resulting in an unbalanced panel of $3,236$ U.S. publicly traded non-financial firms observed at a quarterly frequency over the period 2007:Q1 - 2018:Q3. Robust standard errors (in parentheses) are computed using the delta method (*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$).

| | Dependent variable: debt to assets (DA) | | | | | |
|---|---|---|---|---|---|---|
| | $\gamma_{pre} = \gamma_{post} = \gamma$ | | | $\gamma_{pre} \neq \gamma_{post}$ | | |
| | Par. Adj. | ARDL(1) | ARDL(2) | Par. Adj. | ARDL(1) | ARDL(2) |
| $\pi_{DA}$ | 0.6253*** | 0.1342 | 0.1628 | 0.6679*** | 0.1299 | 0.1308 |
| | (0.1058) | (0.0990) | (0.1257) | (0.1060) | (0.1034) | (0.1317) |
| $LSAPs \times \pi_{DA}$ | 0.0817*** | 0.1258*** | 0.1424*** | 0.1266*** | 0.1381*** | 0.1633*** |
| | (0.0265) | (0.0379) | (0.0505) | (0.0311) | (0.0364) | (0.0481) |
| $\pi_{CR}$ | 0.0323 | 0.0502 | 0.1147 | 0.0205 | 0.0411 | 0.0786 |
| | (0.2415) | (0.2718) | (0.3171) | (0.2404) | (0.2764) | (0.3227) |
| $LSAPs \times \pi_{CR}$ | 0.1134** | 0.0779 | 0.0509 | 0.0983** | 0.0818 | 0.0604 |
| | (0.0546) | (0.0591) | (0.0785) | (0.0501) | (0.0585) | (0.0777) |
| Cash to assets | -0.6019*** | -0.4757*** | -0.4754*** | -0.6028*** | -0.4767*** | -0.4757*** |
| | (0.0805) | (0.0803) | (0.0931) | (0.0807) | (0.0805) | (0.0932) |
| PPE to assets | 0.0563 | 0.0297 | -0.0335 | 0.0579 | 0.0319 | -0.0297 |
| | (0.1190) | (0.1231) | (0.1432) | (0.1193) | (0.1233) | (0.1434) |
| Size | 0.0022 | 0.0024 | 0.0093 | 0.0023 | 0.0022 | 0.0092 |
| | (0.0192) | (0.0205) | (0.0235) | (0.0193) | (0.0206) | (0.0235) |
| Industry Leverage | 1.8885*** | 0.8155*** | 0.8620*** | 1.9366*** | 0.9063*** | 0.9169*** |
| | (0.2309) | (0.1683) | (0.2107) | (0.2358) | (0.2037) | (0.2573) |
| Industry Growth | -0.8301*** | -1.9574*** | -2.1511*** | -0.8638*** | -1.9995*** | -2.1822*** |
| | (0.2559) | (0.4398) | (0.6018) | (0.2579) | (0.4456) | (0.6077) |
| Fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Time effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry linear trends | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 82,092 | 82,092 | 82,092 | 82,092 | 82,092 | 82,092 |
| $N$ | 3,236 | 3,236 | 3,236 | 3,236 | 3,236 | 3,236 |
| $max(T_i)$ | 44 | 44 | 44 | 44 | 44 | 44 |
| $avg(T_i)$ | 25.4 | 25.4 | 25.4 | 25.4 | 25.4 | 25.4 |
| $med(T_i)$ | 22 | 22 | 22 | 22 | 22 | 22 |
| $min(T_i)$ | 4 | 4 | 4 | 4 | 4 | 4 |