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1 Introduction

The 2007-2009 financial crisis affected the U.S. corporate sector in a number of important respects. Due to the reduction in the supply of external finance, many non-financial firms found it difficult to roll over their debt obligations, with consequent cuts in spending, investment, and employment (e.g., Almeida et al. (2012), Campello et al. (2010), and Duchin et al. (2010)). To revitalize the economy, after cutting the policy rate close to zero, the Federal Reserve resorted to large-scale asset purchases (LSAPs). The empirical evidence so far suggests that these LSAPs have been successful at easing financial conditions (Bernanke (2020)).[1] Yet the debate on the effectiveness of such policies is still far from being settled. 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, 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, Ihrig et al. (2018) and Swanson (2021) find that the effects of LSAPs on yields were quite persistent.

The literature so far has also 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' leverage responses, and ask whether LSAPs facilitated non-financial firms' access to external financing. By characterizing the time profile of the effects of LSAPs, we also investigate whether the Fed's purchases systematically affected the way firms finance their operations beyond the transitory responses around policy announcements. Thus, we extend the evidence on the persistence of the effects of LSAPs on interest rates to quantities, namely firm leverage. To this end, we estimate dynamic panel data models with threshold effects using quarterly 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.

The key challenge is to isolate the effects of LSAPs on firms' financing decisions from that

[1] The empirical literature on the effects of quantitative easing (QE) has grown very rapidly in the last decade. Bhattarai and Neely (2022), and Kuttner (2018) provide recent reviews.

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 light of 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 address the identification problem by exploiting the heterogeneity that exists in firms' debt capacity constraints both before and after LSAPs. Specifically, we interact measures of LSAPs, generically denoted by q_t, with indicators of firms' spare debt capacity to be defined below. In line with Myers (1984), we say that a firm has exhausted its debt capacity if its debt to asset ratio reaches a level where further debt issuance could result in substantial additional costs or increased default risk. In practice, this threshold debt level is unknown. Leary and Roberts (2010) define debt capacities in terms of the leverage ratios of investment-grade rated firms in the same industry-year combination. We propose a new indicator of debt capacity which does not require to specify an *a priori* given threshold value.

We start by considering firm-specific indicator variables, $d_{is,t}(\gamma)$, that take the value of one if firm i in industry s at time t has a debt to asset ratio ($y_{is,t}$) below a given threshold quantile, γ. At the same time, because 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. (2022), Leary and Roberts (2014), and MacKay and Phillips (2005)), we average $d_{is,t}(\gamma)$ across firms within a given industry to obtain an industry-specific indicator of debt capacity, which we denote by $\pi_{st}(\gamma)$. This gives the proportion of firms within industry s, whose $y_{is,t}$ lie below the threshold quantile, γ. We investigate the relevance of this measure of debt capacity empirically. To avoid simultaneity bias we interact q_t with one-quarter lagged values of this proportion. 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.[2]

We estimate the quantile threshold parameter, γ, by grid search together with other unknown parameters. Thresholding has been widely used in the time series literature and more recently in panel data regressions to capture differential impacts of macroeconomic shocks or policy interventions across groups or categories.[3] Similar ideas are used in corporate finance,

[2]In the paper we focus on the industry-specific debt capacity indicator as it provides an even stronger differentiation between the effects of dynamics (past firm-leverage) from the effects of debt capacity. This choice is also in line with the findings in the literature that industry variables are powerful predictors of firms' leverage. Results based on firm-specific indicators, $d_{is,t}(\gamma)$, are reported in Section G of the online supplement, and are generally in line with our conclusions obtained using industry-specific measures of debt capacity.

[3]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.

but often using threshold values that are fixed *a priori*. For example, firms are classified based on lowest/highest tercile or quartile of the empirical distribution of some particular firm or industry characteristic of interest.[4] In our empirical strategy, the unknown quantile threshold values are estimated, allowing for possible changes in such threshold values due to the policy intervention under consideration.

The main hypothesis behind our identification strategy is that the effects of LSAPs are heterogeneous and depend on the ability of firms in an industry to raise debt (as indicated by our debt capacity indicator). This assumption is motivated by the most frequently discussed channels through which LSAPs may reduce interest rates and ease financial conditions.[5] Here, we highlight three main channels. According to the "portfolio balance channel", by purchasing a large quantity of assets held by the private sector, central banks increase their prices. In order to rebalance their portfolios, the sellers of these financial assets may use the proceeds to purchase other assets that have similar characteristics to the assets sold, thus pushing up prices of other "safe" substitute assets. A second channel is the so called "bank lending channel" via which the Fed's LSAPs increase the value of existing assets on banks' balance sheets. This raises banks' capital ratios making them more willing to lend. A third mechanism is the "signalling channel", whereby purchases of assets by the Fed reinforce its commitment to maintain interest rates low for long. Our hypothesis is that for each of these channels, firms with adequate debt capacity and more financial flexibility ought to benefit more from the Fed's asset purchases, 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.[6]

We find that existing firms' debt burdens play an important role in the transmission of LSAPs. In our main specifications, the threshold parameter, γ, is estimated to be 0.77, just above the upper quartile of the cross-section distribution of firms' leverage 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 debt to assets ratio below the 77^{th} quantile experienced, on average, a larger increase in external debt financing in response to LSAPs.

At the same time, by considering a dynamic panel data model we are able to estimate the time profile of the effects of LSAPs on firms' capital structure, providing a clear and strong evidence that such effects are long-lasting. We find that the effects of LSAPs have a half-life of

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

[5]See Bernanke (2020), Krishnamurthy and Vissing-Jorgensen (2011), and Kuttner (2018) for detailed discussions on the transmission mechanisms of quantitative easing.

[6]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. Greenwood et al. (2010) show that bond issuance of firms that are relatively unconstrained is more elastic to changes in the supply of government debt. Ottonello and Winberry (2020) find that firms with low default risk were the most responsive to changes in (conventional) monetary policy during the period preceding the global financial crisis.

4-5 quarters and a mean lag length of approximately 6 quarters. Nevertheless, the magnitudes of these effects are relatively small, suggesting 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)).

In one additional exercise, we separate the effects of MBS from Treasury purchases to show that both programs facilitated non-financial firms' access to external financing. Also in this case, we find that both type of purchases had long-lasting effects on firm debt to asset ratios but the magnitudes are rather small. Finally, we also replace our quantitative measures of LSAPs with four qualitative variables equal to one during policy on periods and zero otherwise. Consistently with the literature that studies the effects of LSAPs on yields, we find that the first LSAP program (typically referred to as QE1) had the strongest impact on firm leverage. This corroborates the view that LSAPs can be particularly effective during periods of dysfunctions in financial markets (e.g., D'Amico and King (2013)). Among the other programs, we find that both the so called QE2 and QE3 programs had positive and statistically significant effects on firm leverage. This suggests that LSAPs can also be an effective tool outside periods of market stress. In contrast, the maturity extension program (MEP) of 2011, where the Fed purchased long-term Treasuries offset by the sale of short-term government bonds, didn't have a statistically significant impact on firms' debt to asset ratios.

Our empirical results are robust to a number of specification choices. The main paper reports short-term and long-term estimates obtained using a relatively general panel autoregressive distributed lag (PanARDL) model of order two. To show the robustness of our results to the choice of dynamic specification, in the online supplement we also report results for the standard partial adjustment model and the PanARDL(1) specification. Regarding the control variables, in addition to firm-specific fixed effects we also control for several time-varying industry-specific covariates to account for differential growth opportunities and 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. In addition to time effects, we also allow for industry-specific trend differentials and hence allow firms' leverage to follow different time trends across industries. We also check the robustness of our results to another popular measure of common effects whereby real output growth is interacted with industry-specific dummies. 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 could be small for some of the firms included in the panel, due to its unbalanced nature.

In summary, we find statistically highly significant effects of LSAPs on corporate debt financing, but at the same time we find the magnitude of such effects to be rather small in the short run (on impact) as well as in a longer run when the business cycle effects are allowed to iron out.

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) document that firms tend to issue more long-term (short-term) debt when the maturity of government debt decreases (increases). This gap filling is more pronounced for firms with more financial flexibility. Badoer and James (2016) argue that this gap filling behaviour is more prominent in the issuance of long-term (LT) corporate bonds and that the supply of LT government bonds affect both the maturity choice and the level of corporate borrowing. Graham et al. (2014) find that government debt is negatively correlated with corporate debt, especially for larger and less risky firms. 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 with greater dependence on longer-term debt issued more long-term debt as a result of the Fed's MEP.[7] Our analysis differs from this study in at least two respects. First, we quantify the effects of both MBS and Treasury purchases on firms' capital structure. Second, we characterize the time profile of these effects, evaluating whether they persist or dissipate immediately after the implementation of one particular program. Assessing the overall long-term effects of LSAPs and their persistence is particularly important from a policy perspective given that quantitative easing (QE) is now part of the standard central bank toolkit in the U.S..

When evaluating the first major four Fed's programs separately using qualitative policy indicators, we find that the effects of the MEP are positive but not statistically significant. Thus, while FRY document a significant impact on long-term debt growth, we find that the MEP didn't lead to higher debt to asset ratios. We focus on debt to assets instead of debt growth consistently with the fact that asset and liability side of a firm's balance sheet are jointly determined.

Our paper also contributes to the methodological discussion on the identification of macro policy effects. First, while FRY's research question only requires a static specification, our empirical model is dynamic and thus accounts for the highly persistence nature of firm leverage (e.g., Flannery and Rangan (2006) and Lemmon et al. (2008)). Second, 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. More importantly, our empirical strategy doesn't require to specify a single treatment date.

Our study is also related to the literature which studies the link between QE and bank

[7]Giambona et al. (2020) also use firm-level data at annual frequency (2004-2011) and identify the effects of QE on firm investment by exploiting differences in firms' access to the bond market. The same arguments that differentiate our paper from Foley-Fisher et al. (2016) apply to this study as well.

lending. Rodnyansky and Darmouni (2017) use a difference-in-difference approach which exploits the fact that banks differ in their relative exposure to 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. Chakraborty et al. (2020) also exploit the fact that banks differ in their exposure to MBS purchase to find that banks benefiting from MBS purchases increased mortgage origination. 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 focus on non-financial firms' capital structure, distinguishing between short- and long-term effects. We find that firms' debt to asset ratios increased as a results of both Treasuries and MBS purchases.

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. Our paper highlights the important role of pre-existing firms' debt capacity within an industry in the transmission of LSAPs.

More generally, our paper relates to the vast literature which studies the relative importance of various factors in non-financial firms' capital structure decisions. Excellent reviews are provided by DeAngelo (2022), Frank and Goyal (2022), and Graham and Leary (2011). In line with the findings of MacKay and Phillips (2005), Frank and Goyal (2009), and Leary and Roberts (2014), amongst others, we find that industry factors are powerful predictors of firms' leverage. Our study is also connected to 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).

2 Panel data and sources

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 by 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 variables at the industry level.

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.[8]

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).[9] In total, our data consists of $95,489$ firm-quarter observations, comprised of $3,647$ distinct firms observed on average over 26 quarters. Firms in our sample have at least 5 time observations (T) while the maximum T is 47. For 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.

2.1 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 (MBS) purchased by the Fed, denoted by q_t. The use of gross instead of net amount is in line with Chakraborty et al. (2020) who focus on gross purchases 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 qualitative (0,1) policy variables. While we report results for both the quantitative and qualitative measure of LSAPs, our main focus is on the quantitative measure which is better suited to capture the magnitude of the Fed's purchases.[10]

[8]In line with the existing literature, we employ the three-digit SIC industry classification instead of the two-digit SIC industry classification which would also result in fewer industry groups, namely 41.

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

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

3 Identification of macro policy effects with heterogeneous outcomes

3.1 Firm-specific and industry-average debt capacity measures

The rationale for our identification strategy is based on the *a priori* belief that firms with higher debt capacity and financial flexibility are likely to be more responsive to the Fed's LSAPs.[11] 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 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, over-leveraged 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 (e.g., Bolton et al. (2021), Leary and Roberts (2010)). It is in fact well recognized that higher debt burdens are powerful predictors of future default probabilities and, as such, constitute an important measure of credit risk (e.g., Bhamra et al. (2010), 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), Hadlock and Pierce (2010)).

To account for differences in debt exposure we consider both firm-specific and industry-average measures. We measure firm-specific debt capacity by the indicator, $d_{is,t}(\gamma)$, defined by

$$d_{is,t}(\gamma) = \mathcal{I}\left[y_{is,t} < g_{st}(\gamma)\right], \tag{1}$$

where $y_{is,t}$ is the ratio of debt to assets (DA) of firm i in industry s for quarter t, $g_{st}(\gamma)$ is the γ^{th} quantile of the cross-sectional distribution of DA over all firms in industry s at time t, and $\mathcal{I}(\mathcal{A})$ is an indicator variable that takes the value of one if $\mathcal{A}$ is true and zero otherwise. The industry-average measure of debt capacity is defined by

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

where $g_t(\gamma)$ is the γ^{th} quantile of the cross-sectional distribution of DA of all firms at time t, and N_{st} denotes the number of firms in industry s during quarter t. In effect, $\pi_{st}(\gamma)$ is the proportion of firms in industry s in quarter t with DA below $g_t(\gamma)$, an economy-wide time-varying threshold. The industry-average measure, $\pi_{st}(\gamma)$, recognizes that firms in a given

[11] See for example, Graham et al. (2014), and Greenwood et al. (2010) on the heterogeneous responses of firms to government debt issuance. Bolton et al. (2021), Leary and Roberts (2010), and Lemmon and Zender (2010) provide discussions on the ability of firms to issue debt according to their debt capacity.

industry tend to closely align their own financing decisions with the financial choices made by firms from the same industry.[12] The quantile threshold parameter γ ($0 < \gamma < 1$) is estimated using a grid search procedure to be explained in Subsection 5.1.

Both firm-specific and industry-average measures of debt capacity are important in classifying firms with respect to their debt exposure relative to the existing debt levels within an industry or in the economy. In the main paper we focus on $\pi_{st}(\gamma)$ which yields results that are more readily interpretable and in some respects more convincing. However, for completeness we provide estimation results based on $d_{is,t}(\gamma)$ in Section G of the online supplement.

3.2 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' lending (e.g., Chakraborty et al. (2020), and Rodnyansky and Darmouni (2017)). 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 capacity across industries.

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

$$y_{is,t} = \mu_{is} + \phi_{st} + \beta_0 \pi_{s,t-1}(\gamma) + \beta_1 q_t \times \pi_{s,t-1}(\gamma) + u_{is,t}, \tag{3}$$

where as before $y_{is,t}$, is the DA ratio of firm i in industry $s = 1, 2, ..., S$, for quarter t, while q_t is the quantitative policy variable measuring the size of the Fed's U.S. Treasury and agency MBS purchases, which we interact with our industry-specific debt capacity proportion, $\pi_{s,t-1}(\gamma)$. Note that equation (3) only includes a one-quarter lag of $\pi_{st}(\gamma)$ to avoid simultaneous determination of this proportion and the dependent variable, that could occur when the number of firms in a given industry is rather small.

We use firm-specific effects, μ_{is}, to remove systematic differences across firms in different industries, and consider industry-time fixed effects, ϕ_{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, ϕ_{st} is included to capture such time-industry effects that fully take account of non-policy macro factors with differential industry effects.

[12] See, for example, Frank and Goyal (2009), Grieser et al. (2022), and Leary and Roberts (2014).

It is clear that at this level of generality it is not possible to identify β_1, which is the policy effectiveness coefficient of interest. Some restrictions on ϕ_{st} must be entertained. One possible option is to consider an interactive time effect by specifying

$$\phi_{st} = \delta_t + \phi_s f_t, \tag{4}$$

where δ_t is the common component of ϕ_{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 ϕ_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

$$\bar{\phi}_\circ = S^{-1}\sum_{s=1}^{S}\phi_s = 0. \tag{5}$$

Under this (normalization) restriction, δ_t is identified as the common component of non-policy macro variables. But to identify ϕ_s, and hence β_1, further restrictions are required. One possibility is to assume ϕ_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 ϕ_s to be treated as free parameters to be estimated subject to (5) and for alternative specifications of f_t. Using (4) in (3) we have

$$y_{is,t} = \mu_{is} + \delta_t + \phi_s f_t + \beta_0\pi_{s,t-1}(\gamma) + \beta_1 q_t \times \pi_{s,t-1}(\gamma) + u_{is,t}. \tag{6}$$

The fixed and time effects, μ_{is} and δ_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 β_1 for arbitrary choices of ϕ_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 β_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 ϕ_s, with no consequence for the policy effectiveness coefficient, β_1. In view of the uncertainty surrounding the choice of f_t, the robustness of the estimates of β_0 and β_1 are further investigated by also including U.S. real GDP growth as a proxy for f_t, which is a commonly used indicator of macroeconomic conditions in the corporate finance literature (e.g., Erel et al. (2011), Frank

[13]In our empirical applications, where the panel is unbalanced, we use Wansbeek and Kapteyn (1989) transformations to eliminate μ_{is} and δ_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.

and Goyal (2009)).[14]

Identification of β_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 β_0 and β_1 to our estimation problem. This is indeed the case in our application, as shown in Section B of the online supplement.

3.3 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 (6). 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

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

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

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

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

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

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

$$\overline{PE} = \beta_1 \left[\frac{1}{T - T_0} \sum_{t=T_0+1}^{T} q_t \times \sum_{s=1}^{S} w_s \pi_{s,t-1}(\gamma) \right], \tag{8}$$

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

[14] In Section D.5 of the online supplement we also experiment with alternative observed macro-variables as proxies for f_t. When using the firm-specific debt capacity indicator, $d_{is,t}(\gamma)$, we also allow for industry-time fixed effects (without imposing restrictions on ϕ_{st}). We find that using industry-time fixed effects or the restriction described in equation (4) leads to very similar results.

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. 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 MBS and Treasuries purchases (TY), namely $Q_t = MBS_t + TY_t$. 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.

3.4 Possible confounding effects of policy changes on threshold parameters

The above analysis assumes the threshold parameter, γ, 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

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

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 (6) 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

$$y_{is,t} = \mu_{is} + \delta_t + \phi_s f_t + \beta_0 \pi_{s,t-1}(\gamma_{pre}) + \beta_1 q_t \times \pi_{s,t-1}(\gamma_{post}) + u_{is,t}, \tag{9}$$

which then ensures that

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

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

4 Panel ARDL regressions with debt capacity thresholds

In our empirical analysis, we extend the simple static models described in equation (9) by adding dynamics as well as firm- and industry-specific control variables. We consider the following general p^{th} order threshold panel autoregressive distributed lag, PanARDL(p), model:

$$\lambda(L,p)y_{is,t} = \mu_{is} + \delta_t + \boldsymbol{\phi}_s'\mathbf{f}_t + \beta_0(L,p)\pi_{s,t-1}(\gamma_{pre}) + \beta_1(L,p)\left[q_t \times \pi_{s,t-1}(\gamma_{post})\right] \\ + \boldsymbol{\varphi}'(L,p)\mathbf{w}_{st} + \boldsymbol{\psi}'(L,p)\mathbf{x}_{is,t} + u_{is,t}, \tag{10}$$

where $\lambda(L,p)$, $\beta_0(L,p)$, $\beta_1(L,p)$, $\boldsymbol{\varphi}(L,p)$ and $\boldsymbol{\psi}(L,p)$ are p^{th}-order polynomials in the lag operator, $Ly_{is,t} = y_{is,t-1}$.[15] As before, $y_{is,t}$ is the DA ratio of firm i in industry s for quarter t, μ_{is} and δ_t are firm and time fixed effects, $\boldsymbol{\phi}_s'\mathbf{f}_t$ is industry interactive effects, with $\mathbf{f}_t$ proxied by a linear time trend, real GDP growth, or both. q_t is the scaled measure of the Fed's asset purchases as described in Subsection 2.1, and $\pi_{st}(\gamma_{post})$ is the proportion of firms in industry s with DA below the γ_{post}-th quantile, as defined by equation (2).

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 $\mathbf{w}_{st}$ 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). We also control for firm-specific covariates, $\mathbf{x}_{is,t}$, that include 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). The choice of control variables is motivated by the findings of Frank and Goyal (2009), and is in line with the corporate finance literature.[16]

Regarding the model choice, the PanARDL(p) 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 PanARDL 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.

[15] Specifically, $\lambda(L,p) = 1 - \lambda_1 L - ... - \lambda_p L^p$; $\beta_j(L,p) = \beta_{j,0} + \beta_{j,1}L + ... + \beta_{j,p}L$, for $j = 0, 1$, $\boldsymbol{\varphi}(L,p) = \boldsymbol{\varphi}_0 + \boldsymbol{\varphi}_1 L + ... + \boldsymbol{\varphi}_p L^p$, and $\boldsymbol{\psi}(L,p) = \boldsymbol{\psi}_0 + \boldsymbol{\psi}_1 L + ... + \boldsymbol{\psi}_p L^p$.

[16] Frank and Goyal (2009) document that the most relevant variables for explaining firm leverage are firm size, market to book ratio, measures of tangibility and profitability, the median industry leverage, and expected inflation. 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 main model because the associated coefficients were often insignificant, both in statistical and economic terms. At the same time, as we shall see, our estimation results are robust to the inclusion of additional explanatory variables, such as market to book ratio, median industry Tobin's Q, and other industry-specific variables.

The policy parameters of interest are $\beta_{1,\ell}$, for $\ell = 0, 1, ..., p$, namely the coefficients of $\beta_1(L, p) = \beta_{1,0} + \beta_{1,1}L + ... + \beta_{1,p}L$, and the lagged dependent variable coefficients, λ_ℓ, for $\ell = 1, 2, ..., p$. The policy impact is given by $\beta_{1,0}$ while the policy long-run effects are defined by

$$\theta = \frac{\sum_{\ell=0}^{p} \beta_{1,\ell}}{(1 - \sum_{\ell=1}^{p} \lambda_\ell)}. \tag{11}$$

The numerator of θ, $\beta_1 = \sum_{\ell=0}^{p} \beta_{1,\ell}$, is often referred to as the net short-run effect, and will be reported as a summary measure for short-run effects. Due to the highly persistent nature of debt-to-asset ratios, the net short-run effects will be smaller (in absolute value) than the long-run effects.

To estimate β_1 and θ we need to choose the lag order, p, and the threshold parameter, $\boldsymbol{\gamma} = (\gamma_{pre}, \gamma_{post})'$. A simultaneous estimation of p and $\boldsymbol{\gamma}$ is computationally demanding and could involve a considerable degree of data mining. Here we follow the literature and estimate $\boldsymbol{\gamma}$ for $p = 1$ and 2 as well as for the partial adjustment model, a commonly used specification in the empirical capital structure research (Graham and Leary (2011)).[17] Also, since allowing for different lag orders for policy and control variables involves many permutations with a large number of dynamic specifications to choose from, we use the same lag order across the regressors which seems a reasonable empirical strategy. For the sake of brevity, in the remainder of the paper, we focus on reporting the estimates for the PanARDL(2) model.[18]

As to the estimation of $\boldsymbol{\gamma}$, we follow the threshold literature and estimate $\boldsymbol{\gamma}$ by grid search, and treat the resultant estimate as given when it comes to estimating 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.

[17] The partial adjustment model is given by

$$\begin{aligned} y_{is,t} = \mu_{is} + \delta_t + \boldsymbol{\phi}_s'\mathbf{f}_t + \lambda_1 y_{is,t-1} + \beta_0 \pi_{s,t-1}(\gamma_{pre}) \\ + \beta_1 q_t \times \pi_{s,t-1}(\gamma_{post}) + \boldsymbol{\varphi}'\mathbf{w}_{st} + \boldsymbol{\psi}'\mathbf{x}_{is,t} + u_{is,t}, \end{aligned}$$

which is a special case of the PanARDL model, where $p = 0$, except for the lag operator applied to $y_{is,t}$ whose order is set to $p = 1$.

[18] Results for both the panel partial adjustment model and PanARDL(1), which are special cases of the PanARDL(2) specification, are reported in Section D.7 of the online supplement.

5 Estimation and empirical findings

5.1 Quantile threshold parameter estimates

The quantile threshold parameter $\boldsymbol{\gamma}$ in (2), is estimated by minimizing the sum of squared residuals (SSR) for different values of $\boldsymbol{\gamma}$ in the range $0.25 \leq \gamma_{pre}, \gamma_{post} \leq 0.9$ in increments of 0.01.[19] Specifically, for a given choice of p and for each value of $\boldsymbol{\gamma}$ 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.

Table 1: **Estimated quantile threshold parameters**

Estimates of the quantile threshold parameters from a grid search procedure for the PanARDL(2) model described in equation (10). Panel A shows the estimated threshold parameters for the single-threshold panel regression model, where $\gamma_{pre} = \gamma_{post}$. Panel B displays results for the two-threshold model, where $\gamma_{pre} \neq \gamma_{post}$. In column (1) and (2), we use linear time trends or real GDP growth as a proxy for f_t, respectively. Column (3) reports results when including both linear trends and real GDP growth at the same time. 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.

	(1)	(2)	(3)
Panel A:	$\gamma_{pre} = \gamma_{post} = \gamma$		
$\hat{\gamma}$	0.76	0.56	0.56
Panel B:	$\gamma_{pre} \neq \gamma_{post}$		
$\hat{\gamma}_{pre}$	0.56	0.56	0.56
$\hat{\gamma}_{post}$	0.77	0.77	0.77
linear trends	Yes	No	Yes
RGDP growth	No	Yes	Yes

Panel A of Table 1 reports the estimated threshold parameters for the single-threshold PanARDL(2) model (where $\gamma_{pre} = \gamma_{post} = \gamma$) across different choices of f_t. The estimated quantile threshold parameter, $\hat{\gamma}$, is equal to 0.76 when using linear trends as a proxy for f_t, and it is smaller at 0.56 when proxying f_t by either real GDP growth or both linear trends and GDP at the same time.

The difference in the estimates obtained for γ, depending on the choice of f_t, only applies to the single-threshold case. Following the more general model discussed in Subsection 3.4, we re-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 γ_{pre} and γ_{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 γ_{pre} and γ_{post}. The estimation results for this case are reported in panel

[19] We start our grid search for γ 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.

B 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 choices of f_t. Both threshold estimates lie well within the grid, with the estimate for the post LSAPs period being higher.

The estimates of γ_{pre} suggest that the higher the proportions of firms in an industry with relatively low levels of leverage (below median levels), 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. In addition, the estimates of γ_{post} suggest that the Fed's purchases may have also benefited firms with somewhat high debt levels conditional on not being over-leveraged (i.e. with leverage below the upper quartile), 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 and increase their leverage ratios.

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

5.2 Short-run effects of LSAPs and other drivers of firms' capital structure

Given the estimated 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 allow for possible over-shooting of the estimates whereby a large positive initial impact may be reversed subsequently with some negative lagged effects. For example, as seen in Section 4, the policy net short-run (SR) effect is defined by $\beta_1 = \sum_{\ell=0}^{p} \beta_{1,\ell}$, where $\beta_{1,\ell}$ is the coefficient of $q_{t-\ell} \times \pi_{s,t-\ell-1}(\hat{\gamma}_{post})$ in the threshold-panel regression defined by (10), with $p = 2$ for the PanARDL(2) model.

The first three columns of Table 2 show results for the single-threshold panel regression model across different choices of f_t, while the last three columns report the estimates for the two-threshold model, which is our preferred (more general) specification. Full panel regression estimation results are provided in Section D of the online supplement.

The estimates of policy SR effects are positive and highly statistically significant under all specifications while the magnitudes differ across them. We find that the higher the *ex ante* proportion of not over-leveraged firms 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. Nevertheless, even the largest estimate of the policy SR effect obtained for the two-threshold PanARDL(2) model at 0.0088 (0.0017) is rather small in economic importance.

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 the PanARDL(2) model described in equation (10). Net short-run effects are defined as the sum of the estimated coefficients of current and 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. Columns (1) and (4) include industry-specific linear time trends, columns (2) and (5) include the interaction of industry dummies and real GDP growth, while columns (3) and (6) include both. $LSAP$ is the (scaled) amount of U.S. Treasuries and agency MBS purchased by the Fed; $\pi_{-1}(\gamma)$ denotes the one-quarter lagged proportion of firms in an industry with DA below the γ-th quantile. 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)					
	$\gamma_{pre} = \gamma_{post} = \gamma$			$\gamma_{pre} \neq \gamma_{post}$		
	(1)	(2)	(3)	(4)	(5)	(6)
$\pi_{-1}(\hat{\gamma}_{pre})$	0.0156***	0.0101**	0.0167***	0.0186***	0.0123***	0.0194***
	(0.0049)	(0.0047)	(0.0054)	(0.0050)	(0.0046)	(0.0051)
$LSAP \times \pi_{-1}(\hat{\gamma}_{post})$	0.0068***	0.0035**	0.0041***	0.0088***	0.0060***	0.0077***
	(0.0019)	(0.0014)	(0.0015)	(0.0017)	(0.0017)	(0.0018)
Lagged DA	0.8386***	0.8408***	0.8386***	0.8386***	0.8409***	0.8387***
	(0.0050)	(0.0050)	(0.0050)	(0.0050)	(0.0050)	(0.0050)
Cash to assets	-0.0365***	-0.0368***	-0.0365***	-0.0364***	-0.0368***	-0.0364***
	(0.0030)	(0.0029)	(0.0030)	(0.0030)	(0.0029)	(0.0030)
PPE to assets	0.0219***	0.0208***	0.0218***	0.0220***	0.0207***	0.0219***
	(0.0047)	(0.0046)	(0.0047)	(0.0047)	(0.0046)	(0.0047)
Size	0.0034***	0.0037***	0.0034***	0.0034***	0.0037***	0.0034***
	(0.0008)	(0.0007)	(0.0008)	(0.0008)	(0.0007)	(0.0008)
Industry leverage	0.0626***	0.0519***	0.0645***	0.0710***	0.0548***	0.0688***
	(0.0075)	(0.0079)	(0.0092)	(0.0090)	(0.0080)	(0.0092)
Industry growth	-0.1004***	-0.1334***	-0.1053***	-0.1064***	-0.1366***	-0.1093***
	(0.0209)	(0.0206)	(0.0218)	(0.0210)	(0.0206)	(0.0219)
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Time effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry linear trends	Yes	No	Yes	Yes	No	Yes
Ind. dummy×RGDP	No	Yes	Yes	No	Yes	Yes
Observations	84548	84548	84548	84548	84548	84548
N	3647	3647	3647	3647	3647	3647
$max(T_i)$	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

The effects of the industry-specific debt capacity indicator, π_{st} (without the interaction with the LSAPs variable) on firms' leverage are also positive and statistically significant. This indicates that the proportion of firms without high debt burdens within an industry helps predicting firms' financing decisions. This is in line with the findings of Flannery and Rangan (2006) and Lemmon and Zender (2010), among others, who show that concerns over debt capacity influence firm financing behaviour.

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 one of the most important in magnitude. 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)).

Additional control variables. In addition to the variables included in our main model, we also estimate the panel regressions with additional firm-specific regressors (such as market to book ratio (MB), and research and development (R&D) expense scaled by total assets) and industry-specific controls, such as the industry median MB and Tobin's Q ratio. Together with industry growth, industry MB and Q ratio are used to control for differential growth opportunities across industries. To further reduce possible omitted bias concerns, we also include the industry medians of the firm-specific regressors contained in $\mathbf{x}_{is,t}$, which together with industry leverage and industry growth help to control for differences in industry conditions. On top of this, our regression always include fixed and time effects, as well as the interactions of ϕ_s with f_t. The results reported in Section D.4 of the online supplement, show that the estimates of the policy effectiveness coefficients and their statistical significance are not affected by the inclusion of these additional control variables.

On the choice of f_t. We have seen that our estimation results hold across the three choices of f_t, with the strongest estimation results obtained when simply allowing for firm leverage to follow different time trends across industries. Let $M1$, $M2$, and $M3$ denote the model for each choice of f_t, namely linear trends, real GDP growth, and both linear trends and GDP at the same time, respectively. To compare these three specifications, we test the joint significance of the associated industry coefficients, ϕ_s, using simple Chow-type tests. Focusing on the more general two-threshold specification, we obtain a F-test equal to 2.26 and 1.32 in

$M1$ and $M2$, respectively.[20] This means we are able to reject the null of $\phi_s = 0$ for all s at the 0.01 and 0.05 significance level, respectively. Thus, we find stronger statistical support for the case of simple linear trends. Finally, we test the joint significance of the ϕ_s in $M3$. Also in this case we are able to reject the null at the 0.05 significance level. When comparing $M3$ directly with $M1$ (which is a restricted version of $M3$), the F-test is equal to 1.13 which is below the 10% critical F-value, meaning we are not able to reject the null of all ϕ_s associated with real GDP growth being zero when the model also includes linear trends. Overall, we find that estimation results hold across the three models but with stronger statistical support when simply using (scaled) linear trends as a proxy for f_t, possibly because the model already includes fixed time effects. Similar reasoning apply to the single-threshold panel regressions.

5.3 Half-life, mean lag, and long-run effects of LSAPs

Another important question is whether the Fed's asset 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, we estimate the long-run effects of LSAPs on firms' leverage ratios to measure the magnitude of the total impact of such purchases.

Results are shown in panel A of Table 3 where as before, the first three columns report results for the single-threshold panel regression model while the last three columns display results for the two-threshold panel regression, for each choice of f_t. For brevity, we focus on the long-run effects of LSAPs, defined by equation (11), with $p = 2$ for the PanARDL(2) mode.[21] We find more economically meaningful effects of LSAPs on firms' capital structure in the long-run. Our results are in line with the findings of Ihrig et al. (2018) on the persistent effects of the Fed's asset purchases on yields, extending this evidence to firm leverage. We show 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.

Taking advantage of our empirical approach, we can also compute the mean lag of the effects of LSAPs, i.e. the average number of quarters it takes for firms' leverage to return to the long-run equilibrium. Another important measure of persistence is the half-life, which we define as the number of periods required for the peak response of firm debt to assets to LSAPs

[20]For a 0.05 level of significance, the critical F-value with 66 degrees of freedom in the numerator and more than 120 degrees of freedom in the denominator is equal to 1.3.

[21]In Section D.2 of the online supplement we also report the long-run effects of the other regressors.

to dissipate by one half.[22]

Table 3: **Half-life, mean lag, and long-run effects of LSAPs on debt to asset ratios of non-financial firms**

Panel A reports estimates of the long-run effects of LSAPs, defined in equation (11), on firms' debt to asset ratios (DA) for the PanARDL(2) model described in equation (10). $LSAP$ denotes the (scaled) amount of U.S. Treasuries and agency MBS purchased by the Fed; $\pi_{-1}(\gamma)$ denotes the one-quarter lagged proportion of firms in an industry with DA below the γ-th quantile. Panel B displays the estimated mean lag and half-life of LSAPs. 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. Columns (1) and (4) include industry-specific linear time trends, columns (2) and (5) include the interaction of industry dummies and real GDP growth, while columns (3) and (6) include both. Further information on the sample used can be found in Table 2. Robust standard errors (in parentheses) are computed using the delta method (*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$).

	$\gamma_{pre} = \gamma_{post} = \gamma$			$\gamma_{pre} \neq \gamma_{post}$		
	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A: Long-run effects of LSAPs					
$\pi_{-1}(\hat{\gamma}_{pre})$	0.0966***	0.0637**	0.1033***	0.1152***	0.0772***	0.1203***
	(0.0306)	(0.0300)	(0.0335)	(0.0316)	(0.0291)	(0.0321)
$LSAP \times \pi_{-1}(\hat{\gamma}_{post})$	0.0424***	0.0220**	0.0254***	0.0546***	0.0379***	0.0475***
	(0.0116)	(0.0087)	(0.0092)	(0.0108)	(0.0106)	(0.0112)
	Panel B: Mean lag and half-life of LSAPs					
Mean lag	6.1	5.6	5.6	6.0	5.7	5.8
Half-life	5.0	4.0	5.0	5.0	4.0	5.0
linear trends	Yes	No	Yes	Yes	No	Yes
RGDP growth	No	Yes	Yes	No	Yes	Yes

As shown in Panel B of Table 3, the mean lags vary between 5.6 and 6.1 quarters, while our estimates of half-life vary between 4 to 5 quarters depending on the model specification used. These results show that the effects of LSAPs do not dissipate immediately. It may take a few quarters for these effects to play out, supporting the view that the impact of LSAPs on firm leverage can be quite persistent. Our results align more closely with the findings of Swanson (2021) showing that the effects of LSAPs on yields tended to be very persistent as opposed to Wright (2012) who document that the effects of the Fed's unconventional monetary policy announcements on yields have a half-life of less than three months.[23]

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.

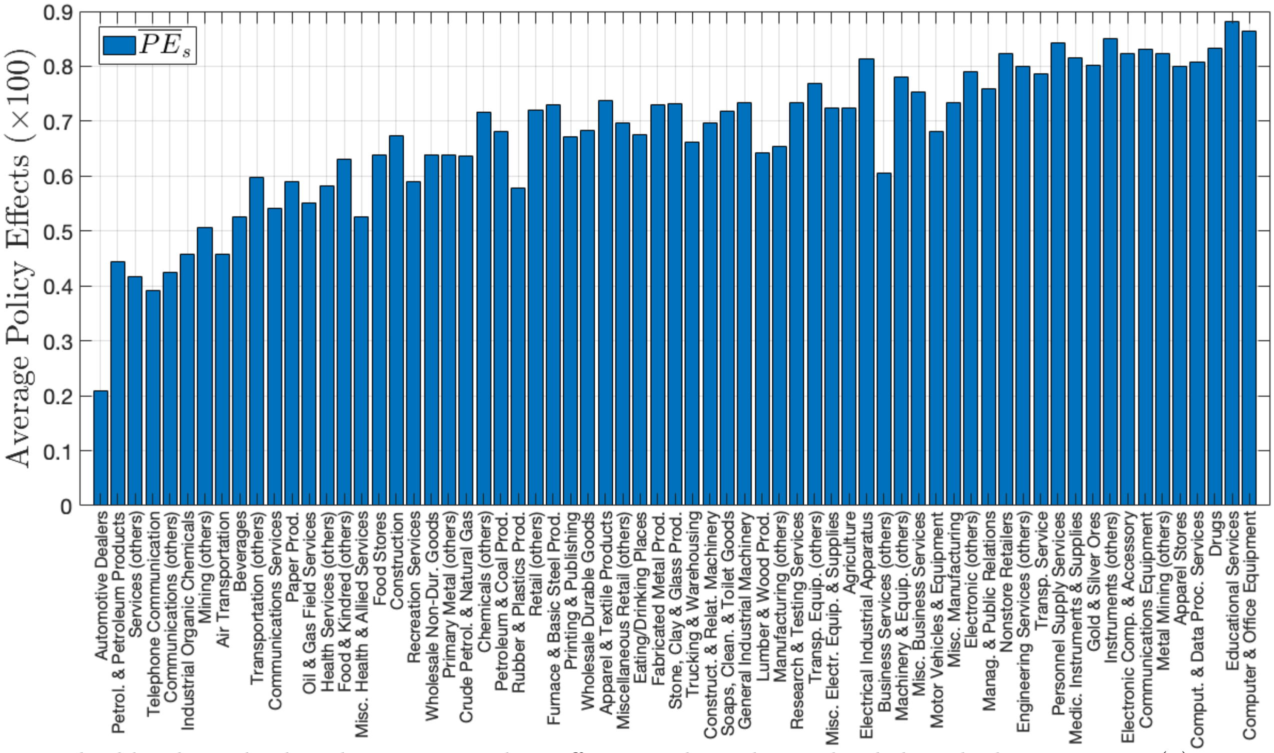
[22] See Section C of the online supplement for calculations of half-life and mean lag.

[23] It should be noted that event studies, by construction, tend to capture asset market reactions over only a short period (Bernanke (2020)).

5.4 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 (7) and (8), respectively. For brevity, we focus on the results for our preferred specification, namely the two-threshold PanARDL(2) model with f_t denoting industry linear trends. The estimates are displayed in Figure 1. The blue bars report the estimated APE by industry based on the interaction of our quantitative measure of LSAPs and lagged the leverage threshold variable (π). Three-digit SIC industries are sorted from largest to smallest industry median leverage (averaged over time).

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 (7), based on the interaction of our quantitative measure of LSAPs and one-quarter lagged values of $\pi(\hat{\gamma}_{post})$. The x-axis reports the three-digit SIC industries 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, driven by cross-industry variation in the proportions of firms without high debt burdens ($\pi(\hat{\gamma}_{post})$). 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 0.0088 for educational services' industry, one of the least leveraged industry in our sample. As another example, we note that airlines which typically rely more on debt financing than software companies (see Baker (2009)) also tended to benefit less 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.[24] The estimated APE at the national level is equal to 0.0065 and 0.0066 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 highlight the rather small magnitude of the LSAPs' effects despite the statistical significance of the underlying estimates.

5.5 Robustness of the results to small–T bias

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 D.6 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.

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). Therefore, as a second robustness check, we examine the extent to which our estimation results hold after correcting for the small–T bias by applying

[24]To compute the employment shares we use annual data at the firm-level from the Compustat annual database. See Section D.3 of the online supplement for more details on the weights used.

the half-panel jackknife method also proposed by CPY.[25] 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.[26]

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.[27]

The first notable implication of this new estimation strategy is the larger estimates obtained for the coefficients of the lagged dependent variables, 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 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.

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 the SR for the two-threshold PanARDL(2) model vary between 0.0061 and 0.0080 depending on the choice of f_t, in line with standard FE-TE estimates shown in column (4) to (6) of Table 2. 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 for the two-threshold PanARDL(2) model are estimated to vary between 0.0379 and 0.0546 across the various specifications considered (as shown in Table 3). By comparison, the jackknife estimates vary between 0.1224 and 0.1584, depending on the choice of f_t.

[25]See Section D.6 of the online supplement for more details.

[26]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.

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

6 Heterogeneous effects of various Fed's asset purchase programs

6.1 Short- and long-run effects across LSAP programs

In the previous section, we have quantified the overall effects of the Fed's total Treasuries and MBS purchases on firm leverage. We now consider the effects of each asset class purchases separately. Thus, our regression model now includes two distinct quantitative measures of LSAPs interacted with our one-quarter lagged industry debt capacity indicator. These two policy measures are defined as follows:

$$ty_t = \frac{TY_t}{\frac{1}{T-T_0}\sum_{\tau=T_0+1}^{T} Q_\tau}, \qquad mbs_t = \frac{MBS_t}{\frac{1}{T-T_0}\sum_{\tau=T_0+1}^{T} Q_\tau}, \tag{12}$$

where $Q_t = MBS_t + TY_t$, with TY and MBS denoting the gross amount of U.S. Treasuries and agency MBS purchased by the Fed, respectively.

For brevity, we focus on the more general two-threshold PanARDL(2) specification which includes both fixed and time effects while allowing industries to follow different time-trends.[28] We re-estimate the quantile threshold parameters associated with the debt capacity indicator, $\pi_{st}(\gamma)$, by grid search obtaining the same results to those described in Table 1, namely $\hat{\gamma}_{pre}$ is equal to 0.56 while $\hat{\gamma}_{post}$ is equal to 0.77.

Estimation results are provided in Panel A of Table 4 where we report both the net short-run (SR) and long-run (LR) effects of both MBS and Treasury purchases. We find that both type of purchases facilitated firm credit access. MBS purchases have a slightly higher impact on firm debt to assets relative to Treasuries purchases, which in turn results into marginally stronger long-run effects. The estimated coefficients associated with MBS purchases have also a higher degree of statistical significance. These results seem in line with the argument of Krishnamurthy and Vissing-Jorgensen (2013) that MBS purchases tended to be more beneficial for the economy than Treasury purchases.

A slightly different picture emerges when using the firm-specific debt capacity indicator, $d_{is,t}(\gamma)$. As shown in Section G of the online supplement, both Treasury and MBS purchases have significant impacts on firm leverage but the effects are now stronger for Treasuries.[29] Taken together, these results suggest that both MBS and Treasury purchases can facilitate firms' access to credit, although the magnitude of the effects is rather small.

Our estimates, whether based on industry-average or firm-specific measures of debt capacity, provide strong empirical evidence in support of the hypothesis that non-financial firms

[28] Additional results are provided in Section E of the online supplement.

[29] The identification strategy based on $d_{is,t}(\gamma)$ exploits cross-firm variation within an industry, implying that firms which are not over-leveraged should benefit more from LSAPs relative to peers in the same industry. However, estimation based on $\pi_{st}(\gamma)$ exploits cross-industry variation, suggesting that firms in less leveraged industries should benefit more, thus allowing for spillover effects within an industry. This may explain some of the differences in the estimation results based on the two approaches.

with spare debt capacity benefited from MBS purchases. This finding is in line with the results obtained by Rodnyansky and Darmouni (2017) and corroborates the evidence of Gagnon et al. (2011) which suggest that LSAPs had wide ranging effects on borrowing costs not limited exclusively to the type of asset being purchased by the Fed.[30] Because our identification strategy does not confine the effects of LSAPs to firm-bank relationships, we do not find a "crowding out" effect as in Chakraborty et al. (2020), and instead document that MBS purchases had positive effects on firm leverage.[31]

Table 4: **FE–TE estimates of the net short-run (SR) and long-run (LR) effects of various LSAPs on debt to asset ratios of non-financial firms**

Estimates of the net short-run (SR) and long-run (LR) effects, defined in Section 4, of various Fed's asset purchase programs on firms' debt to asset ratios (DA) for the two-threshold PanARDL(2) model described in equation (10). Panel A focuses on two quantitative measure of LSAPs, whereby ty and mbs denote the (scaled) amount of U.S. Treasuries and agency MBS purchased by the Fed, respectively. Panel B displays results for the qualitative measures of LSAPs, a set of dummy variables which take the value of one during policy on periods and zero otherwise. $\pi_{-1}(\gamma)$ denotes the one-quarter lagged proportion of firms in an industry with DA below the γ-th quantile. All regressions include both firm-specific effects and time effects as well as industry-specific linear time trends. Further information on the sample used can be found in Table 2. Robust standard errors (in parentheses) are computed using the delta method (*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$).

Panel A: Treasuries versus MBS purchases

	SR	LR
$\pi_{-1}(\hat{\gamma}_{pre})$	0.0188***	0.1166***
	(0.0050)	(0.0317)
$ty \times \pi_{-1}(\hat{\gamma}_{post})$	0.0078**	0.0482**
	(0.0031)	(0.0191)
$mbs \times \pi_{-1}(\hat{\gamma}_{post})$	0.0092***	0.0569***
	(0.0021)	(0.0134)

Panel B: Major QE programs

	SR	LR
$\pi_{-1}(\hat{\gamma}_{pre})$	0.0199***	0.1233***
	(0.0051)	(0.0321)
$QE_1 \times \pi_{-1}(\hat{\gamma}_{post})$	0.0189***	0.1169***
	(0.0044)	(0.0278)
$QE_2 \times \pi_{-1}(\hat{\gamma}_{post})$	0.0114**	0.0705**
	(0.0053)	(0.0332)
$MEP \times \pi_{-1}(\hat{\gamma}_{post})$	0.0019	0.0120
	(0.0038)	(0.0234)
$QE_3 \times \pi_{-1}(\hat{\gamma}_{post})$	0.0069**	0.0426**
	(0.0033)	(0.0204)

[30] There is not a consensus on this in the literature. For example, Krishnamurthy and Vissing-Jorgensen (2013) emphasize the so called narrow channel, whereby asset purchases have a stronger impact on the yields of the asset being purchased. At the same time, it is widely accepted that asset purchases may have broader effects on financial markets (beyond those on the asset being purchased) through the reduction of investors' expectations on the path of the federal funds rate (e.g., Woodford (2012)), and by easing financial conditions. Our empirical findings demonstrate that these financial market impacts have translated into greater reliance on external financing for non-financial firms.

[31] According to the "crowding out" behaviour documented by Chakraborty et al. (2020), following the Fed's MBS purchases, banks increased their mortgage origination at the expense of commercial and industrial lending.

It is also interesting to compare the effects of each Fed's program separately by replacing the two aforementioned quantitative measures of LSAPs with four qualitative variables which take the value of one during policy on periods and zero otherwise. Following the literature, we label these policy indicators as QE1 (covering the period 2008Q4 to 2010Q1), QE2 (2010Q4 - 2011Q2), MEP (the maturity extension program of 2011Q3 - 2012Q4), and QE3 (2012Q3 - 2014Q4).[32] Also in this case, we re-estimate the quantile threshold parameters by grid search obtaining results in line with previous findings, namely $\hat{\gamma}_{pre}$ is equal to 0.56, while $\hat{\gamma}_{post}$ is equal to 0.73.[33]

Estimation results for the $(0,1)$ policy indicators are shown in Panel B of Table 4, where we report both the SR and LR effects of each LSAP episode. Our results show some degree of variation in the effectiveness of the four Fed's programs covered in our sample. In particular, QE1 had the largest impact of firm debt to assets. This result is consistent with previous findings in the literature where QE1 is typically found to have the largest impact on MBS and Treasury yields, as well as corporate bond yields (e.g., Kuttner (2018)). Our results also corroborate the view that LSAPs can be particularly effective during periods of dysfunctions in financial markets (e.g., D'Amico and King (2013)).

In line with the arguments of Bernanke (2020), we also find that LSAPs can also be effective outside periods of market stress. In particular, we find that both QE2 and QE3 had statistically significant effects on firm leverage albeit smaller in magnitude than QE1. Instead, the effects of MEP are much lower in magnitude and not statically significant.[34]

6.2 Half-life and mean lag lengths of different Fed's QE programs

We now discuss the time profile of the effects of the various Fed's asset purchase programs separately. In particular, we report the mean lags and half-life of the effects of each program in Table 5. The first two columns focus on our quantitative measures. We find that Treasuries and MBS purchases have the same mean lag length of 4 quarters although the half-life of MBS purchases is higher. In particular, the effects of Treasury purchase dissipate by one half (from peak) after four quarters as opposed to six quarters for MBS purchases, while the average number of periods after which the effects of both purchases dissipate is about six quarters. These results further corroborate the hypothesis that the effects of LSAPs do not die out immediately but are instead quite persistent, in line with the arguments of Bernanke (2020).

[32] Additional information on these four large-scale asset purchase programs can be found in Section A.1 of the online supplement.

[33] Here, we focus on the two-threshold PanARDL(2) specification allowing industries to follow different time-trends. Additional results are provided in Section F of the online supplement.

[34] Differences across the QE1, QE2, and QE3 are less pronounced when employing the firm-specific debt capacity indicator. MEP continues to have the lowest impact, and is generally non significant at the 5 per cent level.

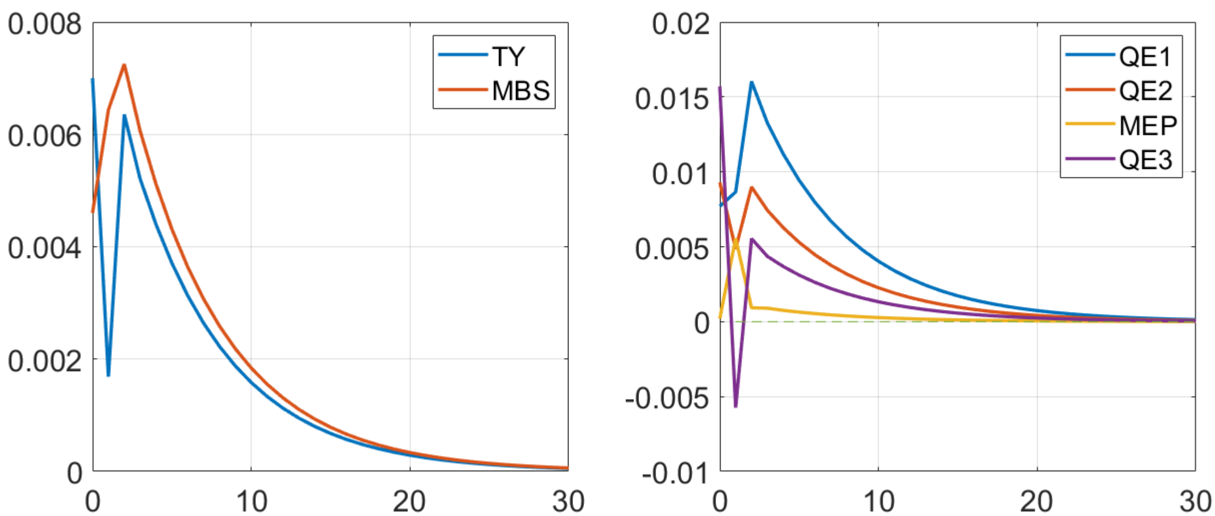
Table 5: **Half-life and mean lag of various LSAP programs**

Estimates of mean-lag and half-life for the policy effectiveness coefficient, β_1, associated with the interaction of our measures of LSAPs and $\pi_{-1}(\gamma)$, the one-quarter lagged proportion of firms in an industry with debt to assets below the γ-th quantile. Estimates are based on two-threshold PanARDL(2) model described in equation (10), which includes both fixed and time effects as well as industry-specific linear trends.

	ty	mbs	QE_1	QE_2	MEP	QE_3
Mean lag	6.1	6.1	6.4	6.0	4.5	5.5
Half-life	4.0	6.0	4.0	5.0	0.0	0.0

Turning on each individual LSAP episode, using the four qualitative policy indicators, we find that the mean lag lengths are higher for the first two programs, with the magnitude being in line with those obtained under the quantitative measures.

Figure 2: **Distributed effects of LSAPs on non-financial firms' debt to asset ratios**



Plots of the distributed effects of LSAPs on firm debt to asset ratios. The left-hand side panel displays results for the quantitative measure of LSAPs described in (12), namely ty and mbs, denoting the scaled gross amount of U.S. Treasuries and agency MBS purchased by the Fed, respectively. The right-hand side panel shows results for the four qualitative policy indicators. The distributed effects are computed after rewriting the two-threshold ARDL(2) model described in equation (10) in its distributed lag form.

One notable difference emerges in the estimated half-lives. In particular, the half-lives of both MEP and QE3 are zero, meaning that their effects on firm leverage decrease by more than half immediately after having reached their peak. This can be clearly seen in Figure 2, where we plot the lag distribution of the effects of each LSAP program on firm debt to asset ratios, computed after re-writing the PanARDL(2) model in its distributed lag form.[35] While the initial impact is closer to zero, the effects of MEP reach its peak the subsequent quarter

[35]Details on the derivation of the distributed lag form, and the computation of mean lag and half-life are provided in Section C of the online supplement.

to then fall close to zero immediately after. QE3 has a substantial immediate impact on firm leverage which is partly offset the next quarter.

6.3 Robustness of the results to small–T bias

Results continue to hold after correcting for potential small-sample bias.[36] In particular, the effects of our quantitative measure of MBS purchases are similar when only including firms with at least 8 or 10 time series observations. The magnitude of the impact of MBS purchases increases to 0.0107 (0.0025) when applying the half-panel jackknife method, resulting in a much more meaningful long-term impact (0.2124 (0.0580)). Turning to Treasury purchases, their effects continue to hold when selecting firms with at least 8 or 10 observations but they become insignificant when implementing the jackknife bias correction.

Regarding the four qualitative measures of LSAPs, we note that the findings on QE1 continue to hold even after applying the aforementioned small-T bias corrections. Results are less clear-cut for QE2 and QE3. The effects of QE3 remain statistically significant when applying the half-panel jackknife method but the same cannot be said for QE2. The effects of MEP remain statistically insignificant.

7 Concluding remarks

We estimate panel ARDL 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 variations, within and across industries, in the ability of firms to raise additional external funds without exhausting their debt capacity. To this end, we construct firm- and industry-specific measures of spare debt capacity, which we then interact with our measures of LSAPs.

The industry-specific measure of debt capacity is defined as the proportion of firms in an industry with debt to assets below a given threshold, and has the merit of taking into account interdependencies in financing decisions across firms within each industry. We treat the threshold quantile 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 $77th$ 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.

[36] See Section E.3 and F.3 of the online supplement for more details on the estimation results for the quantitative and qualitative measures of LSAPs, respectively.

When separating the effects of MBS from Treasury purchases, we find that both programs facilitated firm credit access and that their effects do not dissipate immediately. We also examine the effects of the first four episodes of LSAPs separately, to find that the first round of purchases (QE1) had the largest positive impact on firms' external financing. At the same time, our results show that LSAPs can be also effective outside periods of market stress.

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, extending the existing findings on the persistence of the effects of LSAPs on interest rates to firm leverage. 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 raise new debt "safely". 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 six 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, while Section C describes the concept of half-life and mean lag, and their calculations.

Section D reports the estimation results for the threshold panel autoregressive distributed lag, PanARDL(2), specifications where the macro policy intervention variable, q_t, is the scaled gross amount of U.S. Treasuries and mortgage-backed securities (MBS) purchased by the Fed. We also report several robustness exercises. Subsection D.4 presents the estimates of the policy effectiveness coefficients when including several additional control variables to the main regressions. Subsection D.5 shows estimation results using a number of alternative macro-variables interacted with industry-specific dummies. Subsection D.6 shows estimation results after correcting for potential small-sample bias. In Subsection D.7 we also report results for the standard partial adjustment model and the PanARDL(1) specification.

In Section E, we show estimation results when separating the effects of MBS from Treasury purchases. In Section F, we compare the effects of each Fed's asset purchase program by replacing the two aforementioned quantitative measures of LSAPs with four qualitative variables which take the value of one during policy on periods and zero otherwise.

In Section G, we report results using a firm-specific measure of debt capacity.

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. 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 the main 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
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	

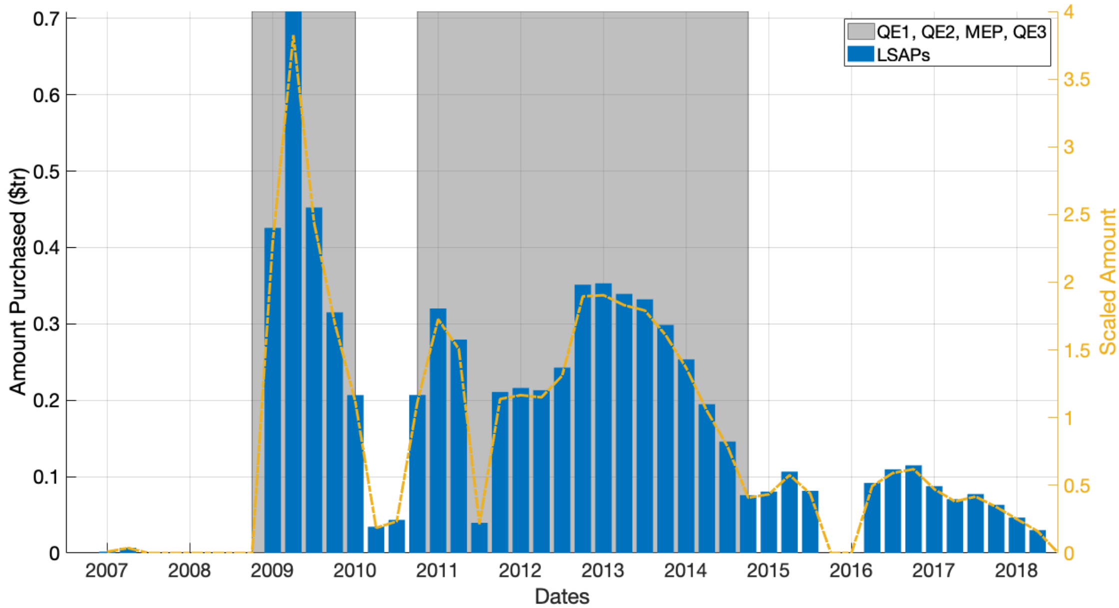
Large-scale asset purchases (LSAPs). In our empirical analysis, our preferred measure of LSAPs is the total gross amount of U.S. Treasuries and agency mortgage-backed securities (MBS) purchased by the Fed. To construct this quantitative measure, we obtain data from the New York Fed's website. U.S. Treasuries' purchases include notes, bonds, and to a much smaller extent Treasury Inflation-Protected Securities (TIPS). We also report results using qualitative measures of LSAPs. In this case, our policy variable is a set of dummy variables equal to one during policy on periods and zero otherwise. To construct these variables 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. MBS 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. Principal payments from agency debt and MBS were also reinvested.
QE3	Sep 2012	Oct 2014	The Fed purchased \$40bn in agency MBS 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. In total, the Fed purchased \$790bn in Treasury securities and \$823bn in agency MBS.

To make our quantitative measure of LSAPs directly comparable to the qualitative (dummy) policy variables, 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 LSAPs are depicted in Figure 3.

Figure 3: **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.

Macroeconomic indicators. In addition, to linear trends we also 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.

- *World real GDP growth* is the annualized log difference of (seasonally adjusted) world real GDP obtained from the World Bank.

- *Unemployment rate* is the U.S (seasonally adjusted) unemployment rate in percent, obtained from the Federal Reserve Bank of St. Louis (FRED). Quarterly data are obtained by averaging monthly observations within a quarter.

- *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.

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 (PanARDL) models.

We exclude firms with total debt to TA greater than one, and exclude firms with negative total debt. 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 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

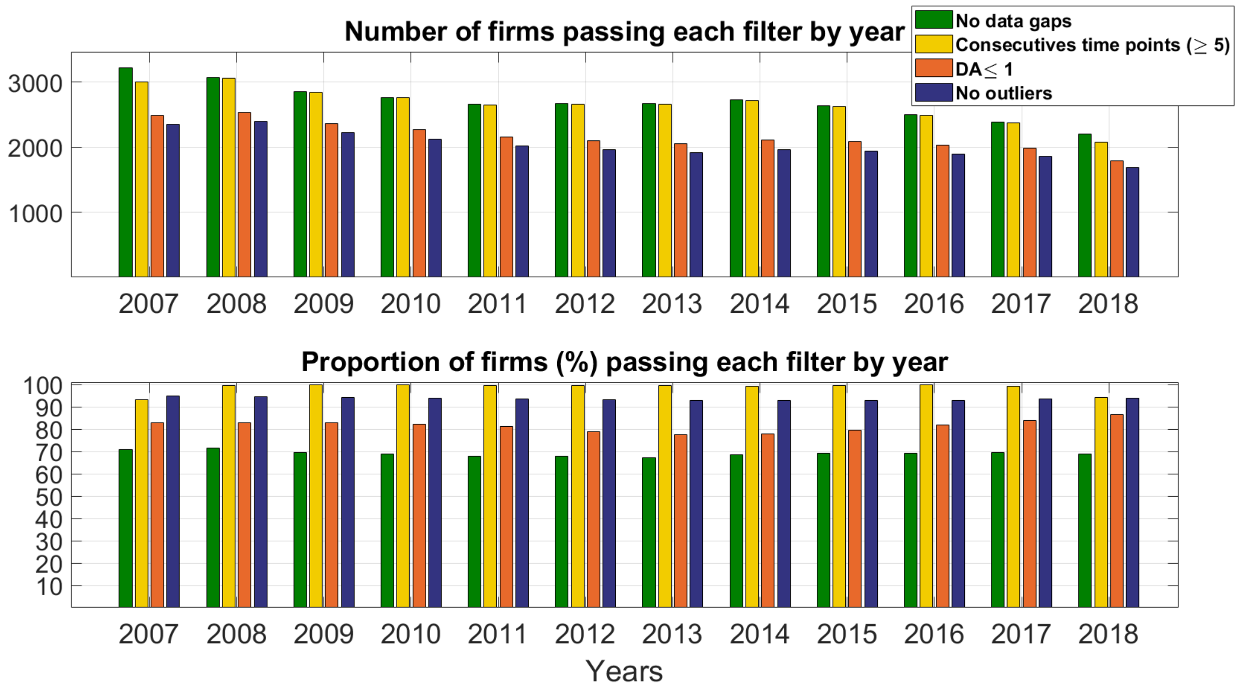
Table A.4: **Number of firms dropped while removing outliers**

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 4 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 4: **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 (≥ 5 time points), and the percentage of firms that pass the third filter (debt to asset (DA) ratios less or equal to 1), respectively. Column *% Pass F4* shows the percentage of selected firms with no outliers. 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 (≥ 5)**	**DA ≤ 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.[37] 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. Table A.8 reports the frequency of firms by number of consecutive data points (based on the filtered sample).

[37]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 ≥ 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. 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			

Table A.10: (cont.)

n.	3-dig SIC	3-dig SIC description	# (3-dig)	2-dig SIC	2-dig SIC description	# (2-dig)
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	381; 382; 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
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.

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

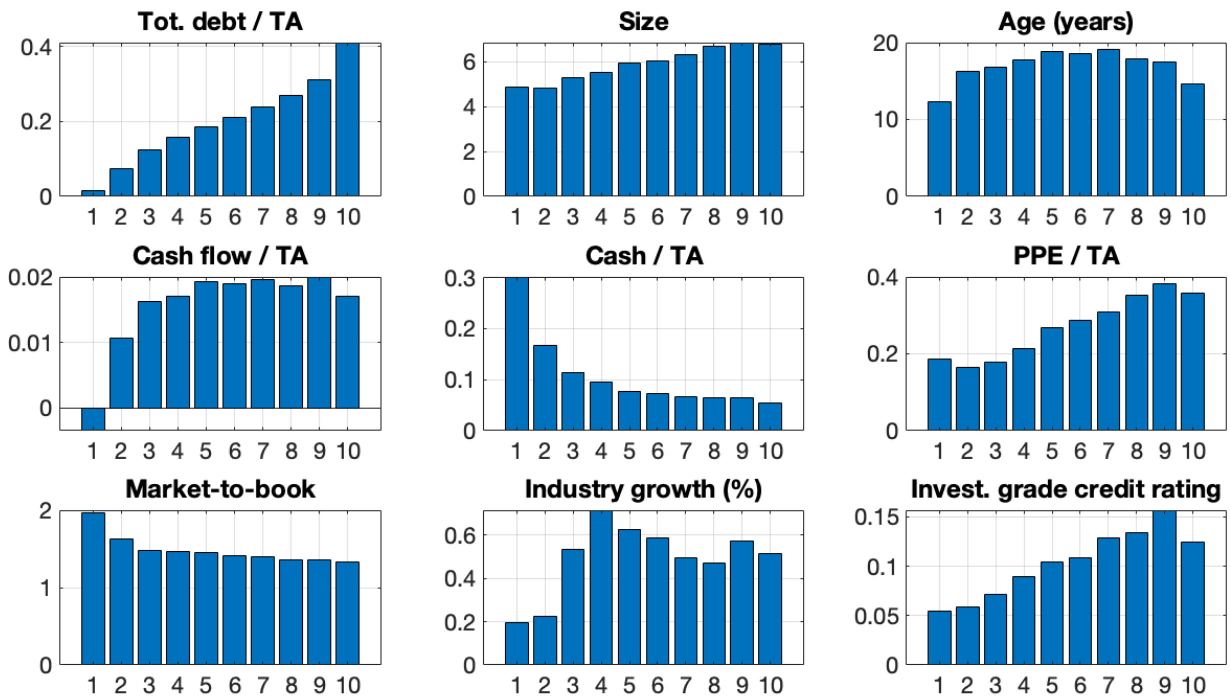
	Cash to assets quintile				
	1	2	3	4	5
Tot. debt to TA	0.29	0.24	0.20	0.18	0.08
Size (log of TA)	6.69	6.30	5.89	5.62	5.04
Age (years)	17.30	17.93	17.95	17.14	14.43
Cash flow to TA	0.02	0.02	0.02	0.02	0.01
Cash to TA	0.03	0.06	0.08	0.11	0.26
PPE to TA	0.38	0.31	0.26	0.23	0.16
Market to book	1.32	1.41	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

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 5 which shows the average of several industry-quarter observations, sorted into deciles from lowest to highest industry median leverage.

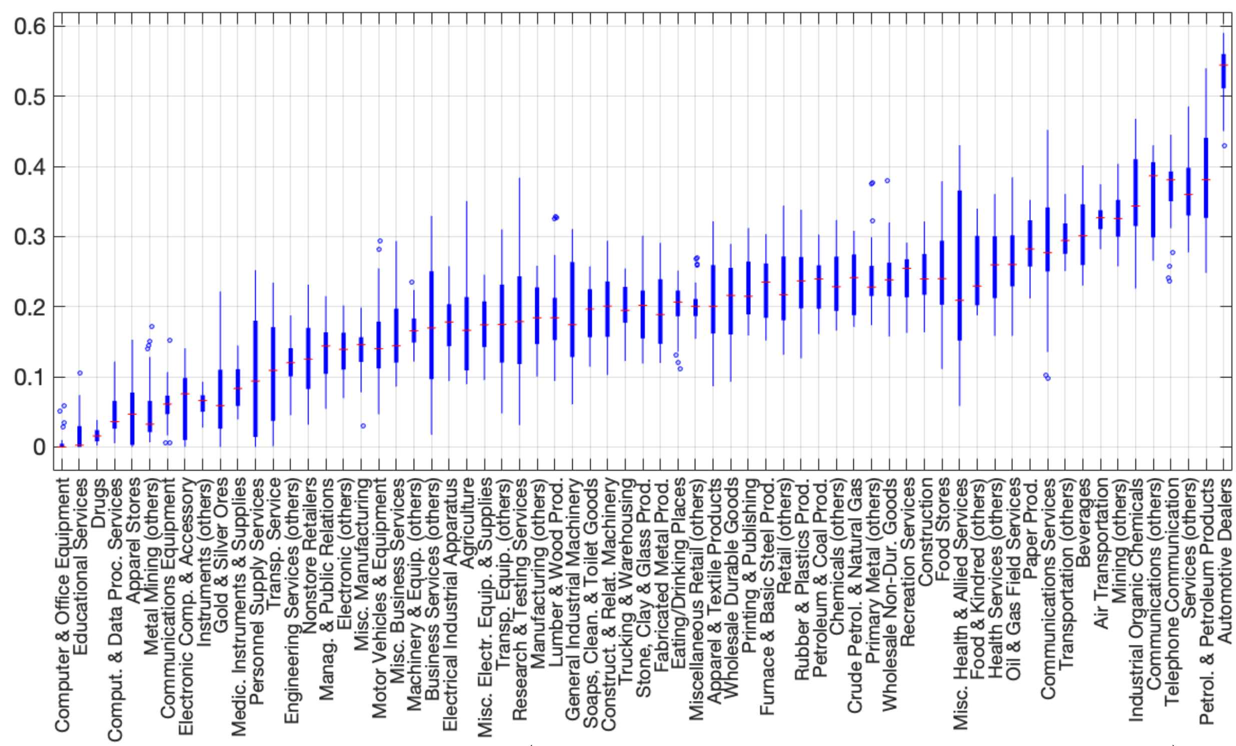
Figure 5: **Industry characteristics across debt to assets deciles**



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.

Figure 6 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 6: **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).

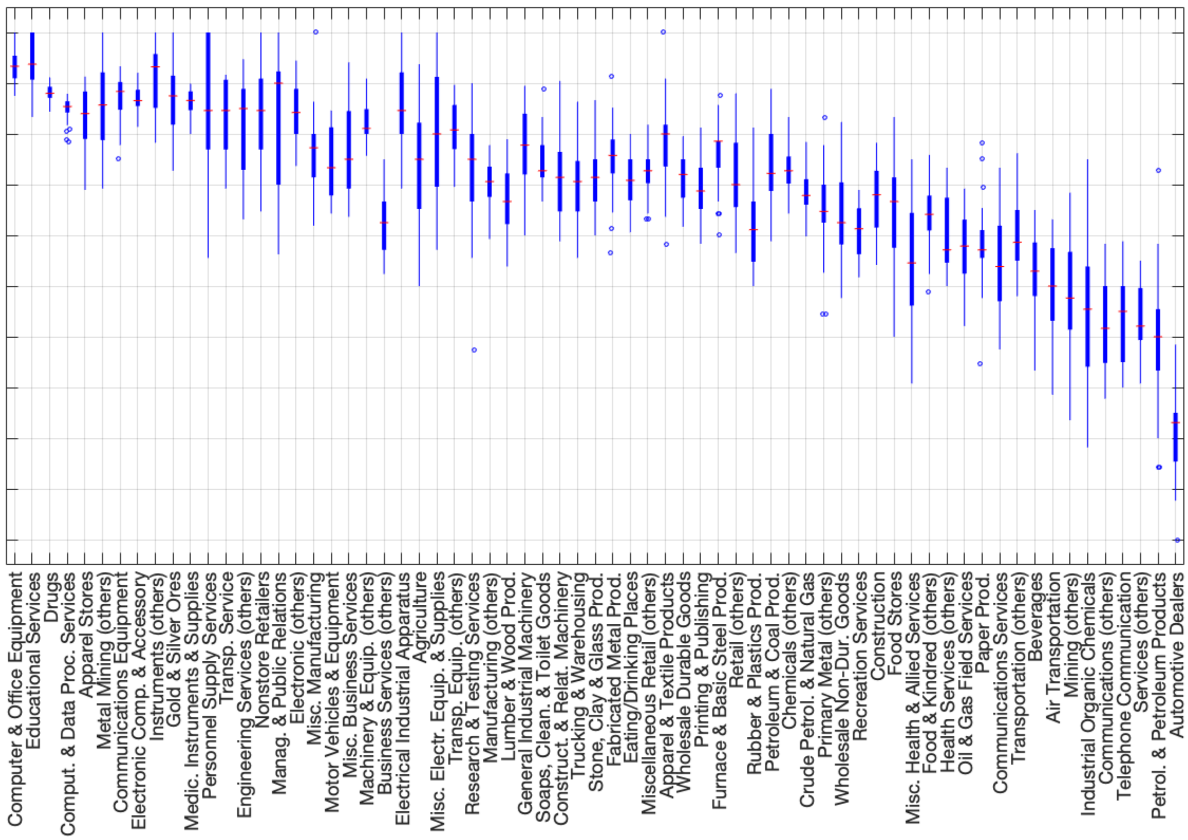
B Identification strategy and estimation

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 Cross-industry variation to identify the policy effects

As discussed in the paper, identification of the policy effectiveness coefficient, β_1, in equation (6), requires a sufficient degree of variations in q_t over time and $\pi_{st}(\gamma)$, defined in equation (2), across industries. We graphically demonstrate that there is a high degree of variation in $\pi_{st}(\gamma)$ across industries. To this end, in Figure 7, we report the box plots for $\pi_{st}(75)$, the proportions of firms with debt to asset ratios (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: **Proportion of firms with debt to asset ratios below the upper quartile by industry**



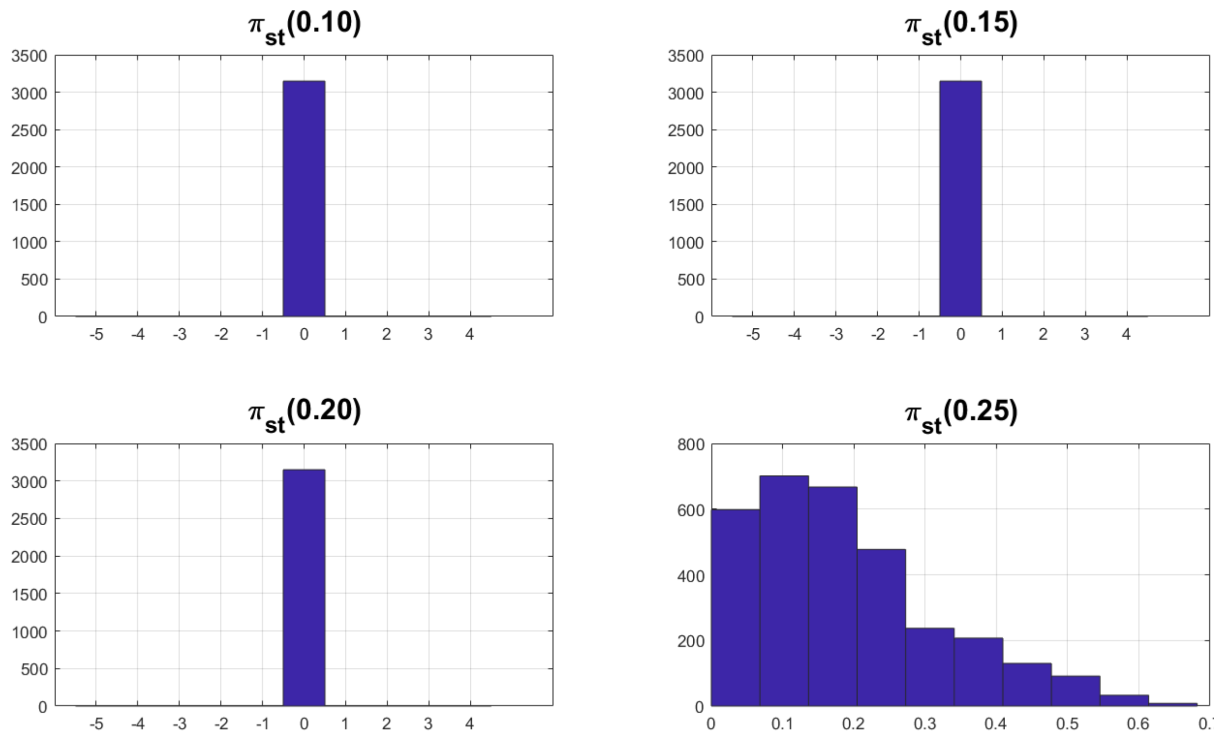
Box plots for the proportion of firms in each industry with debt to asset ratios (DA) below the upper quartile ($\pi_{st}(75)$). On each box, the central mark indicates the median, and the bottom and top edges of the (dark blue) box display the 25th and 75th percentiles, respectively. The x-axis reports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

B.2 Quantile threshold parameter estimates

As discussed in the paper, the grid search procedure used to estimate γ consists in selecting many values of γ 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 γ**



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.

C Computing half-life and mean lag length

In this section, we discuss how to compute the mean lag of a PanARDL(p), and other related measures. For clarity of exposition, and without loss of generality, we rewrite the panel regression model given by equation (10) in the main body of the paper, abstracting from all regressors but the interaction of LSAPs with our industry-specific measure of debt capacity, $\chi_{st} = \chi_{st}(\gamma_{post}) = q_t \times \pi_{s,t-1}(\gamma_{post})$. Hence, focusing solely on the policy coefficients of interest, the PanARDL(p) model is given by

$$\lambda(L) y_{is,t} = B(L)\chi_{st} + u_{is,t}, \tag{C.1}$$

where $\lambda(L) = 1 - \lambda_1 L - ... - \lambda_p L^p$ and $B(L) = \beta_0 + \beta_1 L - ... + \beta_p L^p$.

Multiplying both sides of (C.1) by $\lambda(L)^{-1}$, we get

$$y_{is,t} = C(L)\chi_{st} + \lambda(L)^{-1} u_{is,t}, \tag{C.2}$$

where $C(L) = \lambda(L)^{-1} B(L) = \sum_{h=0}^{\infty} \varphi_h L^h$.

The φ_h $(h = 0, 1, 2, ...)$ can be obtained by noting that

$$\left(1 - \lambda_1 L - ... - \lambda_p L^p\right)\left(\varphi_0 + \varphi_1 L + \varphi_2 L^2 + ...\right) = \beta_0 + \beta_1 L - ... + \beta_p L^p, \tag{C.3}$$

where the left-hand side can be rewritten as

$$\varphi_0 + (\varphi_1 - \varphi_0\lambda_1)\, L + (\varphi_2 - \varphi_1\lambda_1 - \varphi_0\lambda_2)\, L^2 + ... + \left(\varphi_h - \sum_{j=1}^{h} \varphi_{h-j}\lambda_j\right) L^h + ...$$

Thus, from (C.3) we have

$$\varphi_h = \beta_h + \textstyle\sum_{j=1}^{h} \lambda_j \varphi_{h-j}, \qquad h = 1, 2, ... \ , \tag{C.4}$$

where $\varphi_0 = \beta_0$, $\lambda_j = 0$ for $j > p$, and $\beta_h = 0$ for $h > p$.

Scalar lag distribution of χ. The scalar lag distribution of χ is given by

$$\frac{C(L)}{C(1)} = \frac{\sum_{i=0}^{\infty} \varphi_h L^h}{\sum_{h=0}^{\infty} \varphi_h} = \sum_{h=0}^{\infty} \rho_h L^h,$$

where

$$\rho_h = \frac{\varphi_h}{\sum_{h=0}^{\infty} \varphi_h}. \tag{C.5}$$

By construction $\sum_{h=0}^{\infty} \rho_h = 1$.

Mean lag and half-life. The mean lag between χ and y is given by

$$W'(1) = \frac{C'(1)}{C(1)} = \frac{\sum_{h=0}^{\infty} h\varphi_h}{\sum_{h=0}^{\infty} \varphi_h} = \sum_{h=0}^{\infty} h\rho_h. \tag{C.6}$$

In the case of the PanARDL(2):

$$W'(1) = \frac{\beta_1 + 2\beta_2}{\beta_0 + \beta_1 + \beta_2} + \frac{\lambda_1 + 2\lambda_2}{1 - \lambda_1 - \lambda_2}. \tag{C.7}$$

The half-life is defined as the number of periods required for the peak response of y to χ to dissipate by one half. In other words, it is the value of h such that

$$sup\,(\varphi_h) \geq \frac{\varphi_{max}}{2}, \tag{C.8}$$

where φ_{max} denotes the peak response.

D Estimation results for the main specification where q_t denotes the total size of LSAPs

In this section, we report estimation results for the threshold PanARDL(2) specification. We also provide additional details on the industry-specific weights used to compute the policy effects at the national level. We also show that our empirical results are robust to a number alternative choices.

D.1 Full estimation results

This subsection reports additional estimation results for the panel regression model given by equation (10) in the paper.

Table D.13: **FE–TE estimates of the effects of LSAPs on non-financial firm's debt to asset ratios based on the PanARDL(2) model**

Estimates of the coefficients of the PanARDL(2) model described in equation (10). The dependent variable is debt to asset ratio (DA). q_t is the (scaled) amount of U.S. Treasuries and agency MBS purchased by the Fed; $\pi_{s,t}(\hat{\gamma})$ denotes the proportion of firms in an industry with DA below the $\hat{\gamma}$-th quantile. 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. Columns (1) and (4) include industry-specific linear time trends, columns (2) and (5) include the interaction of industry dummies and real GDP growth, while columns (3) and (6) include both. 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)	(6)
$\pi_{s,t-1}(\hat{\gamma}_{pre})$	0.0125**	0.0124**	0.0158* **	0.0176***	0.0144***	0.0181***
	(0.0052)	(0.0052)	(0.0053)	(0.0050)	(0.0049)	(0.0051)
$q_t \times \pi_{s,t-1}(\hat{\gamma}_{post})$	0.0037*	0.0028*	0.0031*	0.0058***	0.0054***	0.0062***
	(0.0021)	(0.0016)	(0.0016)	(0.0020)	(0.0020)	(0.0020)
$\pi_{s,t-2}(\hat{\gamma}_{pre})$	-0.0021	-0.0114**	-0.0095*	-0.0086	-0.0106*	-0.0088
	(0.0061)	(0.0058)	(0.0058)	(0.0055)	(0.0055)	(0.0055)
$q_{t-1} \times \pi_{s,t-2}(\hat{\gamma}_{post})$	0.0012	0.0009	0.0007	0.0001	-0.0002	-0.0002
	(0.0026)	(0.0020)	(0.0020)	(0.0025)	(0.0025)	(0.0025)
$\pi_{s,t-3}(\hat{\gamma}_{pre})$	0.0052	0.0091**	0.0104**	0.0096**	0.0086**	0.0100**
	(0.0050)	(0.0045)	(0.0046)	(0.0043)	(0.0043)	(0.0044)
$q_{t-2} \times \pi_{s,t-3}(\hat{\gamma}_{post})$	0.0019	-0.0001	0.0002	0.003	0.0008	0.0017
	(0.0021)	(0.0017)	(0.0017)	(0.0019)	(0.0020)	(0.0020)
DA_{t-1}	0.8123***	0.8136***	0.8121***	0.8125***	0.8138***	0.8122***
	(0.0091)	(0.0091)	(0.0091)	(0.0091)	(0.0091)	(0.0091)
DA_{t-2}	0.0263***	0.0271***	0.0264***	0.0261***	0.0271***	0.0265***
	(0.0077)	(0.0077)	(0.0077)	(0.0077)	(0.0077)	(0.0077)
$(Cash/A)_t$	-0.0930***	-0.0932***	-0.0929***	-0.0929***	-0.0933***	-0.0929***
	(0.0078)	(0.0078)	(0.0078)	(0.0078)	(0.0078)	(0.0078)
$(Cash/A)_{t-1}$	0.0532***	0.0530***	0.0529***	0.0531***	0.0530***	0.0529***
	(0.0080)	(0.0081)	(0.0080)	(0.0080)	(0.0081)	(0.0080)
$(Cash/A)_{t-2}$	0.0034	0.0034	0.0035	0.0034	0.0035	0.0035
	(0.0044)	(0.0044)	(0.0044)	(0.0044)	(0.0044)	(0.0044)
$(PPE/A)_t$	0.0640***	0.0645***	0.0648* **	0.0640***	0.0644***	0.0647***
	(0.0168)	(0.0169)	(0.0168)	(0.0168)	(0.0169)	(0.0168)
$(PPE/A)_{t-1}$	-0.0336*	-0.0344*	-0.0342*	-0.0336*	-0.0345*	-0.0343*
	(0.0180)	(0.0180)	(0.0180)	(0.0180)	(0.0180)	(0.0180)
$(PPE/A)_{t-2}$	-0.0085	-0.0092	-0.0087	-0.0084	-0.0092	-0.0086
	(0.0088)	(0.0088)	(0.0088)	(0.0088)	(0.0088)	(0.0088)

Continued on next page.

Table D.13: (cont.)

	Dependent variable: debt to assets (DA_t)					
	$\gamma_{pre} = \gamma_{post} = \gamma$			$\gamma_{pre} \neq \gamma_{post}$		
	(1)	(2)	(3)	(4)	(5)	(6)
$Size_t$	0.0287***	0.0290***	0.0287***	0.0287***	0.0290***	0.0287***
	(0.0038)	(0.0038)	(0.0038)	(0.0038)	(0.0038)	(0.0038)
$Size_{t-1}$	-0.0298***	-0.0298***	-0.0298***	-0.0298***	-0.0298***	-0.0298***
	(0.0040)	(0.0041)	(0.0040)	(0.0040)	(0.0041)	(0.0040)
$Size_{t-2}$	0.0045***	0.0044***	0.0045***	0.0045***	0.0044***	0.0045***
	(0.0017)	(0.0017)	(0.0017)	(0.0017)	(0.0017)	(0.0017)
$Industry\ leverage_t$	0.2154***	0.2095***	0.2113***	0.2152***	0.2100***	0.2119***
	(0.0098)	(0.0098)	(0.0100)	(0.0099)	(0.0098)	(0.0100)
$Industry\ leverage_{t-1}$	-0.1488***	-0.1434***	-0.1379***	-0.1377***	-0.1411***	-0.1349***
	(0.0114)	(0.0119)	(0.0119)	(0.0119)	(0.0118)	(0.0119)
$Industry\ leverage_{t-2}$	-0.0039	-0.0142	-0.0089	-0.0064	-0.0140	-0.0082
	(0.0090)	(0.0097)	(0.0099)	(0.0098)	(0.0097)	(0.0099)
$Industry\ growth_t$	-0.0689***	-0.0767***	-0.0672* **	-0.0707***	-0.0771***	-0.0681***
	(0.0137)	(0.0136)	(0.0139)	(0.0137)	(0.0136)	(0.0139)
$Industry\ growth_{t-1}$	-0.0276**	-0.0371***	-0.0280**	-0.0294**	-0.0385***	-0.0296**
	(0.0121)	(0.0123)	(0.0125)	(0.0121)	(0.0123)	(0.0125)
$Industry\ growth_{t-2}$	-0.0039	-0.0196*	-0.0101	-0.0063	-0.0210*	-0.0116
	(0.0115)	(0.0115)	(0.0117)	(0.0115)	(0.0115)	(0.0117)
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Time effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry linear trends	Yes	No	Yes	Yes	No	Yes
Ind. dummy×RGDP	No	Yes	Yes	No	Yes	Yes
Observations	84548	84548	84548	84548	84548	84548
N	3647	3647	3647	3647	3647	3647
$max(T_i)$	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

D.2 Long-run effects of LSAPs

Table D.14 reports the estimated long-run effects of LSAPs and other determinants on firms' debt to asset ratios.

Table D.14: **FE–TE estimates of the long-run effects of LSAPs on debt to asset ratios of non-financial firms**

Estimates of long-run effects of LSAPs, defined in equation (11), on firms' debt to asset ratios (DA) as well as the long-run effects of both firm- and industry-specific variables on DA, for the PanARDL(2) model 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. Columns (1) and (4) include industry-specific linear time trends, columns (2) and (5) include the interaction of industry dummies and real GDP growth, while columns (3) and (6) include both. $LSAP$ is the (scaled) amount of U.S. Treasuries and agency MBS purchased by the Fed; $\pi_{-1}(\gamma)$ denotes the one-quarter lagged proportion of firms in an industry with DA below the γ-th quantile. 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 (*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$).

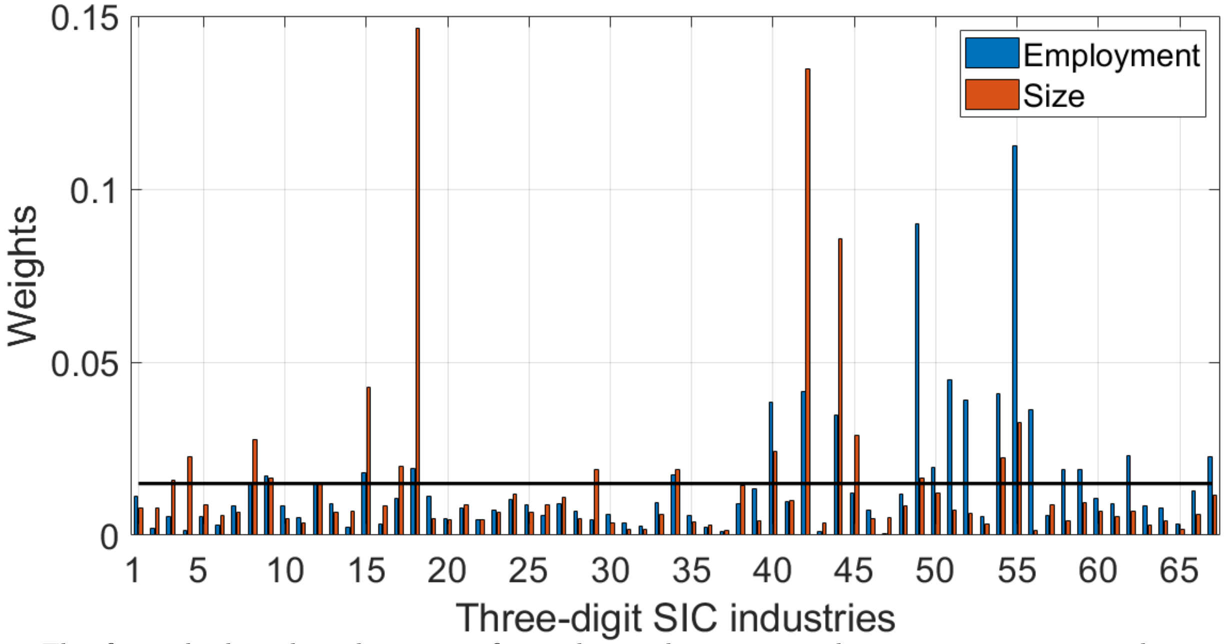
	Dependent variable: debt to assets (DA)					
	$\gamma_{pre} = \gamma_{post} = \gamma$			$\gamma_{pre} \neq \gamma_{post}$		
	(1)	(2)	(3)	(4)	(5)	(6)
$\pi_{-1}(\hat{\gamma}_{pre})$	0.0966***	0.0637**	0.1033***	0.1152***	0.0772***	0.1203***
	(0.0306)	(0.0300)	(0.0335)	(0.0316)	(0.0291)	(0.0321)
$LSAP \times \pi_{-1}(\hat{\gamma}_{post})$	0.0424***	0.0220**	0.0254***	0.0546***	0.0379***	0.0475***
	(0.0116)	(0.0087)	(0.0092)	(0.0108)	(0.0106)	(0.0112)
Cash to assets	-0.2260***	-0.2311***	-0.2261***	-0.2256***	-0.2313***	-0.2259***
	(0.0179)	(0.0179)	(0.0179)	(0.0179)	(0.0179)	(0.0179)
PPE to assets	0.1354***	0.1306***	0.1353***	0.1361***	0.1304***	0.1359***
	(0.0290)	(0.0287)	(0.0290)	(0.0290)	(0.0288)	(0.0290)
Size	0.0213***	0.0231***	0.0213***	0.0213***	0.0231***	0.0214***
	(0.0046)	(0.0046)	(0.0046)	(0.0046)	(0.0046)	(0.0046)
Industry Leverage	0.3882***	0.3258***	0.3997***	0.4402***	0.3443***	0.4264***
	(0.0460)	(0.0497)	(0.0571)	(0.0563)	(0.0501)	(0.0575)
Industry Growth	-0.6223***	-0.8377***	-0.6524***	-0.6596***	-0.8588***	-0.6775***
	(0.1309)	(0.1321)	(0.1368)	(0.1317)	(0.1326)	(0.1373)
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Time effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry linear trends	Yes	No	Yes	Yes	No	Yes
Ind. dummy×RGDP	No	Yes	Yes	No	Yes	Yes
Observations	84548	84548	84548	84548	84548	84548
N	3647	3647	3647	3647	3647	3647
$max(T_i)$	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

D.3 Description of the industry weights used to compute the effects of LSAPs at national level

We now provide some additional details related to the computation of the average policy effects at the national level described in equation (8) of the paper.

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 9.

Figure 9: **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 (7) and (8) for the preferred two-threshold PanARDL(2) model are reported in the paper.

D.4 Additional control variables

In this subsection, we demonstrate that our empirical results are robust to the inclusion of an even larger set of both firm- and industry-level regressors. Table D.15 reports the estimated net short-run effects of LSAPs for the two-threshold PanARDL(2) model augmented with additional explanatory variables. Similar conclusions hold for the single-threshold model.

Table D.15: **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) for the two-threshold PanARDL(2) model described in equation (10). Net short-run effects are defined as the sum of the estimated coefficients of current and lagged values of the regressor under consideration. The estimated quantile threshold parameters are shown in Table 1. All regressions include both firm-specific effects and time effects. Columns (1) and (2) include industry-specific linear time trends, columns (3) and (4) include the interaction of industry dummies and real GDP growth, while columns (5) and (6) include both. $LSAP$ is the (scaled) amount of U.S. Treasuries and agency MBS purchased by the Fed; $\pi_{-1}(\gamma)$ denotes the one-quarter lagged proportion of firms in an industry with DA below the γ-th quantile. 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)
$\pi_{-1}(\hat{\gamma}_{pre})$	0.0200***	0.0201***	0.0126***	0.0146***	0.0205***	0.0206***
	(0.0051)	(0.0051)	(0.0046)	(0.0047)	(0.0052)	(0.0052)
$LSAP \times \pi_{-1}(\hat{\gamma}_{post})$	0.0087***	0.0088***	0.0064***	0.0068***	0.0073***	0.0073***
	(0.0017)	(0.0017)	(0.0017)	(0.0017)	(0.0018)	(0.0018)
Firm-specific variables						
Lagged DA	Yes	Yes	Yes	Yes	Yes	Yes
Cash to assets	Yes	Yes	Yes	Yes	Yes	Yes
MB		Yes		Yes		Yes
PPE to assets	Yes	Yes	Yes	Yes	Yes	Yes
R&D to assets		Yes		Yes		Yes
Size	Yes	Yes	Yes	Yes	Yes	Yes
Industry-specific variables						
Industry Leverage	Yes	Yes	Yes	Yes	Yes	Yes
Industry Growth	Yes	Yes	Yes	Yes	Yes	Yes
Industry Q	Yes		Yes		Yes	
Industry Cash/TA	Yes	Yes	Yes	Yes	Yes	Yes
Industry MB		Yes		Yes		Yes
Industry PPE/TA	Yes	Yes	Yes	Yes	Yes	Yes
Industry R&D/TA		Yes		Yes		Yes
Industry Size	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Time effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry linear trends	Yes	Yes	No	No	Yes	Yes
Ind. dummy×RGDP	No	No	Yes	Yes	Yes	Yes

D.5 Observed macroeconomic indicators as proxies for f_t

As discussed in the main paper, we use real GDP growth and/or linear trends as proxies for f_t. This subsection reports estimation results using alternative observed macroeconomic indicators to those used in the paper. We consider four main alternative macroeconomic indicators: (i) growth in real world output, (ii) the U.S. unemployment rate, (iii) the term spread (computed as the difference between 10-year and 3-month Treasury bond yields), and (iv) the one-year-ahead expected inflation. We re-estimate the threshold parameters, and report the net short-run effects of LSAPs on firms' capital structure below.

D.5.1 Quantile threshold parameter estimates

We re-estimate the threshold parameters associated with $\pi(\gamma)$, the proportion of firms in an industry with DA below the γ-th quantile, for different choices of f_t. The estimated thresholds are shown in Table D.16.

Table D.16: **Estimated quantile threshold parameters**

Estimates of the quantile threshold parameters from a grid search procedure for the PanARDL(2) model described in equation (10). Panel A shows the estimated threshold parameters for the single-threshold panel regression model, where $\gamma_{pre} = \gamma_{post}$. Panel B displays results for the two-threshold model, where $\gamma_{pre} \neq \gamma_{post}$. In column (1) we use the real world GDP growth as a proxy for f_t. In column (2), f_t denotes the unemployment rate. Column (3) includes three macro-indicators interacted with industry dummies: U.S. real GDP growth, the term spread, and expected inflation. 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.

	(1)	(2)	(3)
Panel A:	$\gamma_{pre} = \gamma_{post} = \gamma$		
$\hat{\gamma}$	0.56	0.56	0.56
Panel B:	$\gamma_{pre} \neq \gamma_{post}$		
$\hat{\gamma}_{pre}$	0.56	0.56	0.56
$\hat{\gamma}_{post}$	0.77	0.77	0.78
f_t	WGDP	Unemp	Multi

The first and second columns use real world output and U.S. unemployment rate as a proxy for f_t, respectively. In the third column, we consider we consider a model with multiple observed factors by using three macroeconomic indicators, namely (i) growth in real GDP, (ii) the term spread, and (iii) the one-year-ahead expected inflation. The choice of term spread and inflation expectation is motivated by Frank and Goyal (2009).

D.5.2 Short-run effects of LSAPs using alternative proxies for f_t

Table D.17 reports the estimates of the net short-run effects of LSAPs and other firm- and industry-specific characteristics on firms' leverage.

Table D.17: **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) for the PanARDL(2) model described in equation (10). Net short-run effects are defined as the sum of the estimated coefficients of current and 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.16. All regressions include both firm-specific effects and time effects. Columns (1) and (4) include the interaction of industry dummies and world real GDP growth, columns (2) and (5) include the interaction of industry dummies and unemployment rate, while columns (3) and (6) include three macro-indicators interacted with industry dummies: U.S. real GDP growth, the term spread, and expected inflation. $LSAP$ is the (scaled) amount of U.S. Treasuries and agency MBS purchased by the Fed; $\pi_{-1}(\gamma)$ denotes the one-quarter lagged proportion of firms in an industry with DA below the γ-th quantile. 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)					
	$\gamma_{pre} = \gamma_{post} = \gamma$			$\gamma_{pre} \neq \gamma_{post}$		
	(1)	(2)	(3)	(4)	(5)	(6)
$\pi_{-1}(\hat{\gamma}_{pre})$	0.0096**	0.0127**	0.0132**	0.0122***	0.0160***	0.0148***
	(0.0047)	(0.0051)	(0.0053)	(0.0045)	(0.0048)	(0.0049)
$LSAP \times \pi_{-1}(\hat{\gamma}_{post})$	0.0040***	0.0055***	0.0028	0.0062***	0.0092***	0.0061***
	(0.0014)	(0.0018)	(0.0018)	(0.0017)	(0.0022)	(0.0021)
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Time effects	Yes	Yes	Yes	Yes	Yes	Yes
f_t	WGDP	Unemp.	Multi	WGDP	Unemp.	Multi
Observations	84548	84548	84548	84548	84548	84548
N	3647	3647	3647	3647	3647	3647
$max(T_i)$	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

D.6 Small-T bias and half-panel jackknife FE-TE estimation

In this subsection, we report estimation results for the PanARDL(2) model described in equation (10) 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 D.6.1 and D.6.2 report the estimated short-run effects after dropping firms with few time series observations, namely firms with less than 8 and 10 time observations, respectively.

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.

Subsection D.6.3 reports estimation results after correcting for the small-T bias by applying the half-panel jackknife method.

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), Chudik et al. (2018) 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.

D.6.1 Short-run effects of LSAPs for firms with at least 8 time observations

Table D.18: **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 the PanARDL(2) model described in equation (10). Net short-run effects are defined as the sum of the estimated coefficients of current and 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. Columns (1) and (4) include industry-specific linear time trends, columns (2) and (5) include the interaction of industry dummies and real GDP growth, while columns (3) and (6) include both. $LSAP$ is the (scaled) amount of U.S. Treasuries and agency MBS purchased by the Fed; $\pi_{-1}(\gamma)$ denotes the one-quarter lagged proportion of firms in an industry with DA below the γ-th quantile. 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)					
	$\gamma_{pre} = \gamma_{post} = \gamma$			$\gamma_{pre} \neq \gamma_{post}$		
	(1)	(2)	(3)	(4)	(5)	(6)
$\pi_{-1}(\hat{\gamma}_{pre})$	0.0155***	0.0100**	0.0164***	0.0181***	0.0121***	0.0190***
	(0.0049)	(0.0047)	(0.0053)	(0.0050)	(0.0046)	(0.0051)
$LSAP \times \pi_{-1}(\hat{\gamma}_{post})$	0.0069***	0.0035**	0.0040***	0.0089***	0.0060***	0.0076***
	(0.0019)	(0.0014)	(0.0015)	(0.0017)	(0.0017)	(0.0018)
Lagged DA	0.8415***	0.8436***	0.8414***	0.8415***	0.8438***	0.8416***
	(0.0050)	(0.0050)	(0.0050)	(0.0050)	(0.0050)	(0.0050)
Cash to assets	-0.0360***	-0.0363***	-0.0361***	-0.0359***	-0.0363***	-0.0360***
	(0.0030)	(0.0029)	(0.0030)	(0.0030)	(0.0029)	(0.0030)
PPE to assets	0.0209***	0.0198***	0.0208***	0.0210***	0.0198***	0.0209***
	(0.0047)	(0.0046)	(0.0047)	(0.0047)	(0.0046)	(0.0047)
Size	0.0034***	0.0036***	0.0034***	0.0034***	0.0036***	0.0034***
	(0.0008)	(0.0007)	(0.0008)	(0.0008)	(0.0007)	(0.0008)
Industry Leverage	0.0623***	0.0515***	0.0642***	0.0704***	0.0544***	0.0684***
	(0.0075)	(0.0079)	(0.0092)	(0.0090)	(0.0080)	(0.0092)
Industry Growth	-0.0974***	-0.1304***	-0.1032***	-0.1033***	-0.1336***	-0.1072***
	(0.0209)	(0.0206)	(0.0219)	(0.0210)	(0.0207)	(0.0219)
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Time effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry linear trends	Yes	No	Yes	Yes	No	Yes
Ind. dummy×RGDP	No	Yes	Yes	No	Yes	Yes
Observations	83290	83290	83290	83290	83290	83290
N	3236	3236	3236	3236	3236	3236
$max(T_i)$	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

D.6.2 Short-run effects of LSAPs for firms with at least 10 time observations

Table D.19: **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 the PanARDL(2) model described in equation (10). Net short-run effects are defined as the sum of the estimated coefficients of current and 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. Columns (1) and (4) include industry-specific linear time trends, columns (2) and (5) include the interaction of industry dummies and real GDP growth, while columns (3) and (6) include both. $LSAP$ is the (scaled) amount of U.S. Treasuries and agency MBS purchased by the Fed; $\pi_{-1}(\gamma)$ denotes the one-quarter lagged proportion of firms in an industry with DA below the γ-th quantile. 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)					
	$\gamma_{pre} = \gamma_{post} = \gamma$			$\gamma_{pre} \neq \gamma_{post}$		
	(1)	(2)	(3)	(4)	(5)	(6)
$\pi_{-1}(\hat{\gamma}_{pre})$	0.0153***	0.0098**	0.0160***	0.0178***	0.0120***	0.0188***
	(0.0049)	(0.0047)	(0.0053)	(0.0050)	(0.0046)	(0.0051)
$LSAP \times \pi_{-1}(\hat{\gamma}_{post})$	0.0070***	0.0036***	0.0041***	0.0090***	0.0062***	0.0076***
	(0.0018)	(0.0014)	(0.0015)	(0.0017)	(0.0017)	(0.0018)
Lagged DA	0.8447***	0.8467***	0.8446***	0.8447***	0.8469***	0.8447***
	(0.0050)	(0.0050)	(0.0050)	(0.0050)	(0.0050)	(0.0050)
Cash to assets	-0.0355***	-0.0358***	-0.0356***	-0.0355***	-0.0358***	-0.0355***
	(0.0030)	(0.0029)	(0.0030)	(0.0030)	(0.0029)	(0.0030)
PPE to assets	0.0197***	0.0188***	0.0196***	0.0198***	0.0187***	0.0196***
	(0.0046)	(0.0045)	(0.0046)	(0.0046)	(0.0045)	(0.0046)
Size	0.0035***	0.0038***	0.0035***	0.0035***	0.0038***	0.0035***
	(0.0008)	(0.0007)	(0.0008)	(0.0008)	(0.0007)	(0.0008)
Industry Leverage	0.0605***	0.0494***	0.0618***	0.0685***	0.0524***	0.0661***
	(0.0075)	(0.0079)	(0.0092)	(0.0090)	(0.0079)	(0.0092)
Industry Growth	-0.0960***	-0.1297***	-0.1027***	-0.1017***	-0.1331***	-0.1066***
	(0.0211)	(0.0207)	(0.0220)	(0.0212)	(0.0208)	(0.0220)
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Time effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry linear trends	Yes	No	Yes	Yes	No	Yes
Ind. dummy×RGDP	No	Yes	Yes	No	Yes	Yes
Observations	82038	82038	82038	82038	82038	82038
N	3011	3011	3011	3011	3011	3011
$max(T_i)$	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

D.6.3 Half-panel jackknife FE-TE estimates

Table D.20: **Half-panel jackknife FE–TE estimates of the effects of LSAPs on non-financial firm's debt to asset ratios based on the PanARDL(2) model**

Estimates of the coefficients of the PanARDL(2) model described in equation (10). The dependent variable is debt to asset ratio (DA). q_t is the (scaled) amount of U.S. Treasuries and agency MBS purchased by the Fed; $\pi_{s,t}(\hat{\gamma})$ denotes the proportion of firms in an industry with DA below the $\hat{\gamma}$-th quantile. 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. Columns (1) and (4) include industry-specific linear time trends, columns (2) and (5) include the interaction of industry dummies and real GDP growth, while columns (3) and (6) include both. 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)	(6)
$\pi_{s,t-1}(\hat{\gamma}_{pre})$	0.0118**	0.0122**	0.0137**	0.0125**	0.0147***	0.0159***
	(0.0056)	(0.0057)	(0.0059)	(0.0055)	(0.0055)	(0.0056)
$q_t \times \pi_{s,t-1}(\hat{\gamma}_{post})$	0.0018	0.0024	0.0021	0.0039*	0.0043*	0.0043*
	(0.0023)	(0.0018)	(0.0018)	(0.0022)	(0.0022)	(0.0022)
$\pi_{s,t-2}(\hat{\gamma}_{pre})$	-0.0070	-0.0157***	-0.0155**	-0.0131**	-0.0140**	-0.0139**
	(0.0063)	(0.0060)	(0.0060)	(0.0058)	(0.0058)	(0.0058)
$q_{t-1} \times \pi_{s,t-2}(\hat{\gamma}_{post})$	0.0038	0.0022	0.0021	0.0019	0.0015	0.0016
	(0.0026)	(0.0021)	(0.0021)	(0.0025)	(0.0025)	(0.0025)
$\pi_{s,t-3}(\hat{\gamma}_{pre})$	0.0038	0.0085*	0.0077	0.0068	0.0084*	0.0075
	(0.0054)	(0.0048)	(0.0050)	(0.0046)	(0.0046)	(0.0047)
$q_{t-2} \times \pi_{s,t-3}(\hat{\gamma}_{post})$	0.0013	0.0005	0.0005	0.0022	0.0004	0.0008
	(0.0022)	(0.0018)	(0.0018)	(0.0021)	(0.0022)	(0.0022)
DA_{t-1}	0.9120***	0.9120***	0.9118***	0.9121***	0.9121***	0.9118***
	(0.0102)	(0.0102)	(0.0102)	(0.0102)	(0.0102)	(0.0102)
DA_{t-2}	0.0376***	0.0381***	0.0377***	0.0375***	0.0382***	0.0377***
	(0.0089)	(0.0089)	(0.0089)	(0.0089)	(0.0089)	(0.0089)
$(Cash/A)_t$	-0.0945***	-0.0946***	-0.0943***	-0.0945***	-0.0946***	-0.0944***
	(0.0090)	(0.0090)	(0.0090)	(0.0090)	(0.0090)	(0.0090)
$(Cash/A)_{t-1}$	0.0615***	0.0614***	0.0611***	0.0615***	0.0615***	0.0612***
	(0.0089)	(0.0089)	(0.0089)	(0.0089)	(0.0089)	(0.0089)
$(Cash/A)_{t-2}$	0.0091*	0.0090*	0.0091*	0.0091*	0.0090*	0.0091*
	(0.0052)	(0.0052)	(0.0052)	(0.0052)	(0.0052)	(0.0052)

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Table D.21: (cont.)

	Dependent variable: debt to assets (DA_t)					
	$\gamma_{pre} = \gamma_{post} = \gamma$			$\gamma_{pre} \neq \gamma_{post}$		
	(1)	(2)	(3)	(4)	(5)	(6)
$(PPE/A)_t$	0.0614***	0.0620***	0.0624***	0.0613***	0.0620***	0.0624***
	(0.0197)	(0.0198)	(0.0198)	(0.0197)	(0.0198)	(0.0198)
$(PPE/A)_{t-1}$	-0.0438**	-0.0449**	-0.0451**	-0.0438**	-0.0448**	-0.0451**
	(0.0202)	(0.0202)	(0.0202)	(0.0202)	(0.0202)	(0.0202)
$(PPE/A)_{t-2}$	-0.0193*	-0.0195*	-0.0191*	-0.0190*	-0.0195*	-0.0191*
	(0.0106)	(0.0106)	(0.0106)	(0.0106)	(0.0106)	(0.0106)
$Size_t$	0.0276***	0.0282***	0.0277***	0.0276***	0.0282***	0.0277***
	(0.0045)	(0.0045)	(0.0045)	(0.0045)	(0.0045)	(0.0045)
$Size_{t-1}$	-0.0332***	-0.0332***	-0.0333***	-0.0333***	-0.0332***	-0.0333***
	(0.0046)	(0.0046)	(0.0046)	(0.0046)	(0.0046)	(0.0046)
$Size_{t-2}$	0.0061***	0.0061***	0.0061***	0.0061***	0.0061***	0.0061***
	(0.0020)	(0.0020)	(0.0020)	(0.0020)	(0.0020)	(0.0020)
$Industry\ leverage_t$	0.2166***	0.2118***	0.2146***	0.2167***	0.2126***	0.2151***
	(0.0109)	(0.0110)	(0.0111)	(0.0110)	(0.0110)	(0.0111)
$Industry\ leverage_{t-1}$	-0.1613***	-0.1570***	-0.1542***	-0.1546***	-0.1542***	-0.1513***
	(0.0119)	(0.0125)	(0.0126)	(0.0126)	(0.0125)	(0.0126)
$Industry\ leverage_{t-2}$	-0.0119	-0.0242**	-0.0196*	-0.0167	-0.0228**	-0.0184*
	(0.0098)	(0.0107)	(0.0107)	(0.0107)	(0.0107)	(0.0107)
$Industry\ growth_t$	-0.0706***	-0.0821***	-0.0712***	-0.0719***	-0.0827***	-0.0723***
	(0.0156)	(0.0159)	(0.0156)	(0.0156)	(0.0159)	(0.0156)
$Industry\ growth_{t-1}$	-0.0315**	-0.0440***	-0.0326**	-0.0317**	-0.0453***	-0.0339**
	(0.0137)	(0.0141)	(0.0140)	(0.0137)	(0.0141)	(0.0139)
$Industry\ growth_{t-2}$	-0.0064	-0.0195	-0.0103	-0.0064	-0.0208	-0.0118
	(0.0131)	(0.0133)	(0.0132)	(0.0131)	(0.0133)	(0.0132)
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Time effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry linear trends	Yes	No	Yes	Yes	No	Yes
Ind. dummy×RGDP	No	Yes	Yes	No	Yes	Yes
Observations	82092	82092	82092	82092	82092	82092
N	3236	3236	3236	3236	3236	3236
$max(T_i)$	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 D.22: **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 the PanARDL(2) model described in equation (10). Net short-run effects are defined as the sum of the estimated coefficients of current and 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. Columns (1) and (4) include industry-specific linear time trends, columns (2) and (5) include the interaction of industry dummies and real GDP growth, while columns (3) and (6) include both. $LSAP$ is the (scaled) amount of U.S. Treasuries and agency MBS purchased by the Fed; $\pi_{-1}(\gamma)$ denotes the one-quarter lagged proportion of firms in an industry with DA below the γ-th quantile. 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)					
	$\gamma_{pre} = \gamma_{post} = \gamma$			$\gamma_{pre} \neq \gamma_{post}$		
	(1)	(2)	(3)	(4)	(5)	(6)
$\pi_{-1}(\hat{\gamma}_{pre})$	0.0085	0.0049	0.0059	0.0063	0.0091	0.0095
	(0.0062)	(0.0063)	(0.0067)	(0.0064)	(0.0062)	(0.0065)
$LSAP \times \pi_{-1}(\hat{\gamma}_{post})$	0.0068***	0.0051***	0.0047**	0.0080***	0.0061***	0.0066***
	(0.0022)	(0.0018)	(0.0018)	(0.0021)	(0.0021)	(0.0022)
Lagged DA	0.9496***	0.9500***	0.9494***	0.9496***	0.9502***	0.9495***
	(0.0067)	(0.0067)	(0.0067)	(0.0067)	(0.0067)	(0.0067)
Cash to assets	-0.0239***	-0.0241***	-0.0241***	-0.0239***	-0.0241***	-0.0241***
	(0.0043)	(0.0042)	(0.0043)	(0.0043)	(0.0042)	(0.0043)
PPE to assets	-0.0017	-0.0024	-0.0018	-0.0014	-0.0023	-0.0017
	(0.0072)	(0.0071)	(0.0072)	(0.0072)	(0.0071)	(0.0072)
Size	0.0005	0.0010	0.0005	0.0005	0.0010	0.0005
	(0.0012)	(0.0012)	(0.0012)	(0.0012)	(0.0012)	(0.0012)
Industry Leverage	0.0434***	0.0307***	0.0408***	0.0454***	0.0356***	0.0454***
	(0.0097)	(0.0113)	(0.0119)	(0.0117)	(0.0114)	(0.0120)
Industry Growth	-0.1085***	-0.1456***	-0.1141***	-0.1100***	-0.1489***	-0.1180***
	(0.0267)	(0.0281)	(0.0273)	(0.0268)	(0.0282)	(0.0274)
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Time effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry linear trends	Yes	No	Yes	Yes	No	Yes
Ind. dummy×RGDP	No	Yes	Yes	No	Yes	Yes
Observations	82092	82092	82092	82092	82092	82092
N	3236	3236	3236	3236	3236	3236
$max(T_i)$	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 D.23: **Half-panel jackknife FE–TE estimates of the long-run effects of LSAPs on debt to asset ratios of non-financial firms**

Estimates of long-run effects of LSAPs, defined in equation (11), on firms' debt to asset ratios (DA) as well as the long-run effects of both firm- and industry-specific variables on DA, for the PanARDL(2) model 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. Columns (1) and (4) include industry-specific linear time trends, columns (2) and (5) include the interaction of industry dummies and real GDP growth, while columns (3) and (6) include both. $LSAP$ is the (scaled) amount of U.S. Treasuries and agency MBS purchased by the Fed; $\pi_{-1}(\gamma)$ denotes the one-quarter lagged proportion of firms in an industry with DA below the γ-th quantile. 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)					
	$\gamma_{pre} = \gamma_{post} = \gamma$			$\gamma_{pre} \neq \gamma_{post}$		
	(1)	(2)	(3)	(4)	(5)	(6)
$\pi_{-1}(\hat{\gamma}_{pre})$	0.1683	0.0985	0.1174	0.1253	0.1832	0.1884
	(0.1248)	(0.1285)	(0.1353)	(0.1293)	(0.1285)	(0.1328)
$LSAP \times \pi_{-1}(\hat{\gamma}_{post})$	0.1353***	0.1022***	0.0931**	0.1584***	0.1224***	0.1312***
	(0.0483)	(0.0382)	(0.0385)	(0.0466)	(0.0461)	(0.0466)
Cash to assets	-0.4745***	-0.4832***	-0.4772***	-0.4742***	-0.4839***	-0.4778***
	(0.0929)	(0.0930)	(0.0929)	(0.0930)	(0.0934)	(0.0931)
PPE to assets	-0.0331	-0.0481	-0.036	-0.0288	-0.0464	-0.034
	(0.1431)	(0.1416)	(0.1428)	(0.1432)	(0.1422)	(0.1431)
Size	0.0091	0.0209	0.0102	0.0092	0.0210	0.0104
	(0.0235)	(0.0230)	(0.0234)	(0.0235)	(0.0231)	(0.0235)
Industry Leverage	0.8597***	0.6142***	0.8067***	0.9005***	0.7155***	0.8995***
	(0.2109)	(0.2326)	(0.2526)	(0.2554)	(0.2395)	(0.2596)
Industry Growth	-2.1510***	-2.9141***	-2.2566***	-2.1827***	-2.9914***	-2.3394***
	(0.6018)	(0.6975)	(0.6184)	(0.6076)	(0.7072)	(0.6263)
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Time effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry linear trends	Yes	No	Yes	Yes	No	Yes
Ind. dummy×RGDP	No	Yes	Yes	No	Yes	Yes
Observations	82092	82092	82092	82092	82092	82092
N	3236	3236	3236	3236	3236	3236
$max(T_i)$	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

D.7 Robustness to the choice of dynamic specification

In the main the paper, we focus on the more general PanARDL(2) specification, described in equation (10). For completeness, we also provide estimation results for the partial adjustment model, a commonly used specification in the empirical capital structure research (Graham and Leary (2011)), and the PanARDL(1) model.

Table D.24 summarises the estimates of the threshold parameters associated with $\pi(\gamma)$, the proportion of firms in an industry with DA below the γ-th quantile, across the three choice of dynamic specification, including the PanARDL(2) model for ease of reference. Each panel focuses on a different choice of f_t.

In Subsection D.7.2 we report the FE-TE estimates of the coefficients of the partial adjustment model. We also report the long-run effects of LSAPs and other regressors on firms' capital structure. Subsection D.7.3 shows the net short-run and long-run effects of LSAPs on firms' capital structure based on the PanARDL(1) specification.

D.7.1 Quantile threshold parameter estimates

Table D.24: **Estimated quantile threshold parameters**

Estimates of the quantile threshold parameters from a grid search procedure across both the partial adjustment model and the PanARDL specifications described in equation (10). In Panel A and B, f_t denotes linear time trends and real GDP growth, respectively. In Panel C, $\mathbf{f}_t$ includes both linear time trends and real GDP growth. 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.

A: scaled linear trends

	Par. Adj.	PanARDL(1)	PanARDL(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

B: real GDP growth

	Part. Adj.	PanARDL(1)	PanARDL(2)
		$\gamma_{pre} = \gamma_{post} = \gamma$	
$\hat{\gamma}$	0.52	0.52	0.56
		$\gamma_{pre} \neq \gamma_{post}$	
$\hat{\gamma}_{pre}$	0.52	0.52	0.56
$\hat{\gamma}_{post}$	0.77	0.77	0.77

C: lin. trends & RGDP growth

	Part. Adj.	PanARDL(1)	PanARDL(2)
		$\gamma_{pre} = \gamma_{post} = \gamma$	
$\hat{\gamma}$	0.56	0.69	0.56
		$\gamma_{pre} \neq \gamma_{post}$	
$\hat{\gamma}_{pre}$	0.56	0.56	0.56
$\hat{\gamma}_{post}$	0.77	0.77	0.77

D.7.2 FE-TE estimates based on the partial adjustment model

Table D.25: **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 (10). The dependent variable is debt to asset ratio (DA). q_t is the (scaled) amount of U.S. Treasuries and agency MBS purchased by the Fed; $\pi_{s,t}(\hat{\gamma})$ denotes the proportion of firms in an industry with DA below the $\hat{\gamma}$-th quantile. 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.24. All regressions include both firm-specific effects and time effects. Columns (1) and (4) include industry-specific linear time trends, columns (2) and (5) include the interaction of industry dummies and real GDP growth, while columns (3) and (6) include both. 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)	(6)
$\pi_{s,t-1}(\hat{\gamma}_{pre})$	0.0447***	0.0406***	0.0450***	0.0460***	0.0418***	0.0463***
	(0.0041)	(0.0039)	(0.0042)	(0.0040)	(0.0037)	(0.0040)
$q_t \times \pi_{s,t-1}(\hat{\gamma}_{post})$	0.0033***	0.0023**	0.0032***	0.0077***	0.0062***	0.0075***
	(0.0012)	(0.0011)	(0.0012)	(0.0014)	(0.0014)	(0.0015)
DA_{t-1}	0.8264***	0.8287***	0.8265***	0.8266***	0.8289***	0.8267***
	(0.0053)	(0.0053)	(0.0053)	(0.0053)	(0.0053)	(0.0053)
$(Cash/A)_t$	-0.0496***	-0.0502***	-0.0496***	-0.0496***	-0.0503***	-0.0496***
	(0.0034)	(0.0034)	(0.0034)	(0.0034)	(0.0034)	(0.0034)
$(PPE/A)_t$	0.0249***	0.0240***	0.0250***	0.0250***	0.0239***	0.0250***
	(0.0053)	(0.0052)	(0.0053)	(0.0053)	(0.0052)	(0.0053)
$Size_t$	0.0051***	0.0054***	0.0051***	0.0051***	0.0054***	0.0051***
	(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0008)
$Industry\ leverage_t$	0.1391***	0.1175***	0.1370***	0.1414***	0.1196***	0.1394***
	(0.0075)	(0.0067)	(0.0076)	(0.0075)	(0.0068)	(0.0077)
$Industry\ growth_t$	-0.0483***	-0.0620***	-0.0427***	-0.0499***	-0.0637***	-0.0442***
	(0.0131)	(0.0131)	(0.0134)	(0.0131)	(0.0131)	(0.0134)
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Time effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry linear trends	Yes	No	Yes	Yes	No	Yes
Ind. dummy×RGDP	No	Yes	Yes	No	Yes	Yes
Observations	84548	84548	84548	84548	84548	84548
N	3647	3647	3647	3647	3647	3647
$max(T_i)$	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.26: **FE–TE estimates of the long-run effects of LSAPs on debt to asset ratios of non-financial firms based on the partial adjustment model**

Estimates of long-run effects of LSAPs, defined in equation (11), on firms' debt to asset ratios (DA) as well as the long-run effects of both firm- and industry-specific variables on DA, for the partial adjustment model from 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 D.24. All regressions include both firm-specific effects and time effects. Columns (1) and (4) include industry-specific linear time trends, columns (2) and (5) include the interaction of industry dummies and real GDP growth, while columns (3) and (6) include both. $LSAP$ is the (scaled) amount of U.S. Treasuries and agency MBS purchased by the Fed; $\pi_{-1}(\gamma)$ denotes the one-quarter lagged proportion of firms in an industry with DA below the γ-th quantile. 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)					
	$\gamma_{pre} = \gamma_{post} = \gamma$			$\gamma_{pre} \neq \gamma_{post}$		
	(1)	(2)	(3)	(4)	(5)	(6)
$\pi_{-1}(\hat{\gamma}_{pre})$	0.2576***	0.2373***	0.2594***	0.2654***	0.2443***	0.2671***
	(0.0250)	(0.0235)	(0.0253)	(0.0242)	(0.0227)	(0.0245)
$LSAP \times \pi_{-1}(\hat{\gamma}_{post})$	0.0192***	0.0136**	0.0186***	0.0441***	0.0363***	0.0433***
	(0.0067)	(0.0064)	(0.0067)	(0.0085)	(0.0082)	(0.0085)
Cash to assets	-0.2858***	-0.2934***	-0.2860***	-0.2858***	-0.2938***	-0.2860***
	(0.0189)	(0.0189)	(0.0189)	(0.0189)	(0.0189)	(0.0189)
PPE to assets	0.1433***	0.1400***	0.1439***	0.1439***	0.1400***	0.1445***
	(0.0306)	(0.0302)	(0.0306)	(0.0306)	(0.0302)	(0.0306)
Size	0.0295***	0.0313***	0.0295***	0.0296***	0.0314***	0.0296***
	(0.0046)	(0.0046)	(0.0047)	(0.0046)	(0.0046)	(0.0047)
Industry Leverage	0.8013***	0.6860***	0.7895***	0.8157***	0.6993***	0.8043***
	(0.0452)	(0.0403)	(0.0459)	(0.0455)	(0.0406)	(0.0462)
Industry Growth	-0.2785***	-0.3620***	-0.2460***	-0.2880***	-0.3724***	-0.2550***
	(0.0761)	(0.0773)	(0.0775)	(0.0762)	(0.0774)	(0.0776)
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Time effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry linear trends	Yes	No	Yes	Yes	No	Yes
Ind. dummy×RGDP	No	Yes	Yes	No	Yes	Yes
Observations	84548	84548	84548	84548	84548	84548
N	3647	3647	3647	3647	3647	3647
$max(T_i)$	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

D.7.3 FE-TE estimates based on the PanARDL(1) model

Table D.27: **FE–TE estimates of the net short-run effects of LSAPs on debt to asset ratios of non-financial firms based on the ARDL(1) model**

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 the PanARDL(1) model from equation (10). Net short-run effects are defined as the sum of the estimated coefficients of current and 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.24. All regressions include both firm-specific effects and time effects. Columns (1) and (4) include industry-specific linear time trends, columns (2) and (5) include the interaction of industry dummies and real GDP growth, while columns (3) and (6) include both. $LSAP$ is the (scaled) amount of U.S. Treasuries and agency MBS purchased by the Fed; $\pi_{-1}(\gamma)$ denotes the one-quarter lagged proportion of firms in an industry with DA below the γ-th quantile. 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)					
	$\gamma_{pre} = \gamma_{post} = \gamma$			$\gamma_{pre} \neq \gamma_{post}$		
	(1)	(2)	(3)	(4)	(5)	(6)
$\pi_{-1}(\hat{\gamma}_{pre})$	0.0136***	0.0093**	0.0162***	0.0148***	0.0118***	0.0153***
	(0.0045)	(0.0043)	(0.0045)	(0.0045)	(0.0041)	(0.0046)
$LSAP \times \pi_{-1}(\hat{\gamma}_{post})$	0.0059***	0.0030***	0.0040***	0.0074***	0.0055***	0.0067***
	(0.0016)	(0.0012)	(0.0014)	(0.0015)	(0.0015)	(0.0016)
Lagged DA	0.8337***	0.8357***	0.8337***	0.8337***	0.8359***	0.8337***
	(0.0052)	(0.0052)	(0.0052)	(0.0052)	(0.0052)	(0.0052)
Cash to assets	-0.0380***	-0.0384***	-0.0381***	-0.0380***	-0.0384***	-0.0381***
	(0.0030)	(0.0030)	(0.0030)	(0.0030)	(0.0030)	(0.0030)
PPE to assets	0.0236***	0.0227***	0.0236***	0.0237***	0.0227***	0.0237***
	(0.0047)	(0.0046)	(0.0047)	(0.0047)	(0.0046)	(0.0047)
Size	0.0030***	0.0033***	0.0031***	0.0030***	0.0033***	0.0031***
	(0.0008)	(0.0007)	(0.0008)	(0.0008)	(0.0007)	(0.0008)
Industry Leverage	0.0631***	0.0554***	0.0633***	0.0715***	0.0588***	0.0694***
	(0.0069)	(0.0072)	(0.0074)	(0.0082)	(0.0073)	(0.0084)
Industry Growth	-0.1024***	-0.1245***	-0.0981***	-0.1056***	-0.1266***	-0.1041***
	(0.0176)	(0.0176)	(0.0182)	(0.0176)	(0.0177)	(0.0183)
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Time effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry linear trends	Yes	No	Yes	Yes	No	Yes
Ind. dummy×RGDP	No	Yes	Yes	No	Yes	Yes
Observations	84548	84548	84548	84548	84548	84548
N	3647	3647	3647	3647	3647	3647
$max(T_i)$	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.28: **FE–TE estimates of the long-run effects of LSAPs on debt to asset ratios of non-financial firms based on the PanARDL(1) model**

Estimates of long-run effects of LSAPs, defined in equation (11), on firms' debt to asset ratios (DA) as well as the effects of both firm- and industry-specific variables on DA, for the PanARDL(1) model from 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 D.24. All regressions include both firm-specific effects and time effects. Columns (1) and (4) include industry-specific linear time trends, columns (2) and (5) include the interaction of industry dummies and real GDP growth, while columns (3) and (6) include both. $LSAP$ is the (scaled) amount of U.S. Treasuries and agency MBS purchased by the Fed; $\pi_{-1}(\gamma)$ denotes the one-quarter lagged proportion of firms in an industry with DA below the γ-th quantile. 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)					
	$\gamma_{pre} = \gamma_{post} = \gamma$			$\gamma_{pre} \neq \gamma_{post}$		
	(1)	(2)	(3)	(4)	(5)	(6)
$\pi_{-1}(\hat{\gamma}_{pre})$	0.0816***	0.0566**	0.0974***	0.0890***	0.0720***	0.0919***
	(0.0271)	(0.0265)	(0.0270)	(0.0276)	(0.0255)	(0.0279)
$LSAP \times \pi_{-1}(\hat{\gamma}_{post})$	0.0353***	0.0185***	0.0243***	0.0446***	0.0334***	0.0405***
	(0.0099)	(0.0071)	(0.0085)	(0.0093)	(0.0091)	(0.0094)
Cash to assets	-0.2287***	-0.2338***	-0.2293***	-0.2284***	-0.2341***	-0.2288***
	(0.0175)	(0.0175)	(0.0176)	(0.0175)	(0.0175)	(0.0175)
PPE to assets	0.1421***	0.1385***	0.1421***	0.1424***	0.1384***	0.1423***
	(0.0283)	(0.0280)	(0.0283)	(0.0283)	(0.0281)	(0.0283)
Size	0.0183***	0.0200***	0.0184***	0.0183***	0.0201***	0.0184***
	(0.0045)	(0.0044)	(0.0045)	(0.0045)	(0.0044)	(0.0045)
Industry Leverage	0.3792***	0.3373***	0.3806***	0.4297***	0.3580***	0.4171***
	(0.0414)	(0.0439)	(0.0445)	(0.0497)	(0.0442)	(0.0505)
Industry Growth	-0.6156***	-0.7581***	-0.5897***	-0.6349***	-0.7711***	-0.6261***
	(0.1074)	(0.1100)	(0.1112)	(0.1081)	(0.1105)	(0.1122)
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Time effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry linear trends	Yes	No	Yes	Yes	No	Yes
Ind. dummy×RGDP	No	Yes	Yes	No	Yes	Yes
Observations	84548	84548	84548	84548	84548	84548
N	3647	3647	3647	3647	3647	3647
$max(T_i)$	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 Separating the effects of large-scale MBS and Treasury purchases

This section reports estimation results when separating the effects of MBS from Treasury purchases. Thus, the panel regression model described in equation (10) now contains two separate quantitative measures of LSAPs interacted with one-quarter lags of $\pi_{s,t}(\gamma)$, our industry-specific measure of debt capacity.

In Subsection E.1, we report the estimated threshold parameters for the PanARDL(2) specification, distinguishing between the case of single *versus* the two-threshold model. The corresponding estimated net short-run and long-run effects of both MBS and Treasury purchases are shown in Subsection E.2. In Subsection E.3, we examine the extent to which our estimation results hold after correcting for the small-T bias.

E.1 Quantile threshold parameter estimates

Table E.29: **Estimated quantile threshold parameters**

Estimates of the quantile threshold parameters from a grid search procedure for the PanARDL(2) model described in equation (10), separating the effects of large-scale MBS and Treasury purchases. Panel A shows the estimated threshold parameters for the single-threshold panel regression model, where $\gamma_{pre} = \gamma_{post}$. Panel B displays results for the two-threshold model, where $\gamma_{pre} \neq \gamma_{post}$. In column (1) and (2), we use linear time trends or real GDP growth as a proxy for f_t, respectively. Column (3) reports results when including both linear trends and real GDP growth at the same time. 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.

	(1)	(2)	(3)
Panel A:	$\gamma_{pre} = \gamma_{post} = \gamma$		
$\hat{\gamma}$	0.76	0.56	0.56
Panel B:	$\gamma_{pre} \neq \gamma_{post}$		
$\hat{\gamma}_{pre}$	0.56	0.56	0.56
$\hat{\gamma}_{post}$	0.77	0.78	0.77
linear trends	Yes	No	Yes
RGDP growth	No	Yes	Yes

E.2 Short- and long-run effects of large-scale MBS and Treasury purchases

Table E.30: **FE–TE estimates of the net short-run and long-run effects of of large-scale MBS and Treasury purchases on debt to asset ratios of non-financial firms**

Panel A (Panel B) reports the net short-run (long-run) effects of MBS and Treasury purchases on firms' debt to asset ratios (DA), for the PanARDL(2) model described in equation (10). Net short-run effects are defined as the sum of the estimated coefficients of current and lagged values of the regressor under consideration. The long-run effects are defined in equation (11). 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 E.29. All regressions include both firm-specific effects and time effects. Columns (1) and (4) include industry-specific linear time trends, columns (2) and (5) include the interaction of industry dummies and real GDP growth, while columns (3) and (6) include both. *ty* and *mbs* denote the (scaled) amount of U.S. Treasuries and agency MBS purchased by the Fed, respectively; $\pi_{-1}(\gamma)$ denotes the one-quarter lagged proportion of firms in an industry with DA below the γ-th quantile. 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)					
	$\gamma_{pre} = \gamma_{post} = \gamma$			$\gamma_{pre} \neq \gamma_{post}$		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Short-run effects						
$\pi_{-1}(\hat{\gamma}_{pre})$	0.0159***	0.0108**	0.0174***	0.0188***	0.0124***	0.0196***
	(0.0050)	(0.0048)	(0.0055)	(0.0050)	(0.0046)	(0.0051)
$ty \times \pi_{-1}(\hat{\gamma}_{post})$	0.0059*	0.0018	0.0026	0.0078**	0.0053*	0.0067**
	(0.0033)	(0.0025)	(0.0026)	(0.0031)	(0.0031)	(0.0032)
$mbs \times \pi_{-1}(\hat{\gamma}_{post})$	0.0070***	0.0041**	0.0045***	0.0092***	0.0060***	0.0080***
	(0.0022)	(0.0017)	(0.0017)	(0.0021)	(0.0021)	(0.0022)
Panel B: Long-run effects						
$\pi_{-1}(\hat{\gamma}_{pre})$	0.0988***	0.0676**	0.1077***	0.1166***	0.0780***	0.1216***
	(0.0312)	(0.0302)	(0.0341)	(0.0317)	(0.0290)	(0.0322)
$ty \times \pi_{-1}(\hat{\gamma}_{post})$	0.0368*	0.0112	0.0162	0.0482**	0.0331*	0.0418**
	(0.0202)	(0.0157)	(0.0164)	(0.0191)	(0.0193)	(0.0198)
$mbs \times \pi_{-1}(\hat{\gamma}_{post})$	0.0433***	0.0255**	0.0280***	0.0569***	0.0379***	0.0493***
	(0.0138)	(0.0105)	(0.0107)	(0.0134)	(0.0134)	(0.0137)
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Time effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry linear trends	Yes	No	Yes	Yes	No	Yes
Ind. dummy×RGDP	No	Yes	Yes	No	Yes	Yes
Observations	84548	84548	84548	84548	84548	84548
N	3647	3647	3647	3647	3647	3647
$max(T_i)$	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.3 Robustness of the results to small-T bias

Table E.31: **FE–TE estimates of the net short-run and long-run effects of of large-scale MBS and Treasury purchases on debt to asset ratios of non-financial firms with at least 8 observations**

Panel A (Panel B) reports the net short-run (long-run) effects of MBS and Treasury purchases on firms' debt to asset ratios (DA), for the PanARDL(2) model described in equation (10). Net short-run effects are defined as the sum of the estimated coefficients of current and lagged values of the regressor under consideration. The long-run effects are defined in equation (11). 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 E.29. All regressions include both firm-specific effects and time effects. Columns (1) and (4) include industry-specific linear time trends, columns (2) and (5) include the interaction of industry dummies and real GDP growth, while columns (3) and (6) include both. *ty* and *mbs* denote the (scaled) amount of U.S. Treasuries and agency MBS purchased by the Fed, respectively; $\pi_{-1}(\gamma)$ denotes the one-quarter lagged proportion of firms in an industry with DA below the γ-th quantile. he 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)					
	$\gamma_{pre} = \gamma_{post} = \gamma$			$\gamma_{pre} \neq \gamma_{post}$		
	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A: Short-run effects					
$\pi_{-1}(\hat{\gamma}_{pre})$	0.0159***	0.0107**	0.0172***	0.0183***	0.0123***	0.0193***
	(0.0050)	(0.0048)	(0.0054)	(0.0050)	(0.0046)	(0.0051)
$ty \times \pi_{-1}(\hat{\gamma}_{post})$	0.0059*	0.0016	0.0023	0.0078**	0.0051*	0.0064**
	(0.0033)	(0.0025)	(0.0026)	(0.0031)	(0.0031)	(0.0032)
$mbs \times \pi_{-1}(\hat{\gamma}_{post})$	0.0071***	0.0041**	0.0045***	0.0093***	0.0061***	0.0080***
	(0.0022)	(0.0017)	(0.0017)	(0.0021)	(0.0021)	(0.0022)
	Panel B: Long-run effects					
$\pi_{-1}(\hat{\gamma}_{pre})$	0.1001***	0.0686**	0.1083***	0.1155***	0.0788***	0.1217***
	(0.0317)	(0.0307)	(0.0347)	(0.0322)	(0.0295)	(0.0327)
$ty \times \pi_{-1}(\hat{\gamma}_{post})$	0.0371*	0.0100	0.0145	0.0490**	0.0324*	0.0406**
	(0.0206)	(0.0160)	(0.0167)	(0.0194)	(0.0196)	(0.0202)
$mbs \times \pi_{-1}(\hat{\gamma}_{post})$	0.0449***	0.0263**	0.0286***	0.0589***	0.0390***	0.0502***
	(0.0140)	(0.0107)	(0.0109)	(0.0137)	(0.0136)	(0.0139)
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Time effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry linear trends	Yes	No	Yes	Yes	No	Yes
Ind. dummy×RGDP	No	Yes	Yes	No	Yes	Yes
Observations	83290	83290	83290	83290	83290	83290
N	3236	3236	3236	3236	3236	3236
$max(T_i)$	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 E.32: **FE–TE estimates of the net short-run and long-run effects of of large-scale MBS and Treasury purchases on debt to asset ratios of non-financial firms with at least 10 observations**

Panel A (Panel B) reports the net short-run (long-run) effects of MBS and Treasury purchases on firms' debt to asset ratios (DA), for the PanARDL(2) model described in equation (10). Net short-run effects are defined as the sum of the estimated coefficients of current and lagged values of the regressor under consideration. The long-run effects are defined in equation (11). 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 E.29. All regressions include both firm-specific effects and time effects. Columns (1) and (4) include industry-specific linear time trends, columns (2) and (5) include the interaction of industry dummies and real GDP growth, while columns (3) and (6) include both. *ty* and *mbs* denote the (scaled) amount of U.S. Treasuries and agency MBS purchased by the Fed, respectively; $\pi_{-1}(\gamma)$ denotes the one-quarter lagged proportion of firms in an industry with DA below the γ-th quantile. he 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)					
	$\gamma_{pre} = \gamma_{post} = \gamma$			$\gamma_{pre} \neq \gamma_{post}$		
	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A: Short-run effects					
$\pi_{-1}(\hat{\gamma}_{pre})$	0.0158***	0.0105**	0.0169***	0.0181***	0.0122***	0.0192***
	(0.0050)	(0.0048)	(0.0054)	(0.0050)	(0.0046)	(0.0051)
$ty \times \pi_{-1}(\hat{\gamma}_{post})$	0.0056*	0.0015	0.0023	0.0076**	0.0049	0.0062*
	(0.0032)	(0.0025)	(0.0026)	(0.0031)	(0.0031)	(0.0032)
$mbs \times \pi_{-1}(\hat{\gamma}_{post})$	0.0074***	0.0043***	0.0048***	0.0097***	0.0065***	0.0082***
	(0.0022)	(0.0017)	(0.0017)	(0.0021)	(0.0021)	(0.0022)
	Panel B: Long-run effects					
$\pi_{-1}(\hat{\gamma}_{pre})$	0.1015***	0.0686**	0.1087***	0.1167***	0.0800***	0.1234***
	(0.0324)	(0.0313)	(0.0354)	(0.0328)	(0.0301)	(0.0334)
$ty \times \pi_{-1}(\hat{\gamma}_{post})$	0.0363*	0.0100	0.0145	0.0487**	0.0318	0.0398*
	(0.0210)	(0.0163)	(0.0170)	(0.0198)	(0.0200)	(0.0206)
$mbs \times \pi_{-1}(\hat{\gamma}_{post})$	0.0476***	0.0283***	0.0306***	0.0622***	0.0422***	0.0528***
	(0.0142)	(0.0109)	(0.0111)	(0.0139)	(0.0138)	(0.0141)
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Time effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry linear trends	Yes	No	Yes	Yes	No	Yes
Ind. dummy×RGDP	No	Yes	Yes	No	Yes	Yes
Observations	82038	82038	82038	82038	82038	82038
N	3011	3011	3011	3011	3011	3011
$max(T_i)$	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 E.33: **Half-panel jackknife FE–TE estimates of the net short-run and long-run effects of of large-scale MBS and Treasury purchases on debt to asset ratios of non-financial firms**

Panel A (Panel B) reports the net short-run (long-run) effects of MBS and Treasury purchases on firms' debt to asset ratios (DA), for the PanARDL(2) model described in equation (10). Net short-run effects are defined as the sum of the estimated coefficients of current and lagged values of the regressor under consideration. The long-run effects are defined in equation (11). 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 E.29. All regressions include both firm-specific effects and time effects. Columns (1) and (4) include industry-specific linear time trends, columns (2) and (5) include the interaction of industry dummies and real GDP growth, while columns (3) and (6) include both. *ty* and *mbs* denote the (scaled) amount of U.S. Treasuries and agency MBS purchased by the Fed, respectively; $\pi_{-1}(\gamma)$ denotes the one-quarter lagged proportion of firms in an industry with DA below the γ-th quantile. 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)					
	$\gamma_{pre} = \gamma_{post} = \gamma$			$\gamma_{pre} \neq \gamma_{post}$		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Short-run effects						
$\pi_{-1}(\hat{\gamma}_{pre})$	0.0098	0.0067	0.0072	0.0074	0.0096	0.0105
	(0.0063)	(0.0064)	(0.0069)	(0.0064)	(0.0062)	(0.0065)
$ty \times \pi_{-1}(\hat{\gamma}_{post})$	-0.0007	0.0010	0.0014	0.0012	0.0035	0.0006
	(0.0042)	(0.0034)	(0.0034)	(0.0040)	(0.0041)	(0.0041)
$mbs \times \pi_{-1}(\hat{\gamma}_{post})$	0.0099***	0.0063***	0.0061***	0.0107***	0.0066**	0.0090***
	(0.0026)	(0.0020)	(0.0021)	(0.0025)	(0.0026)	(0.0026)
Panel B: Long-run effects						
$\pi_{-1}(\hat{\gamma}_{pre})$	0.1950	0.1349	0.1416	0.1463	0.1930	0.2078
	(0.1280)	(0.1306)	(0.1386)	(0.1303)	(0.1286)	(0.1340)
$ty \times \pi_{-1}(\hat{\gamma}_{post})$	-0.0130	0.0196	0.0280	0.0232	0.0706	0.0113
	(0.0839)	(0.0677)	(0.0677)	(0.0792)	(0.0835)	(0.0804)
$mbs \times \pi_{-1}(\hat{\gamma}_{post})$	0.1959***	0.1260***	0.1209***	0.2124***	0.1321**	0.1785***
	(0.0581)	(0.0444)	(0.0448)	(0.0580)	(0.0548)	(0.0576)
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Time effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry linear trends	Yes	No	Yes	Yes	No	Yes
Ind. dummy×RGDP	No	Yes	Yes	No	Yes	Yes
Observations	82092	82092	82092	82092	82092	82092
N	3236	3236	3236	3236	3236	3236
$max(T_i)$	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

F Estimating the effects of four asset purchase programs using qualitative measures of LSAPs

Here, we compare the effects of each Fed's asset purchase program by replacing the two aforementioned quantitative measures of LSAPs with four qualitative variables which take the value of one during policy on periods and zero otherwise. Following the literature, we label these policy indicators as QE1 (covering the period 2008Q4 to 2010Q1), QE2 (2010Q4 - 2011Q2), MEP (the maturity extension program of 2011Q3 - 2012Q4), and QE3 (2012Q3 - 2012Q4). Further information on these programs can be found in Table A.2 of Subsection A.1 in this online supplement.

In Subsection F.1, we report the estimated threshold parameters for the PanARDL(2) panel regression model. The estimated net short-run and long-run effects of the various Fed's programs are shown in Subsection F.2. In Subsection F.3, we show the estimation results after correcting for potential small-sample bias.

F.1 Quantile threshold parameter estimates

Table F.34: **Estimated quantile threshold parameters**

Estimates of the quantile threshold parameters from a grid search procedure for the PanARDL(2) model described in equation (10), using qualitative measures of LSAPs. Panel A shows the estimated threshold parameters for the single-threshold panel regression model, where $\gamma_{pre} = \gamma_{post}$. Panel B displays results for the two-threshold model, where $\gamma_{pre} \neq \gamma_{post}$. In column (1) and (2), we use linear time trends or real GDP growth as a proxy for f_t, respectively. Column (3) reports results when including both linear trends and real GDP growth at the same time. 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.

	(1)	(2)	(3)
Panel A:	$\gamma_{pre} = \gamma_{post} = \gamma$		
$\hat{\gamma}$	0.72	0.55	0.56
Panel B:	$\gamma_{pre} \neq \gamma_{post}$		
$\hat{\gamma}_{pre}$	0.56	0.56	0.56
$\hat{\gamma}_{post}$	0.73	0.72	0.72
linear trends	Yes	No	Yes
RGDP growth	No	Yes	Yes

F.2 Short- and long-run effects of four episodes of LSAPs

Table F.35: **FE–TE estimates of the net short-run effects of four episodes of LSAPs on debt to asset ratios of non-financial firms**

Estimates of net short-run effects of the first four asset purchase programs on firms' debt to asset ratios (DA) for the PanARDL(2) model described in equation (10). Net short-run effects are defined as the sum of the estimated coefficients of current and 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.34. All regressions include both firm-specific effects and time effects. Columns (1) and (4) include industry-specific linear time trends, columns (2) and (5) include the interaction of industry dummies and real GDP growth, while columns (3) and (6) include both. $QE1$ and $QE2$ are two indicator variables equal to one during the period 2008Q4 - 2010Q1, and 2010Q4 - 2011Q2 and zero otherwise, respectively. MEP denotes the maturity extension program of 2011Q3 - 2012Q4, while $QE3$ is equal to one between 2012Q3 - 2012Q4; $\pi(\gamma)$ denotes the proportion of firms in an industry with DA below the γ-th quantile. 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)					
	$\gamma_{pre} = \gamma_{post} = \gamma$			$\gamma_{pre} \neq \gamma_{post}$		
	(1)	(2)	(3)	(4)	(5)	(6)
$\pi_{-1}(\hat{\gamma}_{pre})$	0.0173***	0.0135***	0.0215***	0.0199***	0.0136***	0.0212***
	(0.0053)	(0.0048)	(0.0056)	(0.0051)	(0.0046)	(0.0052)
$QE_1 \times \pi_{-1}(\hat{\gamma}_{post})$	0.0140***	0.0066**	0.0105***	0.0189***	0.0092**	0.0156***
	(0.0045)	(0.0032)	(0.0039)	(0.0044)	(0.0038)	(0.0044)
$QE_2 \times \pi_{-1}(\hat{\gamma}_{post})$	0.0081	0.0021	0.0048	0.0114**	0.0043	0.0089*
	(0.0054)	(0.0046)	(0.0050)	(0.0053)	(0.0050)	(0.0053)
$MEP \times \pi_{-1}(\hat{\gamma}_{post})$	-0.0018	-0.0015	-0.0007	0.0019	-0.0036	-0.0012
	(0.0039)	(0.0033)	(0.0034)	(0.0038)	(0.0037)	(0.0038)
$QE_3 \times \pi_{-1}(\hat{\gamma}_{post})$	0.0045	-0.0009	0.0000	0.0069**	0.0029	0.0040
	(0.0035)	(0.0029)	(0.0030)	(0.0033)	(0.0033)	(0.0034)
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Time effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry linear trends	Yes	No	Yes	Yes	No	Yes
Ind. dummy×RGDP	No	Yes	Yes	No	Yes	Yes
Observations	84548	84548	84548	84548	84548	84548
N	3647	3647	3647	3647	3647	3647
$max(T_i)$	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.36: **FE–TE estimates of the long-run effects of four episodes of LSAPs on debt to asset ratios of non-financial firms**

Estimates of long-run effects, defined in equation (11), of the first four asset purchase programs on firms' debt to asset ratios (DA) for the PanARDL(2) model 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 F.34. All regressions include both firm-specific effects and time effects. Columns (1) and (4) include industry-specific linear time trends, columns (2) and (5) include the interaction of industry dummies and real GDP growth, while columns (3) and (6) include both. $QE1$ and $QE2$ are two indicator variables equal to one during the period 2008Q4 - 2010Q1, and 2010Q4 - 2011Q2 and zero otherwise, respectively. MEP denotes the maturity extension program of 2011Q3 - 2012Q4, while $QE3$ is equal to one between 2012Q3 - 2012Q4; $\pi(\gamma)$ denotes the proportion of firms in an industry with DA below the γ-th quantile. 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)					
	$\gamma_{pre} = \gamma_{post} = \gamma$			$\gamma_{pre} \neq \gamma_{post}$		
	(1)	(2)	(3)	(4)	(5)	(6)
$\pi_{-1}(\hat{\gamma}_{pre})$	0.1074***	0.0847***	0.1331***	0.1233***	0.0855***	0.1315***
	(0.0328)	(0.0304)	(0.0351)	(0.0321)	(0.0294)	(0.0328)
$QE_1 \times \pi_{-1}(\hat{\gamma}_{post})$	0.0867***	0.0413**	0.0652***	0.1169***	0.0577**	0.0967***
	(0.0279)	(0.0205)	(0.0242)	(0.0278)	(0.0238)	(0.0276)
$QE_2 \times \pi_{-1}(\hat{\gamma}_{post})$	0.0502	0.0135	0.0297	0.0705**	0.0267	0.0551*
	(0.0334)	(0.0291)	(0.0308)	(0.0332)	(0.0314)	(0.0331)
$MEP \times \pi_{-1}(\hat{\gamma}_{post})$	-0.0109	-0.0095	-0.0046	0.0120	-0.0228	-0.0072
	(0.0244)	(0.0205)	(0.0211)	(0.0234)	(0.0232)	(0.0238)
$QE_3 \times \pi_{-1}(\hat{\gamma}_{post})$	0.0279	-0.0055	0.0000	0.0426**	0.0183	0.0249
	(0.0215)	(0.0182)	(0.0186)	(0.0204)	(0.0209)	(0.0208)
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Time effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry linear trends	Yes	No	Yes	Yes	No	Yes
Ind. dummy×RGDP	No	Yes	Yes	No	Yes	Yes
Observations	84548	84548	84548	84548	84548	84548
N	3647	3647	3647	3647	3647	3647
$max(T_i)$	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

F.3 Robustness of the results to small-T bias

F.3.1 Estimates when firms have at least 8 or 10 observations

Table F.37: **FE–TE estimates of the net short-run effects of four episodes of LSAPs on debt to asset ratios of non-financial firms with at least 8 or 10 observations**

Estimates of net short-run effects of the first four asset purchase programs on firms' debt to asset ratios (DA) for the PanARDL(2) model described in equation (10), focusing on the two-threshold panel regression, where $\gamma_{pre} \neq \gamma_{post}$. The estimated quantile threshold parameters are shown in Table F.34. Net short-run effects are defined as the sum of the estimated coefficients of current and lagged values of the regressor under consideration. All regressions include both firm-specific effects and time effects. Columns (1) and (4) include industry-specific linear time trends, columns (2) and (5) include the interaction of industry dummies and real GDP growth, while columns (3) and (6) include both. In the first (last) three columns, the sample only includes firms with at least 8 (10) observations. $QE1$ and $QE2$ are two indicator variables equal to one during the period 2008Q4 - 2010Q1, and 2010Q4 - 2011Q2 and zero otherwise, respectively. MEP denotes the maturity extension program of 2011Q3 - 2012Q4, while $QE3$ is equal to one between 2012Q3 - 2012Q4; $\pi_{-1}(\gamma)$ denotes the one-quarter lagged proportion of firms in an industry with DA below the γ-th quantile. 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)					
	At least 8 observations			*At least 10 observations*		
	(1)	(2)	(3)	(4)	(5)	(6)
$\pi(\hat{\gamma}_{pre})$	0.0194***	0.0137***	0.0210***	0.0193***	0.0136***	0.0209***
	(0.0051)	(0.0046)	(0.0052)	(0.0051)	(0.0046)	(0.0052)
$QE_1 \times \pi(\hat{\gamma}_{post})$	0.0189***	0.0095**	0.0154***	0.0182***	0.0091**	0.0148***
	(0.0044)	(0.0038)	(0.0044)	(0.0044)	(0.0037)	(0.0044)
$QE_2 \times \pi(\hat{\gamma}_{post})$	0.0113**	0.0040	0.0082	0.0109**	0.0039	0.0079
	(0.0053)	(0.0050)	(0.0053)	(0.0053)	(0.0050)	(0.0053)
$MEP \times \pi(\hat{\gamma}_{post})$	0.0018	-0.0039	-0.0016	0.0016	-0.0040	-0.0018
	(0.0038)	(0.0037)	(0.0038)	(0.0038)	(0.0037)	(0.0038)
$QE_3 \times \pi(\hat{\gamma}_{post})$	0.0069**	0.0025	0.0035	0.0065**	0.0023	0.0033
	(0.0033)	(0.0033)	(0.0034)	(0.0033)	(0.0033)	(0.0034)
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Time effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry linear trends	Yes	No	Yes	Yes	No	Yes
Ind. dummy×RGDP	No	Yes	Yes	No	Yes	Yes
Observations	83290	83290	83290	82038	82038	82038
N	3236	3236	3236	3011	3011	3011
$max(T_i)$	44	44	44	44	44	44
$avg(T_i)$	25.7	25.7	25.7	27.2	27.2	27.2
$med(T_i)$	23	23	23	25	25	25
$min(T_i)$	5	5	5	7	7	7

F.3.2 Half-panel jackknife FE–TE estimates of the short- and long-run effects of four episodes of LSAPs

Table F.38: **Half-panel jackknife FE–TE estimates of the net short-run effects of four episodes 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), for the PanARDL(2) model described in equation (10). Net short-run effects are defined as the sum of the estimated coefficients of current and 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.34. All regressions include both firm-specific effects and time effects. Columns (1) and (4) include industry-specific linear time trends, columns (2) and (5) include the interaction of industry dummies and real GDP growth, while columns (3) and (6) include both. $QE1$ and $QE2$ are two indicator variables equal to one during the period 2008Q4 - 2010Q1, and 2010Q4 - 2011Q2 and zero otherwise, respectively. MEP denotes the maturity extension program of 2011Q3 - 2012Q4, while $QE3$ is equal to one between 2012Q3 - 2012Q4; $\pi_{-1}(\gamma)$ denotes the one-quarter lagged proportion of firms in an industry with DA below the γ-th quantile. 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)					
	$\gamma_{pre} = \gamma_{post} = \gamma$			$\gamma_{pre} \neq \gamma_{post}$		
	(1)	(2)	(3)	(4)	(5)	(6)
$\pi_{-1}(\hat{\gamma}_{pre})$	0.0147**	0.0090	0.0100	0.0082	0.0105*	0.0115*
	(0.0066)	(0.0063)	(0.0070)	(0.0065)	(0.0062)	(0.0066)
$QE_1 \times \pi_{-1}(\hat{\gamma}_{post})$	0.0112**	0.0031	0.0121**	0.0111**	0.0023	0.0112**
	(0.0056)	(0.0045)	(0.0050)	(0.0055)	(0.0052)	(0.0055)
$QE_2 \times \pi_{-1}(\hat{\gamma}_{post})$	0.0092	0.0004	0.0102*	0.0036	-0.0002	0.0072
	(0.0065)	(0.0059)	(0.0060)	(0.0064)	(0.0063)	(0.0063)
$MEP \times \pi_{-1}(\hat{\gamma}_{post})$	0.0032	0.0015	0.0072*	0.0021	-0.0024	0.0022
	(0.0048)	(0.0042)	(0.0042)	(0.0046)	(0.0047)	(0.0046)
$QE_3 \times \pi_{-1}(\hat{\gamma}_{post})$	0.0110**	0.0007	0.0056	0.0104**	0.0068	0.0092**
	(0.0045)	(0.0037)	(0.0038)	(0.0043)	(0.0043)	(0.0043)
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Time effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry linear trends	Yes	No	Yes	Yes	No	Yes
Ind. dummy×RGDP	No	Yes	Yes	No	Yes	Yes
Observations	82092	82092	82092	82092	82092	82092
N	3236	3236	3236	3236	3236	3236
$max(T_i)$	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 F.39: **Half-panel jackknife FE–TE estimates of the long-run effects of four episodes of LSAPs on debt to asset ratios of non-financial firms**

Estimates of long-run effects of LSAPs, defined in equation (11), on firms' debt to asset ratios (DA), for the PanARDL(2) model 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 F.34. All regressions include both firm-specific effects and time effects. Columns (1) and (4) include industry-specific linear time trends, columns (2) and (5) include the interaction of industry dummies and real GDP growth, while columns (3) and (6) include both. $QE1$ and $QE2$ are two indicator variables equal to one during the period 2008Q4 - 2010Q1, and 2010Q4 - 2011Q2 and zero otherwise, respectively. MEP denotes the maturity extension program of 2011Q3 - 2012Q4, while $QE3$ is equal to one between 2012Q3 - 2012Q4;; $\pi(\gamma)$ denotes the proportion of firms in an industry with DA below the γ-th quantile. 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)					
	$\gamma_{pre} = \gamma_{post} = \gamma$			$\gamma_{pre} \neq \gamma_{post}$		
	(1)	(2)	(3)	(4)	(5)	(6)
$\pi_{-1}(\hat{\gamma}_{pre})$	0.2936**	0.1802	0.1986	0.1634	0.2104	0.2285*
	(0.1381)	(0.1312)	(0.1436)	(0.1322)	(0.1299)	(0.1364)
$QE_1 \times \pi_{-1}(\hat{\gamma}_{post})$	0.2237*	0.0626	0.2397**	0.2212*	0.0452	0.2218*
	(0.1162)	(0.0914)	(0.1052)	(0.1156)	(0.1048)	(0.1159)
$QE_2 \times \pi_{-1}(\hat{\gamma}_{post})$	0.1828	0.0086	0.2021*	0.0717	-0.0039	0.1433
	(0.1323)	(0.1174)	(0.1222)	(0.1281)	(0.1272)	(0.1281)
$MEP \times \pi_{-1}(\hat{\gamma}_{post})$	0.064	0.0294	0.1419*	0.0419	-0.0481	0.0444
	(0.0964)	(0.0840)	(0.0860)	(0.0915)	(0.0941)	(0.0926)
$QE_3 \times \pi_{-1}(\hat{\gamma}_{post})$	0.2185**	0.0131	0.1112	0.2072**	0.1358	0.1820**
	(0.0932)	(0.0749)	(0.0776)	(0.0884)	(0.0876)	(0.0887)
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Time effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry linear trends	Yes	No	Yes	Yes	No	Yes
Ind. dummy×RGDP	No	Yes	Yes	No	Yes	Yes
Observations	82092	82092	82092	82092	82092	82092
N	3236	3236	3236	3236	3236	3236
$max(T_i)$	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

G Estimation results using firm-specific debt capacity indicators

In this section, we report estimates of the effects of LSAPs on firm capital structure using an identification strategy which exploits variation in debt capacity across firms within each industry. To this end, we interact our measures of LSAPs with one-quarter lag of a firm-specific debt capacity indicator, $d_{is,t}(\gamma)$, defined as a dummy variable equal to one if firm i's debt to assets ratio (DA) is below the γ^{th} quantile of the cross-sectional distribution of DA across all firms in industry s at time t. Specifically,

$$d_{is,t}(\gamma) = \mathcal{I}\left[y_{is,t} < g_{st}(\gamma)\right], \tag{G.9}$$

where $y_{is,t}$ is the ratio of debt to assets of firm i in industry s for quarter t, and $\mathcal{I}(A)$ is an indicator variable that takes the value of one if A is true and zero otherwise.

Because $d_{is,t}(\gamma)$ varies across firms, we can now include industry-time fixed effects, ϕ_{st}, in the panel regression model without the need of imposing restrictions of the type described in equation (4) in Subsection 3.2 of the paper. In this case, because of industry-time fixed effects, we do not include industry-specific variables (such as industry leverage and industry growth) among the regressors and consider only firm-specific variables.

For comparison, we also consider the case where the regression model includes both firm- and industry-specific variables, replacing the industry-time fixed effects, ϕ_{st}, with time effects and the interaction of industry dummies and selected macro-variables, namely $\phi_{st} = \delta_t + \boldsymbol{\phi}_s' \mathbf{f}_t$.

G.1 Quantile threshold parameter estimates

As before, for a given choice of the lag order, p, for the panel ARDL specification, we estimate the quantile threshold parameter, γ, by grid search over the values of γ in the range $0.25 \leq \gamma_{pre}, \gamma_{post} \leq 0.9$ in increments of 0.01. For $p = 2$, the estimates of γ are reported in Table G.40. Panel A shows the estimated thresholds when our measure of LSAPs, q_t, is the (scaled) amount of U.S. Treasuries and agency MBS purchased by the Fed.[38] Panel B reports the estimates when the PanARDL(2) model includes two separate measures of LSAPs, namely MBS and Treasury purchases. Panel C displays results when including four qualitative measures of LSAPs, namely a set of dummy variables which take the value of one during policy on periods and zero otherwise.

When using the firm-specific debt capacity indicator, we find that the estimated threshold parameters are either identical or extremely close before and after the introduction of LSAPs. Therefore, here we focus on the single-threshold parameter case, where $\gamma_{pre} = \gamma_{post} = \gamma$.

The estimated quantile threshold parameter, $\hat{\gamma}$, is around 0.69 in all PanARDL(2) regres-

[38] See subsection 2.1 in the main paper for further details.

sions when using the quantitative measures of LSAPs, regardless of whether the model includes industry-time fixed effects (as in column (1)) or time effects and macro-variables interacted with industry dummies (columns (2) to (4)). We estimate a similar threshold when using the qualitative measures of LSAPs. In this case the estimated threshold parameter varies between 0.65 and 0.69, as shown in Panel C.

Table G.40: **Estimated quantile threshold parameters**

Estimates of the quantile threshold parameters from a grid search procedure for the single-threshold PanARDL(2) model. Panel A shows results for the case where our measure of LSAPs is the (scaled) amount of U.S. Treasuries and agency MBS purchased by the Fed. Panel B displays results when separating the effects of MBS from Treasury purchases. Panel C displays results for the qualitative measures of LSAPs, a set of dummy variables which take the value of one during policy on periods and zero otherwise. In column (1) the regression model does not include industry-specific regressors, noting that ϕ_{st} is unconstrained. In the remaining columns, the regression model includes both firm- and industry-specific regressors. Column (2), (3), and (4) report results when including industry linear trends, real GDP growth, or both as a proxy for f_t, respectively. 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.

	(1)	(2)	(3)	(4)
Panel A:	*Tot. MBS and TY*			
$\hat{\gamma}$	0.69	0.69	0.69	0.69
Panel B:	*MBS versus TY*			
$\hat{\gamma}$	0.69	0.69	0.69	0.69
Panel C:	*4 QE episodes*			
$\hat{\gamma}$	0.69	0.65	0.65	0.65
Time effects	No	Yes	Yes	Yes
Ind. $\times$ quarter	Yes	No	No	No
Ind. $\times$ lin. trend	No	Yes	No	Yes
Ind. $\times$ RGDP gr.	No	No	Yes	Yes

Given the estimated threshold parameters, in the next sections we present the estimates of the policy parameters of interest. In particular, in Section G.2, we report results when q_t is the (scaled) total amount of MBS and Treasuries purchased by the Fed. In Section G.3, we separate the effects of MBS from Treasury purchases. In Section G.4, we evaluate the first four large-scale asset purchases by the Fed, using qualitative measures of LSAPs.

G.2 Estimation results when q_t measures the total size of LSAPs

Table G.41 displays the estimates of the net short-run (SR) effects defined as the sum of estimated coefficients of current and lagged values of the regressor under consideration. In column (1), the regression model includes firm-specific fixed effects and industry-time fixed effects. The estimates under columns (2) to (4) are based on PanARDL(2) regressions that include both firm-specific fixed effects and time effects as well as the interaction of selected macro-variables with industry dummies.

The estimates of the policy SR effects ($LSAP \times d_{-1}(\hat{\gamma})$ in Table G.41) are positive and highly statistically significant under all specifications, although the magnitude is rather small. The estimates for the other regressors are very much in line with the results obtained using the industry-specific debt capacity indicators ($\pi_{st}(\gamma)$), shown in Table 2 of the paper. Interestingly, the estimated SR effects are very close regardless of whether we use industry-time fixed effects, ϕ_{st}, or its restricted version with time effects and the interaction of industry dummies and selected macro-variables. This further corroborates the identification strategy described in Subsection 3.2.

Table G.42 reports the estimates of the long-run (LR) effects of LSAPs and other determinants of firms' debt to asset ratios. The policy long-run effects are defined by equation (11), in Section 4. Also in this case, we find that the effects of LSAPs on firm capital structure are long-lasting.

Table G.41: **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 the single-threshold PanARDL(2) model, using the firm-specific debt capacity indicator, $d_{is,t}(\gamma)$, defined by (G.9). Net short-run effects are defined as the sum of the estimated coefficients of current and lagged values of the regressor under consideration. The estimated quantile threshold parameters are shown in Panel A of Table G.40. All regressions include firm-specific fixed effects. Column (1) includes industry-time fixed effects. Columns (2) to (4) include time effects and the interaction of industry dummies with either linear trend, real GDP growth, or both. $LSAP$ is the (scaled) amount of U.S. Treasuries and agency MBS purchased by the Fed; $d_{-1}(\gamma)$ denotes the one-quarter lagged firm-specific debt capacity indicator. 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)
$d_{-1}(\hat{\gamma})$	-0.0118***	-0.0122***	-0.0121***	-0.0122***
	(0.0014)	(0.0014)	(0.0014)	(0.0014)
$LSAP \times d_{-1}(\hat{\gamma})$	0.0041***	0.0040***	0.0040***	0.0040***
	(0.0006)	(0.0007)	(0.0007)	(0.0007)
Lagged DA	0.8228***	0.8205***	0.8231***	0.8205***
	(0.0063)	(0.0063)	(0.0063)	(0.0063)
Cash to assets	-0.0365***	-0.0365***	-0.0366***	-0.0365***
	(0.0030)	(0.0030)	(0.0029)	(0.0030)
PPE to assets	0.0221***	0.0229***	0.0221***	0.0228***
	(0.0046)	(0.0047)	(0.0046)	(0.0047)
Size	0.0033***	0.0033***	0.0035***	0.0033***
	(0.0008)	(0.0008)	(0.0007)	(0.0008)
Industry leverage		0.0558***	0.0482***	0.0525***
		(0.0071)	(0.0060)	(0.0073)
Industry growth		-0.0860***	-0.1202***	-0.0921***
		(0.0207)	(0.0203)	(0.0216)
Fixed effects	Yes	Yes	Yes	Yes
Time effects	No	Yes	Yes	Yes
Industry × quarter	Yes	No	No	No
Industry × linear trend	No	Yes	No	Yes
Industry × RGDP	No	No	Yes	Yes
Observations	84548	84548	84548	84548
N	3647	3647	3647	3647
$max(T_i)$	44	44	44	44
$avg(T_i)$	23.2	23.2	23.2	23.2
$med(T_i)$	19	19	19	19
$min(T_i)$	2	2	2	2

Table G.42: **Estimates of the long-run effects of LSAPs on debt to asset ratios of non-financial firms**

Estimates of long-run effects of LSAPs, defined in equation (11), on firms' debt to asset ratios (DA) as well as the effects of both firm- and industry-specific variables on DA, for the single-threshold PanARDL(2) model, using the firm-specific debt capacity indicator, $d_{is,t}(\gamma)$, defined by (G.9). The estimated quantile threshold parameters are shown in Panel A of Table G.40. All regressions include firm-specific fixed effects. Column (1) includes industry-time fixed effects. Columns (2) to (4) include time effects and the interaction of industry dummies with either linear trend, real GDP growth, or both. $LSAP$ is the (scaled) amount of U.S. Treasuries and agency MBS purchased by the Fed; $d_{-1}(\gamma)$ denotes the one-quarter lagged firm-specific debt capacity indicator. 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)
$d_{-1}(\hat{\gamma})$	-0.0665***	-0.0680***	-0.0684***	-0.0682***
	(0.0065)	(0.0065)	(0.0066)	(0.0065)
$LSAP \times d_{-1}(\hat{\gamma})$	0.0230***	0.0224***	0.0229***	0.0225***
	(0.0036)	(0.0036)	(0.0037)	(0.0036)
Cash to assets	-0.2062***	-0.2032***	-0.2067***	-0.2036***
	(0.0165)	(0.0163)	(0.0163)	(0.0163)
PPE to assets	0.1248***	0.1274***	0.1249***	0.1272***
	(0.0263)	(0.0261)	(0.0259)	(0.0261)
Size	0.0188***	0.0183***	0.0200***	0.0184***
	(0.0042)	(0.0042)	(0.0041)	(0.0042)
Industry leverage		0.3110***	0.2724***	0.2928***
		(0.0378)	(0.0321)	(0.0389)
Industry growth		-0.4793***	-0.6794***	-0.5130***
		(0.1161)	(0.1168)	(0.1216)
Fixed effects	Yes	Yes	Yes	Yes
Time effects	No	Yes	Yes	Yes
Industry ×quarter	Yes	No	No	No
Industry × linear trend	No	Yes	No	Yes
Industry × RGDP	No	No	Yes	Yes
Observations	84548	84548	84548	84548
N	3647	3647	3647	3647
$max(T_i)$	44	44	44	44
$avg(T_i)$	23.2	23.2	23.2	23.2
$med(T_i)$	19	19	19	19
$min(T_i)$	2	2	2	2

G.3 Separating the effects of MBS and Treasury purchases

In this subsection, we separate the effects of Treasury and MBS purchases. Panel A and B of Table G.43 report the policy SR and LR effects, respectively.

When using $d_{is,t}(\gamma)$, we find that both Treasury and MBS purchases have significant impacts on firm leverage but the effects are now stronger for Treasuries. The opposite holds when using $\pi_{st}(\gamma)$. Part of this difference can be explained by the different nature of the two indicators. The identification strategy based on $d_{is,t}(\gamma)$ exploits cross-firm variation within an industry, implying that firms which are not over-leveraged should benefit more from LSAPs relative to peers in the same industry. Instead, estimation based on $\pi_{st}(\gamma)$ exploits cross-industry variation, suggesting that firms in less leveraged industries should benefit more, thus allowing for spillover effects within an industry. Taken together, these results suggest that both MBS and Treasury purchases can facilitate firms' access to external financing, although the magnitude of the effects is rather small.

Table G.43: **Net short-run and long-run effects of large-scale MBS and Treasury purchases on debt to asset ratios of non-financial firms**

Panel A (Panel B) reports the net short-run (long-run) effects of MBS and Treasury purchases on firms' debt to asset ratios (DA), for the single-threshold PanARDL(2) model, using the firm-specific debt capacity indicator, $d_{is,t}(\gamma)$, defined by G.9. The estimated quantile threshold parameters are shown in Panel B of Table G.40. All panel regressions include firm-specific effects. Column (1) includes industry-time fixed effects. Columns (2) to (4) include time effects and the interaction of industry dummies with linear trend, real GDP growth, or both. *ty* and *mbs* denote the (scaled) amount of U.S. Treasuries and agency MBS purchased by the Fed, respectively; $d_{-1}(\gamma)$ denotes the one-quarter lagged firm-specific debt capacity indicator, defined in equation (G.9). 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)
	Panel A: Short-run effects			
$d_{-1}(\hat{\gamma})$	-0.0122***	-0.0126***	-0.0125***	-0.0128***
	(0.0014)	(0.0014)	(0.0014)	(0.0023)
$ty \times d_{-1}(\hat{\gamma})$	0.0062***	0.0062***	0.0062***	0.0064***
	(0.0012)	(0.0012)	(0.0012)	(0.0022)
$mbs \times d_{-1}(\hat{\gamma})$	0.0034***	0.0034***	0.0034***	0.0033**
	(0.0008)	(0.0008)	(0.0008)	(0.0015)
	Panel B: Long-run effects			
$d_{-1}(\hat{\gamma})$	-0.0687***	-0.0701***	-0.0705***	-0.0714***
	(0.0066)	(0.0065)	(0.0066)	(0.0110)
$ty \times d_{-1}(\hat{\gamma})$	0.0351***	0.0342***	0.0351***	0.0358***
	(0.0066)	(0.0066)	(0.0068)	(0.0122)
$mbs \times d_{-1}(\hat{\gamma})$	0.0191***	0.0186***	0.0189***	0.0186**
	(0.0044)	(0.0044)	(0.0044)	(0.0083)
Fixed effects	Yes	Yes	Yes	Yes
Time effects	No	Yes	Yes	Yes
Industry × quarter	Yes	No	No	No
Industry × linear trend	No	Yes	No	Yes
Industry × RGDP	No	No	Yes	Yes
Observations	84548	84548	84548	84548
N	3647	3647	3647	3647
$max(T_i)$	44	44	44	44
$avg(T_i)$	23.2	23.2	23.2	23.2
$med(T_i)$	19	19	19	19
$min(T_i)$	2	2	2	2

G.4 Estimating the effects of the first four asset purchase programs

We now compare the effects of each Fed's program separately by replacing the two aforementioned quantitative measures of LSAPs with four qualitative variables which take the value of one during policy on periods and zero otherwise. More details on each program can be found in Table A.2.

The estimates of policy SR and LR effects can be found in Panel A and B of Table G.44, respectively. We find that QE1, QE2, and QE3 had positive and statistically significant effects on firm leverage, both in the short- and the long-term. When using $d_{is,t}(\gamma)$, differences in magnitudes across these programs are less marked. MEP continues to have the lowest impact, and is generally non significant at the 5 per cent level.

Table G.44: **Net short-run and long-run effects of of large-scale MBS and Treasury purchases on debt to asset ratios of non-financial firms**

Panel A (Panel B) reports net short-run (long-run) effects of the first four asset purchase programs by Fed on firms' debt to asset ratios (DA), for the single-threshold PanARDL(2) model using the firm-specific debt capacity indicator, $d_{is,t}(\gamma)$, defined by (G.9). Net short-run effects are defined as the sum of the estimated coefficients of current and lagged values of the regressor under consideration. The long-run effects are defined in equation (11). The estimated quantile threshold parameters are shown in Panel C of Table G.40. All regressions include firm-specific fixed effects. Column (1) includes industry-time fixed effects. Columns (2) to (4) include time effects and the interaction of industry dummies with either linear trend, real GDP growth, or both. $QE1$ and $QE2$ are two indicator variables equal to one during the period 2008Q4 - 2010Q1, and 2010Q4 - 2011Q2 and zero otherwise, respectively. MEP denotes the maturity extension program of 2011Q3 - 2012Q4, while $QE3$ is equal to one between 2012Q3 - 2012Q4; $d_{-1}(\gamma)$ denotes the one-quarter lagged firm-specific debt capacity indicator. 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)
	Panel A: Short-run effects			
$d_{-1}(\hat{\gamma})$	-0.0115***	-0.0110***	-0.0109***	-0.0110***
	(0.0014)	(0.0014)	(0.0014)	(0.0014)
$QE_1 \times d_{-1}(\hat{\gamma})$	0.0072***	0.0067***	0.0067***	0.0068***
	(0.0016)	(0.0015)	(0.0015)	(0.0015)
$QE_2 \times d_{-1}(\hat{\gamma})$	0.0092***	0.0086***	0.0087***	0.0086***
	(0.0021)	(0.0020)	(0.0020)	(0.0020)
$MEP \times d_{-1}(\hat{\gamma})$	0.0018	0.0024*	0.0025*	0.0024*
	(0.0015)	(0.0015)	(0.0015)	(0.0015)
$QE_3 \times d_{-1}(\hat{\gamma})$	0.0056***	0.0043***	0.0044***	0.0043***
	(0.0013)	(0.0013)	(0.0013)	(0.0013)
	Panel B: Long-run effects			
$d_{-1}(\hat{\gamma})$	-0.0646***	-0.0615***	-0.0620***	-0.0616***
	(0.0066)	(0.0066)	(0.0066)	(0.0066)
$QE_1 \times d_{-1}(\hat{\gamma})$	0.0402***	0.0376***	0.0381***	0.0378***
	(0.0090)	(0.0085)	(0.0086)	(0.0085)
$QE_2 \times d_{-1}(\hat{\gamma})$	0.0515***	0.0482***	0.0491***	0.0481***
	(0.0119)	(0.0112)	(0.0114)	(0.0112)
$MEP \times d_{-1}(\hat{\gamma})$	0.0102	0.0137*	0.0140*	0.0137*
	(0.0086)	(0.0083)	(0.0084)	(0.0083)
$QE_3 \times d_{-1}(\hat{\gamma})$	0.0316***	0.0240***	0.0251***	0.0242***
	(0.0074)	(0.0071)	(0.0073)	(0.0071)
Fixed effects	Yes	Yes	Yes	Yes
Time effects	No	Yes	Yes	Yes
Industry ×quarter	Yes	No	No	No
Industry × linear trend	No	Yes	No	Yes
Industry × RGDP	No	No	Yes	Yes
Observations	84548	84548	84548	84548
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$min(T_i)$	2	2	2	2